Essays in Cryptocurrency Markets

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Abstract

This thesis examines how the cryptocurrency market responds to major external announcements, with particular attention to the heterogeneity of that response across asset classes, individual cryptocurrencies, and trading platforms. Through three empirical chapters, it investigates whether this market absorbs external pressure uniformly or redistributes value, volatility, and liquidity differently across its internal structure. Chapter 2 examines market reactions to the EU's Markets in Crypto-Assets regulatory proposal using a difference-in-differences framework across six asset categories. Unidentifiable-issuer cryptocurrencies exhibit strong positive responses while DeFi protocols decline despite exemption, and issuer identifiability emerges as a priced characteristic with a 2.1 percentage point divergence between identifiable and unidentifiable issuer cryptocurrencies. These results demonstrate that regulatory accountability, not just asset function, shapes crypto-asset valuations under comprehensive regulatory frameworks. Chapter 3 investigates volatility transmission among eight major cryptocurrencies using time-varying parameter vector autoregression with Diebold-Yilmaz spillover indices. Ethereum emerges as the dominant net volatility transmitter, surpassing Bitcoin, while MiCA exerts stronger structural impact on transmission dynamics than the Russia-Ukraine War or COVID-19, indicating that crypto-specific regulation now dominates traditional macroeconomic and geopolitical factors in shaping internal market risk. Chapter 4 examines liquidity dynamics between centralised and decentralised exchanges across three regulatory jurisdictions using two-way fixed effects panel regression. DEX trading activity declines relative to CEX across all three events, while price impact liquidity improves for DEX-linked assets in two of the three cases, confirming that liquidity dimensions respond differently under regulatory pressure and that centralised oversight produces measurable effects on decentralised venues even when formally exempt. Chapter 5 concludes the thesis by summarising key findings, discussing limitations, and identifying directions for future research.

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Declaration

I hereby declare that this thesis is an original work conducted by me, Sarah Almershed, under the supervision of Doctor Konstantinos Baltas and Professor Franco Fiordelisi at Essex Business School, University of Essex. This research was undertaken in fulfilment of the requirements for the degree of Doctor of Philosophy in Finance.

I confirm that the work presented in this thesis is my own and has not been submitted for any other degree or professional qualification at any other academic institution. Where information has been derived from other sources, I confirm that this has been duly indicated in the thesis. All material and results that are not original to this work have been properly cited and referenced in accordance with academic rules and ethical conduct. Any errors or omissions in this work are my own.

During the writing of this thesis, I made use of generative AI to improve the readability and accuracy of the written English. The tools used were Claude (Anthropic, 2026) and [ChatGPT (OpenAI, 2026)]. Their role was limited to proofreading and refining wording. They did not contribute to the research design, data, analysis, or findings. I checked every suggested change before accepting it and remain fully responsible for the content of this thesis.

Sarah Almershed

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CHAPTER 1

1. Introduction

1.1. Thesis Introduction

This thesis examines how the cryptocurrency market responds to major external announcements, with particular attention to the heterogeneity of that response across asset classes, individual cryptocurrencies, and trading platforms. Through three empirical chapters, it investigates whether this market absorbs external pressure uniformly or redistributes value, volatility, and liquidity differently across its internal structure.

The cryptocurrency market operated for years beyond the reach of formal oversight. It was volatile, fragmented, and largely ungoverned, with participants trading at their own risk on platforms that offered no guarantees (Makarov and Schoar, 2020). For much of this period, scepticism about its long-term viability remained strong, and cryptocurrency was widely regarded as a speculative novelty rather than a serious instrument for portfolio diversification (Baur et al., 2018). This changed with the onset of the COVID-19 pandemic, which accelerated institutional adoption and expanded market capitalisation beyond $2.7 trillion US Dollars. Today, equity funds hold cryptocurrency positions, corporations list digital assets on their balance sheets, and El Salvador has adopted Bitcoin as legal tender. The market that once existed on the margins now operates within the perimeter of mainstream finance, and with that integration has come regulatory attention. In September 2020, the European Union announced the Markets in Crypto-Assets regulation (MiCA), the first comprehensive framework to govern a broad spectrum of digital assets across a major economic bloc. MiCA represented the first attempt by a major jurisdiction to regulate diverse crypto-assets under a unified structure, and

its announcement provides a setting for examining how markets process regulatory information.

Prior research has examined aggregate market responses to regulatory announcements (Auer and Claessens, 2018; Chokor and Alfieri, 2021), leaving gaps in understanding how policies affect diverse crypto-asset classes simultaneously (Corbet et al., 2020a). Centralised exchanges face compliance obligations directly because they are identifiable and custodial, while decentralised platforms operating through smart contracts remain comparatively outside the scope of most current frameworks (Giménez Roche et al., 2025). Recent work has called for analysing crypto-assets individually rather than as a homogeneous market (Goodell et al., 2023; Karim et al., 2022; Yousaf and Yarovaya, 2022a, 2022b). This thesis examines the crypto ecosystem across three dimensions: how regulatory classification reshapes relative asset performance, how individual cryptocurrencies differ in their roles as transmitters and receivers of volatility, and how centralised and decentralised trading infrastructure respond differently when regulation arrives. Because each empirical chapter examines different events, the sample periods differ across chapters. The post-COVID-19 period brought a rapid succession of regulatory initiatives, geopolitical events and structural changes in crypto markets, and the sample periods were extended where needed to capture these developments. The sample periods also reflect data availability, which became increasingly limited over time, particularly for the exchange-level and token-level data required in Chapter 4.

Chapter 2 examines market reactions to MiCA's proposal across six crypto-asset categories, namely identifiable-issuer cryptocurrencies, unidentifiable-issuer cryptocurrencies, stablecoins, DeFi protocols, NFTs, and utility tokens. Prior work on cryptocurrency regulation has focused predominantly on Bitcoin (Corbet et al., 2020a), and no prior study has applied causal identification methods to a comprehensive regulatory framework across simultaneously observed heterogeneous asset classes, nor tested whether regulatory classification itself

becomes a priced characteristic. The chapter introduces the first empirical separation of cryptocurrencies by issuer identifiability status, a classification that maps directly to MiCA's regulatory scope and extends prior work that has distinguished crypto-assets by function or technology but not by the accountability structure of their issuers (Howell et al., 2020). Using a difference-in-differences framework with fixed effects around MiCA's September 2020 announcement, performance is measured through returns, abnormal returns, and cumulative abnormal returns over one-, three-, and five-day windows, benchmarked against a market-capitalisation-weighted index of 405 cryptocurrencies following Liu et al. (2022), spanning 2018 to 2023. The findings reveal that unidentifiable-issuer cryptocurrencies exhibit strong positive responses while DeFi protocols decline despite exemption, demonstrating that exemption alone does not determine market reaction. Issuer identifiability emerges as a priced characteristic, with a 2.1 percentage point divergence between identifiable and unidentifiable issuer cryptocurrencies despite identical functionality, establishing that regulatory accountability structures, not just asset function, shape how markets value crypto-assets. Regulated and exempt classes display consistent behavioural patterns within their respective groups, consistent with investors pricing MiCA's classification logic before any implementation or enforcement. For policymakers, the results demonstrate that regulatory spillovers operate through ecosystem dependencies, meaning formal exemptions offer incomplete protection when assets depend on regulated infrastructure. For investors, issuer identifiability as a priced characteristic suggests that regulatory accountability structures may become an increasingly relevant factor in portfolio valuation as formal oversight expands. Methodologically, the chapter uses a difference-in-differences design estimated with two-way fixed effects across several return measures, using daily data from 1 January 2018 to 21 May 2023.

Chapter 3 investigates volatility transmission dynamics among major cryptocurrencies and examines how different types of external announcements reshape market interconnections. The literature examining internal dynamics of the crypto ecosystem and their evolution over time requires further examination (Kumar et al., 2022), with three gaps remaining unaddressed: limited comparative analysis of volatility measures in connectedness research (Zhang and Li, 2020; Shen et al., 2024), uncertainty over whether Bitcoin retains market leadership as Ethereum gains influence (Bouri et al., 2022), and the absence of direct comparison across pandemic, geopolitical, and regulatory events within a unified framework (Umar et al., 2021; Khalfaoui et al., 2023). The chapter contributes by providing the first systematic comparison of price-based and idiosyncratic volatility measures in cryptocurrency connectedness analysis, incorporating the World Uncertainty Index in spillover dynamics for the first time rather than as a control variable (Roche et al., 2025; Hodula, 2025), and comparing COVID-19, the Russia-Ukraine War, the Gaza War, and MiCA within a single staggered difference-in-differences framework. Volatility is measured using Parkinson Range-Based Volatility, GARCH(1,1), and two idiosyncratic volatility specifications constructed using Liu et al.'s (2022) factors, with connectedness estimated via time-varying parameter vector autoregression with Diebold-Yilmaz spillover indices across eight cryptocurrencies over 2018 to 2024, extending prior literature that largely ends in late 2022. The findings reveal that volatility measure choice substantially affects conclusions, with price-based measures indicating total connectedness of approximately 67 per cent while idiosyncratic measures indicate 43 to 48 per cent. Ethereum has emerged as the dominant net volatility transmitter across three of four measures, surpassing Bitcoin's historically assumed centrality, while Ripple consistently functions as the primary net receiver. MiCA exerts the largest structural impact among all announcements examined, with Wald statistics substantially exceeding those of the Russia-Ukraine War and COVID-19, while the Gaza War produces statistically insignificant effects. The finding that crypto-specific

regulation now produces stronger structural effects than major armed conflicts suggests that the cryptocurrency market has matured and its sensitivity hierarchy has shifted. For investors, Ethereum's emergence as dominant transmitter has direct implications for portfolio risk assessment and hedging strategies. For researchers, the divergence across volatility measures implies that methodological choices affect substantive conclusions in ways the literature has not yet fully confronted. The chapter estimates spillover indices within the Diebold and Yilmaz (2012) framework, relates net spillovers to global risk factors through robust OLS regressions, and compares events using a staggered difference-in-differences design with the Sun and Abraham (2021) estimator, using daily data from 1 January 2018 to 12 July 2024.

Chapter 4 examines liquidity dynamics between centralised and decentralised exchanges in response to regulatory announcements across three jurisdictions. The chapter applies a difference-in-differences design to CEX-linked and DEX-linked token indices, with baseline and event window specifications, using daily data from 1 January 2020 to 31 October 2025. We find crypto regulation does not produce uniform effects across market segments (Corbet et al., 2020a; Huang, 2024), and even assets outside direct regulatory scope can be affected through infrastructure dependence and liquidity channels (Makarov and Schoar, 2020; Farag et al., 2025). Prior work on CEX-DEX linkages has focused on listing events and liquidity provision conditions rather than regulatory announcements as a driver of divergence (Aspris et al., 2021; Griffith and Clancey-Shang, 2023). The chapter constructs CEX-linked and DEX-linked indices from the top 15 and top 12 tokens by market capitalisation respectively, classified by ecosystem character, with daily data from Coin Metrics covering January 2020 to October 2025. Three regulatory events are examined: MiCA as a compliance framework, China's 2021 cryptocurrency ban as prohibition, and the US GENIUS Act as regulatory integration. Liquidity is decomposed into trading intensity, price impact, and transaction costs following Amihud (2002), Roll (1984), and Huang (2024), using two-way

fixed effects panel regressions across event windows of one, three, five, and thirty days. The findings show that DEX trading activity declines relative to CEX across all three events in the sustained post-announcement period, regardless of the form or intensity of the regulatory approach. In the short term, the European and Chinese announcements are associated with a temporary relative increase in DEX-linked trading activity, but this does not persist. Price-impact liquidity improves for DEX-linked assets in two of the three announcements despite the concurrent decline in trading activity, confirming that liquidity dimensions do not move together under regulatory pressure. For policymakers, exemption from direct regulatory oversight does not redirect participants away from centralised exchanges when oversight increases, and regulatory announcements affecting one venue type produce measurable responses in the other. Future research could examine how compliance costs and governance requirements shape longer-run responses as implementation of these frameworks progresses.

This thesis contributes to our understanding of how the cryptocurrency market responds to external announcements. Across three chapters, we show that the market does not respond as a single unit. Returns, volatility and liquidity respond differently depending on how assets are classified, which assets transmit risk, and where trading takes place. The thesis extends the regulatory finance literature beyond Bitcoin and aggregate market responses, introduces issuer identifiability as a priced characteristic, compares price-based and idiosyncratic volatility measures in connectedness analysis, and shows that regulatory announcements, not only listing events, are associated with differences between centralised and decentralised venues. MiCA runs through all three chapters, allowing us to examine the same regulatory event through its effects on returns, volatility and liquidity.

This thesis makes three contributions. First, it shows that the market treats a legal category as a financial one. MiCA distinguishes crypto-assets by whether an identifiable issuer

stands behind them, a line drawn for accountability purposes, and we show that the market prices this distinction at the proposal stage, before any rule applies. Issuer identifiability therefore emerges as a priced characteristic, and regulatory classification becomes a dimension along which crypto-assets are valued. Second, it places regulation on the same scale as major global events. By examining MiCA alongside COVID-19, the Russia-Ukraine War and the Gaza War within one framework, we show that a regulatory proposal is associated with a larger change in how volatility transmits across the market than a pandemic or a war, reversing the assumption that regulation is a secondary shock. Third, it shows that regulating centralised exchanges does not push activity towards decentralised ones. Across three jurisdictions with different regulatory designs, DEX trading activity declines relative to CEX in the sustained post-announcement period, and exempt assets that depend on regulated infrastructure decline with it. Exemption is therefore not insulation, and regulatory boundaries do not contain market effects. Taken together, the thesis documents how an unregulated market responds to its first comprehensive regulatory framework, and shows that it differentiates by status, by role and by venue before a single rule applies.

CHAPTER 2

2. Crypto Asset Market Reaction to the European Union's Regulation

2.1 Introduction

The European Union's Markets in Crypto-Assets (MiCA) regulation, proposed in 2020 and approved in 2023, represents the first comprehensive policy framework to regulate diverse crypto-assets within a unified economic bloc. We examine MiCA's impact as a single regulatory regime implemented across a major jurisdiction, providing a distinct setting to assess how coordinated policy can influence global crypto markets. This framework marks a departure from the historically limited and fragmented cryptocurrency regulation that has constrained both early and recent studies (Gordon and Marthinsen, 2023). Prior regulatory approaches primarily relied on outright bans (Auer and Claessens, 2018; Borri and Shakhnov, 2020; Copestake et al., 2023; Griffith and Clancey-Shang, 2023), taxation frameworks (Cong et al., 2023), specific crypto exchange policy (Galati and De Blasis, 2025), or restrictive policies (Borri and Shakhnov, 2020; Corbet et al., 2019; Chokor and Alfieri, 2021). While several studies explore individual regulatory actions, a clear gap persists in crypto-assets governance given their borderless nature and the supervision challenges they pose (Gordon and Marthinsen, 2023; Financial Stability Board; United States Securities and Exchange Commission; Chokor and Alfieri, 2021; Werbach, 2018). Accordingly, MiCA addresses this gap through a classification system based on function and issuer identifiability, enabling us to evaluate how different crypto-assets respond to a single regulatory framework.

MiCA's framework assigns distinct regulatory treatments across crypto-asset classes while exempting others. While there exist several crypto classes in the ecosystem, the mainstream assets include cryptocurrencies, stablecoins, utility tokens, decentralised finance (DeFi) protocols, and non-fungible tokens (NFTs). MiCA applies its rules selectively based on issuer identifiability. Therefore, cryptocurrencies and utility tokens with identifiable issuers fall under MiCA and must operate through regulated Crypto-Asset Service Providers (CASPs), while those without identifiable issuers remain outside direct regulation (Conlon et al., 2024; Regulation (EU) 2023/1114, Recital 22). Stablecoins face the most stringent obligation and are classified into asset-referenced tokens (ARTs) and e-money tokens (EMTs) (Annunziata, 2023; Ferreira and Sandner, 2021). Fully decentralised DeFi protocols, NFTs, and cryptocurrencies with unidentified issuers, such as Bitcoin, are exempt from MiCA's framework and oversight. By formalising issuer identifiability as a criterion for regulatory accountability, MiCA introduces a new dimension that could itself become a priced attribute in crypto-asset markets. This differentiated structure offers a unique opportunity to assess whether crypto markets can distinguish between tailored regulatory classifications or react uniformly across asset categories.

Following earlier studies, we focus on official announcements rather than media coverage to isolate genuine regulatory effects. While extensive research documents crypto markets' responsiveness to social media sentiment (Naeem et al., 2020; Shen et al., 2019; Kraaijeveld and Smedt, 2020; Maître et al., 2025), Auer and Claessens (2018) show that cryptocurrency markets react primarily to formal regulatory communications, particularly announcements clarifying legal status or enforcement actions, while general warnings or informal commentary cause minimal response. Market participants adapt accordingly, with regulatory scrutiny increasing demand for regulated exchanges while enforcement shifts trading toward less transparent venues (Cong et al., 2023). Cross-country evidence shows

institutional trading volumes can fall by up to 55 per cent after bans (Copestake et al., 2023), and China's 2017 and 2021 restrictions produced international spillovers with lasting effects (Borri and Shakhnov, 2020; Griffith and Clancey-Shang, 2023). Importantly, different crypto-asset classes exhibit heterogeneous responses, where stablecoins react most strongly to CBDC announcements while protocol-layer assets remain insulated (Corbet et al., 2020a; Ayadi et al., 2023), and utility-token investors react negatively to proposals increasing compliance requirements (Koenraadt and Leung, 2024). However, most regulatory research centres on Bitcoin (Dyhrberg, 2016a, 2016b; Li and Wang, 2017; Corbet et al., 2020b; Lyócsa et al., 2020), leaving gaps in understanding how comprehensive frameworks affect diverse crypto-asset classes simultaneously.

Therefore, given MiCA's framework and differentiated treatment across asset classes, we encompass the majority of the ecosystem in our examination of three main questions. First, does the market respond to regulatory proposals before implementation, demonstrating that investors price anticipated compliance costs at the announcement stage? Second, within this response, do different crypto-asset classes exhibit heterogeneous performance, or does impending regulation produce uniform effects? Third, does MiCA's novel criteria of issuer identifiability become a priced characteristic, creating gains for exempt classes and losses for regulated ones? Thus, we proceed in three steps. First, we separate crypto-assets into categories to observe their responses to MiCA’s regulatory distinctions. After dividing the crypto-market into the five main classifications: cryptocurrencies, stablecoins, utility tokens, NFTs and DeFis, we add one more class because of MiCA’s distinction. MiCA's differentiated approach introduces a novel dimension, namely issuer identifiability as the primary criterion for regulatory scope. We test whether markets price this characteristic, by introducing the first empirical separation of cryptocurrencies by issuer status, dividing them into identifiable-issuer (iCrypto) and unidentifiable-issuer (uCrypto) groups that directly map to MiCA's compliance

requirements versus exemptions. This classification extends beyond traditional functional categories to capture whether regulatory accountability itself becomes a priced attribute. This extension is consistent with evidence that crypto-asset valuations incorporate issuer-provided information and disclosure quality in utility tokens (Howell et al., 2020), suggesting that characteristics tied to the issuing entity can become priced attributes in cryptocurrencies. MiCA's focus on issuer identifiability therefore provides a natural regulatory basis for distinguishing assets along this dimension. For NFTs, which are digital art and collectibles transacted via utility tokens, we proxy activity using the most traded NFT-related tokens from CoinMarketCap, positioning them as formally exempt but functionally dependent on regulated assets. This approach addresses calls to analyse crypto-assets individually rather than as a homogeneous market (Goodell et al., 2023; Corbet et al., 2020a; Karim et al., 2022; Yousaf and Yarovaya, 2022a, 2022b; Fakhfekh et al., 2024; Almeida et al., 2024).

Second, to analyse crypto-asset performance within regulatory contexts requires empirical strategies capable of isolating policy effects across heterogeneous assets. While event studies capture announcement effects (Shanaev et al., 2020; Chokor and Alfieri, 2021; Corbet et al., 2019; Yue et al., 2021; Marmora, 2022; Flori, 2019), difference-in-differences (DiD) frameworks are particularly effective in establishing causal inference. They have been applied to crypto taxation (Cong et al., 2023), price discrepancies (Chen et al., 2022), structural changes (Grobys, 2021a), broader policy shocks (Shen et al., 2024), and crypto-exchange policy changes in crypto markets (Galati and De Blasis, 2025). We employ a DiD framework to compare pre and post MiCA regimes, extending Conlon et al.'s (2024) event study by capturing performance differentials across regulated and exempt categories. Third, our performance measures comprise returns, abnormal returns, and cumulative abnormal returns over 1-day (CAR1), 3-day (CAR3), and 5-day (CAR5) event windows, following studies that examine multi-day windows around policy events in cryptocurrency markets (Cumming et al., 2025;

Dunbar et al., 2025; Polyzos and Youssef, 2025; Schwenkler and Zheng, 2025). We also follow Galati and De Blasis (2025), who employ CARs measures within a DiD framework to evaluate a policy change in a cryptocurrency exchange. Collectively, these studies demonstrate that cumulative windows effectively capture regulatory impacts in cryptocurrency markets, particularly when announcements generate delayed price adjustments (Schwenkler and Zheng, 2025; Polyzos and Youssef, 2025). CAR1 therefore captures immediate market reactions, while CAR5 reflects the short-horizon adjustment as regulatory information diffuses and investors rebalance positions (Maffiola and Sevim, 2025). To measure abnormal returns for our CARs, we require a benchmark that captures cryptocurrency-specific dynamics. Liu et al. (2022) show that market, size, and momentum are the dominant common risk factors in crypto markets, effectively explaining cross-sectional return variation. Following their methodology, we construct a market-capitalisation-weighted crypto index using over 1,200 cryptocurrencies and spanning 2018–2023, an approach widely adopted in recent crypto-asset research (Schwenkler and Zheng, 2025; Dombrowski et al., 2023; Dunbar and Owusu-Amoako, 2022). Hence, we conduct our analysis using MiCA's official proposal announcement date, enabling us to isolate the policy shock and assess whether it generates a regime shift across heterogeneous crypto-asset classes.

First**,** our results provide evidence that markets anticipate and price regulatory proposals before formal implementation, with all six crypto asset classes reacting within our five-day event windows. This demonstrates heightened investor sensitivity to institutional announcements (Huang et al., 2022; Hu et al., 2019), particularly for crypto-specific regulation. Our findings align with studies showing institutional policy signals drive significant market responses and amplify investor attention (Auer and Claessens, 2018; Corbet et al., 2020a; Copestake et al., 2023; Aloui et al., 2024). In fact, we find that crypto classes' immediate reactions were divided according to their regulatory status. Regulated classes had muted

immediate reactions, while unregulated classes responded significantly immediately. Moreover, we document that EU policy impacts crypto markets at the proposal stage, supporting Panagiotidis et al. (2019) who find EU economic policy uncertainty significantly affects Bitcoin returns, and extending Gambarelli et al. (2023) who demonstrate European regulatory signals shape global crypto dynamics.

Second, our results reveal pronounced heterogeneity in market responses to MiCA's proposal, contributing to the growing literature on crypto asset segmentation. Exempt assets show dramatic sign reversals post-MiCA while regulated assets display muted responses, some materializing only over longer windows. Notably, uCrypto records the strongest positive response (2.1 percentage points over five days), while DeFi and NFTs experience immediate severe declines despite exemption. This challenges simple substitution theories (Foley et al., 2019; Borri and Shakhnov, 2020) and reveals ecosystem dependencies (Koutmos, 2018; Yousaf and Yarovaya, 2022b). Stablecoins and utility tokens show delayed negative effects consistent with their structural roles as market infrastructure (Lyons and Viswanath-Natraj, 2023; Corbet et al., 2020a). These findings demonstrate that functional roles, structural characteristics, and issuer identifiability, not merely regulatory inclusion, drive distinct market behaviours under comprehensive regulation.

Third, our introduction of issuer identifiability as a novel priced characteristic in traditional cryptocurrency markets extends theoretical frameworks that link valuation to issuer characteristics. While Howell et al. (2020) demonstrate that issuer quality and transparency predict token success, and Koenraadt and Leung (2024) show transparency mitigates negative regulatory reactions, we reveal that issuer identifiability itself, the mere presence or absence of an accountable entity, becomes priced under MiCA's framework. The 2.1 percentage point divergence between uCrypto and iCrypto despite identical functionality establishes a novel

form of intra-class heterogeneity distinct from functional roles (Corbet et al., 2020a) or technological quality (Cong et al., 2021; Maître et al., 2025). Prior to the announcement, uCryptos were already showing significantly negative returns while iCryptos displayed muted performance. However, post-MiCA, uCryptos surged immediately with sustained growth through the five-day window, demonstrating that regulatory clarity amplifies the value of anonymity when compliance requirements target identifiable issuers. This divergence reveals that MiCA establishes a regulatory regime where issuer identifiability becomes a key determinant of market performance.

Fourth, our analysis of exempt assets reveals unexpected vulnerabilities that advance understanding of regulatory spillovers in crypto markets. DeFi's negative response despite exemption aligns with Corbet et al. (2020), who find that currency layer and protocol layer assets move in opposite directions under policy shocks, which is precisely what we observe with uCrypto surging while DeFi declines. This supports Dunbar et al.'s (2025) 'decentralization illusion' thesis, showing DeFi remains vulnerable through dependencies on regulated infrastructure. Similarly, NFTs exhibited immediate negative responses across all windows while underlying utility tokens showed losses only at CAR5. This divergence despite shared technological infrastructure validates Cong et al.'s (2021) theoretical prediction that functional purpose rather than technology drives valuation, and extends their framework to show how regulation amplifies these functional differences. Traditional cryptocurrencies, as the original digital assets dominating the ecosystem, behave differently from newer asset classes like DeFi and NFTs, supporting recent studies that document distinct behavioural patterns between established and emerging cryptocurrencies (Polyzos and Youssef, 2025).

The remainder of the article is organised as follows: Section 2 presents literature review and hypotheses development; Section 3 describes data and methodology; Section 4

discusses our empirical findings; Section 5 discusses results; Section 6 reports robustness; and Section 6 concludes.

2.2 Prior Literature and Hypotheses Development

2.2.1. Literature Review

Early research established that despite widespread agreement on the need to regulate crypto-assets, significant disagreement persists on how this should be accomplished, reflecting the ambiguous legal status of these assets across jurisdictions where some governments treat them as securities and others as commodities or means of exchange (Chokor and Alfieri, 2021; Werbach, 2018). This regulatory uncertainty has itself become a market-moving force, with Auer and Claessens (2018) demonstrating through a cross-jurisdictional event study that regulatory news has significant and measurable impacts on cryptocurrency valuations, transaction volumes, and user bases. Critically, they document an asymmetry in regulatory effects: general bans and securities law treatment produce the strongest negative valuation impacts, while the establishment of tailored legal frameworks generates positive market reactions, suggesting that regulatory clarity and structure can enhance rather than suppress market confidence. We aim to observe this impact on the major classes of the crypto ecosystem.

Since crypto operates without border constraints, the cross-border dimension of regulatory effects is observed in research. Borri and Shakhnov (2019), using a structural spillover model, show that China's 2017 policy changes generated large and heterogeneous international spillovers, with significant increases in Bitcoin trading volumes across Korean Won, Japanese Yen, and US dollar exchanges, demonstrating that domestic regulatory actions in major crypto markets transmit globally rather than remaining locally contained. Griffith and Clancey-Shang (2023) extend this analysis to China's 2021 ban, employing GARCH methods to show that the later restriction produced deeper and more persistent price and volatility impacts than 2017, though it failed to suppress global adoption. Copestake et al. (2023), using

panel data across more than fifty countries, quantify that trading volumes decline by up to 55 per cent after ban announcements, with institutional traders driving the decline while retail activity proves more resilient, and volumes subsequently recovering unless enforcement is sustained. These studies show that the nature, scope, and institutional credibility of regulatory announcements shape the magnitude and persistence of market responses.

Within the European Union specifically, crypto markets display pronounced sensitivity to institutional policy signals. Panagiotidis et al. (2018), using LASSO regression across a broad set of macroeconomic and financial determinants, find that European economic policy uncertainty is among the most important drivers of Bitcoin returns. Their follow-up study (Panagiotidis et al., 2019) using generalised impulse responses and local projections confirms that EU policy uncertainty shocks generate positive Bitcoin responses, contrasting with the negative impacts of Chinese policy uncertainty. Aloui et al. (2024) demonstrate that ECB monetary policy interventions shape cryptocurrency hedging effectiveness, while Gambarelli et al. (2023) show that European market conditions influence crypto dynamics through volatility transmission channels. Conlon et al. (2024) provide early evidence on MiCA's impact across asset categories employing an event study approach. We build on their work by formally testing whether regulatory classification drives these differences through a DiD framework while adding issuer identifiability as an additional analytical layer.

These findings bring attention to the fact that the market is not homogeneous. A growing empirical literature documents that crypto-asset classes constitute functionally distinct markets requiring separate analysis. The early literature treated the market as homogeneous and Bitcoin-centric, but Corbet et al. (2020a) provide a foundational challenge by demonstrating through a study of FOMC announcement responses that functional roles within the crypto ecosystem determine regulatory sensitivity, where currency-layer tokens transmit

monetary policy shocks while protocol-layer assets remain insulated, establishing that asset architecture rather than market capitalisation drives policy responses. Goodell et al. (2023), examining US regulatory announcement impacts across multiple asset types, find significant heterogeneity in how assets respond even to the same regulatory signal. Karim et al. (2022) use extreme risk transmission analysis across NFTs, DeFi tokens, and cryptocurrencies during multiple stress periods, finding that DeFi and cryptocurrencies show substantial positive spillovers during volatile periods while NFTs demonstrate more muted responses with distinct diversification properties. Fakhfekh et al. (2024), using Archimax copula methods, demonstrate that dependence structures between asset classes shift meaningfully during turbulent periods, confirming that aggregated crypto market analysis obscures important cross-class dynamics.

Beyond official regulatory channels, crypto markets process information through sentiment and attention mechanisms that interact with and sometimes amplify regulatory signals. Shen et al. (2019) demonstrate that Twitter sentiment has a substantial and measurable impact on Bitcoin return volatility, while Li et al. (2017) and Naeem et al. (2020) establish significant causal relationships between online investor sentiment and cryptocurrency returns using happiness sentiment indices and natural language processing approaches respectively. Kraaijeveld and De Smedt (2020) show through textual analysis that Twitter activity reliably predicts returns for Bitcoin, Litecoin, and Bitcoin Cash. More recently, Maître et al. (2025) demonstrate that social media-based attention explains cross-sectional variation in cryptocurrency returns, confirming that information channels remain a primary pricing mechanism across the asset class. Alongside social media, search-based attention measures provide a complementary channel: Zhang et al. (2018) and Dastgir et al. (2019) document strong connections between Google Trends and Bitcoin market dynamics, while Aalborg et al. (2019) find that transaction volume marginally predicts daily returns and that demand from

transactional needs drives price formation. Smales (2021) extends attention measures across cryptocurrency markets more broadly, and Polasik et al. (2015) establish that newspaper tone affects Bitcoin prices directly. A critical nuance emerges from Lyócsa et al. (2020), who find that Bitcoin's volatility responds significantly to regulatory news and cyberattacks but not to general macroeconomic announcements, suggesting that crypto markets filter information selectively and respond to crypto-specific signals while remaining largely insulated from conventional macroeconomic channels. This selectivity justifies our focus on official regulatory announcements as the relevant treatment, a finding further supported by Kulbhaskar and Subramaniam (2023), who confirm that news headline sentiment about cryptocurrency specifically drives measurable trading activity responses.

Institutional investor participation has intensified the market's sensitivity to these channels. Huang et al. (2022) document a growing trend of institutional crypto adoption, with institutional traders showing greater responsiveness to formal regulatory communications than retail participants. Auer et al. (2022) confirm that institutional trading volumes are most reactive to announcements clarifying legal status or enforcement intent. As crypto-assets have been integrated into investment portfolios for diversification and safe-haven purposes (Bouri et al., 2017; Urquhart and Zhang, 2019), the transmission channel between official regulatory announcements and asset prices has strengthened considerably.

The theoretical literature on cryptocurrency valuation provides the foundation for understanding why different asset classes respond differently to the same regulatory event. Foundational work by Cong et al. (2019), Sockin and Xiong (2022), Pagnotta and Buraschi (2018), and Biais et al. (2019) establishes that cryptocurrency prices are driven by network effects and platform adoption dynamics rather than cash flows or physical assets, generating predictions that regulatory interventions affecting adoption expectations produce significant

and heterogeneous price effects. Liu and Tsyvinski (2021), through cross-sectional analysis, demonstrate that network factors, momentum, and investor attention explain cryptocurrency returns while traditional risk factors do not. Their subsequent work with Wu (Liu et al., 2022) identifies market, size, and momentum as the dominant common risk factors, constructing the three-factor model our index methodology follows. Cong et al. (2021) extend this framework to tokenomics, linking technological quality and platform design to post-issuance valuations, while Maître et al. (2025) empirically confirm that functional and quality characteristics drive cross-sectional return variation beyond the listing period.

The difference-in-differences framework has become the established approach for causal identification of regulatory effects in crypto markets, controlling for common shocks while isolating treatment effects specific to affected asset categories. Cong et al. (2023) apply DiD to cryptocurrency tax regulation, demonstrating that enforcement pressure redirects activity toward less transparent venues. Chen et al. (2022) use DiD to identify policy effects on Bitcoin price discrepancies during COVID-19, while Grobys (2021a) applies it to structural pricing shifts around the COVID-19 outbreak. Shen et al. (2024) employ DiD for broader crypto policy shocks across multiple jurisdictions. Most directly relevant, Galati and De Blasis (2024) use cumulative abnormal returns within a DiD framework to evaluate a specific policy change on a cryptocurrency exchange, providing the closest methodological precedent to our approach. Schwenkler and Zheng (2025), Polyzos and Youssef (2025), Dunbar et al. (2025), Cumming et al. (2025), and Maffiola and Sevim (2025) further demonstrate that multi-day cumulative windows effectively capture regulatory impacts in cryptocurrency markets, particularly where announcements generate delayed price adjustments across heterogeneous asset classes. Collectively, the literature establishes the research gap this study addresses: no prior work applies causal identification methods to a comprehensive structured regulatory framework across simultaneously observed heterogeneous asset classes, nor tests whether

regulatory classification itself becomes a priced characteristic in crypto markets.

2.2.1 Hypotheses Development

The cryptocurrency market responds rapidly to information through multiple channels, with studies linking crypto-asset valuation to social media sentiment (Naeem et al., 2020; Shen et al., 2019; Kraaijeveld and Smedt, 2020; Maître et al., 2025), Google search activity (Zhang et al., 2018; Dastgir et al., 2019; Smales, 2021), regulatory announcements (Panagiotidis et al., 2019; Griffith and Clancey-Shang, 2023; Borri and Shakhnov, 2020), and market disruptions (Foley et al., 2019; Griffin and Shams, 2020). This sensitivity has intensified as institutional investors now play a growing role in crypto markets (Auer et al., 2022; Huang et al., 2022; Copestake et al., 2023), integrating crypto-assets into portfolios for diversification and safe-haven purposes (Bouri et al., 2017; Urquhart and Zhang, 2019). The direction and magnitude of market responses depend critically on the nature and timing of regulation. For instance, Borri and Shakhnov (2020) report global spillovers from China's 2017 restrictions, while Griffith and Clancey-Shang (2023) show that the 2021 Chinese ban produced deeper and longer-lasting impacts. Auer and Claessens (2018) find that general bans depress prices, whereas structured frameworks can enhance market confidence. Market participants adjust behaviour accordingly: broad regulatory scrutiny increases use of regulated exchanges, whereas targeted enforcement drives trading towards less transparent venues (Cong et al., 2023). Copestake et al. (2023) show that trading volumes decline by up to 55 per cent after ban announcements, primarily among institutional traders.

Within the European Union, crypto markets display pronounced responsiveness to institutional policy signals. Panagiotidis et al. (2019) identify European policy uncertainty as a key determinant of Bitcoin returns, while Aloui et al. (2024) and Gambarelli et al. (2023)

demonstrate that monetary policy interventions and market conditions shape cryptocurrencies' hedging effectiveness. MiCA, representing the EU's unified framework across twenty-seven member states, provides a unique setting to assess this influence at a global scale. Its proposal stage offers an opportunity to test whether investors adjust expectations and asset positions in anticipation of regulation, rather than waiting for enforcement.

H1: *The MiCA policy proposal generates significant price reactions across crypto-asset classes, demonstrating market sensitivity to crypto-specific regulatory proposals prior to policy implementation.*

Theoretical frameworks emphasise valuation drivers such as network effects, platform adoption, production factors, and investor attention (Sockin and Xiong, 2023; Pagnotta and Buraschi, 2018; Liu and Tsyvinski, 2021). Cong et al. (2021) link valuations to technological quality, while Corbet et al. (2020) show that functional roles determine policy sensitivity, with currency-layer tokens transmitting policy shocks and protocol-layer assets remaining insulated. These mechanisms suggest that comprehensive regulatory frameworks targeting specific asset functions should produce differentiated market responses. Empirical evidence confirms heterogeneous responses across crypto-asset classes during turbulent periods. Fakhfekh et al. (2024) demonstrate significant performance differentials between NFTs, DeFi, and gold-backed cryptocurrencies, while Karim et al. (2022) document that asset characteristics shape behaviour during shocks through extreme risk transmission patterns. Corbet et al. (2020) find that regulated assets like stablecoins show greater sensitivity to policy announcements than protocol-based assets, a pattern extending to CBDC uncertainty (Ayadi et al., 2023). Conlon et al. (2024) provide early descriptive evidence of heterogeneous responses to MiCA across asset categories but stop short of formally testing regulatory classification as the driver of these

differences. However, these studies focus primarily on monetary policy or fragmented regulatory measures rather than comprehensive frameworks that explicitly classify different asset types. We hypothesise:

H2: *Crypto-asset classes exhibit heterogeneous performance responses to MiCA policy proposal, with significant differentials in assets performances.*

The regulatory status of cryptocurrencies in Europe has been complex. MiFID II provides only partial oversight, applying solely to crypto-assets that qualify as financial instruments while excluding payment-focused cryptocurrencies such as Bitcoin and Ethereum (Ferreira and Sandner, 2021; Annunziata, 2023). These payment-type assets dominate the digital asset market and increasingly attract institutional investors (Auer et al., 2022; Hu et al., 2019). MiCA's regulatory scope is selectively applied based on issuer identifiability, building on theoretical frameworks that recognize issuer characteristics as fundamental determinants of crypto-asset value and market behavior (Howell et al., 2020; Cong et al., 2021). While prior literature examines issuer quality, disclosure practices, and insider sales as factors affecting token performance (Howell et al., 2020), MiCA operationalizes issuer presence itself as the primary regulatory criterion. Under MiCA, cryptocurrencies with identifiable issuers fall under its jurisdiction., while those without clear issuers remain outside direct regulation (Conlon et al., 2024). This creates two distinct regulatory categories within the cryptocurrency ecosystem. For iCrypto, MiCA's approach introduces comprehensive oversight including governance requirements, operational guidelines, and compliance monitoring. While these measures aim to enhance consumer protection and market stability, they also impose significant compliance costs and operational constraints. These measures impose compliance costs, and research demonstrates that targeted regulations can lead to negative performance impacts through dampened market sentiment and liquidity (Cong et al., 2023). Although, some evidence

suggests that well-defined regulatory frameworks can ultimately enhance market confidence (Copestake et al., 2023). For uCrypto, MiCA's regulatory exemption may provide competitive advantages without the burden of compliance costs, potentially making them more attractive during periods of increased oversight. This is consistent with evidence showing that investors seek alternative assets during periods of increased regulatory oversight (Foley et al., 2019) and that traders shift toward less transparent venues under targeted enforcement (Cong et al., 2023). Historical evidence from China's 2017 ICO ban shows that tokens outside regulatory restrictions earned positive abnormal returns relative to in-scope assets (Borri and Shakhnov, 2020), suggesting unidentified issuer cryptocurrencies may benefit from capital flows avoiding regulatory compliance costs. Given this differential regulatory treatment and the documented sensitivity of crypto markets to regulatory developments, we hypothesize:

H3: *The impact of MiCA's policy proposal on traditional cryptocurrencies' performance differs based on issuer identifiability.*

H3.A.: *The impact of MiCA's policy proposal on identified issuer cryptocurrencies' performance is expected to be negative and statistically significant.*

H3.B.: *The impact of MiCA's policy proposal on unidentified issuer cryptocurrencies' performance is expected to be positive and statistically significant.*

Stablecoins maintain stable value by being pegged to traditional assets or fiat currencies to facilitate seamless transactions, enhance liquidity, and serve as a critical link between crypto and traditional financial systems (Lyons and Viswanath-Natraj, 2023). Despite their intended stability, experience during market stress periods has exposed critical vulnerabilities. The collapse of TerraUSD (UST) in May 2022 exemplifies these risks, where the algorithmic stablecoin experienced large peg discounts, trading at 75 cents before dropping to 40 cents

within days, creating temporary contagion effects with Tether experiencing intraday discounts of up to 5 cents and $8 billion in market cap decline (Lyons and Viswanath-Natraj, 2023). MiCA introduces strict governance standards, reserve requirements, and operational guidelines for stablecoins to address these vulnerabilities. Although these measures are intended to enhance consumer protection and market stability, they also create substantial compliance costs and operational constraints. Research on stablecoins shows that while markets can register instantaneous reactions to discrete, public information shocks such as U.S. monetary policy announcements (Corbet et al., 2019) or acute crises like the FTX collapse (Esparcia et al., 2024; Gambarelli et al., 2023), the predominant body of empirical evidence finds that stablecoins reflect their impact over multiple days. Across diverse shock events including the TerraUSD collapse and the Silicon Valley Bank episode, stablecoins typically take several days to return toward their target price (Lyons & Viswanath-Natraj, 2023; Grobys et al., 2021b; Aldasoro et al., 2025), with investor activity responses concentrated within 1–7 days (Łęt et al., 2023; Osman et al., 2024). This multi-day pattern persists even during distinct policy events due to structural market features and settlement constraints that govern price and flow normalization (Catalini et al., 2022; Galati & Capalbo, 2024; Gregory et al., 2024; Grobys et al., 2021b; Osman et al., 2024). Given MiCA's comprehensive regulatory framework specifically targeting stablecoins and the documented tendency for delayed reactions following major shocks, we expect negative performance effects to emerge and develop over longer event windows rather than immediate periods. We hypothesize:

H4: *The impact of MiCA's policy proposal on stablecoins' performance is expected to be negative and statistically significant in longer time windows rather than immediate periods.*

The theoretical foundation for utility token economics, coined tokenomics, demonstrates how these assets promote competitive pricing by committing platform operators to transparent,

decentralized governance structures (Cong et al., 2021). Unlike stablecoins, which primarily function as stores of value, utility tokens derive their value from providing access to platform services and generating network effects through user adoption. The utility token sector developed primarily through Initial Coin Offerings (ICOs), with the vast majority of offerings involving utility tokens rather than security tokens, characterized by their lack of cash flow rights and use as access instruments (Gryglewicz et al., 2021; Chod and Lyandres, 2021). However, this sector has historically faced significant regulatory scrutiny and volatility, with Gryglewicz et al. (2021) showing that regulatory uncertainty influences platform financing decisions, often making traditional equity preferable to token issuance under constrained environments.

This design sensitivity makes utility tokens particularly vulnerable to regulatory intervention. Growing empirical literature confirms that regulatory scrutiny negatively affects utility token performance. Howell et al. (2020) analyze 1,520 ICOs and find that token performance and project outcomes are significantly impacted by regulatory uncertainty, while Lyandres et al. (2022) document that post-ICO performance is highly sensitive to legal clarity and jurisdictional enforcement. Chod and Lyandres (2021) present a theoretical framework showing that utility tokens are vulnerable to information asymmetries and agency problems, with regulatory compliance exacerbating these frictions, reducing platform efficiency and discouraging user participation. Goldstein et al. (2024) emphasize that platform governance structures, such as fee restrictions and token-only payment rules, are integral to utility token value propositions, cautioning that regulatory intervention may compromise the competitive advantages of platform-based token systems. Regulatory interventions that expand disclosure and oversight requirements have been shown to generate negative price adjustments in utility-token markets, as investors incorporate the prospect of higher compliance burdens into valuations even before rules take effect (Koenraadt and Leung, 2024). Under MiCA, a similar

channel is expected for assets with identifiable issuers, whose regulatory obligations may be priced in as anticipated costs. Under MiCA, utility tokens with identifiable issuers are subject to comprehensive oversight, including governance requirements, whitepaper obligations, and operational restrictions. These constraints directly conflict with the decentralized, low-friction design that enables utility tokens to function as efficient instruments of exchange. Because MiCA's requirements attach at the issuer level rather than platform functionality itself, immediate transactional use remains largely unaffected. However, the new governance and disclosure obligations introduce compliance costs that can erode the efficiency advantages of platform-based tokens. Given the accumulated evidence on the sensitivity of utility tokens to regulatory pressures and operational constraints, we hypothesize:

H5 : *The impact of MiCA's policy proposal on utility tokens' performance is expected to be negative and statistically significant.*

NFTs and DeFi tokens occupy a unique market position under MiCA's regulatory framework. While the regulation comprehensively targets stablecoins and utility tokens based on identifiable issuers, both NFTs and DeFi protocols largely remain outside its scope due to structural characteristics and issuer identification challenges. NFTs require utility tokens for transactions, creating a dynamic where unregulated assets depend on regulated payment mechanisms for market access. Research demonstrates that both asset classes exhibit significant sensitivity to market announcements and regulatory developments. Karim et al. (2022) examine extreme risk transmission among NFTs, DeFi tokens, and cryptocurrencies during multiple market stress periods, finding that while DeFi tokens and cryptocurrencies show substantial positive spillovers during volatile periods, NFTs demonstrate more muted responses with lower downside risk exposure and higher diversification potential, particularly for risk-averse investors, portfolio managers, and institutional investors. Both asset classes

experienced notable growth during financial instability periods (Maouchi et al., 2022), suggesting their potential role as alternative investment vehicles during regulatory uncertainty. Chowdhury et al. (2023) demonstrate that adding NFTs and DeFi assets to investment portfolios provides diversification benefits due to their efficiency during financial turmoil.

Yousaf and Yarovaya (2022a, 2022b) document that significant cryptocurrency market announcements lead to measurable return and volatility spillovers, with NFTs and DeFi assets showing dynamic responses to systemic changes. Similarly, Fakhfekh et al. (2024) and Almeida et al. (2024) highlight that NFTs and DeFi display distinct diversification and hedging properties during turbulent periods, reinforcing their potential to attract flows when regulatory pressure rises elsewhere. DeFi protocols claim full decentralization, recent research suggests operational realities may be more complex. Dunbar et al. (2025) introduce the "decentralization illusion" concept, highlighting that DeFi protocols often maintain dependencies on centralized infrastructure despite their decentralized branding. However, MiCA's regulatory framework explicitly focuses on issuer identifiability as its primary criterion, meaning DeFi protocols without identifiable governance entities remain outside its direct regulatory scope regardless of their operational dependencies. Given particularly DeFi's rapid growth trajectory in 2020 (Maouchi et al., 2022), suggests potential for positive performance as investors may view DeFi as a regulatory haven, especially in the immediate term following MiCA's announcement. Moreover, regulators have historically viewed decentralized digital assets as potential threats to financial stability (Jalan et al., 2021), MiCA's selective application based on issuer identifiability creates opportunities for both asset classes. This regulatory exemption could lead to increased market interest, particularly given evidence that investors seek alternative assets during periods of increased regulatory oversight. Furthermore, the NFT ecosystem was already expanding around the time of MiCA’s proposal. Nadini et al. (2021) show that NFT trading activity, which had remained relatively stable through early 2020, began a marked acceleration

from mid-2020 across art, gaming, metaverse, and collectible segments. This early ecosystem growth implies that NFT-related tokens may exhibit distinct performance dynamics independent of direct regulatory coverage. Given the empirical evidence showing both asset classes' exemption benefits and sensitivity to regulatory developments affecting the broader crypto ecosystem, we hypothesize:

H6: *The impact of MiCA's policy proposal on NFT-related tokens' performance is expected to exhibit positive and statistically significant performance effects.*

H7: *The impact of policy proposal on DeFis' performance is expected to exhibit positive and statistically significant performance effects.*

2.3 Data and Econometric Methodology

2.3.1 Data

Our dataset comprises 48 digital assets (12 from each category) from CoinMarketCap, including Cryptocoins, Stablecoins, Utility Tokens, Non-Fungible Tokens (NFTs), and Decentralised Finance (DeFis). Prior literature represents NFTs through liquid, exchange-traded ecosystem tokens (Yousaf and Yarovaya, 2022; Maouchi et al., 2022; Chowdhury et al., 2023). In line with this approach, we proxy NFTs with utility tokens obtained from CoinMarketCap, selecting the top traded coins and tokens used for Collectibles and NFTs, given their unique trading characteristics. Asset selection was based on market capitalization rankings (Hu et al., 2019). Moreover, we cross-checked crypto-assets with Messari.io to confirm their class since utility tokens can be challenging and are not clearly specified. The sample period spans from January 1, 2018, to May 21, 2023, covering over two years before MiCA's announcement to capture pre- and post-regime periods. Following established difference-in-differences methodology in crypto-asset research (Cong et al., 2023; Chen, Qin,

and Zhang, 2022; Grobys, 2020), we examine the period pre- and post- MiCA's regime to analyse its causal impact across different crypto-asset classes. Table 2.1 details the composition of analysed digital assets, including their ticker symbols, currencies, volume, and market capitalization, demonstrating the economic significance of our sample through their substantial market capitalizations.

To construct counterfactuals, we estimated a propensity score (PS) incorporating indices: Cryptocurrency Uncertainty Price Index, Cryptocurrency Uncertainty Policy Index (UCRY; Lucey et al., 2022), the CBDC Uncertainty Index (Wang et al., 2022b), the Index of Cryptocurrency Environmental Attention (Wang et al., 2022a), the NFT Attention Index (Wang, 2022), global commodity benchmarks (gold, silver, copper, crude oil, Brent, natural gas) obtained from Nasdaq, and major exchange rates obtained from the Bank of England. The CBOE Volatility Index (VIX) was included separately as a control. Our crypto prices and trading volumes are acquired from CoinMarketCap.com. Detailed information on the propensity score construction, including the panel logit specification, the definition of each index covariate, and summary statistics of all covariates, is provided in Appendix 2.A (see Table 2.A1). As for the crypto-asset market index, we acquired data of 405 coins from CoinMetrics.io. Figure 2.1 displays the time series of six crypto-asset classes, with the red dashed line marking MiCA announcements (September 24, 2020). The plots reveal clear heterogeneity across asset types: identified issuer cryptocurrencies (iCrypto) exhibit the highest volatility, while stablecoins remain relatively stable throughout the period. NFTs and DeFi assets show pronounced upward movements following the MiCA announcement. These visual patterns provide preliminary evidence for differential market responses across crypto-asset classes, motivating our formal econometric analysis.

To mitigate the influence of extreme values arising from the heterogeneous volatility

profiles across digital asset classes, returns are winsorised at the 1st and 99th percentiles separately for each asset. This means each asset's own return distribution sets its own outlier threshold, instead of one threshold applied to all 48 assets together. Because the empirical analysis in this chapter compares crypto-asset classes with very different volatility profiles, as shown in Figure 2.1, a pooled threshold would be shaped mostly by the most volatile classes, which could distort the cross-sectional differences the analysis is meant to capture.

[Table 2.1 about here]

[Figure 2.1 about here]

2.3.2 Measures

Returns

Returns for all digital assets are defined as the percentage change of the natural logarithm of the digital asset stock price index, as follows

$$r_{it} = \Delta ln(P_{it}) \quad (1)$$

where i=1, …, N refers to the digital asset, t=1,2…, T is time, and P is the observed prices.

Abnormal Returns

In order to compute a more accurate, risk-adjusted measure of financial performance, we calculate abnormal returns as the difference between realized returns and expected returns (Fama et al., 1969; MacKinlay, 1997):

$$AR = r_{it} - E(r_{it}) \quad (2)$$

where expected returns are given by the capital asset pricing model:

$$E(r_{it}) = r_{ft} + \beta_{it}(r_{mt} - r_{ft}) \quad (3)$$

r_m is the return on the market portfolio and β_i is the sensitivity of the stock to the market portfolio (see systematic risk below on how to estimate beta). We used moving windows estimation to obtain the betas. The rolling window approach has been widely used to examine various topics in financial markets, and has the ability to dynamically assess the informational efficiency over time.

Cumulative Abnormal Returns

To examine the cumulative effects on digital asset returns, we employ cumulative abnormal returns (CARs) calculated over multiple event windows. The abnormal returns are first estimated using a three-factor model with rolling windows of 365 days, which accounts for market, size, and momentum factors. We then aggregate these abnormal returns over different time horizons to capture both immediate and extended effects. Specifically, we compute CARs for three distinct windows: a one-day window (-1,1), which encompasses one day before and after; a three-day window (-3,3), which extends to three days before and after; and a five-day window (-5,5), which captures a broader period of five days before and after. These windows are constructed by summing the abnormal returns within each specified period, allowing us to observe how the cumulative effects evolve over different time horizons. This approach enables us to capture both the immediate impact and any potential lead or lag effects in the digital asset market's response, while the varying window lengths serve as a robustness check for the persistence of these effects. We may therefore consider computing the time-series cumulative

average return (CAR) by summing the average returns over several periods, say from time T_1 to T_2:

$$\widehat{CAR}_i(T_1, T_2) = \sum_{t=T_1}^{T_2} \widehat{AR}_{it} \quad (4)$$

Impact (Treatment Variables)

The impact variable denotes the principal treatment of interest in this research, specifically the adoption of the Markets in Crypto-Assets (MiCA) policy framework. The treatment variable is formalised as a binary indicator, which assumes the value of one when the MiCA policy is officially proposed on 24 September 2020, and zero for the pre-policy adoption period. This framework establishes two distinct regimes: the pre-MiCA period, encompassing 1 January 2018 to 23 September 2020, and the post-MiCA period, spanning 24 September 2020 to the end date of the sample. To capture the heterogeneity across digital asset categories, we incorporate asset-specific binary indicators for each type of digital asset. These asset-specific indicators facilitate the examination of differences across asset classifications. Furthermore, we analyse the differential impact of the policy across asset categories through the construction of interaction terms between the policy treatment and asset indicators. This specification enables the estimation of policy effects discretely for each asset classification, thereby providing granular insights into the varying impacts of the regulatory framework across different digital asset categories.

Control Variables

Our analysis incorporates three key control variables. Trading volume serves as a critical measure for understanding market activity and liquidity in crypto markets, with several studies

establishing links between volume and cryptocurrency returns (Bouri et al., 2018; Huang et al., 2019). The VIX (Chicago Board Options Exchange's Volatility Index) is included to control for broader market uncertainty and risk levels. As a measure of expected stock market volatility based on S&P 500 index options, the VIX helps account for broader financial market fluctuations that could influence cryptocurrency prices independently of MiCA announcements (Chowdhury and Damianov, 2024). VIX was also employed by Griffith and Clancey-Shang (2023) in their event study examining the impact of cryptocurrency regulations. This is particularly relevant given evidence that Bitcoin responds to global uncertainty measured by VIX indices (Bouri et al., 2017), and that crypto assets can transmit risks to traditional financial systems through stablecoins (Wu and Leung, 2023). By including the VIX in our analysis, we control for broader market sentiment and global uncertainty, allowing us to isolate the specific effects of MiCA announcements on crypto-asset returns across different asset classes. Finally, we construct a propensity score (PS) incorporating multiple market indicators to establish counterfactual estimates for non-regulatory announcement days. This score includes the cryptocurrency price index constructed from CoinMetrics data; the NFT Attention Index (Wang, 2022); major exchange rates (Bank of England); cryptocurrency adoption and policy measures including the Cryptocurrency Uncertainty (UCRY; Lucey et al., 2022), the CBDC Uncertainty Index (Wang et al., 2022b) and the Index of Cryptocurrency Environmental Attention (Wang et al., 2022a); and the Twitter-Based Economic Uncertainty Index (Baker et al., 2021). Detailed methodology for PS construction is provided in the Appendix.

Crypto-asset Market Cap Weighted Index

Our cryptocurrency market index follows Liu et al.'s (2022) methodology, constructed using daily price data from 405 unique cryptocurrencies from 1 January, 2018, to 21 May, 2023. This framework has been widely adopted across crypto-asset pricing research (Cong et al., 2023;

Chen et al., 2022; Shen et al., 2024; Grobys, 2021a; Maître et al., 2025; Schwenkler and Zheng, 2025; Dombrowski et al., 2023; Dunbar and Owusu-Amoako, 2022). The index employs market capitalisation weighting, a well-established approach providing comprehensive measures of market performance (Fama and French, 1993; Hou et al., 2020) and widely used in cryptocurrency return prediction (Sockin and Xiong, 2023; Liu et al., 2022; Cai and Zhao, 2024; Bhambhwani et al., 2023).

Following Liu et al. (2022), we construct three factors adapted from the Fama-French three-factor model (Fama and French, 1993) and the Carhart four-factor model (Carhart, 1997). The Cryptocurrency Market Factor (CMKT) represents the excess return of the cryptocurrency market index over the risk-free rate, calculated as the logarithmic return of the index minus the risk-free rate.

$$CMKT_t = R_{m,t} - R_{f,t} \quad (5)$$

where $R_{m,t}$ is the logarithmic return of the market-capitalisation-weighted index at time t and $R_{f,t}$ is the risk-free rate at time t, proxied by the 1-month US Treasury bill rate obtained from Kenneth French's data library.

The Cryptocurrency Size Factor (CSMB) is constructed by sorting cryptocurrencies into three size groups based on average market capitalisation and then computing the difference between the average returns of small and big groups:

$$CSMB_t = R_{S,t} - R_{B,t} \quad (6)$$

where $R_{S,t}$ and $R_{B,t}$ are the returns of the small and big groups at time t.

The Cryptocurrency Momentum Factor (CMOM) follows Jegadeesh and Titman (1993) and Carhart (1997), using a 15-day momentum measure. Cryptocurrencies are first sorted into two groups based on market capitalisation, and within each size group into three momentum groups based on past 15-day returns. The momentum factor is computed as the

average return of the two high-momentum portfolios minus the average return of the two low-momentum portfolios:

$$CMOM_t = ½\left(R_{S/H,t} + R_{B/H,t}\right) - ½\left(R_{S/L,t} + R_{B/L,t}\right) \quad (7)$$

where $R_{S/H,t}$ and $R_{B/H,t}$ are the returns of the small/high and big/high momentum portfolios at time t, and $R_{S/L,t}$ and $R_{B/L,t}$ are the returns of the small/low and big/low momentum portfolios at time t.

2.3.3 . Empirical Approach

MiCA's regulation is distinctive for several reasons. First, it establishes the first comprehensive regulatory framework explicitly addressing different crypto-asset classes. Second, the European Union's influential economic position carries particular weight, with Panagiotidis et al. (2019) documenting that EU policy uncertainty significantly impacts cryptocurrency market dynamics compared to other jurisdictions. Third, the EU's entry into crypto-asset oversight fundamentally alters the trading landscape for both regulated and unregulated digital assets. To analyse this regulatory impact empirically, we use panel data methods to model digital assets' performance using a difference-in-differences framework (DiD) (Shen et al., 2024; Cong et al., 2023; Chen et al., 2022; Grobys, 2020). This methodological approach has proven valuable in crypto-asset research - Cong et al. (2023) employed it to examine tax regulation impacts on trading behaviour, while Chen et al. (2022) used it to analyse policy effects on Bitcoin price discrepancies. Given our data's two-dimensional nature (varying across both time and individual assets), panel methods are particularly suitable for estimating DiD effects. We employ a Fixed Effect (FE) model to account for heterogeneity (Woodridge, 2010; Cong et al., 2023), allowing each asset to have its own intercept while maintaining consistent slopes across assets. The model incorporates both unit fixed effects, accounting for time-independent

differences across assets, and time fixed effects, capturing unobserved characteristics common to all assets but varying across time. The general model can formally be expressed as follows:

$$y_{it} = \alpha + \sum_{j=1}^{3} \delta_j DA_{j,it} + \varphi E_{it} + \sum_{j=1}^{3} \gamma_j \left(DA_{j,it} \times E_{it}\right) + \rho PS_{it} + X_{it}'\beta + \omega_{it} \quad (8)$$

where $i = 1, \dots, N$ and $t = 1, \dots, T$ denote digital asset and time, respectively, and y_{it} refers to the outcome variable. This latter is measured using three different measures including returns, abnormal returns and cumulative abnormal returns. The terms α, δ_j, φ, γ_j and ρ are scalars. The coefficients δ_j are the intercept dummies for Cryptos, Stablecoins, NFTs utility tokens and DeFis ($DA_{1,it}, DA_{2,it}$ and $DA_{3,it}$, respectively). The utility tokens are the base dummy in this specification. The slope φ captures the impact of the regulatory announcements on the intercept of the outcome variable, y_{it}. This also can be considered as the DiD estimates of the effect of regulatory announcement on NFTs returns since they are the base dummy. The DiD estimates of the impact of regulatory announcement on Cryptos, Stablecoins and DeFis are captured by γ_1, γ_2 and γ_3, which are the slopes of the interaction terms between digital assets dummies and the regulatory announcement dummy (i.e. $DA_{j,it} \times E_{it}$). The slope ρ represent the effect of propensity scores, *PS*. The estimated propensity scores are measures of the counterfactuals and offer an insight on the likelihood of a randomly selected day to be a regulatory announcement day. Finally, β is $K \times 1$ and X_{it} is the *ith* observation on *K* control variables.

While much of the work utilise a one-way error component model to describe the disturbances, ω_{it}, we employ a two-way error component model, with:

$$\omega_{it} = \mu_i + m_t + \varepsilon_{it} \quad (9)$$

where μ_i captures the unobservable individual time-invariant effect, m_t represents the unobservable individual-invariant month effect and ε_{it} is the remainder of the random disturbance term. Under the presence of the fixed effects, both μ_i and m_t are assumed to be fixed parameters, while the remainder disturbance term ε_{it} is assumed to independent of the set of explanatory variables for all *i* and *t* and $\varepsilon_{it} \sim IID(0, \sigma_\varepsilon^2)$.

The model in (8) is estimated using FE estimator, which is based on within transformation of the data consisting of de-meaning the data (i.e. subtracting from each observation of each variable the average of all observations of that variable) Then, ordinary least squares, OLS, is implemented on these demeaned data to obtain the desired estimates. Furthermore, the FE model is a valid choice over pooling the data as long as the presence of the fixed effect hypothesis is not rejected.

2.4 Empirical Findings

2.4.1 MiCA's Impact and Crypto Asset Performance Analysis

The MiCA policy proposal generates significant price reactions across crypto-asset classes, demonstrating market sensitivity to crypto-specific regulatory proposals prior to policy implementation. Our findings in Tables 2.3–2.32 provide strong empirical support for H1. Notably, three crypto-asset classes show consistent significance throughout all measures: uCryptos (Tables 2.8–2.12), DeFis (Tables 2.28–2.32), and NFTs (Tables 2.23–2.27), precisely the assets outside MiCA's direct scope. To aid comparison, Table 2.38 brings together the interaction estimates from the fully specified model (Model 3) for all six asset classes and five outcome measures. Meanwhile, the included crypto-assets show different behaviours, demonstrating the EU's broad influence across all segments of the global crypto market. Our analysis builds on Panagiotidis et al. (2019)'s findings that EU economic policy uncertainty

significantly affects Bitcoin returns by demonstrating that a specific and comprehensive regulatory framework like MiCA can influence even unregulated segments of the crypto market. Additional research reinforces crypto markets' sensitivity to European institutional signals, with Aloui et al. (2024) showing that ECB monetary policy interventions impact crypto prices during crisis periods. This early-stage sensitivity in our findings underscores the EU's potential influence within the global crypto ecosystem. Moreover, the results support Auer and Claessens (2018)'s findings that regulatory clarity generates market reactions, particularly positive ones. Gambarelli et al. (2023) further show that the hedging effectiveness of cryptocurrencies is shaped by European market conditions, confirming the EU's role as a key driver of crypto dynamics. We build on these strands by showing that even proposal-stage announcements from major economic blocs such as the EU can drive significant price adjustments across the entire crypto ecosystem.

The broad-based market reaction observed across asset classes, regardless of their direct regulatory status under MiCA, suggests that investors pay close attention to institutional signals, as documented by Huang et al. (2022) and Hu et al. (2019), even at the proposal stage. This sensitivity aligns with research showing that institutional policy signals drive significant market responses (Auer and Claessens, 2018; Lyócsa et al., 2020; Copestake, 2023; Aloui et al., 2024), amplify investor attention (Huang et al., 2022; Corbet et al., 2020a; Auer et al., 2022; Auer and Tercero-Lucas, 2021; Marmora, 2022), and trigger portfolio adjustments (Flori, 2019; Białkowski et al., 2021). Taken together, these findings support the view that the EU is an influential player in the crypto ecosystem, with comprehensive regulatory frameworks like MiCA affecting markets well beyond their direct regulatory scope. They also demonstrate that investors interpret such frameworks as system-wide events that reshape the entire crypto ecosystem rather than affecting only directly regulated assets. Notably, our findings reveal that

markets processed MiCA by reshuffling crypto assets into regulated versus exempt categories, with regulated assets (iCrypto, stablecoins, utility tokens) exhibiting muted or delayed responses, while exempt assets demonstrated significant sign reversals. This grouping behavior, rather than uniform market-wide effects, demonstrates that investors distinguish between regulatory categories even at the proposal stage, processing MiCA as a system-wide event that would reshape the ecosystem through differential treatment.

While H1 establishes crypto markets' sensitivity to comprehensive regulatory proposals, the heterogeneous responses observed across asset classes demand closer examination. As Tables 2.3–2.32 demonstrate, crypto-asset classes exhibit distinct rather than uniform reactions to MiCA's proposal announcement, with heterogeneity evident in both immediate and longer event windows. Our findings reinforce the growing consensus that crypto assets are not one monolithic market but one with differentiated reactions depending on class (Corbet et al., 2019). Our analysis uncovers three critical patterns. First, assets within the same regulatory category exhibited remarkably similar responses. Among regulated assets, iCrypto showed muted behaviour with only short-lived significance (Table 2.3), stablecoins displayed minimal immediate reactions but significant delayed effects in CAR5 (Table 2.17), and utility tokens also responded with delayed significance (Table 2.32). This muted or lagged pattern aligns with Auer and Claessens (2018), who argue that regulatory clarity reinforces rather than constrains digital currencies by providing investor security and is consistent with Lyons & Viswanath-Natraj (2023), who show that stablecoin responses are typically muted rather than explosive, with deviations corrected over time (Łęt et al., 2023; Galati & Capalbo, 2024). By contrast, prior studies of cryptocurrencies under policy shocks often find capital reallocation (Borri & Shakhnov, 2020) or heterogeneous behaviour driven more by sentiment than regulation (Goodell et al., 2023).

Second, exempt assets displayed contrasting behavior through significant sign reversals. uCrypto shifted from negative pre-MiCA to uniformly positive post-MiCA performance (Tables 2.8–2.12), while DeFi (Tables 2.28–2.32) and NFTs (Tables 2.23–2.27) showed strong negative reversals. The NFT results are particularly striking given their reliance on utility tokens for trading. While pre-MiCA patterns were nearly identical, post-MiCA NFTs diverged sharply, following DeFi's negative trajectory rather than utility tokens' muted response. This is consistent with prior studies showing DeFi and NFTs are prone to speculative swings (Fakhfekh et al., 2024; Maouchi, 2022; Proelss et al., 2023). However, the split within exempt classes reveals an important distinction. MiCA explicitly excluded DeFi and NFTs with clear statements, while cryptocurrencies' exemption required detailed technical explanations about issuer identification. This communication difference from a significant economic bloc may discourage investors in emerging digital assets who now have regulated alternatives, since cryptocurrencies remain established payment instruments that technically preserve operational freedom, whereas DeFi and NFTs are emerging technologies where explicit exclusion may be discouraging or interpreted as higher risk rather than freedom. The positive uCrypto response suggests a "flight to less-regulated safety" within mainstream assets, consistent with Foley et al. (2019) who document investor preference for unregulated cryptocurrencies when scrutiny intensifies.

Third, our distinction between iCrypto and uCrypto reveals that regulatory classification based on issuer identification drives opposing performance patterns within the same asset class. While intra-class heterogeneity has been documented for stablecoins due to different pegging mechanisms (Lyons & Viswanath-Natraj, 2023; Galati & Capalbo, 2024), issuer-based regulatory differentiation is strongly present in MiCA. The stark contrast between iCrypto's muted response versus uCrypto's hyperbolic positive swing suggests markets price issuer anonymity as valuable under impending regulation, consistent with preferences for

regulatory avoidance documented by Foley et al. (2019) and Borri and Shakhnov (2020). It also resonates with Corbet et al. (2020), who demonstrate that certain subclasses of crypto respond only weakly or not at all to monetary policy shocks, and Almeida et al. (2024), who show that mainstream cryptocurrencies can benefit relative to other categories under geopolitical policy shocks. Together, these findings reinforce the idea that investor flows concentrate in assets perceived as both unregulated and established.

Overall, we build on Conlon et al. (2024), who provide the first MiCA-specific evidence of heterogeneous reactions across asset categories by documenting differential abnormal returns. We extend their findings through a systematic framework that explicitly evaluates whether regulatory status drives performance patterns. Our analysis demonstrates that classification assists in understanding the direction, magnitude, and timing of market responses in light of new comprehensive regulations. This supports Auer & Tercero-Lucas (2021)'s call for tailored regulation across coins due to differing investor bases. This addresses a critical gap: while prior work establishes the need to examine asset classes separately to observe heterogeneity under institutional shocks (Goodell et al., 2023; Borri & Shakhnov, 2020; Yousaf & Yarovaya, 2022b,c; Fakhfekh et al., 2024; Maouchi, 2022; Galati & Capalbo, 2024), policy changes (Corbet et al., 2020a; Auer & Claessens, 2018; Auer & Tercero-Lucas, 2021; Cong et al., 2023), and macroeconomic uncertainty (Almeida et al., 2024; Lyons & Viswanath-Natraj, 2023; Łęt et al., 2023), none link these differences to regulatory classification. Since no tailored frameworks existed before MiCA, our regulated-asset pattern provides new evidence that investors adapt behaviour once formal rules are introduced. With class-based heterogeneity under regulatory announcements established, the following sections (H3–H7) examine each asset category in detail to uncover the mechanisms behind their distinct responses to MiCA's proposal.

2.4.2 Individual Asset Analysis

Identified Issuer Cryptocurrencies (iCrypto)

The individual analysis of identified issuer cryptocurrencies provides limited and inconsistent support for H3.A, which predicted negative and statistically significant impacts from MiCA regulation. The returns analysis presented in Table 2.3 reveals that the core interaction term Post MiCA × iCrypto demonstrates a positive coefficient of 0.22 percentage points (pp) ($p < 0.05$) only in the fully specified Model 3, directly contradicting the expected negative impact. This positive effect emerges exclusively when both asset and time fixed effects are included, suggesting that the apparent benefit may reflect the absorption of broader market movements rather than a genuine regulatory premium. The pre-MiCA iCrypto dummy coefficient remains statistically insignificant across all specifications, indicating no systematic performance differential before the announcement. The returns regressions also show that the announcement shock itself (the Post MiCA dummy) is negative and significant in Model 1, yet this effect is absorbed once fixed effects are introduced in Models 2 and 3.

Abnormal-return results in Table 2.4 likewise fail to support H3.A. The announcement dummy remains consistently negative and significant (-0.071 pp in Model 1, $p < 0.05$; -0.309 pp in Model 2, $p < 0.01$), but neither the iCrypto dummy nor its interaction term is significant in any specification. Cumulative abnormal returns (Tables 2.5–2.7) show only sporadic significance: the announcement dummy is weakly negative in CAR1, Model 2 (-0.104 pp, $p < 0.10$), and the pre-announcement iCrypto dummy turns positive only once, in CAR5, Model 1. Interaction terms are insignificant across all windows. In short, the evidence does not substantiate H3.A: while the announcement itself affects returns and, to a lesser extent, short-window abnormal returns, there is no sustained, issuer-specific impact.

The failure to find consistent negative effects for iCrypto challenges H3.A but aligns with regulatory economics literature suggesting that clarity can offset compliance costs (Auer and Claessens, 2018). The sporadic positive effects may reflect market appreciation for regulatory certainty, even when accompanied by compliance obligations, though the lack of robustness across specifications suggests these effects may represent artefacts of model specification rather than genuine regulatory responses.

Unidentified Issuer Cryptocurrencies (uCrypto)

The analysis of unidentified issuer cryptocurrencies in Tables (2.8-2.12) provides strong and consistent support for H3.B across all performance metrics and model specifications, representing one of the most robust findings in the study. The returns analysis presented in Table 2.8 demonstrates that the Post MiCA × uCrypto interaction term exhibits increasing magnitude and statistical significance as model sophistication increases: 0.142 pp (insignificant) in Model 1, 0.258 pp ($p < 0.05$) in Model 2, and 0.398 pp ($p < 0.01$) in Model 3. This progression suggests that controlling for unobserved heterogeneity reveals the true extent of the regulatory benefit for unidentified issuers, supporting the notion that these assets gained a competitive advantage from regulatory arbitrage opportunities.

The pattern strengthens considerably in the abnormal returns analysis presented in Table 2.9, with interaction coefficients of 0.218 pp ($p < 0.01$), 0.397 pp ($p < 0.01$), and 0.446 pp ($p < 0.01$) across the three models. The magnitude approximately doubles from the baseline to the fully specified model, indicating that the regulatory benefit is substantial and robust to alternative specifications. The increasingly negative Post MiCA main effect (-0.147 pp to -0.430 pp, $p<0.01$) suggests general market pessimism that uCrypto assets successfully avoided, highlighting their characteristics during regulatory uncertainty.

The cumulative abnormal returns analysis presented in Tables 2.10-2.12 reveals not only persistence but amplification of positive effects over time. The interaction coefficients are significant at the 1 percent level in every window: CAR1 rises from about +0.38 to +0.49 percentage points, CAR3 from +1.11 to +1.37 points, and CAR5 from +1.81 to +2.11 points. The step-up from the one-day to the five-day window shows that the initial price adjustment was reinforced rather than reversed during the first week of trading, indicating a possible durable upward revaluation of cryptocurrencies that lie outside MiCA's issuer-based perimeter.

Identified vs. Unidentified Issuer Cryptocurrencies

While both iCrypto and uCrypto belong to the same asset class, they differ in one crucial respect: issuer identifiability. This distinction determines their regulatory treatment under MiCA, placing iCrypto within the issuer-based scope of regulation, while uCrypto remains outside it. Our analysis reveals robust and significant positive effects for uCrypto following the MiCA announcement, whereas iCrypto exhibits limited and inconsistent significance across specifications. These findings suggest that markets may be pricing issuer identity as a risk factor, with investors responding more favorably to assets not subject to identifiable issuer obligations under MiCA.

This distinction reveals a novel form of intra-class heterogeneity within cryptocurrencies, introducing a dimension distinct from functional roles (Corbet et al., 2020a) and technological quality (Cong et al., 2021; Maître et al., 2025). While regulatory differentiation has been documented for other classes due to their unique mechanisms (Lyons & Viswanath-Natraj, 2023; Galati & Capalbo, 2024) as well as within major cryptocurrencies such as BTC, LTC, and ETH (Goodell et al., 2023), MiCA's issuer-based classification creates opposing performance patterns within the same asset class. The stark contrast between iCrypto's muted response versus uCrypto's robust positive effects suggests markets price issuer

anonymity as valuable under impending regulation, consistent with preferences for regulatory avoidance documented by Foley et al. (2019) and Borri and Shakhnov (2020). This aligns with evidence that certain crypto subclasses respond weakly to policy shocks (Corbet et al., 2020a) and that mainstream cryptocurrencies can benefit relative to other categories under geopolitical policy uncertainty (Almeida et al., 2024). These findings suggest that investor flows concentrate in assets perceived as both unregulated and established.

For iCrypto, coefficients turn negative only in the most unrestricted abnormal-return specification and lose both size and significance once coin and day fixed effects are added or when the window is extended. Auer and Claessens (2018) document a comparable pattern for early regulatory frameworks: initial announcements can provide clarity that markets view favorably, while any compliance costs may be anticipated rather than surprising. This also aligns with Panagiotidis et al. (2019), who observe that Bitcoin's responses to European policy uncertainty tend to be temporary. The limited evidence for sustained negative effects suggests H3.A receives only partial support, while some specifications show negative coefficients for identifiable issuers, the effects are not robust across models or time windows.

uCrypto behaves very differently. Across returns, abnormal returns, CAR1, CAR3 and CAR5, the Post MiCA × uCrypto term is positive, highly significant, and grows to about +2.1 percentage points over five trading days. These results align with Foley et al. (2019)'s evidence of investor migration toward less regulated alternatives**,** suggesting investors migrate toward assets with greater regulatory distance. Similarly, Cong et al. (2023) show that traders adjust their exchange preferences in response to regulatory changes, with targeted enforcement actions driving activity toward less transparent venues. The sustained positive effects for uCrypto suggest investors reward coins that remain outside regulatory scope. These results provide strong support for H3.B that uCryptos experience positive performance following MiCA's announcement.

The contrast between iCrypto and uCrypto aligns with Goodell et al.'s (2023) evidence that cryptocurrencies exhibit heterogeneous responses to regulatory announcements, with some major altcoins acting as diversifiers against regulatory risk. Borri and Shakhnov (2020) show that after China's 2017 ICO ban, tokens not explicitly covered by the ban earned positive abnormal returns relative to in-scope coins, illustrating investors' tendency to rotate into assets outside the regulatory perimeter. Our findings extend this literature by demonstrating that MiCA establishes a new regulatory regime where issuer identifiability, and potentially the anticipated compliance costs within the EU, may become key determinants of market performance. This regime shift explains the differential pre- and post-MiCA performance patterns we observe, as markets adapt to MiCA's novel framework that explicitly differentiates treatment based on issuer characteristics rather than treating all cryptocurrencies uniformly.

Stablecoins

The stablecoin-only analysis provides further insight into H4, which predicted that MiCA's policy proposal would produce negative and statistically significant effects over longer post-event windows rather than in immediate periods. The returns analysis presented in Table 2.13 shows that the interaction term *Post MiCA* × *Stablecoin* demonstrates consistent negative coefficients but fails to reach statistical significance in any specification. The positive and statistically significant treatment dummy, *Post MiCA*, in Model 1 (0.225 pp, $p<0.01$), indicates that the MiCA announcement had a positive effect on the broader crypto market during the announcement period. The abnormal returns specification presented in Table 2.14 shows no significant results neither pre and post-MiCA. However, announcement *Post MiCA* is significantly negative only in Models 1 and 2, indicating that the broader market experienced negative abnormal returns during the announcement period, though this effect disappears when additional controls are introduced in Model 3. The cumulative abnormal returns across Tables

2.15-2.16 provide no evidence of sustained regulatory impact. The interaction terms remain insignificant across all specifications for CAR1 and CAR3. Moreover, Tables 2.13-2.16 show that there is no immediate reaction to the announcement of MiCA's proposal, even when extended to 3-day CARs. This contrasts with Esparcia et al. (2024) and Gambarelli et al. (2023), who document instant stablecoin adjustments during crisis events such as exchange failures. These prior findings relate to operational and solvency shocks, whereas MiCA represents a regulatory policy announcement. Accordingly, the lack of a short-horizon response indicates that markets differentiate between crisis-driven information and regulatory news.

In Table 2.17's five-day window, the interaction term *Post MiCA* × *Stablecoin* shows negative significance in Models 2 and 3. These results provide support for H4, demonstrating that stablecoin-specific negative effects emerge only in extended time windows (5-day CARs) rather than immediate periods, consistent with the majority of the literature showing that stablecoins exhibit delayed reactions rather than immediate responses (Catalini et al. 2022; Galati & Capalbo, 2024; Gregory et al., 2024; Grobys et al., 2025; Osman et al., 2024).

These results align with stablecoins' fundamental market role. As Lyons and Viswanath-Natraj (2023) emphasized, stablecoins serve as critical infrastructure for the crypto ecosystem, designed specifically to maintain price stability. Corbet et al. (2020) likewise report that stablecoins display smaller price swings than other crypto assets when policy uncertainty rises, a pattern reproduced by our results. The emergence of negative significance only in the 5-day window provides support for H4's prediction of delayed rather than immediate effects. While this could reflect the delayed adjustment mechanism documented in the literature, the absence of effects in shorter windows demonstrates that any negative impact unfolds gradually rather than immediately. However, the isolated nature of this result in the longest window examined raises questions about the longer-term persistence of the effect, suggesting that while the delayed reaction pattern aligns with theoretical expectations, the ultimate economic

significance remains limited. This delayed emergence aligns with the structural market features and settlement constraints that govern stablecoin price adjustments documented in the literature (Grobys et al., 2025; Osman et al., 2024; Aldasoro et al., 2025).

Utility Tokens

The utility tokens analysis provides limited support for H5, which predicted negative and statistically significant impacts from MiCA's regulatory requirements. Instead, the results reveal a more muted and complex pattern that differs notably from other regulated asset classes. Examining the returns analysis in Table 2.18, the announcement, *Post MiCA* main effect shows some positive significance in Model 1, but Tokens show no significance pre and post MiCA. The abnormal returns in Table 2.19 show positive pre-MiCA *Tokens* in Model 1, but the interaction terms show insignificant results post-MiCA. The event dummy *Post MiCA* shows significant negative reactions in Models 1 and 2. These results suggests minimal immediate impact on utility token returns, similar to its regulated counterparts iCrypto and stablecoins.

The cumulative abnormal returns across Tables 2.20-2.32 reveal a progressive pattern that strengthens over longer event windows. CAR1 in Table 2.20 shows complete insignificance across all specifications, indicating no immediate market reaction to the MiCA announcement. This absence of immediate effects aligns with the delayed adjustment patterns documented by Cong et al. (2023) for crypto assets under regulatory pressure, though utility tokens exhibit even more muted initial responses than other asset classes. In Table 2.21's CAR3 analysis, the interaction term *Post MiCA* × *Tokens* becomes negative and significant at the 10% level in Models 2 and 3 (-0.0032 and -0.0031 respectively), while the pre-MiCA Tokens dummy shows positive significance (0.0026, $p<0.10$) in Model 1. This emerging pattern suggests that while utility tokens maintained positive performance before the regulatory announcement, they began experiencing modest negative effects as markets had more time to

process MiCA's implications. The delayed emergence of significance is consistent with evidence from regulatory-news event studies (e.g., Chokor and Alfieri, 2021) that announcements increasing the probability of regulation adoption are associated with negative abnormal returns, with timing and magnitude varying across assets.

Table 2.2's CAR5 results demonstrate the full development of this building pattern. The pre-MiCA *Tokens* dummy strengthens to 0.0037 ($p<0.05$), while the interaction term intensifies to negative significance at the 5% level (-0.0058 and -0.0056 in Models 2 and 3). This progression from positive pre-MiCA performance to negative post-MiCA effects, with increasing statistical significance over longer windows, reflects the measured market response that Gryglewicz et al. (2021) and Goldstein et al. (2024) associate with regulatory uncertainty's impact on platform-based tokens. Since MiCA's requirements target issuer obligations rather than platform functionality itself, the tokens' core transactional utility, which drives their valuation, remains largely unchanged in the immediate term. The delayed negative effects in CAR3 and CAR5 likely reflect markets gradually pricing increased compliance costs that may indirectly affect platform adoption and transaction volumes over time.

Taken together, utility tokens show muted immediate reactions but increasingly negative CARs over longer windows. The sign and timing align with a literature that links utility-token performance to regulatory frictions in ICO/issuance settings (Howell et al., 2020; Gryglewicz et al., 2021; Lyandres et al., 2022) and to platform-productivity valuation (Cong et al., 2021; Goldstein et al., 2024). Our results therefore support H5 on the negative impact, while clarifying that market repricing is gradual as MiCA’s compliance and governance obligations are digested. This pattern aligns with Cong et al.’s (2021) framework: the immediate functionality of established platforms is unchanged at announcement, so near-term reactions remain muted. As compliance obligations and governance restrictions become salient, however, markets gradually adjust expectations of platform productivity, producing the

negative CARs observed over longer windows. These results support H5, indicating gradual market repricing as MiCA's compliance and governance obligations are internalized.

Non-Fungible Tokens (NFTs)

The NFT analysis reveals the most consistently negative and intensifying reaction among all asset classes, directly contradicting H6 and providing unique insights into ecosystem interdependencies within crypto markets. Moreover, it challenges the assumption that regulatory exemption guarantees resilience and instead demonstrates that functional purpose, rather than regulatory classification, drives market performance under comprehensive frameworks. As stated above, we proxy NFTs with utility tokens from CoinMarketCap that are listed as the top traded for purchasing NFTs since they are essentially digital art and collectibles. Our results show how two tokens within the same technical category, utility-based, can diverge dramatically in performance once their functions differ, despite identical regulatory treatment.

Pre-MiCA, NFT tokens and regular utility tokens performed nearly identically, which aligns with their shared technological foundation as utility tokens serving different platform purposes. The returns analysis in Table 2.23 shows insignificant pre-MiCA *NFT* dummy, while the abnormal returns specification in Table 2.24 demonstrates a positive coefficient of 0.0017 ($p<0.05$), similar to tokens but at a larger significance. The cumulative abnormal returns provide further evidence of similarity. CAR1 in Table 2.25 shows 0.0016, CAR3 in Table 2.26 shows 0.0041 ($p<0.05$), and CAR5 in Table 2.27 shows 0.0056 ($p<0.05$). The CARs behave nearly identically to utility tokens respectively, with CAR3 being less significant in tokens at ($p<0.10$) in Table 2.21.

Post-MiCA, the performance divergence becomes dramatic and statistically robust across all specifications. The returns analysis in Table 2.23 demonstrates that the Post MiCA × NFT interaction reaches -0.0032 ($p<0.01$) in Model 3, while the abnormal returns specification in Table 2.24 shows increasing negative magnitude across models, reaching -0.0044 ($p<0.01$) in the fully specified model. The cumulative abnormal returns analysis in Tables 2.25-2.27 reveals an accelerating pattern of negative effects over extended windows. CAR1 in Table 2.25 shows immediate negative impacts with interaction effects reaching -0.0046 ($p<0.01$) in Model 3. CAR3 in Table 2.26 demonstrates substantial deterioration with effects intensifying to -0.0128 ($p<0.01$), while CAR5 in Table 2.27 reaches severe negative magnitudes of -0.0189 ($p<0.01$). The progression from positive performance pre-MiCA to increasingly negative post-MiCA effects demonstrates that markets recognized NFTs'' ecosystem vulnerability, despite their technical regulatory equivalence to other utility tokens.

While we assumed NFTs would benefit from exemption our results reveal the opposite. Instead, their pre-MiCA gains reversed into sustained losses with CAR5 declines of nearly –1.9 pp. This suggests that NFTs are priced through their dependence on regulated infrastructure as MiCA imposed strict obligations on utility tokens and concerns over NFT liquidity, settlement costs, and market functionality mounted. Prior studies show investors often rotate into exempt assets under regulatory pressure (Foley et al. 2019; Borri and Shakhnov 2020; Cong et al. 2023) and NFTs' diversification potential reinforced this expectation (Karim et al. 2022; Fakhfekh et al. 2024; Almeida et al. 2024). Yet, exemption did not provide resilience which directly contradicts H6. Unlike utility tokens which despite regulation reacted only mildly, NFTs became vulnerable through their dependence on regulated components.

Our results demonstrate that functional ecosystem roles create indirect vulnerabilities that offset the expected benefits of regulatory exemption. This pattern validates Cong et al.'s (2021) theoretical framework, which predicts that token value derives from platform functionality and transactional utility rather than regulatory classification alone. Maître et al. (2025) provide complementary empirical evidence, showing that technological quality and functional characteristics, not regulatory status, drive cryptocurrency returns. Our NFT utility token divergence offers decisive evidence of this mechanism: despite sharing identical technological infrastructure and regulatory exemption, these assets produced opposite market reactions because their functional purposes, facilitating digital art purchases versus general platform access, generated different transactional demands under regulatory pressure. This finding extends Corbet et al.'s (2020) demonstration that functional roles shape policy sensitivity. Where Corbet showed currency layer versus decentralised protocol layer differences under general monetary policy, we show that even within the same technological layer, functional specialization creates differential regulatory vulnerabilities under comprehensive crypto specific frameworks. The evidence further builds on Yousaf and Yarovaya (2022c) and Mercik et al. (2024), who document that regulatory frameworks generate indirect effects through ecosystem spillovers and dependencies. Our contribution establishes that these dependencies operate through functional channels: NFTs' reliance on utility token infrastructure for transaction settlement made their specialised collectibles function vulnerable when regulation targeted that infrastructure, despite formal exemption. Overall, the NFT case demonstrates that comprehensive regulation like MiCA reshapes market behavior beyond its explicit scope, affecting exempt assets through functional interdependencies. This underscores a critical regulatory design principle: exemptions provide incomplete protection when assets depend on regulated infrastructure to perform their core functions, and markets price this vulnerability independent of formal classification.

DeFi Assets

The DeFi-only analysis demonstrate an immediate and severe negative reaction to MiCA announcements but reveals interesting dynamics across different time windows. The returns analysis presented in Table 2.28 demonstrates a dramatic reversal from positive pre-regulation performance to significant post-regulation decline. The pre-MiCA DeFi dummy shows positive significance (0.439 pp, $p < 0.01$ in Model 1), indicating these assets may have thrived in the unregulated environment, whilst the Post MiCA × DeFi interaction reveals substantial negative impacts: (-0.428 pp, $p < 0.01$) in Model 1, (-0.711 pp, $p < 0.01$) in Model 2, and (-0.943 pp, $p < 0.01$) in Model 3. The announcement Post MiCA is positively significant at (0.268 pp, $p<0.01$). This progression suggests that controlling for unobserved factors reveals an even more severe regulatory impact.

The abnormal returns specification presented in Table 2.29 confirms the severity of the negative reaction with interaction coefficients from (-0.210 to -0.618 pp, $p < 0.01$). The pre-MiCA DeFi dummy remains positive and significant (0.241 pp, $p < 0.01$), emphasising the stark regulatory reversal that these assets experienced. The cumulative abnormal returns in Tables 2.30-2.32 reveal more nuanced patterns. In CAR1 (Table 2.30), the interaction effects are negatively significant in Models 2 and 3 while pre MiCA, DeFis had positive returns at 10% significance. By CAR3, Table 2.31, the negative effect becomes highly significant in the interaction term and the level of significance increases in pre-MiCA, suggesting the immediate impact takes time to fully materialize. Interestingly, in the five-day window (Table 2.32), the negative impact persists post-MiCA but at reduced significance levels ($p<0.10$) while pre-MiCA maintains its significance.

Like NFTs, DeFi's response contradicts our exemption hypothesis. We assumed DeFi would benefit from freedom from MiCA's crypto-specific framework, making them attractive

as investors rotated away from regulated assets. Instead, DeFi experienced immediate and severe declines, with pre-MiCA gains (0.439 pp) reversing into substantial losses (-0.943 pp by Model 3). Corbet et al. (2020a) showed that traditional currency-layer assets reacted strongly to monetary policy shocks, while decentralized protocol-layer assets often moved in opposite directions. We find this same dynamic under crypto-specific regulation. Strikingly, the only asset class to surge positively was uCrypto, the traditional currency-layer exempt asset, which directly parallels Corbet's observation that currency and protocol layers react oppositely to policy shocks.

Explicit exemption did not make DeFi immune or attractive as expected. The consistently positive pre-MiCA coefficients show these assets thrived unregulated, making the post-MiCA reversal especially notable. Both DeFi and NFTs failed to benefit from exemption despite prior evidence that investors rotate into exempt assets under regulatory pressure (Foley et al., 2019; Borri and Shakhnov, 2020; Cong et al., 2023; Karim et al., 2022; Fakhfekh et al., 2024; Almeida et al., 2024), directly contradicting H7. Yet their trajectories diverge: NFTs' losses accelerated over longer windows, while DeFi's negative effects moderated after the initial shock. This moderation suggests different vulnerability mechanisms operate. Where NFTs depend on regulated utility token infrastructure for transaction settlement, creating acute vulnerability when MiCA targeted that infrastructure, DeFi protocols' decentralized operational structure may provide some resilience despite initial regulatory uncertainty. Markets appear to price both immediate shock (comprehensive regulation threatens DeFi's unregulated innovation space) and longer-term reassessment (decentralized protocols retain operational independence), consistent with Galati and Capalbo (2024)'s evidence that investors reallocate within crypto ecosystems rather than exit entirely and Werbach (2018)'s caution that regulation constrains innovation even when protocols remain formally outside its scope.

2.4.3 Full Sample Regression Results

The individual regressions capture the total regulatory effect for each asset class in isolation, whereas the full-sample specification identifies class-specific effects conditional on all other categories being included simultaneously. The full sample regression analysis presented in Tables 2.33-2.37 of the main results provides strong confirmation of the individual asset findings whilst revealing additional insights into cross-asset regulatory dynamics. The full sample specification includes interaction terms for all major asset classes (iCrypto, uCrypto, Stablecoins, DeFi, NFTs, and Utility Tokens) within a single econometric framework, allowing for simultaneous estimation of treatment effects whilst controlling for common market movements through comprehensive fixed effects structures.

The returns analysis presented in Table 2.33 demonstrates that the key findings from individual asset regressions remain robust in the full sample specification. The Post MiCA × uCrypto interaction term shows consistent positive significance across all three model specifications (0.492 pp in Model 1, $p < 0.01$; 0.186 percentage points in Model 2; 0.266 percentage points in Model 3, $p < 0.01$). The magnitude and significance of these effects closely match those observed in the standalone uCrypto regression, indicating that the individual asset results are not driven by specification-specific factors or omitted common variables. The Post MiCA × iCrypto interaction demonstrates positive effects (0.542 percentage points in Model 1, $p < 0.01$) that diminish with fixed effects inclusion, replicating the pattern observed in individual regressions and confirming the limited support for H3.A.

The full sample regression reveals particularly striking results for assets hypothesised to benefit from substitution effects. The Post MiCA × DeFi interaction demonstrates substantial negative coefficients across all specifications, reaching -0.498 percentage points ($p < 0.05$) in Model 2 and -0.801 percentage points ($p < 0.01$) in Model 3.

These effects are virtually identical to those observed in the individual DeFi regression, confirming that the negative impact represents a genuine regulatory response rather than an artefact of single-asset specification. Similarly, the Post MiCA × NFT interaction shows consistently negative effects that strengthen with fixed effects inclusion, reaching -0.324 percentage points ($p < 0.10$) in Model 3, closely matching the individual asset results.

The abnormal returns analysis presented in Table 2.34 provides even stronger confirmation of individual asset findings. The Post MiCA × uCrypto interaction maintains highly significant positive effects (0.573 percentage points in Model 1, $p < 0.01$; 0.313 percentage points in Model 2, $p < 0.05$; 0.349 percentage points in Model 3, $p < 0.01$), with magnitudes that closely correspond to the individual regression estimates. The DeFi and NFT interactions continue to show significant negative effects (-0.631 percentage points and -0.427 percentage points respectively in Model 2, both $p < 0.05$), confirming that these asset classes experienced genuine regulatory harm rather than benefiting from substitution effects as originally hypothesised.

The cumulative abnormal returns analysis presented in Tables 2.35-2.37 reveals the temporal consistency of regulatory effects across the full sample and individual specifications. The five-day CAR results in Table 2.37 show that uCrypto maintains substantial positive effects (2.044 percentage points in Model 3, $p < 0.01$), DeFi continues to demonstrate negative impacts, and NFT effects intensify over time (-1.386 percentage points in Model 1, $p < 0.01$). The close correspondence between full sample and individual estimates across all time horizons provides strong evidence that the regulatory effects identified in this study represent genuine market responses to MiCA announcements rather than econometric artefacts.

The full sample regression framework also allows for formal statistical testing of cross-asset differences in regulatory impact. The stark contrast between the positive uCrypto

effects and negative DeFi/NFT effects in the same model provides direct evidence of the heterogeneous regulatory impacts predicted by H2. The magnitude of these differences—with uCrypto gaining over 2 percentage points whilst NFTs lose nearly 1.4 percentage points over five days, this represents economically meaningful valuation shifts that confirm the importance of asset-specific regulatory analysis in cryptocurrency markets.

Overall, we can confirm all these asset classes had a reaction towards MiCA, confirming that markets respond to institutional regulatory proposals. This supports evidence that institutional announcements matter even pre-implementation and that investors pay attention to them (Auer & Claessens, 2018; Conlon et al., 2024; Copestake et al., 2023; Dunbar, 2023; Huang et al., 2022). More specifically, we contribute to the literature that revolves around whether certain economic blocs are more influential, especially the EU. The pre- and post-MiCA patterns lend weight to this limited strand that highlights the EU's role as an influential player in global crypto markets (Panagiotidis et al., 2019; Aloui et al., 2024). Beyond this, we identify four novel contributions. First, our overall results provide evidence that markets anticipate and price regulatory proposals before formal implementation, with all six crypto asset classes reacting within our five-day event windows. This demonstrates heightened investor sensitivity to institutional announcements (Huang et al., 2022; Hu et al., 2019), particularly for crypto-specific regulation. Our findings align with studies showing institutional policy signals drive significant market responses and amplify investor attention (Auer and Claessens, 2018; Corbet et al., 2020a; Copestake et al., 2023; Aloui et al., 2024). In fact, we find that crypto classes' immediate reactions were divided according to their regulatory status. Regulated classes had muted immediate reactions, while unregulated classes responded significantly immediately. This is consistent and supportive of our H1. This sensitivity is evident across all performance measures, from raw returns through to abnormal returns and cumulative windows, confirming that the announcement effect is not window-specific but

persistent across measurement approaches. Moreover, we document that EU policy impacts crypto markets at the proposal stage, supporting Panagiotidis et al. (2019) who find EU economic policy uncertainty significantly affects Bitcoin returns, and extending Gambarelli et al. (2023) who demonstrate European regulatory signals shape global crypto dynamics.

Second, our results are consistent with H2 where it reveals pronounced heterogeneity in market responses to MiCA's proposal, contributing to the growing literature on crypto asset segmentation. Exempt assets show dramatic sign reversals post-MiCA while regulated assets display muted responses, some materializing only over longer windows. This pattern is consistent across returns, abnormal returns, and all three CAR windows, with exempt assets showing immediate reactions while regulated assets required extended windows to reveal their effects. Notably, uCrypto records the strongest positive response (2.1 percentage points over five days), while DeFi and NFTs experience immediate severe declines despite exemption. This challenges simple substitution theories (Foley et al., 2019; Borri and Shakhnov, 2020) and reveals ecosystem dependencies (Koutmos, 2018; Yousaf and Yarovaya, 2022b). Stablecoins and utility tokens show delayed negative effects consistent with their structural roles as market infrastructure (Lyons and Viswanath-Natraj, 2023; Corbet et al., 2020a). These findings demonstrate that functional roles, structural characteristics, and issuer identifiability, not merely regulatory inclusion, drive distinct market behaviours under comprehensive regulation.

Third, our introduction of issuer identifiability as a novel priced characteristic in traditional cryptocurrency markets extends theoretical frameworks that link valuation to issuer characteristics. While Howell et al. (2020) demonstrate that issuer quality and transparency predict token success, and Koenraadt and Leung (2024) show transparency mitigates negative regulatory reactions, we reveal that issuer identifiability itself, the mere presence or absence of

an accountable entity, becomes priced under MiCA's framework. The 2.1 percentage point divergence between uCrypto and iCrypto despite identical functionality establishes a novel form of intra-class heterogeneity distinct from functional roles (Corbet et al., 2020a) or technological quality (Cong et al., 2021; Maître et al., 2025). Prior to the announcement, uCryptos were already showing significantly negative returns while iCryptos displayed muted performance. However, post-MiCA, uCryptos surged immediately with sustained growth through the five-day window, demonstrating that regulatory clarity amplifies the value of anonymity when compliance requirements target identifiable issuers. This divergence reveals that MiCA establishes a regulatory regime where issuer identifiability becomes a key determinant of market performance. Therefore, H3 is supported by issuer identifiability becoming a factor, however H3.A we find no negative response but H3.B is the only exempt asset that is consistent and shows a positive response.

Fourth, our analysis of exempt assets reveals unexpected vulnerabilities that advance understanding of regulatory spillovers in crypto markets. DeFi's negative response is inconsistent with H7, despite exemption aligns with Corbet et al. (2020), who find that currency layer and protocol layer assets move in opposite directions under policy shocks, which is precisely what we observe with uCrypto surging while DeFi declines. This supports Dunbar et al.'s (2025) 'decentralization illusion' thesis, showing DeFi remains vulnerable through dependencies on regulated infrastructure. Similarly, NFTs exhibited immediate negative responses across all windows opposing H6, while underlying utility tokens showed losses only at CAR5 which is consistent with H5’s negative expectations. This divergence despite shared technological infrastructure validates Cong et al.'s (2021) theoretical prediction that functional purpose rather than technology drives valuation, and extends their framework to show how regulation amplifies these functional differences. Across all performance measures, DeFi and NFT declines are immediate and persistent, while stablecoin and utility token effects emerge

progressively from CAR3 to CAR5, confirming that the timing of regulatory repricing reflects each asset's functional relationship to MiCA's framework. Finally, stablecoins remained consistent with previous studies and demonstrated negative response at the five day window, consistent with H4. Traditional cryptocurrencies, as the original digital assets dominating the ecosystem, behave differently from newer asset classes like DeFi and NFTs, supporting recent studies that document distinct behavioural patterns between established and emerging cryptocurrencies (Polyzos and Youssef, 2025).

[Tables 2.3-2.32]

[Tables 2.32-2.37]

2.5 Robustness Tests

We implement placebo tests using a six-month pre-treatment window (24 March to 23 September 2020). This period coincides with exceptional market turbulence due to COVID-19 and the rapid growth of emerging crypto segments such as DeFi and NFTs. Importantly, no major regulatory events occurred, making it suitable for testing whether our post-MiCA effects are genuine rather than driven by broader volatility. Moreover, because our dataset captures the full spectrum of major crypto categories, cryptocurrencies, DeFi, stablecoins, utility tokens, and NFTs, this placebo functions not only as a falsification test but also as a natural stress test for the crypto ecosystem. If our empirical approach were overly sensitive to general volatility or coincidental patterns, we would expect widespread significance across asset classes, particularly given the extreme market stress during this period. Instead, we find a much more selective pattern.

In Tables 2.1B through 2.5B, iCrypto and DeFi show consistently insignificant effects across all outcome measures, providing clean falsification evidence for these asset classes. Stablecoins show significant positive effects in the CAR windows, attributable to the DAI liquidation crisis

in March 2020 and broader flight-to-stability dynamics during COVID-19 market stress, representing asset-specific shocks rather than generalised regulatory sensitivity. uCrypto shows consistent negative significance across CAR1, CAR3, and CAR5, reflecting the sharp negative disruption during the Bitcoin crash of March 12, 2020. Importantly, this negative pre-treatment trend for uCrypto contrasts directly with the strong positive post-MiCA effects documented in the main results, strengthening the identification by confirming that the post-announcement surge represents a genuine reversal rather than a continuation of prior trends. NFTs show persistent effects consistent with their early 2020 market expansion. Nadini et al. (2021) document that NFT market activity, which remained relatively flat until early 2020, began to accelerate substantially from mid-2020 onward, with trading volumes and platform participation rising sharply well before the mainstream surge of 2021. This early expansion was driven by increased activity across art, gaming, metaverse, and collectible segments, which are precisely the ecosystems represented by our NFT proxy tokens. Similarly, Balietti et al. (2025) highlight that GameFi platforms such as Axie Infinity exhibited growing user engagement during 2022 to 2023, reflecting sustained ecosystem development. Because our NFT proxy comprises the fungible platform tokens that underpin these ecosystems, including AXS, SAND, MANA, FLOW, and others, their significance during the placebo window reflects genuine, asset-specific growth dynamics rather than spurious pre-treatment trends or general market noise. Overall, the placebo tests support our identification strategy, indicating that the post-MiCA effects reflect a response to the regulatory announcement rather than background market volatility. Concurrent regulatory developments around the announcement date were also reviewed, and, to the best of our knowledge, no other major regulatory announcement affecting crypto-assets coincided with the MiCA proposal. While other news, such as asset-specific events, cannot be fully excluded, the evidence points towards the MiCA announcement as a likely source of the observed response.

2.6 Concluding Remarks

MiCA represents the EU's first comprehensive regulatory framework for crypto assets, providing a rare opportunity to examine how markets price regulation across heterogeneous digital asset classes. While prior studies assessed crypto market behaviour in largely unregulated environments (Hu et al., 2019; Corbet et al., 2019; Foley et al., 2019), our study offers the first systematic analysis of market reactions to a structured regulatory regime. Using a difference-in-differences approach established in recent crypto research (Cong et al., 2023; Chen et al., 2022; Grobys, 2021), we measure MiCA's causal impact across distinct asset classes.

Our results show that markets reshuffled crypto assets into regulated versus exempt categories at MiCA's announcement, but this binary split produced more complex dynamics than simple inclusion-exclusion effects. Regulated assets exhibited muted or delayed reactions, consistent with evidence that regulatory clarity can stabilise performance (Auer and Claessens, 2018; Lyons and Viswanath-Natraj, 2023). Exempt assets, however, displayed sharp reversals: uCrypto posted robust gains across all measures, reversing pre-MiCA losses, consistent with investor migration toward unregulated venues under regulatory pressure (Foley et al., 2019; Borri and Shakhnov, 2019; Cong et al., 2023). In contrast, DeFi protocols declined sharply despite exemption, echoing Corbet et al. (2020a), who show that currency-layer and protocol-layer assets react oppositely to monetary policy shocks. NFTs recorded the strongest and most persistent declines, reflecting their dependence on regulated infrastructure.

Firstly, we establish that a single regulatory event does not impact the market uniformly, but compelling evidence of performance differentials is observed. This shows that investors follow institutional announcements closely (Huang et al., 2022; Hu et al., 2019) and react to proposals at the announcement stage (Aloui et al., 2024), validating our hypothesis that

markets exhibit pronounced sensitivity to comprehensive regulatory frameworks from specific institutions such as the European Union (Panagiotidis et al., 2019; Auer and Claessens, 2018; Gambarelli et al., 2023). The prior literature supports EU policy influence on crypto markets, and our findings extend this work by showing that even proposal-stage announcements from the EU can drive significant price adjustments across the entire crypto ecosystem. This is a critical finding with implications for investors, regulators, and researchers alike.

Secondly, regulated assets such as iCrypto, stablecoins, and utility tokens exhibited muted or delayed effects, consistent with prior findings that regulatory clarity can stabilize performance (Auer and Claessens, 2018; Lyons and Viswanath-Natraj, 2023; Corbet et al., 2020a). In contrast, exempt assets demonstrated significant sign reversal reactions. uCrypto, which remains outside the issuer-based perimeter, recorded robust and sustained gains contrasting with its significant negative performance pre-MiCA, extending earlier substitution evidence that investors migrate toward unregulated venues during regulatory pressure (Foley et al., 2019; Borri and Shakhnov, 2019; Cong et al., 2023). However, negative reversals in DeFi and NFTs challenge this substitution expectation by showing that exemption can heighten vulnerability when assets depend on regulated infrastructure. This pattern parallels Corbet et al.'s (2020a) finding that traditional currency-layer assets and decentralized protocol-layer assets move in opposite directions under policy shocks. Where uCrypto surged positively, DeFi protocols declined severely despite both being exempt, demonstrating that functional dependencies override formal classification even within exempt categories.

Thirdly, within cryptocurrencies we examine a unique form of intra-class heterogeneity driven by issuer identity, consistent with MiCA's classification criteria. uCrypto consistently experienced positive and economically significant gains of more than two percentage points over five trading days, while iCrypto displayed limited and inconsistent reactions. This pattern

is in line with investor preference for anonymity under regulatory uncertainty (Foley et al., 2019) and supports Auer and Tercero-Lucas's (2021) call for tailored regulation across investor bases. Moreover, we extend prior heterogeneity research (Karim et al., 2022; Almeida et al., 2024) by establishing that issuer identifiability itself becomes a priced characteristic under comprehensive regulation, introducing a dimension distinct from functional roles (Corbet et al., 2020a) and technological quality (Cong et al., 2021; Maître et al., 2025).

Fourthly, NFTs diverge dramatically from their underlying utility token infrastructure, transitioning from similar pre-MiCA performance to significantly negative post-MiCA outcomes compared to regular utility tokens. This validates Cong et al.'s (2021) theoretical prediction that platform functionality determines token value: despite sharing identical technological infrastructure and exemption status, NFT tokens' specialized function in facilitating digital art purchases proved more vulnerable than utility tokens' broader platform functions. Maître et al. (2025) provide empirical support, which we complement, demonstrating that functional characteristics drive cryptocurrency returns. Where Corbet et al. (2020a) showed currency-layer versus decentralized protocol-layer differences under monetary policy, we extend this by demonstrating that within the same technological layer, functional specialization creates differential regulatory vulnerabilities under comprehensive crypto-specific frameworks.

Our asset-specific findings demonstrate robust empirical support for these theoretical contributions. Full sample regressions confirm these patterns with high statistical significance across specifications, and placebo tests validate that observed effects represent genuine regulatory responses rather than coincidental market movements. Our study highlights the importance of research on MiCA-specific impacts and crypto-specific regulation more broadly. The literature examining comprehensive crypto-asset frameworks remains nascent (Gordon

and Marthinsen, 2023) due to its recency, with limited empirical evidence on how tailored regulatory proposals affect different asset classes. While Conlon et al. (2024) provide early evidence that crypto assets respond differently to MiCA announcements using event study methodology, we extend this by demonstrating that heterogeneity is not incidental but reflects structured performance differentials aligned with MiCA's design, examining pre- and post-MiCA regimes through our framework. Our findings contribute to both the emerging MiCA literature and broader understanding of how crypto-specific regulatory frameworks systematically affect different asset classes. These results support calls for heterogeneous examination of crypto assets (Auer and Tercero-Lucas, 2021; Karim et al., 2022; Yousaf and Yarovaya, 2022a, 2022b; Fakhfekh et al., 2024) and establish that formal regulation creates structured market divergence.

Our findings carry three implications for regulatory design. First, institutional announcements from major economic blocs generate immediate and sustained market repricing well beyond their formal regulatory perimeter. The speed and breadth of reactions across all six asset classes, including formally exempt ones, confirms that markets process comprehensive regulatory frameworks as ecosystem-wide events rather than narrowly scoped rules. Within this broader reaction, exempt assets are not necessarily insulated: NFTs declined through their transactional dependence on regulated utility token infrastructure, while DeFi's losses reflect markets pricing operational dependencies on centralised components regardless of formal classification. Policymakers should therefore map functional and operational dependencies across the ecosystem before defining regulatory perimeters, since formal exemption does not guarantee market insulation. Second, the strong positive response of unidentifiable-issuer cryptocurrencies suggests that issuer-based regulation may unintentionally reward anonymity. Regulators face a genuine tension between promoting transparency, protecting consumers, and avoiding capital flows toward less identifiable assets.

Third, our results demonstrate that market participants pay close attention to institutional announcements, and this attention materialises at the proposal stage rather than at implementation or enforcement. The mere official announcement that MiCA would happen was sufficient to trigger significant and sustained repricing across the entire crypto ecosystem. This has direct implications for policymakers: regulatory proposals from influential economic blocs carry market consequences from the moment they are made public, and the design of those proposals matters as much as their eventual content.

Our findings open several research avenues. First, examining MiCA's implementation phase from June 2024 onwards will reveal whether announcement effects persist through enforcement, particularly for stablecoins facing immediate compliance deadlines. Second, as jurisdictions develop competing frameworks, cross-border regulatory arbitrage and spillovers merit investigation. Third, the behavioural mechanisms driving our results, whether risk preferences, information processing, or strategic positioning, remain unexplored. Finally, future research could also test whether issuer identifiability remains a priced characteristic across other regulatory events and jurisdictions, to examine the generalisability of this finding.These findings demonstrate that comprehensive regulatory frameworks create complex market dynamics extending beyond simple compliance costs, with implications for policymakers designing digital asset regulations and investors navigating evolving digital markets.

Tables

Table 2.1: Observed Digital Assets

Digital Asset	Symbol	Currency	Volume	Market Capitalization
Cryptocoins with Identified Issuers				
Binance Coin	BNB	USD	$1,057,531,865	$43.44B
XRP	XRP	USD	$2,217,059,685	$26.65B
Cardano	ADA	USD	$362,267,281	$12.18B
Solana	SOL	USD	$637,553,135	$7.9B
Polygon	MATIC	USD	$470,674,568	$7.48B
TRON	TRX	USD	$271,296,386	$7.05B
Polkadot	DOT	USD	$174,636,996	$6.05B
Cosmos	ATOM	USD	$141,565,348	$3.02B
Stellar	XLM	USD	$70,929,098	$2.19B
Algorand	ALGO	USD	$71,141,683	$1.44B
EOS	EOS	USD	$202,216,604	$1.14B
MultiversX	EGLD	USD	$27,076,894	$1.03B
Cryptocoins with Unidentified Issuers				
Bitcoin	BTC	USD	$23,044,019,534	$504.7B
Ethereum	ETH	USD	$8,212,701,701	$225.98B
Monero	XMR	USD	$95,149,821	$2.75B
Ethereum Classic	ETC	USD	$222,960,394	$2.52B
Bitcoin Cash	BCH	USD	$362,267,281	$2.34B
Dogecoin	DOGE	USD	$634,696,467	$9.51B
Litecoin	LTC	USD	$925,097,458	$6.45B
Shiba Inu	SHIB	USD	$168,407,941	$4.67B
Bitcoin SV	BSV	USD	$36,787,512	$673.39M
Dash	DASH	USD	$117,970,595	$594.3M
Zcash	ZEC	USD	$40,884,516	$561.97M
Dash	DASH	USD	$117,970,595	$594.3M
Bitcoin SV	BSV	USD	$36,787,512	$673.39M
Ravencoin	RVN	USD	$11,528,655	$295.5M
Stablecoins				
Tether	USDT	USD	$36,098,018,332	$83.25B
USD Coin	USDC	USD	$4,923,965,332	$28.1B
Lido Staked Ether	STETH	USD	$9,428,868	$16.43B
Binance USD	BUSD	USD	$3,167,807,537	$5.09B
Dai	DAI	USD	$169,102,502	$4.79B
TrueUSD	TUSD	USD	$3,578,657,313	$2.06B
Pax Dollar	USDP	USD	$14,384,425	$1.01B
Frax	FRAX	USD	$19,804,862	$1B
USDD	USDD	USD	$13,834,215	$747.37M
Gemini Dollar	GUSD	USD	$640,477	$566.28M
Stasis Euro	EURS	USD	$10,865,095	$132.39M
TerraClassicUSD	USTC	USD	$11,076,443	$124.22M
DeFi Coins				
Avalanche	AVAX	USD	$161,576,133	$4.96B
Wrapped Bitcoin	WBTC	USD	$157,864,593	$4.13B
Chainlink	LINK	USD	$184,634,452	$3.24B
Uniswap	UNI	USD	$44,390,848	$2.79B
Lido DAO	LDO	USD	$97,156,510	$2.11B
Injective	INJ	USD	$83,755,556	$1.71B
The Graph	GRT	USD	$43,160,424	$1.07B
Rocket Pool	RPL	USD	$8,186,042	$941.56M
Aave	AAVE	USD	$41,580,174	$890.6M
Fantom	FTM	USD	$97,309,433	$850.27M
Tezos	XTZ	USD	$16,841,926	$822.29M
Conflux	CFX	USD	$121,340,830	$707.08M
Top Collectibles & NFTs Tokens				
Internet Computer	ICP	USD	$40,126,555	$1.9B
ApeCoin	APE	USD	$202,509,963	$1.17B
The Sandbox	SAND	USD	$313,067,300	$952.04M

Render Token	RNDR	USD	$332,139,005	$856.19M
Decentraland	MANA	USD	$182,949,814	$849.25M
Stacks	STX	USD	$114,797,157	$802.98M
Theta Network	THETA	USD	$15,644,230	$788.12M
Axie Infinity	AXS	USD	$70,156,435	$771.14M
Flow	FLOW	USD	$34,628,767	$678.98M
Immutable	IMX	USD	$31,663,285	$665.72M
Chiliz	CHZ	USD	$66,908,710	$657.59M
Gala	GALA	USD	$118,689,814	$190.8M
Top Utility Tokens				
Toncoin	TON	USD	$23,182,393	$8.93B
Unus Sed Leo	LEO	USD	$470,747	$3.68B
OKB	OKB	USD	$20,188,223	$2.79B
Hedera Hashgraph	HBAR	USD	$24,850,000	$1.87B
Filecoin	FIL	USD	$108,000,000	$1.73B
Aptos	APT	USD	$61,200,000	$1.72B
Cronos	CRO	USD	$11,920,000	$1.72B
NEAR Protocol	NEAR	USD	$75,390,000	$1.50B
VeChain	VET	USD	$23,710,000	$1.48B
KuCoin Token	KCS	USD	$222,960,394	$856.24M
Huobi Token	HT	USD	$19,239,190	$681.49M
GateToken	GT	USD	$1,525,009	$525.06M

Note: This table provides the full list of digital assets used in this study, grouped according to six asset classes: cryptocurrencies with identifiable issuers (iCrypto), cryptocurrencies without identifiable issuers (uCrypto), stablecoins, DeFi protocols, NFT-related tokens, and utility tokens. Each class includes 12 assets selected based on market capitalization as reported on CoinMarketCap. **Source of data:** www.CoinMarketCap.com

Table 2.2 Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Returns Measures					
Abnormal Returns	92956	0.00015	0.04091	-0.2548	0.31789
1 Day Cumulative Abnormal Returns	92956	0.00028	0.05727	-0.37698	0.48667
5 Day Cumulative Abnormal Returns	92956	0.00157	0.12887	-0.9976	1.09707
Crypto Common Risk Factors (Liu et al, 2022)					
CMKT	92956	-0.00863	0.11352	-0.5957	2.00133
CSMB	92956	0.00081	0.03984	-0.1958	0.51998
CMOM	92956	-0.00236	0.01943	-0.23934	0.10623
Control Variables					
Propensity Score	92956	0.51015	0.03456	0.41521	0.60449
*ln(*Volume)	92956	18.42677	2.97444	0	32.05289
VIX	92956	21.40181	9.14115	0	82.69

Note: The table reports the key descriptive statistics of all the variables used in this study. FF refers to Fama-French. Counterfactual measures are used to construct the propensity score. Crypto Dummy takes a value of 1 if the asset is a cryptocurrency, and 0 otherwise. Stablecoin Dummy takes value 1 if the asset is stablecoin, 0 otherwise. DeFi Dummy takes value 1 if the asset is DeFi, 0 otherwise. NFT Dummy takes value 1 if the asset is NFT, 0 otherwise. E is the event dummy. It takes value 1 for the days of MiCA announcements, 0 otherwise.

Table 2.3: Returns DiD Analysis - iCrypto Only

	(1)	(2)	(3)
Post MiCA	0.0021***	-0.0001	
	(0.0005)	(0.0006)	
iCrypto	-0.0010		
	(0.0007)		
Post MiCA × iCrypto	0.0015	0.0016	0.0017**
	(0.0009)	(0.0010)	(0.0008)
PS	0.0562***	0.0439***	
	(0.0061)	(0.0064)	
ln Volume	0.0004***	0.0013***	0.0019***
	(0.0001)	(0.0001)	(0.0001)
VIX	-0.0002***	-0.0002***	
	(0.0000)	(0.0000)	
Intercept	-0.0319***	-0.0420***	-0.0351***
	(0.0033)	(0.0035)	(0.0018)
N	93245	93245	93244
Adj. R-squared	0.0019	0.0035	0.4311
Control Variables	Yes	Yes	Yes
Individual Effects	No	Yes	Yes
Time Effects	No	No	Yes

Note: *This table reports the difference-in-differences estimation of MiCA's impact on iCrypto returns. Post MiCA is a binary treatment variable equalling 1 after the MiCA announcement (September 24, 2020) and 0 before. iCrypto identifies identified issuer cryptocurrencies. The interaction term Post MiCA × iCrypto captures the treatment effect. Control variables include the propensity score (PS) for matching, ln(Volume) for trading activity, and VIX for global market volatility. Column (1) presents the baseline specification, Column (2) adds individual fixed effects, and Column (3) includes both individual and time fixed effects. N denotes sample size. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.*

Table 2.4: Abnormal Returns DiD Analysis - iCrypto Only

	(1)	(2)	(3)
Post MiCA	-0.0007**	-0.0031***	
	(0.0004)	(0.0004)	
iCrypto	-0.0004		
	(0.0005)		
Post MiCA × iCrypto	-0.0002	0.0005	0.0005
	(0.0007)	(0.0007)	(0.0007)
PS	-0.0060	-0.0193***	
	(0.0045)	(0.0047)	
ln Volume	0.0004***	0.0014***	0.0015***
	(0.0001)	(0.0001)	(0.0001)
VIX	0.0000*	0.0000*	
	(0.0000)	(0.0000)	
Intercept	-0.0046*	-0.0138***	-0.0281***
	(0.0025)	(0.0026)	(0.0017)
N	92956	92956	92956
Control Variables	Yes	Yes	Yes
Individual Effects	No	Yes	Yes
Time Effects	No	No	Yes

Note: *This table reports the difference-in-differences estimation of MiCA's impact on iCrypto abnormal returns. Post MiCA is a binary treatment variable equalling 1 after the MiCA announcement (September 24, 2020) and 0 before. iCrypto identifies identified issuer cryptocurrencies. The interaction term Post MiCA × iCrypto captures the treatment effect. Control variables include the propensity score (PS) for matching, ln(Volume) for trading activity, and VIX for global market volatility. Column (1) presents the baseline specification, Column (2) adds individual fixed effects, and Column (3) includes both individual and time fixed effects. N denotes sample size. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.*

Table 2.5: 1-Day CAR DiD Analysis - iCrypto Only

	(1)	(2)	(3)
Post MiCA	-0.0005	-0.0010*	
	(0.0005)	(0.0006)	
iCrypto	0.0005		
	(0.0007)		
Post MiCA × iCrypto	-0.0005	-0.0002	-0.0002
	(0.0010)	(0.0010)	(0.0010)
PS	-0.0088	-0.0156**	
	(0.0064)	(0.0066)	
ln Volume	0.0002***	0.0005***	0.0006***
	(0.0001)	(0.0001)	(0.0001)
VIX	0.0001***	0.0001***	
	(0.0000)	(0.0000)	
Intercept	0.0006	-0.0020	-0.0099***
	(0.0035)	(0.0037)	(0.0023)
N	92956	92956	92956
Adj. R-squared	0.0002	0.0017	0.1044
Control Variables	Yes	Yes	Yes
Individual Effects	No	Yes	Yes
Time Effects	No	No	Yes

Note: *This table reports the difference-in-differences estimation of MiCA's impact on iCrypto 1-day cumulative abnormal returns. Post MiCA is a binary treatment variable equalling 1 after the MiCA announcement (September 24, 2020) and 0 before. iCrypto identifies identified issuer cryptocurrencies. The interaction term Post MiCA × iCrypto captures the treatment effect. Control variables include the propensity score (PS) for matching, ln(Volume) for trading activity, and VIX for global market volatility. Column (1) presents the baseline specification, Column (2) adds individual fixed effects, and Column (3) includes both individual and time fixed effects. N denotes sample size. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.*

Table 2.6: 3-Day CAR DiD Analysis - iCrypto Only

	(1)	(2)	(3)
Post MiCA	-0.0006	-0.0012	
	(0.0009)	(0.0010)	
iCrypto	0.0018		
	(0.0013)		
Post MiCA × iCrypto	-0.0018	-0.0011	-0.0010
	(0.0017)	(0.0018)	(0.0017)
PS	-0.0176	-0.0323***	
	(0.0110)	(0.0114)	
ln Volume	0.0003***	0.0009***	0.0011***
	(0.0001)	(0.0002)	(0.0002)
VIX	0.0001**	0.0001*	
	(0.0000)	(0.0000)	
Intercept	0.0026	-0.0005	-0.0187***
	(0.0060)	(0.0063)	(0.0040)
N	92956	92956	92956
Adj. R-squared	0.0002	0.0046	0.1002
Control Variables	Yes	Yes	Yes
Individual Effects	No	Yes	Yes
Time Effects	No	No	Yes

Note: *This table reports the difference-in-differences estimation of MiCA's impact on iCrypto 3-day cumulative abnormal returns. Post MiCA is a binary treatment variable equalling 1 after the MiCA announcement (September 24, 2020) and 0 before. iCrypto identifies identified issuer cryptocurrencies. The interaction term Post MiCA × iCrypto captures the treatment effect. Control variables include the propensity score (PS) for matching, ln(Volume) for trading activity, and VIX for global market volatility. Column (1) presents the baseline specification, Column (2) adds individual fixed effects, and Column (3) includes both individual and time fixed effects. N denotes sample size. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.*

Table 2.7: 5-Day CAR DiD Analysis - iCrypto Only

	(1)	(2)	(3)
Post MiCA	-0.0007	0.0004	
	(0.0011)	(0.0013)	
iCrypto	0.0038**		
	(0.0017)		
Post MiCA × iCrypto	-0.0033	-0.0027	-0.0025
	(0.0022)	(0.0023)	(0.0022)
PS	-0.0341**	-0.0491***	
	(0.0143)	(0.0148)	
ln Volume	0.0002	0.0005*	0.0007**
	(0.0002)	(0.0003)	(0.0003)
VIX	0.0002***	0.0002***	
	(0.0001)	(0.0001)	
Intercept	0.0121	0.0150*	-0.0103**
	(0.0078)	(0.0082)	(0.0053)
N	92956	92956	92956
Adj. R-squared	0.0002	0.0073	0.1063
Control Variables	Yes	Yes	Yes
Individual Effects	No	Yes	Yes
Time Effects	No	No	Yes

Note: *This table reports the difference-in-differences estimation of MiCA's impact on iCrypto 5-day cumulative abnormal returns. Post MiCA is a binary treatment variable equalling 1 after the MiCA announcement (September 24, 2020) and 0 before. iCrypto identifies identified issuer cryptocurrencies. The interaction term Post MiCA × iCrypto captures the treatment effect. Control variables include the propensity score (PS) for matching, ln(Volume) for trading activity, and VIX for global market volatility. Column (1) presents the baseline specification, Column (2) adds individual fixed effects, and Column (3) includes both individual and time fixed effects. N denotes sample size. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.*

Table 2.8: Returns DiD Analysis - uCrypto Only

	(1)	(2)	(3)
Post MiCA	0.0018***	-0.0006	
	(0.0005)	(0.0006)	
uCrypto	-0.0019***		
	(0.0007)		
Post MiCA × uCrypto	0.0011	0.0024**	0.0035***
	(0.0009)	(0.0010)	(0.0007)
PS	0.0542***	0.0420***	
	(0.0062)	(0.0064)	
ln Volume	0.0004***	0.0013***	0.0020***
	(0.0001)	(0.0001)	(0.0001)
VIX	-0.0002***	-0.0002***	
	(0.0000)	(0.0000)	
Intercept	-0.0316***	-0.0416***	-0.0369***
	(0.0033)	(0.0036)	(0.0019)
N	93245	93245	93244
Adj. R-squared	0.0020	0.0035	0.4312
Control Variables	Yes	Yes	Yes
Individual Effects	No	Yes	Yes
Time Effects	No	No	Yes

Note: *This table reports the difference-in-differences estimation of MiCA's impact on uCrypto returns. Post MiCA is a binary treatment variable equalling 1 after the MiCA announcement (September 24, 2020) and 0 before. uCrypto identifies unidentified issuer cryptocurrencies. The interaction term Post MiCA × uCrypto captures the treatment effect. Control variables include the propensity score (PS) for matching, ln(Volume) for trading activity, and VIX for global market volatility. Column (1) presents the baseline specification, Column (2) adds individual fixed effects, and Column (3) includes both individual and time fixed effects. N denotes sample size. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.*

Table 2.9: Abnormal Returns DiD Analysis - uCrypto Only

	(1)	(2)	(3)
Post MiCA	-0.0015***	-0.0043***	
	(0.0004)	(0.0005)	
uCrypto	-0.0022***		
	(0.0005)		
Post MiCA × uCrypto	0.0022***	0.0040***	0.0045***
	(0.0007)	(0.0007)	(0.0007)
PS	-0.0085*	-0.0228***	
	(0.0046)	(0.0048)	
ln Volume	0.0005***	0.0015***	0.0017***
	(0.0001)	(0.0001)	(0.0001)
VIX	0.0000*	0.0000*	
	(0.0000)	(0.0000)	
Intercept	-0.0034	-0.0133***	-0.0308***
	(0.0025)	(0.0026)	(0.0017)
N	92956	92956	92956
Control Variables	Yes	Yes	Yes
Individual Effects	No	Yes	Yes
Time Effects	No	No	Yes

Note: *This table reports the difference-in-differences estimation of MiCA's impact on uCrypto abnormal returns. Post MiCA is a binary treatment variable equalling 1 after the MiCA announcement (September 24, 2020) and 0 before. uCrypto identifies unidentified issuer cryptocurrencies. The interaction term Post MiCA × uCrypto captures the treatment effect. Control variables include the propensity score (PS) for matching, ln(Volume) for trading activity, and VIX for global market volatility. Column (1) presents the baseline specification, Column (2) adds individual fixed effects, and Column (3) includes both individual and time fixed effects. N denotes sample size. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.*

Table 2.10: 1-Day CAR DiD Analysis - uCrypto Only

	(1)	(2)	(3)
Post MiCA	-0.0016***	-0.0026***	
	(0.0005)	(0.0006)	
uCrypto	-0.0024***		
	(0.0007)		
Post MiCA × uCrypto	0.0038***	0.0046***	0.0049***
	(0.0009)	(0.0010)	(0.0009)
PS	-0.0118*	-0.0198***	
	(0.0064)	(0.0067)	
ln Volume	0.0002***	0.0006***	0.0007***
	(0.0001)	(0.0001)	(0.0001)
VIX	0.0001***	0.0001***	
	(0.0000)	(0.0000)	
Intercept	0.0022	-0.0013	-0.0131***
	(0.0035)	(0.0037)	(0.0024)
N	92956	92956	92956
Adj. R-squared	0.0004	0.0020	0.1047
Control Variables	Yes	Yes	Yes
Individual Effects	No	Yes	Yes
Time Effects	No	No	Yes

Note: *This table reports the difference-in-differences estimation of MiCA's impact on uCrypto 1-day cumulative abnormal returns. Post MiCA is a binary treatment variable equalling 1 after the MiCA announcement (September 24, 2020) and 0 before. uCrypto identifies unidentified issuer cryptocurrencies. The interaction term Post MiCA × uCrypto captures the treatment effect. Control variables include the propensity score (PS) for matching, ln(Volume) for trading activity, and VIX for global market volatility. Column (1) presents the baseline specification, Column (2) adds individual fixed effects, and Column (3) includes both individual and time fixed effects. N denotes sample size. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.*

Table 2.11: 3-Day CAR DiD Analysis - uCrypto Only

	(1)	(2)	(3)
Post MiCA	-0.0040***	-0.0057***	
	(0.0009)	(0.0011)	
uCrypto	-0.0065***		
	(0.0012)		
Post MiCA × uCrypto	0.0111***	0.0129***	0.0137***
	(0.0016)	(0.0017)	(0.0016)
PS	-0.0259**	-0.0443***	
	(0.0111)	(0.0115)	
ln Volume	0.0004***	0.0012***	0.0015***
	(0.0001)	(0.0002)	(0.0002)
VIX	0.0001**	0.0001*	
	(0.0000)	(0.0000)	
Intercept	0.0073	0.0013	-0.0277***
	(0.0060)	(0.0063)	(0.0042)
N	92956	92956	92956
Adj. R-squared	0.0007	0.0053	0.1009
Control Variables	Yes	Yes	Yes
Individual Effects	No	Yes	Yes
Time Effects	No	No	Yes

Note: *This table reports the difference-in-differences estimation of MiCA's impact on uCrypto 3-day cumulative abnormal returns. Post MiCA is a binary treatment variable equalling 1 after the MiCA announcement (September 24, 2020) and 0 before. uCrypto identifies unidentified issuer cryptocurrencies. The interaction term Post MiCA × uCrypto captures the treatment effect. Control variables include the propensity score (PS) for matching, ln(Volume) for trading activity, and VIX for global market volatility. Column (1) presents the baseline specification, Column (2) adds individual fixed effects, and Column (3) includes both individual and time fixed effects. N denotes sample size. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.*

Table 2.12: 5-Day CAR DiD Analysis - uCrypto Only

	(1)	(2)	(3)
Post MiCA	-0.0062***	-0.0069***	
	(0.0012)	(0.0014)	
uCrypto	-0.0099***		
	(0.0016)		
Post MiCA × uCrypto	0.0181***	0.0200***	0.0211***
	(0.0021)	(0.0022)	(0.0021)
PS	-0.0468***	-0.0677***	
	(0.0144)	(0.0150)	
ln Volume	0.0004**	0.0009***	0.0013***
	(0.0002)	(0.0003)	(0.0003)
VIX	0.0002***	0.0001***	
	(0.0001)	(0.0001)	
Intercept	0.0197**	0.0177**	-0.0244***
	(0.0078)	(0.0082)	(0.0054)
N	92956	92956	92956
Adj. R-squared	0.0010	0.0081	0.1073
Control Variables	Yes	Yes	Yes
Individual Effects	No	Yes	Yes
Time Effects	No	No	Yes

Note: *This table reports the difference-in-differences estimation of MiCA's impact on uCrypto 5-day cumulative abnormal returns. Post MiCA is a binary treatment variable equalling 1 after the MiCA announcement (September 24, 2020) and 0 before. uCrypto identifies unidentified issuer cryptocurrencies. The interaction term Post MiCA × uCrypto captures the treatment effect. Control variables include the propensity score (PS) for matching, ln(Volume) for trading activity, and VIX for global market volatility. Column (1) presents the baseline specification, Column (2) adds individual fixed effects, and Column (3) includes both individual and time fixed effects. N denotes sample size. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.*

Table 2.13: Returns DiD Analysis - Stablecoins only

	(1)	(2)	(3)
Post MiCA	0.0023***	0.0002	
	(0.0005)	(0.0006)	
Stablecoin	-0.0004		
	(0.0008)		
Post MiCA × Stablecoin	0.0007	0.0004	0.0006
	(0.0010)	(0.0011)	(0.0008)
PS	0.0567***	0.0443***	
	(0.0062)	(0.0064)	
ln Volume	0.0003***	0.0013***	0.0019***
	(0.0001)	(0.0001)	(0.0001)
VIX	-0.0002***	-0.0002***	
	(0.0000)	(0.0000)	
Intercept	-0.0323***	-0.0420***	-0.0348***
	(0.0033)	(0.0036)	(0.0018)
N	93245	93245	93244
Adj. R-squared	0.0019	0.0034	0.4310
Control Variables	Yes	Yes	Yes
Individual Effects	No	Yes	Yes
Time Effects	No	No	Yes

Note: *This table reports the difference-in-differences estimation of MiCA's impact on Stablecoin returns. Post MiCA is a binary treatment variable equalling 1 after the MiCA announcement (September 24, 2020) and 0 before Stablecoin is a dummy variable that equals 1 for Stablecoin assets and 0 for other digital asset classes. The interaction term Post MiCA × Stablecoin captures the treatment effect. Control variables include the propensity score (PS) for matching, ln(Volume) for trading activity, and VIX for global market volatility. Column (1) presents the baseline specification, Column (2) adds individual fixed effects, and Column (3) includes both individual and time fixed effects. N denotes sample size. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.*

Table 2.14: Abnormal Returns DiD Analysis - Stablecoins only

	(1)	(2)	(3)
Post MiCA	-0.0007**	-0.0030***	
	(0.0003)	(0.0004)	
Stablecoin	-0.0000		
	(0.0006)		
Post MiCA × Stablecoin	-0.0000	-0.0002	-0.0002
	(0.0008)	(0.0008)	(0.0008)
PS	-0.0059	-0.0193***	
	(0.0045)	(0.0047)	
ln Volume	0.0004***	0.0014***	0.0015***
	(0.0001)	(0.0001)	(0.0001)
VIX	0.0000*	0.0000*	
	(0.0000)	(0.0000)	
Intercept	-0.0044*	-0.0138***	-0.0280***
	(0.0025)	(0.0026)	(0.0017)
N	92956	92956	92956
Control Variables	Yes	Yes	Yes
Individual Effects	No	Yes	Yes
Time Effects	No	No	Yes

Note: *This table reports the difference-in-differences estimation of MiCA's impact on Stablecoin's abnormal returns. Post MiCA is a binary treatment variable equalling 1 after the MiCA announcement (September 24, 2020) and 0 before. Stablecoin is a dummy variable that equals 1 for Stablecoin assets and 0 for other digital asset classes. The interaction term Post MiCA × Stablecoin captures the treatment effect. Control variables include the propensity score (PS) for matching, ln(Volume) for trading activity, and VIX for global market volatility. Column (1) presents the baseline specification, Column (2) adds individual fixed effects, and Column (3) includes both individual and time fixed effects. N denotes sample size. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.*

Table 2.15: 1-Day CAR DiD Analysis - Stablecoins only

	(1)	(2)	(3)
Post MiCA	-0.0005	-0.0010	
	(0.0005)	(0.0006)	
Stablecoin	-0.0000		
	(0.0008)		
Post MiCA × Stablecoin	-0.0003	-0.0008	-0.0009
	(0.0010)	(0.0011)	(0.0011)
PS	-0.0089	-0.0159**	
	(0.0064)	(0.0066)	
ln Volume	0.0002***	0.0005***	0.0006***
	(0.0001)	(0.0001)	(0.0001)
VIX	0.0001***	0.0001***	
	(0.0000)	(0.0000)	
Intercept	0.0007	-0.0018	-0.0098***
	(0.0034)	(0.0037)	(0.0023)
N	92956	92956	92956
Adj. R-squared	0.0002	0.0017	0.1044
Control Variables	Yes	Yes	Yes
Individual Effects	No	Yes	Yes
Time Effects	No	No	Yes

Note: *This table reports the difference-in-differences estimation of MiCA's impact on Stablecoin's 1-day cumulative abnormal returns. Post MiCA is a binary treatment variable equalling 1 after the MiCA announcement (September 24, 2020) and 0 before. Stablecoin is a dummy variable that equals 1 for Stablecoin assets and 0 for other digital asset classes. The interaction term Post MiCA × Stablecoin captures the treatment effect. Control variables include the propensity score (PS) for matching, ln(Volume) for trading activity, and VIX for global market volatility. Column (1) presents the baseline specification, Column (2) adds individual fixed effects, and Column (3) includes both individual and time fixed effects. N denotes sample size. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.*

Table 2.16: 3-Day CAR DiD Analysis - Stablecoins only

	(1)	(2)	(3)
Post MiCA	-0.0009	-0.0010	
	(0.0008)	(0.0010)	
Stablecoin	-0.0001		
	(0.0014)		
Post MiCA × Stablecoin	-0.0010	-0.0025	-0.0029
	(0.0018)	(0.0019)	(0.0019)
PS	-0.0180	-0.0334***	
	(0.0110)	(0.0114)	
ln Volume	0.0003***	0.0009***	0.0011***
	(0.0001)	(0.0002)	(0.0002)
VIX	0.0001**	0.0001*	
	(0.0000)	(0.0000)	
Intercept	0.0028	0.0000	-0.0185***
	(0.0060)	(0.0063)	(0.0040)
N	92956	92956	92956
Adj. R-squared	0.0002	0.0047	0.1002
Control Variables	Yes	Yes	Yes
Individual Effects	No	Yes	Yes
Time Effects	No	No	Yes

Note: *This table reports the difference-in-differences estimation of MiCA's impact on Stablecoin's 3-day cumulative abnormal returns. Post MiCA is a binary treatment variable equalling 1 after the MiCA announcement (September 24, 2020) and 0 before. Stablecoin is a dummy variable that equals 1 for Stablecoin assets and 0 for other digital asset classes. The interaction term Post MiCA × Stablecoin captures the treatment effect. Control variables include the propensity score (PS) for matching, ln(Volume) for trading activity, and VIX for global market volatility. Column (1) presents the baseline specification, Column (2) adds individual fixed effects, and Column (3) includes both individual and time fixed effects. N denotes sample size. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.*

Table 2.17: 5-Day CAR DiD Analysis - Stablecoins only

	(1)	(2)	(3)
Post MiCA	-0.0012	0.0005	
	(0.0011)	(0.0013)	
Stablecoin	-0.0001		
	(0.0018)		
Post MiCA × Stablecoin	-0.0019	-0.0044*	-0.0050**
	(0.0024)	(0.0025)	(0.0024)
PS	-0.0349**	-0.0510***	
	(0.0143)	(0.0149)	
ln Volume	0.0003*	0.0005*	0.0007**
	(0.0002)	(0.0003)	(0.0003)
VIX	0.0002***	0.0002***	
	(0.0001)	(0.0001)	
Intercept	0.0124	0.0159*	-0.0102*
	(0.0078)	(0.0083)	(0.0052)
N	92956	92956	92956
Adj. R-squared	0.0002	0.0073	0.1064
Control Variables	Yes	Yes	Yes
Individual Effects	No	Yes	Yes
Time Effects	No	No	Yes
Placebo Test			1.14

Note: *This table reports the difference-in-differences estimation of MiCA's impact on Stablecoin's 5-day cumulative abnormal returns. Post MiCA is a binary treatment variable equalling 1 after the MiCA announcement (September 24, 2020) and 0 before. Stablecoin is a dummy variable that equals 1 for Stablecoin assets and 0 for other digital asset classes. The interaction term Post MiCA × Stablecoin captures the treatment effect. Control variables include the propensity score (PS) for matching, ln(Volume) for trading activity, and VIX for global market volatility. Column (1) presents the baseline specification, Column (2) adds individual fixed effects, and Column (3) includes both individual and time fixed effects. N denotes sample size. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.*

Table 2.18: Returns DiD Analysis – Utility Tokens only

	(1)	(2)	(3)
Post MiCA	0.0024***	0.0002	
	(0.0005)	(0.0006)	
Tokens	0.0008		
	(0.0008)		
Post MiCA × Tokens	-0.0003	0.0001	0.0003
	(0.0010)	(0.0011)	(0.0008)
PS	0.0560***	0.0442***	
	(0.0061)	(0.0064)	
ln Volume	0.0004***	0.0013***	0.0019***
	(0.0001)	(0.0001)	(0.0001)
VIX	-0.0002***	-0.0002***	
	(0.0000)	(0.0000)	
Intercept	-0.0324***	-0.0420***	-0.0347***
	(0.0033)	(0.0036)	(0.0018)
N	93245	93245	93244
Adj. R-squared	0.0019	0.0034	0.4310
Control Variables	Yes	Yes	Yes
Individual Effects	No	Yes	Yes
Time Effects	No	No	Yes

Note: *This table reports the difference-in-differences estimation of MiCA's impact on Utility Tokens returns. Post MiCA is a binary treatment variable equalling 1 after the MiCA announcement (September 24, 2020) and 0 before. Tokens is a dummy variable that equals 1 for Tokens assets and 0 for other digital asset classes. The interaction term Post MiCA × Tokens captures the treatment effect. Control variables include the propensity score (PS) for matching, ln(Volume) for trading activity, and VIX for global market volatility. Column (1) presents the baseline specification, Column (2) adds individual fixed effects, and Column (3) includes both individual and time fixed effects. N denotes sample size. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.*

Table 2.19: Abnormal Returns DiD Analysis – Utility Tokens only

	(1)	(2)	(3)
Post MiCA	-0.0007**	-0.0030***	
	(0.0003)	(0.0004)	
Tokens	0.0011*		
	(0.0006)		
Post MiCA × Tokens	-0.0004	-0.0001	-0.0001
	(0.0007)	(0.0008)	(0.0008)
PS	-0.0065	-0.0193***	
	(0.0045)	(0.0047)	
ln Volume	0.0004***	0.0014***	0.0015***
	(0.0001)	(0.0001)	(0.0001)
VIX	0.0000*	0.0000*	
	(0.0000)	(0.0000)	
Intercept	-0.0047*	-0.0138***	-0.0280***
	(0.0025)	(0.0026)	(0.0017)
N	92956	92956	92956
Control Variables	Yes	Yes	Yes
Individual Effects	No	Yes	Yes
Time Effects	No	No	Yes

Note: *This table reports the difference-in-differences estimation of MiCA's impact on Utility Tokens abnormal returns. Post MiCA is a binary treatment variable equalling 1 after the MiCA announcement (September 24, 2020) and 0 before. Tokens is a dummy variable that equals 1 for Tokens assets and 0 for other digital asset classes. The interaction term Post MiCA × Tokens captures the treatment effect. Control variables include the propensity score (PS) for matching, ln(Volume) for trading activity, and VIX for global market volatility. Column (1) presents the baseline specification, Column (2) adds individual fixed effects, and Column (3) includes both individual and time fixed effects. N denotes sample size. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.*

Table 2.20: 1-Day CAR DiD Analysis -Utility Tokens only

	(1)	(2)	(3)
Post MiCA	-0.0005	-0.0009	
	(0.0005)	(0.0006)	
Tokens	0.0010		
	(0.0008)		
Post MiCA × Tokens	-0.0006	-0.0011	-0.0010
	(0.0010)	(0.0011)	(0.0011)
PS	-0.0095	-0.0159**	
	(0.0064)	(0.0066)	
ln Volume	0.0002***	0.0005***	0.0006***
	(0.0001)	(0.0001)	(0.0001)
VIX	0.0001***	0.0001***	
	(0.0000)	(0.0000)	
Intercept	0.0005	-0.0018	-0.0098***
	(0.0034)	(0.0037)	(0.0023)
N	92956	92956	92956
Adj. R-squared	0.0002	0.0017	0.1044
Control Variables	Yes	Yes	Yes
Individual Effects	No	Yes	Yes
Time Effects	No	No	Yes

Note: *This table reports the difference-in-differences estimation of MiCA's impact on Utility Tokens 1-day cumulative abnormal returns. Post MiCA is a binary treatment variable equalling 1 after the MiCA announcement (September 24, 2020) and 0 before. Tokens is a dummy variable that equals 1 for Tokens assets and 0 for other digital asset classes. The interaction term Post MiCA × Tokens captures the treatment effect. Control variables include the propensity score (PS) for matching, ln(Volume) for trading activity, and VIX for global market volatility. Column (1) presents the baseline specification, Column (2) adds individual fixed effects, and Column (3) includes both individual and time fixed effects. N denotes sample size. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.*

Table 2.21: 3-Day CAR DiD Analysis – Utility Tokens only

	(1)	(2)	(3)
Post MiCA	-0.0009	-0.0009	
	(0.0008)	(0.0010)	
Tokens	0.0026*		
	(0.0014)		
Post MiCA × Tokens	-0.0016	-0.0032*	-0.0031*
	(0.0018)	(0.0019)	(0.0018)
PS	-0.0195*	-0.0334***	
	(0.0110)	(0.0114)	
ln Volume	0.0004***	0.0009***	0.0011***
	(0.0001)	(0.0002)	(0.0002)
VIX	0.0001**	0.0001*	
	(0.0000)	(0.0000)	
Intercept	0.0023	0.0002	-0.0184***
	(0.0060)	(0.0063)	(0.0040)
N	92956	92956	92956
Adj. R-squared	0.0002	0.0047	0.1002
Control Variables	Yes	Yes	Yes
Individual Effects	No	Yes	Yes
Time Effects	No	No	Yes

Note: *This table reports the difference-in-differences estimation of MiCA's impact on Utility Tokens 3-day cumulative abnormal returns. Post MiCA is a binary treatment variable equalling 1 after the MiCA announcement (September 24, 2020) and 0 before. Tokens is a dummy variable that equals 1 for Tokens assets and 0 for other digital asset classes. The interaction term Post MiCA × Tokens captures the treatment effect. Control variables include the propensity score (PS) for matching, ln(Volume) for trading activity, and VIX for global market volatility. Column (1) presents the baseline specification, Column (2) adds individual fixed effects, and Column (3) includes both individual and time fixed effects. N denotes sample size. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.*

Table 2.22: 5-Day CAR DiD Analysis – Utility Tokens only

	(1)	(2)	(3)
Post MiCA	-0.0012	0.0008	
	(0.0011)	(0.0013)	
Tokens	0.0037**		
	(0.0018)		
Post MiCA × Tokens	-0.0026	-0.0058**	-0.0056**
	(0.0024)	(0.0025)	(0.0024)
PS	-0.0371***	-0.0511***	
	(0.0143)	(0.0148)	
ln Volume	0.0003**	0.0005*	0.0007**
	(0.0002)	(0.0003)	(0.0003)
VIX	0.0002***	0.0002***	
	(0.0001)	(0.0001)	
Intercept	0.0118	0.0162**	-0.0099*
	(0.0078)	(0.0083)	(0.0052)
N	92956	92956	92956
Adj. R-squared	0.0002	0.0073	0.1064
Control Variables	Yes	Yes	Yes
Individual Effects	No	Yes	Yes
Time Effects	No	No	Yes

Note: *This table reports the difference-in-differences estimation of MiCA's impact on Utility Tokens 5-day cumulative abnormal returns. Post MiCA is a binary treatment variable equalling 1 after the MiCA announcement (September 24, 2020) and 0 before. Tokens is a dummy variable that equals 1 for Tokens assets and 0 for other digital asset classes. The interaction term Post MiCA × Tokens captures the treatment effect. Control variables include the propensity score (PS) for matching, ln(Volume) for trading activity, and VIX for global market volatility. Column (1) presents the baseline specification, Column (2) adds individual fixed effects, and Column (3) includes both individual and time fixed effects. N denotes sample size. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.*

Table 2.23: Returns DiD Analysis - NFTs only

	(1)	(2)	(3)
Post MiCA	0.0025***	0.0004	
	(0.0005)	(0.0005)	
NFT	0.0011		
	(0.0011)		
Post MiCA × NFT	-0.0017	-0.0018	-0.0032***
	(0.0013)	(0.0015)	(0.0011)
PS	0.0563***	0.0438***	
	(0.0061)	(0.0064)	
ln Volume	0.0004***	0.0013***	0.0019***
	(0.0001)	(0.0001)	(0.0001)
VIX	-0.0002***	-0.0002***	
	(0.0000)	(0.0000)	
Intercept	-0.0322***	-0.0420***	-0.0351***
	(0.0033)	(0.0035)	(0.0018)
N	93245	93245	93244
Adj. R-squared	0.0019	0.0035	0.4311
Control Variables	Yes	Yes	Yes
Individual Effects	No	Yes	Yes
Time Effects	No	No	Yes

Note: *This table reports the difference-in-differences estimation of MiCA's impact on NFT's returns. Post MiCA is a binary treatment variable equalling 1 after the MiCA announcement (September 24, 2020) and 0 before. NFT is a dummy variable that equals 1 for NFT assets and 0 for other digital asset classes. The interaction term Post MiCA × NFT captures the treatment effect. Control variables include the propensity score (PS) for matching, ln(Volume) for trading activity, and VIX for global market volatility. Column (1) presents the baseline specification, Column (2) adds individual fixed effects, and Column (3) includes both individual and time fixed effects. N denotes sample size. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.*

Table 2.24: Abnormal Returns DiD Analysis - NFTs only

	(1)	(2)	(3)
Post MiCA	-0.0005	-0.0028***	
	(0.0003)	(0.0004)	
NFT	0.0017**		
	(0.0008)		
Post MiCA × NFT	-0.0021**	-0.0038***	-0.0044***
	(0.0009)	(0.0011)	(0.0011)
PS	-0.0061	-0.0199***	
	(0.0045)	(0.0047)	
ln Volume	0.0004***	0.0014***	0.0016***
	(0.0001)	(0.0001)	(0.0001)
VIX	0.0000*	0.0000	
	(0.0000)	(0.0000)	
Intercept	-0.0046*	-0.0139***	-0.0286***
	(0.0025)	(0.0026)	(0.0017)
N	92956	92956	92956
Control Variables	Yes	Yes	Yes
Individual Effects	No	Yes	Yes
Time Effects	No	No	Yes

Note: *This table reports the difference-in-differences estimation of MiCA's impact on NFT's abnormal returns. Post MiCA is a binary treatment variable equalling 1 after the MiCA announcement (September 24, 2020) and 0 before. NFT is a dummy variable that equals 1 for NFT assets and 0 for other digital asset classes. The interaction term Post MiCA × NFT captures the treatment effect. Control variables include the propensity score (PS) for matching, ln(Volume) for trading activity, and VIX for global market volatility. Column (1) presents the baseline specification, Column (2) adds individual fixed effects, and Column (3) includes both individual and time fixed effects. N denotes sample size. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.*

Table 2.25: 1-Day CAR DiD Analysis - NFTs only

	(1)	(2)	(3)
Post MiCA	-0.0002	-0.0008	
	(0.0005)	(0.0006)	
NFT	0.0016		
	(0.0011)		
Post MiCA × NFT	-0.0031**	-0.0041***	-0.0046***
	(0.0013)	(0.0015)	(0.0015)
PS	-0.0092	-0.0163**	
	(0.0064)	(0.0066)	
ln Volume	0.0002***	0.0006***	0.0006***
	(0.0001)	(0.0001)	(0.0001)
VIX	0.0001***	0.0001***	
	(0.0000)	(0.0000)	
Intercept	0.0007	-0.0021	-0.0106***
	(0.0035)	(0.0037)	(0.0023)
N	92956	92956	92956
Adj. R-squared	0.0002	0.0018	0.1045
Control Variables	Yes	Yes	Yes
Individual Effects	No	Yes	Yes
Time Effects	No	No	Yes

Note: *This table reports the difference-in-differences estimation of MiCA's impact on NFT's 1-day cumulative abnormal returns. Post MiCA is a binary treatment variable equalling 1 after the MiCA announcement (September 24, 2020) and 0 before. NFT is a dummy variable that equals 1 for NFT assets and 0 for other digital asset classes. The interaction term Post MiCA × NFT captures the treatment effect. Control variables include the propensity score (PS) for matching, ln(Volume) for trading activity, and VIX for global market volatility. Column (1) presents the baseline specification, Column (2) adds individual fixed effects, and Column (3) includes both individual and time fixed effects. N denotes sample size. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.*

Table 2.26: 3-Day CAR DiD Analysis - NFTs only

	(1)	(2)	(3)
Post MiCA	-0.0001	-0.0008	
	(0.0008)	(0.0010)	
NFT	0.0041**		
	(0.0019)		
Post MiCA × NFT	-0.0087***	-0.0115***	-0.0128***
	(0.0023)	(0.0026)	(0.0026)
PS	-0.0188*	-0.0346***	
	(0.0110)	(0.0114)	
ln Volume	0.0003***	0.0011***	0.0012***
	(0.0001)	(0.0002)	(0.0002)
VIX	0.0001**	0.0001*	
	(0.0000)	(0.0000)	
Intercept	0.0030	-0.0008	-0.0207***
	(0.0060)	(0.0063)	(0.0040)
N	92956	92956	92956
Adj. R-squared	0.0004	0.0048	0.1004
Control Variables	Yes	Yes	Yes
Individual Effects	No	Yes	Yes
Time Effects	No	No	Yes

Note: *This table reports the difference-in-differences estimation of MiCA's impact on NFT's 3-day cumulative abnormal returns. Post MiCA is a binary treatment variable equalling 1 after the MiCA announcement (September 24, 2020) and 0 before. NFT is a dummy variable that equals 1 for NFT assets and 0 for other digital asset classes. The interaction term Post MiCA × NFT captures the treatment effect. Control variables include the propensity score (PS) for matching, ln(Volume) for trading activity, and VIX for global market volatility. Column (1) presents the baseline specification, Column (2) adds individual fixed effects, and Column (3) includes both individual and time fixed effects. N denotes sample size. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.*

Table 2.27: 5-Day CAR DiD Analysis - NFTs only

	(1)	(2)	(3)
Post MiCA	0.0001	0.0008	
	(0.0011)	(0.0012)	
NFT	0.0056**		
	(0.0025)		
Post MiCA × NFT	-0.0135***	-0.0169***	-0.0189***
	(0.0029)	(0.0034)	(0.0033)
PS	-0.0361**	-0.0527***	
	(0.0143)	(0.0148)	
ln Volume	0.0002	0.0007**	0.0009***
	(0.0002)	(0.0003)	(0.0003)
VIX	0.0002***	0.0001***	
	(0.0001)	(0.0001)	
Intercept	0.0129*	0.0145*	-0.0135**
	(0.0078)	(0.0082)	(0.0052)
N	92956	92956	92956
Adj. R-squared	0.0005	0.0075	0.1067
Control Variables	Yes	Yes	Yes
Individual Effects	No	Yes	Yes
Time Effects	No	No	Yes

Note: *This table reports the difference-in-differences estimation of MiCA's impact on NFT's 5-day cumulative abnormal returns. Post MiCA is a binary treatment variable equalling 1 after the MiCA announcement (September 24, 2020) and 0 before. NFT is a dummy variable that equals 1 for NFT assets and 0 for other digital asset classes. The interaction term Post MiCA × NFT captures the treatment effect. Control variables include the propensity score (PS) for matching, ln(Volume) for trading activity, and VIX for global market volatility. Column (1) presents the baseline specification, Column (2) adds individual fixed effects, and Column (3) includes both individual and time fixed effects. N denotes sample size. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.*

Table 2.28: Returns DiD Analysis - DeFis only

	(1)	(2)	(3)
Post MiCA	0.0027***	0.0006	
	(0.0005)	(0.0005)	
DeFi	0.0044***		
	(0.0010)		
Post MiCA × DeFi	-0.0043***	-0.0071***	-0.0094***
	(0.0011)	(0.0014)	(0.0011)
PS	0.0559***	0.0422***	
	(0.0061)	(0.0064)	
ln Volume	0.0004***	0.0015***	0.0022***
	(0.0001)	(0.0001)	(0.0001)
VIX	-0.0002***	-0.0002***	
	(0.0000)	(0.0000)	
Intercept	-0.0340***	-0.0440***	-0.0392***
	(0.0034)	(0.0036)	(0.0019)
N	93245	93245	93244
Adj. R-squared	0.0021	0.0037	0.4315
Control Variables	Yes	Yes	Yes
Individual Effects	No	Yes	Yes
Time Effects	No	No	Yes

Note: *This table reports the difference-in-differences estimation of MiCA's impact on DeFi's returns. Post MiCA is a binary treatment variable equalling 1 after the MiCA announcement (September 24, 2020) and 0 before. DeFi is a dummy variable that equals 1 for DeFi assets and 0 for other digital asset classes. The interaction term Post MiCA × DeFi captures the treatment effect. Control variables include the propensity score (PS) for matching, ln(Volume) for trading activity, and VIX for global market volatility. Column (1) presents the baseline specification, Column (2) adds individual fixed effects, and Column (3) includes both individual and time fixed effects. N denotes sample size. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.*

Table 2.29: Abnormal Returns DiD Analysis - DeFis only

	(1)	(2)	(3)
Post MiCA	-0.0006*	-0.0027***	
	(0.0003)	(0.0004)	
DeFi	0.0024***		
	(0.0007)		
Post MiCA × DeFi	-0.0021**	-0.0055***	-0.0062***
	(0.0008)	(0.0010)	(0.0010)
PS	-0.0062	-0.0208***	
	(0.0045)	(0.0047)	
ln Volume	0.0005***	0.0015***	0.0017***
	(0.0001)	(0.0001)	(0.0001)
VIX	0.0000*	0.0000*	
	(0.0000)	(0.0000)	
Intercept	-0.0055**	-0.0154***	-0.0310***
	(0.0025)	(0.0026)	(0.0017)
N	92956	92956	92956
Control Variables	Yes	Yes	Yes
Individual Effects	No	Yes	Yes
Time Effects	No	No	Yes

Note: *This table reports the difference-in-differences estimation of MiCA's impact on DeFi's abnormal returns. Post MiCA is a binary treatment variable equalling 1 after the MiCA announcement (September 24, 2020) and 0 before. DeFi is a dummy variable that equals 1 for DeFi assets and 0 for other digital asset classes. The interaction term Post MiCA × DeFi captures the treatment effect. Control variables include the propensity score (PS) for matching, ln(Volume) for trading activity, and VIX for global market volatility. Column (1) presents the baseline specification, Column (2) adds individual fixed effects, and Column (3) includes both individual and time fixed effects. N denotes sample size. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.*

Table 2.30: 1-Day CAR DiD Analysis - DeFis only

	(1)	(2)	(3)
Post MiCA	-0.0005	-0.0009*	
	(0.0005)	(0.0006)	
DeFi	0.0017*		
	(0.0010)		
Post MiCA × DeFi	-0.0017	-0.0029**	-0.0029**
	(0.0012)	(0.0014)	(0.0014)
PS	-0.0091	-0.0164**	
	(0.0064)	(0.0066)	
ln Volume	0.0002***	0.0006***	0.0007***
	(0.0001)	(0.0001)	(0.0001)
VIX	0.0001***	0.0001***	
	(0.0000)	(0.0000)	
Intercept	-0.0000	-0.0028	-0.0114***
	(0.0035)	(0.0037)	(0.0024)
N	92956	92956	92956
Adj. R-squared	0.0002	0.0018	0.1045
Control Variables	Yes	Yes	Yes
Individual Effects	No	Yes	Yes
Time Effects	No	No	Yes

Note: *This table reports the difference-in-differences estimation of MiCA's impact on DeFi's 1-day cumulative abnormal returns. Post MiCA is a binary treatment variable equalling 1 after the MiCA announcement (September 24, 2020) and 0 before. DeFi is a dummy variable that equals 1 for DeFi assets and 0 for other digital asset classes. The interaction term Post MiCA × DeFi captures the treatment effect. Control variables include the propensity score (PS) for matching, ln(Volume) for trading activity, and VIX for global market volatility. Column (1) presents the baseline specification, Column (2) adds individual fixed effects, and Column (3) includes both individual and time fixed effects. N denotes sample size. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.*

Table 2.31: 3-Day CAR DiD Analysis - DeFis only

	(1)	(2)	(3)
Post MiCA	-0.0007	-0.0011	
	(0.0008)	(0.0010)	
DeFi	0.0040**		
	(0.0017)		
Post MiCA × DeFi	-0.0042**	-0.0062**	-0.0062***
	(0.0020)	(0.0024)	(0.0024)
PS	-0.0186*	-0.0343***	
	(0.0110)	(0.0114)	
ln Volume	0.0004***	0.0011***	0.0013***
	(0.0001)	(0.0002)	(0.0002)
VIX	0.0001**	0.0001*	
	(0.0000)	(0.0000)	
Intercept	0.0012	-0.0022	-0.0220***
	(0.0060)	(0.0064)	(0.0042)
N	92956	92956	92956
Adj. R-squared	0.0002	0.0047	0.1003
Control Variables	Yes	Yes	Yes
Individual Effects	No	Yes	Yes
Time Effects	No	No	Yes

Note: *This table reports the difference-in-differences estimation of MiCA's impact on DeFi's 3-day cumulative abnormal returns. Post MiCA is a binary treatment variable equalling 1 after the MiCA announcement (September 24, 2020) and 0 before. DeFi is a dummy variable that equals 1 for DeFi assets and 0 for other digital asset classes. The interaction term Post MiCA × DeFi captures the treatment effect. Control variables include the propensity score (PS) for matching, ln(Volume) for trading activity, and VIX for global market volatility. Column (1) presents the baseline specification, Column (2) adds individual fixed effects, and Column (3) includes both individual and time fixed effects. N denotes sample size. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.*

Table 2.32: 5-Day CAR DiD Analysis - DeFis only

	(1)	**(2)**	**(3)**
Post MiCA	-0.0010	0.0001	
	(0.0011)	(0.0012)	
DeFi	0.0050**		
	(0.0023)		
Post MiCA × DeFi	-0.0056**	-0.0062*	-0.0060*
	(0.0027)	(0.0032)	(0.0031)
PS	-0.0357**	-0.0513***	
	(0.0143)	(0.0149)	
ln Volume	0.0004**	0.0007**	0.0009***
	(0.0002)	(0.0003)	(0.0003)
VIX	0.0002***	0.0002***	
	(0.0001)	(0.0001)	
Intercept	0.0104	0.0132	-0.0139**
	(0.0078)	(0.0083)	(0.0054)
N	92956	92956	92956
Adj. R-squared	0.0002	0.0073	0.1064
Control Variables	Yes	Yes	Yes
Individual Effects	No	Yes	Yes
Time Effects	No	No	Yes

Note: *This table reports the difference-in-differences estimation of MiCA's impact on DeFi's 5-day cumulative abnormal returns. Post MiCA is a binary treatment variable equalling 1 after the MiCA announcement (September 24, 2020) and 0 before. DeFi is a dummy variable that equals 1 for DeFi assets and 0 for other digital asset classes. The interaction term Post MiCA × DeFi captures the treatment effect. Control variables include the propensity score (PS) for matching, ln(Volume) for trading activity, and VIX for global market volatility. Column (1) presents the baseline specification, Column (2) adds individual fixed effects, and Column (3) includes both individual and time fixed effects. N denotes sample size. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.*

Table 2.33: Returns DiD Analysis - Full Sample

	(1)	(2)	(3)
Post MiCA	-0.0022*	-0.0002	
	(0.0011)	(0.0010)	
iCrypto	-0.0055***		
	(0.0012)		
Post MiCA × iCrypto	0.0054***	0.0012	0.0012
	(0.0014)	(0.0013)	(0.0010)
uCrypto	-0.0060***		
	(0.0011)		
Post MiCA × uCrypto	0.0049***	0.0019	0.0027***
	(0.0013)	(0.0013)	(0.0010)
Stablecoin	-0.0047***		
	(0.0012)		
Post MiCA × Stablecoin	0.0021*	-0.0001	-0.0001
	(0.0011)	(0.0010)	(0.0010)
DeFi			
Post MiCA × DeFi	-0.0002	-0.0052***	-0.0060***
	(0.0012)	(0.0012)	(0.0012)
NFT	-0.0007		
	(0.0010)		
Post MiCA × NFT		-0.0038***	-0.0045***
		(0.0013)	(0.0012)
Tokens	-0.0015*		
	(0.0008)		
Post MiCA × Tokens	0.0017		
	(0.0011)		
PS	-0.0094**	-0.0244***	
	(0.0046)	(0.0048)	
ln Volume	0.0006***	0.0016***	0.0019***
	(0.0001)	(0.0001)	(0.0001)
VIX	0.0000*	0.0000*	
	(0.0000)	(0.0000)	
Intercept	-0.0029	-0.0150***	-0.0339***
	(0.0025)	(0.0026)	(0.0018)
N	92956	92956	92956
Adj. R-squared	0.0013	0.0042	0.1107
Control Variables	Yes	Yes	Yes
Individual Effects	No	Yes	Yes
Time Effects	No	No	Yes

Note: *This table reports the impact of MiCA on returns across the full sample of digital assets using a difference-in-differences framework. The dependent variable is the returns. Post MiCA is the treatment variable that takes the value 1 for the period following the MiCA announcement (September 24, 2020) and 0 for the pre-announcement period. Asset class dummies (e.g., iCrypto, uCrypto, Stablecoin, NFT, Tokens) identify the category of each asset. The interaction terms (Post MiCA × Asset Class) capture the differential treatment effects across categories, measuring how each asset class responded to the MiCA proposal. PS represents the propensity score used for matching. ln Volume is the natural logarithm of trading volume, while VIX captures global market volatility. Column (1) presents the baseline model with no fixed effects; Column (2) includes individual (asset) fixed effects; and Column (3) controls for both individual and time fixed effects. Standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1*

Table 2.34: Abnormal Returns DiD Analysis - Full Sample

	(1)	(2)	(3)
Post MiCA	-.00314***	-.00367***	
	(.00091)	(.00076)	
iCrypto	-.00318***		
	(.00085)		
Post MiCA x iCrypto	.00202*	.00055	.00058
	(.00108)	(.00098)	(.00093)
uCrypto	-.00443***		
	(.00083)		
Post MiCA x uCrypto	.00373***	.00315***	.00356***
	(.00106)	(.00093)	(.00089)
Stablecoin	-.00264***		
	(.00087)		
Post MiCA x Stablecoin	.00212*	-.00008	-.00014
	(.00112)	(.00102)	(.00097)
DeFi			
Post MiCA x DeFi	-.00016	-.00522***	-.00598***
	(.00117)	(.0012)	(.00115)
NFT	-.00069		
	(.001)		
Post MiCA x NFT		-.00379***	-.00452***
		(.00127)	(.00122)
Tokens	-.00146*		
	(.00084)		
Post MiCA x Tokens	.00174		
	(.00112)		
PS	-.00942**	-.02439***	
	(.00459)	(.00477)	
ln Volume	.00057***	.00161***	.00188***
	(.00005)	(.00009)	(.0001)
VIX	.00003*	.00003*	
	(.00002)	(.00002)	
Intercept	-.0029	-.01495***	-.03394***
	(.00251)	(.00264)	(.0018)
N	92956	92956	92956
Control Variables	Yes	Yes	Yes
Individual Effects	No	Yes	Yes
Time Effects	No	No	Yes

Note: *This table reports the impact of MiCA on returns across the full sample of digital assets using a difference-in-differences framework. The dependent variable is the returns. Post MiCA is the treatment variable that takes the value 1 for the period following the MiCA announcement (September 24, 2020) and 0 for the pre-announcement period. Asset class dummies (e.g., iCrypto, uCrypto, Stablecoin, NFT, Tokens) identify the category of each asset. The interaction terms (Post MiCA × Asset Class) capture the differential treatment effects across categories, measuring how each asset class responded to the MiCA proposal. PS represents the propensity score used for matching. ln Volume is the natural logarithm of trading volume, while VIX captures global market volatility. Column (1) presents the baseline model with no fixed effects; Column (2) includes individual (asset) fixed effects; and Column (3) controls for both individual and time fixed effects. Standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1*

Table 2.35: 1-Day Cumulative Abnormal Returns DiD Analysis - Full Sample

	(1)	(2)	(3)
Post MiCA	-0.0036***	-0.0024**	
	(0.0013)	(0.0011)	
iCrypto	-0.0015		
	(0.0012)		
Post MiCA × iCrypto	0.0025	0.0008	0.0008
	(0.0015)	(0.0014)	(0.0013)
uCrypto	-0.0035***		
	(0.0012)		
Post MiCA × uCrypto	0.0057***	0.0044***	0.0046***
	(0.0015)	(0.0013)	(0.0013)
Stablecoin	-0.0017		
	(0.0012)		
Post MiCA × Stablecoin	0.0026*	0.0002	0.0001
	(0.0016)	(0.0014)	(0.0014)
DeFi			
Post MiCA × DeFi	0.0012	-0.0021	-0.0023
	(0.0016)	(0.0017)	(0.0016)
NFT	-0.0001		
	(0.0014)		
Post MiCA × NFT		-0.0032*	-0.0037**
		(0.0018)	(0.0017)
Tokens	-0.0008		
	(0.0012)		
Post MiCA × Tokens	0.0023		
	(0.0016)		
PS	-0.0120*	-0.0208***	
	(0.0064)	(0.0067)	
ln Volume	0.0003***	0.0007***	0.0008***
	(0.0001)	(0.0001)	(0.0001)
VIX	0.0001***	0.0001***	
	(0.0000)	(0.0000)	
Intercept	0.0026	-0.0021	-0.0147***
	(0.0035)	(0.0037)	(0.0025)
N	92956	92956	92956
Adj. R-squared	0.0004	0.0021	0.1048
Control Variables	Yes	Yes	Yes
Individual Effects	No	Yes	Yes
Time Effects	No	No	Yes

Note: *This table reports the impact of MiCA on abnormal returns across the full sample of digital assets using a difference-in-differences framework. The dependent variable is the abnormal returns. Post MiCA is the treatment variable that takes the value 1 for the period following the MiCA announcement (September 24, 2020) and 0 for the pre-announcement period. Asset class dummies (e.g., iCrypto, uCrypto, Stablecoin, NFT, Tokens) identify the category of each asset. The interaction terms (Post MiCA × Asset Class) capture the differential treatment effects across categories, measuring how each asset class responded to the MiCA proposal. PS represents the propensity score used for matching. ln Volume is the natural logarithm of trading volume, while VIX captures global market volatility. Column (1) presents the baseline model with no fixed effects; Column (2) includes individual (asset) fixed effects; and Column (3) controls for both individual and time fixed effects. Standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1*

Table 2.36: 3-Day Cumulative Abnormal Returns DiD Analysis - Full Sample

	(1)	(2)	(3)
Post MiCA	-0.0095***	-0.0053***	
	(0.0022)	(0.0019)	
iCrypto	-0.0027		
	(0.0021)		
Post MiCA × iCrypto	0.0066**	0.0019	0.0019
	(0.0026)	(0.0024)	(0.0023)
uCrypto	-0.0087***		
	(0.0020)		
Post MiCA × uCrypto	0.0165***	0.0123***	0.0130***
	(0.0026)	(0.0023)	(0.0022)
Stablecoin	-0.0039*		
	(0.0021)		
Post MiCA × Stablecoin	0.0072***	0.0005	0.0001
	(0.0027)	(0.0025)	(0.0024)
DeFi			
Post MiCA × DeFi	0.0040	-0.0040	-0.0044
	(0.0028)	(0.0029)	(0.0028)
NFT	0.0004		
	(0.0024)		
Post MiCA × NFT		-0.0086***	-0.0100***
		(0.0031)	(0.0030)
Tokens	-0.0015		
	(0.0020)		
Post MiCA × Tokens	0.0066**		
	(0.0027)		
PS	-0.0261**	-0.0466***	
	(0.0111)	(0.0115)	
ln Volume	0.0005***	0.0014***	0.0017***
	(0.0001)	(0.0002)	(0.0002)
VIX	0.0001**	0.0001*	
	(0.0000)	(0.0000)	
Intercept	0.0080	-0.0003	-0.0313***
	(0.0061)	(0.0064)	(0.0044)
N	92956	92956	92956
Adj. R-squared	0.0009	0.0054	0.1011
Control Variables	Yes	Yes	Yes
Individual Effects	No	Yes	Yes
Time Effects	No	No	Yes

Note: *This table reports the impact of MiCA on cumulative abnormal returns across the full sample of digital assets using a difference-in-differences framework. The dependent variable is the 3-day cumulative abnormal returns. Post MiCA is the treatment variable that takes the value 1 for the period following the MiCA announcement (September 24, 2020) and 0 for the pre-announcement period. Asset class dummies (e.g., iCrypto, uCrypto, Stablecoin, NFT, Tokens) identify the category of each asset. The interaction terms (Post MiCA × Asset Class) capture the differential treatment effects across categories, measuring how each asset class responded to the MiCA proposal. PS represents the propensity score used for matching. ln Volume is the natural logarithm of trading volume, while VIX captures global market volatility. Column (1) presents the baseline model with no fixed effects; Column (2) includes individual (asset) fixed effects; and Column (3) controls for both individual and time fixed effects. Standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1*

Table 2.37: 5- Day Cumulative Abnormal Returns DiD Analysis - Full Sample

	(1)	(2)	(3)
Post MiCA	-.0142***	-.00676***	
	(.00287)	(.0024)	
iCrypto	-.00193		
	(.00269)		
Post MiCA× iCrypto	.00961***	.00283	.00294
	(.00341)	(.00307)	(.00294)
uCrypto	-.01175***		
	(.00262)		
Post MiCA× uCrypto	.02606***	.01962***	.02044***
	(.00334)	(.00293)	(.00281)
Stablecoin	-.00462*		
	(.00273)		
Post MiCA× Stablecoin	.0105***	.00099	.00038
	(.00353)	(.0032)	(.00307)
DeFi			
Post MiCA× DeFi	.00705*	-.00231	-.00288
	(.0037)	(.00377)	(.00364)
NFT	.00103		
	(.00316)		
Post MiCA× NFT		-.01161***	-.01386***
		(.004)	(.00384)
Tokens	-.00133		
	(.00266)		
Post MiCA× Tokens	.00991***		
	(.00352)		
PS	-.04641***	-.07031***	
	(.01445)	(.01499)	
ln Volume	.0004**	.00113***	.00156***
	(.00017)	(.00029)	(.00031)
VIX	.00015***	.00014***	
	(.00005)	(.00005)	
Intercept	.02049***	.01648**	-.02804***
	(.00791)	(.0083)	(.00567)
N	92956	92956	92956
Adj. R-squared	.00124	.00828	.10751
Control Variables	Yes	Yes	Yes
Individual Effects	No	Yes	Yes
Time Effects	No	No	Yes

Note: *This table reports the impact of MiCA on cumulative abnormal returns across the full sample of digital assets using a difference-in-differences framework. The dependent variable is the 5-day cumulative abnormal returns. Post MiCA is the treatment variable that takes the value 1 for the period following the MiCA announcement (September 24, 2020) and 0 for the pre-announcement period. Asset class dummies (e.g., iCrypto, uCrypto, Stablecoin, NFT, Tokens) identify the category of each asset. The interaction terms (Post MiCA × Asset Class) capture the differential treatment effects across categories, measuring how each asset class responded to the MiCA proposal. PS represents the propensity score used for matching. ln Volume is the natural logarithm of trading volume, while VIX captures global market volatility. Column (1) presents the baseline model with no fixed effects; Column (2) includes individual (asset) fixed effects; and Column (3) controls for both individual and time fixed effects. Standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1*

Table 2.38: Summary of MiCA Announcement Effects Across Crypto Asset Classes

Asset Class	Returns	AR	CAR1	CAR3	CAR5
iCrypto	0.0017**	0.0005	−0.0002	−0.0010	−0.0025
uCrypto	0.0035***	0.0045***	0.0049***	0.0137***	0.0211***
Stablecoins	0.0006	−0.0002	−0.0009	−0.0029	−0.0050**
Utility Tokens	0.0003	−0.0001	−0.0010	−0.0031*	−0.0056**
NFTs	−0.0032***	−0.0044***	−0.0046***	−0.0128***	−0.0189***
DeFi	−0.0094***	−0.0062***	−0.0029**	−0.0062***	−0.0060*

Note: *This table summarises the estimated treatment effect of the Post MiCA × Asset Class interaction term across the five dependent variables used in this study: returns, AR, and 1-day, 3-day, and 5-day CARs. All coefficients are drawn from the fully specified model (Model 3), which includes both crypto asset fixed effects and time fixed effects, as reported in Tables 2.3–2.32. Post MiCA is a binary treatment variable equalling 1 after the MiCA announcement (September 24, 2020) and 0 before. iCrypto and uCrypto refer to cryptocurrencies with and without an identifiable issuer, respectively. Standard errors are omitted for brevity and are reported in full in the corresponding regression tables. *** p<0.01, ** p<0.05, * p<0.1.*

Figures

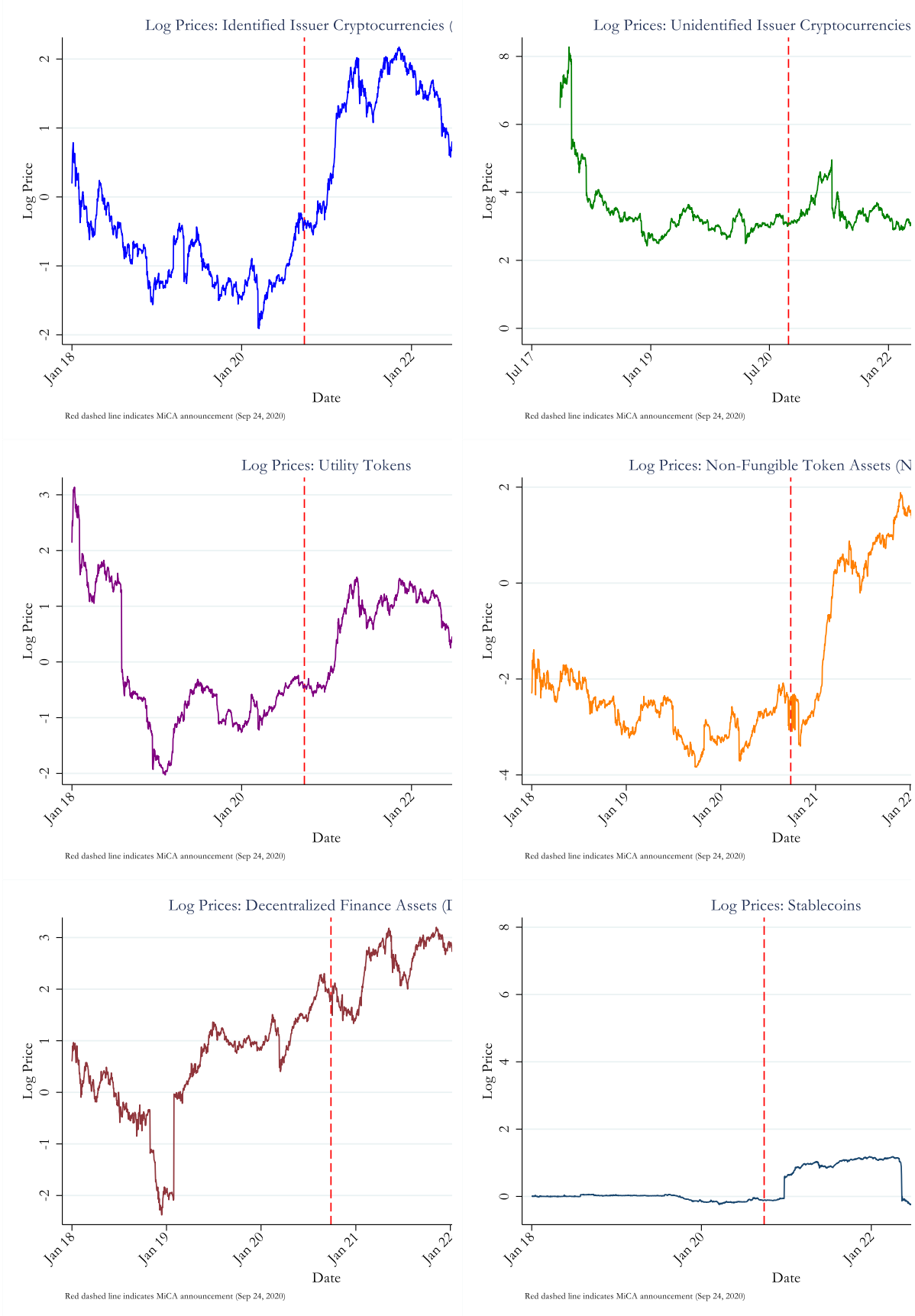


Figure 2.1: Time Series Plots of Digital Assets by Type

Note: This figure displays the time series of log prices for six crypto-asset classes from January 1, 2018, to May 21, 2023. The vertical dashed line marks the MiCA's proposal date (September 24, 2020). The sample period covers over two years before MiCA's announcement to capture pre- and post-regime dynamics.

Appendix

Appendix 2.A: Propensity Score Construction

2.A.1 Panel Logit Specification

Propensity score

We have constructed a propensity score (*PS*) to provide counterfactual estimates for the days on no regulatory announcements. They are estimated using the panel logit model of the following form:

$$\Pr(E_{it} = 1|z_{it}) = \frac{1}{1+e^{-\theta_i - z_{it}\lambda - u_{it}}}$$

where $i = 1, \dots, N$ and $t = 1, \dots, T$, E is a dummy variable that takes value 1 if the day is a regulatory announcement day and zero otherwise; $\boldsymbol{\lambda}$ is $(k \times 1)$ vector of parameters of the k regressors z_{it} and u_{it} is the error term. Note also that θ_i is the fixed effect of the logistic regression. The set of regressors, z_{it}, consists of different commodities prices (gold, silver, copper, natural gas, crude oil, brent crude), 12 exchange rate series of major currencies, financial stability measure (VIX), various digital currencies global indices (CBDC, Crypto Price Index, Crypto Policy Index) and a measure of sentiments based on Twitter (Wang et al., 2022b).

2.A.2 Definitions of the Index Covariates

The propensity score includes three news-based indices constructed by Wang et al. (2022a, 2022b) and Wang (2022). Each is derived from the weekly count of news articles matching a defined search string in the LexisNexis News & Business database, standardised over the construction period with 100 added to the standardised series.

Central Bank Digital Currency Uncertainty Index

Wang et al. (2022b) construct the Central Bank Digital Currency Uncertainty Index (CBDCUI) from articles matching a set of central bank digital currency search terms that also contain an uncertainty term. The index is standardised over the period January 2015 to June 2021 and is defined as

$$CBDCUI_t = \left((N_1 t - \mu_1)/\sigma_1\right) + 100 \quad (1)$$

where $N_1 t$ is the weekly number of news articles matching the CBDC uncertainty search criteria at time t, μ_1 is the mean of the weekly article count over the index construction period, and $\sigma_1$is its standard deviation.

Index of Cryptocurrency Environmental Attention

The Index of Cryptocurrency Environmental Attention (ICEA) of Wang et al. (2022a) measures news attention to environmental issues associated with cryptocurrency markets and is defined as

$$ICEA_t = \left((N_2 t - \mu_2)/\sigma_2\right) + 100 \quad (2)$$

where $N_2 t$ is the weekly number of articles matching the cryptocurrency environmental attention search criteria at time t, μ_2 is the mean of the weekly article count over the index

construction period, and σ_2 is its standard deviation.

Non-Fungible Token Attention Index

The Non-Fungible Token Attention Index (NFTsAI) of Wang (2022) measures news attention to the NFT market from articles matching a set of NFT search terms generated through Latent Dirichlet Allocation topic modelling. The index is standardised over the period January 2017 to June 2022 and is defined as

$$NFTsAI_t = \left((N_3 t - \mu_3)/\sigma_3\right) + 100 \quad (3)$$

where $N_3 t$ is the weekly number of articles matching the NFT attention search criteria at time t, μ_3 is the mean of the weekly article count over the index construction period, and σ_3 is its standard deviation.

Table 2.A.3: Summary Statistics of Propensity Score Covariates

Counterfactuals Measures					
Variable	*Obs*	*Mean*	*Std. Dev.*	*Min*	*Max*
CBDC	81694	101.20567	1.6594	99.1777	106.15661
Policy Index	81847	103.67668	3.64995	99.0242	114.65191
Crypto Prices Index	81847	103.64873	3.52193	99.03057	113.14859
Twitter Based Index	79892	182.2254	92.25703	24.01823	703.30569
NFT Attention Index	81917	101.59775	2.04173	99.50756	108.67275
AUS/USD	81694	.7105	.03905	.5755	.8105
EUR /USD	81680	1.12251	.06333	.9616	1.2488
NZD /USD	81694	.6626	.03962	.5568	.7429
GBP/USD	81680	1.29088	.07361	1.0703	1.4332
CAD/USD	81694	1.30469	.04493	1.2031	1.4539
CNY/USD	81680	6.72241	.26554	6.2649	7.3048
HKD/USD	81694	7.80517	.03831	7.7498	7.8499
INR/USD	81680	75.17198	4.28582	63.38	82.97
JPY/USD	81694	117.36838	12.66319	102.52	149.82
ZAR/USD	81680	15.67196	1.56039	11.55	19.4128
SGD/USD	81694	1.36121	.02715	1.3037	1.4605
CHF/USD	81680	.94453	.03519	.8784	1.0218
Palladium Prices	81693	1967.5726	482.73823	837.2	2981.9
Gold Prices	81903	1719.984	216.68151	1182.3	2069.4
Brent Prices	81693	73.60541	20.71681	19.33	127.98
Silver Prices	81903	21.45276	4.01689	11.772	29.418
Natural Gas Prices	81693	3.86312	1.95877	1.482	9.68
Crude Oil Prices	81903	69.04357	20.7262	-37.63	123.7

Note: Table 2.A1 presents summary statistics for the covariates used in the propensity score estimation. The sample includes 81,917 observations covering the period from January 1, 2018, to May 21, 2023. All variables are measured at daily frequency.

Appendix 2.B: Placebo Tests

Table 2.B1: Returns Placebo Test - 6 Month - Full Sample

	(1)
iCrypto x Placebo	0.0018
	(0.0015)
uCrypto x Placebo	-0.0015
	(0.0015)
Stablecoin x Placebo	-0.0015
	(0.0016)
DeFi x Placebo	0.0016
	(0.0019)
NFTs Tokens x Placebo	0.0057***
	(0.0019)
ln Volume	0.0019***
	(0.0001)
Intercept	-0.0354***
	(0.0018)
N	93244
Adj. R-squared	0.4312
Placebo Period	March 24 2020 to Sep 23 2020
Individual Effects	Yes
Time Effect	Yes

Note: *This table reports fixed effects estimates from placebo tests conducted on the full sample of digital assets using a 6-month pre-treatment window prior to the MiCA announcement. The placebo period spans from March 24, 2020 to September 23, 2020. The dependent variable is the returns. The interaction terms (Asset Class × Placebo) capture differential placebo effects across digital asset categories. Column (1) includes individual (asset-level) and time fixed effects. ln Volume is the natural logarithm of trading volume. A significant coefficient would indicate a non-zero effect during the placebo window, serving as a robustness check of the identification strategy. Standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1*

Table 2.B2: Abnormal Returns Placebo Test - 6 Month - Full Sample

	(1) ar
iCrypto x Placebo	0.0020
	(0.0014)
uCrypto x Placebo	-0.0020
	(0.0014)
Stablecoin x Placebo	0.0026*
	(0.0015)
DeFi x Placebo	-0.0001
	(0.0017)
NFTs Tokens x Placebo	0.0058***
	(0.0018)
ln Volume	0.0016***
	(0.0001)
Intercept	-0.0290***
	(0.0017)
N	92956
Adj. R-squared	0.1101
Placebo Period	March 24 2020 to Sep 23 2020
Individual Effects	Yes
Time Effect	Yes

Note: *This table reports fixed effects estimates from placebo tests conducted on the full sample of digital assets using a 6-month pre-treatment window prior to the MiCA announcement. The placebo period spans from March 24, 2020 to September 23, 2020. The dependent variable is the abnormal returns. The interaction terms (Asset Class × Placebo) capture differential placebo effects across digital asset categories. Column (1) includes individual (asset-level) and time fixed effects. ln Volume is the natural logarithm of trading volume. A significant coefficient would indicate a non-zero effect during the placebo window, serving as a robustness check of the identification strategy. Standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1*

Table 2.B3: 1-Day CAR Placebo Test - 6 Month - Full Sample

	(1) car1
iCrypto x Placebo	0.0016
	(0.0020)
uCrypto x Placebo	-0.0041**
	(0.0019)
Stablecoin x Placebo	0.0034*
	(0.0020)
DeFi x Placebo	-0.0004
	(0.0024)
NFTs Tokens x Placebo	0.0068***
	(0.0025)
ln Volume	0.0006***
	(0.0001)
Intercept	-0.0112***
	(0.0024)
N	92956
Adj. R-squared	0.1047
Placebo Period	March 24 2020 to Sep 23 2020
Individual Effects	Yes
Time Effect	Yes

Note: *This table reports fixed effects estimates from placebo tests conducted on the full sample of digital assets using a 6-month pre-treatment window prior to the MiCA announcement. The placebo period spans from March 24, 2020 to September 23, 2020. The dependent variable is the 1-day cumulative abnormal returns (CAR1). The interaction terms (Asset Class × Placebo) capture differential placebo effects across digital asset categories. Column (1) includes individual (asset-level) and time fixed effects. ln Volume is the natural logarithm of trading volume. A significant coefficient would indicate a non-zero effect during the placebo window, serving as a robustness check of the identification strategy. Standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1*

Table 2.B4: 3-Day CAR Placebo Test - 6 Month - Full Sample

	(1) car3
iCrypto x Placebo	0.0048
	(0.0034)
uCrypto x Placebo	-0.0112***
	(0.0033)
Stablecoin x Placebo	0.0102***
	(0.0035)
DeFi x Placebo	-0.0009
	(0.0042)
NFTs Tokens x Placebo	0.0201***
	(0.0043)
ln Volume	0.0013***
	(0.0002)
Intercept	-0.0226***
	(0.0041)
N	92956
Adj. R-squared	0.1010
Placebo Period	March 24 2020 to Sep 23 2020
Individual Effects	Yes
Time Effect	Yes

Note: *This table reports fixed effects estimates from placebo tests conducted on the full sample of digital assets using a 6-month pre-treatment window prior to the MiCA announcement. The placebo period spans from March 24, 2020 to September 23, 2020. The dependent variable is the 3-day cumulative abnormal returns. The interaction terms (Asset Class × Placebo) capture differential placebo effects across digital asset categories. Column (1) includes individual (asset-level) and time fixed effects. ln Volume is the natural logarithm of trading volume. A significant coefficient would indicate a non-zero effect during the placebo window, serving as a robustness check of the identification strategy. Standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1*

Table 2.B5: 5-Day CAR Placebo Test - 6 Month - Full Sample

	(1) car5
iCrypto x Placebo	0.0073*
	(0.0044)
uCrypto x Placebo	-0.0197***
	(0.0043)
Stablecoin x Placebo	0.0164***
	(0.0046)
DeFi x Placebo	-0.0016
	(0.0054)
NFTs Tokens x Placebo	0.0310***
	(0.0055)
ln Volume	0.0020***
	(0.0003)
Intercept	-0.0167***
	(0.0053)
N	92956
Adj. R-squared	0.1075
Placebo Period	March 24 2020 to Sep 23 2020
Individual Effects	Yes
Time Effect	Yes

Note: *This table reports fixed effects estimates from placebo tests conducted on the full sample of digital assets using a 6-month pre-treatment window prior to the MiCA announcement. The placebo period spans from March 24, 2020 to September 23, 2020. The dependent variable is the 5-day cumulative abnormal returns. The interaction terms (Asset Class × Placebo) capture differential placebo effects across digital asset categories. Column (1) includes individual (asset-level) and time fixed effects. ln Volume is the natural logarithm of trading volume. A significant coefficient would indicate a non-zero effect during the placebo window, serving as a robustness check of the identification strategy. Standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1*

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Appendix 2.C: The Aims and Objectives of MiCA and its Timeline to Implementation

The European Union (EU) already regulated crypto-assets that qualified as financial instruments under its existing financial services framework, including MiFID II. However, many other crypto-assets remained outside the scope of EU financial services legislation, creating a regulatory gap in areas including crypto-asset trading platforms, exchange services and custody (Regulation (EU) 2023/1114, Recitals 3-4). In response, the European Commission presented the MiCA proposal on 24 September 2020 as part of the Digital Finance Package, with the aim of establishing a dedicated regulatory framework for crypto-assets not already covered by existing EU financial services legislation.

The MiCA proposal identifies four main objectives. The first is to provide legal certainty by establishing clear regulatory treatment for crypto-assets not covered by existing financial services legislation. The second is to support innovation and fair competition through a safe and proportionate framework for crypto-assets and distributed ledger technology. The third is to provide an appropriate level of consumer and investor protection and strengthen market integrity. The fourth is to address potential risks to financial stability and monetary policy, particularly those arising from crypto-assets designed to maintain a stable value (European Commission, 2020). These objectives are also reflected in the final MiCA framework, which seeks to support innovation and fair competition while providing a high level of protection for retail holders and maintaining the integrity of crypto-asset markets (Regulation (EU) 2023/1114, Recital 6). Beyond these objectives, MiCA is also intended to contribute to the objective of combating money laundering and terrorist financing, with entities offering services within its scope required to comply with the applicable anti-money laundering and counter-terrorist financing rules of the Union (Regulation (EU) 2023/1114, Recital 16).

Article 1 gives effect to these objectives by establishing uniform requirements for the offer to the public and admission to trading of crypto-assets and for crypto-asset service providers. These include transparency and disclosure requirements; requirements relating to the authorisation, supervision, operation, organisation and governance of issuers and crypto-asset service providers; protection for holders of crypto-assets and clients of crypto-asset service providers; and measures addressing insider dealing, unlawful disclosure of inside information and market manipulation (Regulation (EU) 2023/1114, Article 1).

MiCA does not apply equally to all crypto-assets and activities. Crypto-assets that qualify as financial instruments remain subject to the existing EU financial services framework, while unique and non-fungible crypto-assets are generally outside its scope (Regulation (EU) 2023/1114, Article 2). Furthermore, crypto-assets without an identifiable issuer fall outside Titles II, III and IV, although crypto-asset service providers providing services in relation to those assets remain subject to MiCA. Crypto-asset services provided in a fully decentralised manner without an intermediary also fall outside its scope (Regulation (EU) 2023/1114, Recital 22). These distinctions are particularly relevant to the classification of crypto-assets examined in this chapter.

The development and implementation of MiCA occurred over several stages, as summarised in Table 2.C1.

Table 2.C1: MiCA Legislative and Implementation Timeline

Date	Milestone
19 December 2019	*European Commission launches a public consultation concerning an EU framework for crypto-assets*
24 September 2020	*European Commission presents the MiCA proposal, COM(2020) 593 final, as part of the Digital Finance Package*
24 November 2021	*Council of the European Union adopts its negotiating mandate*
31 March 2022	*Trilogue negotiations between the European Parliament and the Council begin*
30 June 2022	*European Parliament and Council reach a provisional political agreement on MiCA*
20 April 2023	*European Parliament adopts MiCA*
16 May 2023	*Council of the European Union formally adopts MiCA*
31 May 2023	*Regulation (EU) 2023/1114 is signed*
9 June 2023	*MiCA is published in the Official Journal of the European Union*
29 June 2023	*MiCA enters into force*
30 June 2024	*Titles III and IV concerning asset-referenced tokens and e-money tokens begin to apply*
30 December 2024	*The remaining provisions of MiCA begin to apply, including the framework for crypto-asset service providers*
1 July 2026	*Latest end date of the transitional period for crypto-asset service providers already operating under applicable national law*

Note: *Dates of application follow Article 149 of Regulation (EU) 2023/1114. The transitional arrangement for existing crypto-asset service providers follows Article 143(3), which Member States could shorten or disapply. Legislative milestones are drawn from European Commission and Council of the European Union sources.*

The proposal date of 24 September 2020 is used as the regulatory event in this chapter, as this represents the point at which the European Commission formally presented the proposed regulatory framework and its intended treatment of the different categories of crypto-assets to the market.

CHAPTER 3

3. Volatility Transmission in Global Crises: Evidence from the Cryptocurrency Market

3.1 Introduction

The cryptocurrency market remains a complex and dynamic sector characterized by unique volatility dynamics that set it apart from traditional financial markets. Its extreme volatility and changing dynamics over time poses substantial challenges for investors, regulators, and policymakers. Market capitalization has grown from $80 billion in October 2017 to $2.17 trillion today, encompassing new cryptocurrencies and diverse asset classes, with increased participation from both institutional and retail investors. While there is a growing body of literature examining the spillover effects between cryptocurrencies and fiat currencies (Rehman et al., 2023), technology stocks across different industries or sectors (Chen and Lin, 2014; Chen and Wang, 2019; Jawadi et al., 2013; Kumar et al., 2012; Smales, 2019; Symitsi and Chalvatzis, 2018; Le et al., 2020), including the spillover effects between assets including oil, clean energy, and technology-based stocks (Ahmad, 2017; Bondia et al., 2016; Kumar et al., 2012), the literature examining the internal dynamics and potential evolution of the crypto ecosystem over time still needs further examination. This gap becomes increasingly important as COVID-19, despite being a pivotal moment for cryptocurrency markets, was followed by continued market transformation including an influx of diverse investors post-COVID (Auer et al., 2022; Huang et al., 2022; Osman et al., 2024) and exposure to new types of global shocks

requiring analysis. While COVID-19 represented one major crisis, questions remain about the internal dynamics of cryptocurrencies in response to other global events, crises, and factors. Kumar et al. (2022) emphasize the importance of examining cryptocurrencies from a heterogeneous perspective rather than treating them as a homogeneous group. Following their approach, we examine how these heterogeneous behaviours manifest across different cryptocurrencies over extended periods and in response to diverse global events, an area that remains limited.

This study aims to focus specifically on the volatility dynamics between major cryptocurrencies as well as their interplay during macroeconomic and global events, contributing to the existing literature by providing a comprehensive analysis of these relationships. Previous studies have highlighted the changing linkages between cryptocurrencies over time (Boako et al., 2019; Ji et al., 2019; Yi et al., 2018; Katsiampa, 2019; Antonakakis et al., 2019). These linkages change over time as some cryptocurrencies gain prominence or external global factors exert differential influence on individual cryptocurrencies (Umar et al., 2021; Bouri and Jalkh, 2023). Moreover, in recent years with the ecosystem's growth and exposure to major global events such as wars, regulations, and pandemics, and with the established understanding of cryptocurrency heterogeneity (Kumar et al., 2022), questions remain about how these cryptocurrencies behave within themselves and which global factors impact them most as the market continues to evolve (Sakariyahu et al., 2024). Recent studies suggest a shift in market dynamics, with Bitcoin's dominance potentially waning as Ethereum gains influence (Le et al., 2020). The determinants of cryptocurrency returns and volatility have been extensively studied, initially focusing on Bitcoin (Conrad et al., 2018; Pagnotta and Buraschi, 2018; Fang et al., 2019; Biais et al., 2023), and more recently expanding to other major cryptocurrencies like Ethereum, Litecoin, and Ripple (Bouri et al., 2018; Demir et al., 2018; Walther et al., 2019; Gkillas et al., 2022).

Our study builds upon this foundation, focusing on the dynamics within the cryptocurrency market itself and exploring the evolving nature of volatility transmission among major digital assets. We aim to address three critical gaps in the literature that, when examined together, provide a dual perspective on cryptocurrency markets: how volatility transmits internally among cryptocurrencies, and how these transmission patterns respond to external global events. First, there is limited comparative analysis of different volatility measures to understand cryptocurrency market connectedness and risk transmission patterns. Studies point to the importance of idiosyncratic volatility in offering insights into individual digital assets' unique risk profiles (Zhang and Li, 2020; Shen et al., 2024), yet it remains understudied compared to price-based volatility measures. Second, it remains uncertain whether Bitcoin retains its dominant position or if the market has matured with different dynamics as other crypto assets gain prominence. Third, whilst studies have demonstrated cryptocurrency markets' reactivity to external events (Będowska-Sójka et al., 2024; Feng et al., 2024; Dutta et al., 2024; Chen et al., 2024), there is limited comparative examination of which types of events hold the most significant impact on cryptocurrency volatility. We examine pandemic, geopolitical conflicts, and the Markets in Crypto-Assets (MiCA) regulatory framework side by side. To our knowledge, only Conlon et al. (2024) have examined MiCA's impact, making crypto-specific regulatory frameworks of this scope revolutionary and largely unanalysed. Therefore, we focus on the inner dynamics of the cryptocurrency market, exploring the evolving nature of volatility transmission among major digital assets and identifying which external events and global factors most significantly impact these dynamics. Understanding these evolving relationships and risk transmission patterns is crucial for effective risk management, portfolio diversification, and regulatory decision-making. The cryptocurrencies we observe in our study are Bitcoin, Ethereum, Ripple, Dogecoin, Monero, Binance Coin, Cardano and TRON over an extended timeline. Previous literature primarily focused on data

up to late 2022, with most studies not extending beyond this period (Aharon et al., 2023; Będowska-Sójka et al., 2024; Bouri & Jalkh, 2023; Caporale et al., 2021; Chen et al., 2024; Chowdhury et al., 2024; Conlon et al., 2024; Feng et al., 2024; Gonzalez et al., 2021; Kumar et al., 2022). We extend the timeline to incorporate more recent data to capture the latest market dynamics and the impact of recent global events on the cryptocurrency ecosystem.

To conduct our analysis, we divide our methodology into four main sections. First, we examine cryptocurrency volatility using multiple measures, including GARCH (1,1), Parkinson Range-Based Volatility (PRV), and idiosyncratic risk models. We utilise multiple volatility measures to capture the inner dynamics and risk profiles by comparing price-based volatility with idiosyncratic volatility within the cryptocurrency market. By isolating the asset-specific component of volatility, we can better understand the drivers of risk that are unique to each cryptocurrency, complementing traditional measures that focus on overall market volatility. In idiosyncratic risk analysis, we apply Liu et al.'s (2022) factors to construct a cryptocurrency-specific factor index. Secondly, we analyse the connectedness within the selected cryptocurrencies under each volatility measure to gain deeper insights into the overall dynamics of the cryptocurrency market. This analysis is crucial given the frequent market collapses and persistent volatility that have sparked criticisms of digital currencies' viability as hedging mechanisms (Sakariyahu et al., 2024). Our aim here is to examine whether Bitcoin’s dominance remains or other scenarios have developed as the market matures.

Thirdly, we examine the determinants of cryptocurrency spillover dynamics by investigating how global risk factors systematically influence the net spillover contributions of individual cryptocurrencies using robust OLS regression analysis. We analyse eight key global risk indicators including the Chicago Board Options Exchange Volatility Index (VIX), World Uncertainty Index (WUI), Geopolitical Risk Index (GPR), Transition Risk Index (TRI), Physical Risk Index (PRI), Infectious Disease EMV Tracker (INFECT) and Global Economic

Policy Uncertainty Index (GEPU) to test our hypothesis regarding the differential impacts of global risk factors on cryptocurrency market interconnectedness. Finally, we extend the analysis by examining the effects of four major events which are COVID-19, Russia-Ukraine war, Gaza war and MiCA regulation, while incorporating global risk factors by applying staggered difference-in-differences. Our use of two wars allows examination of contrasting geographic impacts: the Russia-Ukraine War affects broader economic regions, whilst the Gaza War has more localised effects (Będowska-Sójka et al., 2024; Ji et al., 2019). Therefore, we collectively analyse a pandemic, wars, and crypto-specific regulations to understand which event holds more impact on cryptocurrencies. Moreover, our staggered difference-in-differences approach is particularly suitable to account for events occurring at different moments as demonstrated by Shen et al. (2024) in their analysis of cryptocurrency information channels. Therefore, our comprehensive analysis of global events and risk factors impact within the crypto market contributes to a growing body of research on the interconnectedness of crypto assets and their relationship to broader economic indicators. Moreover, our analytical framework incorporates multiple robustness dimensions by design: we examine four distinct volatility measures, eight cryptocurrencies, eight global risk factors, and four major events using complementary methodological approaches, with consistent findings across these specifications reinforcing the reliability of our conclusions.

To address the current gaps and understand which type of events impact the volatility of cryptocurrencies, our research incorporates a comprehensive set of global economic, political, and climate risk uncertainty measures and major global events that circulate news. Our approach of examining different volatilities and their inner dynamics while adding external elements aim to contribute to our understanding of crypto-asset behaviour. Our selected factors such as the VIX and GPR have been shown to have predictive power for cryptocurrency volatility and returns (Goodell et al., 2023; Aysan et al., 2019), while several studies have

demonstrated the impact of geopolitical risk on cryptocurrency markets (Będowska-Sójka et al., 2024; Feng et al., 2024; Dutta et al., 2024; Chen et al., 2024). Our inclusion of WUI and climate-related risk factors TRI and PRI, recently developed climate risk indices (Bua et al., 2021), is particularly new and largely unexplored in cryptocurrency research. While recent studies have incorporated WUI as a control variable (Roche et al., 2025; Hodula, 2025) or examined its relationship with individual cryptocurrency performance (Umar et al., 2025; Aras et al., 2025), our study is the first to investigate how WUI influences volatility spillover dynamics across a network of cryptocurrencies, representing a novel contribution to understanding cryptocurrency market interconnectedness. Climate risk is a growing concern of cryptocurrencies, and WUI measures global uncertainty by analysing country reports from the Economist Intelligence Unit across 143 countries; therefore, their incorporation allows us to examine their potential influence on cryptocurrency market dynamics. This approach incorporates both established and emerging factors that have demonstrated importance in recent studies, providing a comprehensive analysis of the market's behaviour.

Our study makes four distinct contributions to the literature. First, we extend the volatility spillover literature (Corbet et al., 2018; Ji et al., 2019; Antonakakis et al., 2019) by providing the first systematic comparison of price-based and idiosyncratic volatility measures in cryptocurrency connectedness analysis, revealing that the choice of volatility measure substantially affects conclusions about market integration. Second, we contribute to the debate on cryptocurrency market leadership (Bouri et al., 2022; Naeem et al., 2022; Yi et al., 2018) by documenting Ethereum's emergence as the dominant volatility transmitter across multiple risk measures, challenging Bitcoin's historically assumed centrality. Third, we advance the external shock literature (Umar et al., 2021; Khalfaoui et al., 2023; Będowska-Sójka et al., 2024) by comparing pandemic, geopolitical, and regulatory events within a unified framework, demonstrating that crypto-specific regulation exerts stronger structural impact than even major

armed conflicts. Fourth, our OLS analysis of global risk factors reveals heterogeneous cryptocurrency responses to uncertainty indices, identifying distinct behavioral clusters rather than treating cryptocurrencies as a homogeneous group, while traditional uncertainty measures (VIX, GEPU, WUI) dominate overall, individual cryptocurrencies exhibit differential sensitivities, with price-based measures more responsive to VIX and idiosyncratic measures to policy uncertainty.

Our study contributes to and extends several strands of literature. The first strand examines volatility spillovers and connectedness within cryptocurrency markets (Corbet et al., 2018; Ji et al., 2019; Antonakakis et al., 2019; Yi et al., 2018; Koutmos, 2018; Ciaian et al., 2018; Wajdi et al., 2020; Zeng et al., 2020). These studies have documented significant interdependencies among cryptocurrencies using various methodological approaches, predominantly focusing on price-based volatility measures. Kumar et al. (2022) notably emphasize examining cryptocurrencies from a heterogeneous perspective rather than as a homogeneous group. We extend this strand by systematically comparing price-based and idiosyncratic volatility measures, demonstrating that conclusions about market integration depend critically on volatility measure choice. The second strand concerns the evolving market leadership dynamics within the cryptocurrency ecosystem (Bouri et al., 2022; Naeem et al., 2022; Katsiampa, 2019; Elsayed et al., 2022). While earlier work identified Bitcoin as the dominant volatility transmitter, more recent studies suggest shifting dynamics. We contribute to this debate by providing evidence across multiple volatility measures that Ethereum has emerged as the dominant net transmitter, reflecting its expanding role in decentralised finance.

The third strand investigates cryptocurrency market responses to external shocks, including COVID-19 (Umar et al., 2021; Aharon et al., 2023; Ha and Nham, 2022), geopolitical events (Khalfaoui et al., 2023; Sakariyahu et al., 2024; Będowska-Sójka et al., 2024), and regulatory developments (Conlon et al., 2024). These studies typically examine single events

or event types in isolation. We advance this literature by comparing pandemic, geopolitical, and regulatory events within a unified framework, enabling direct comparison of their relative structural impacts. The fourth strand explores the determinants of cryptocurrency volatility, particularly the role of global uncertainty indices such as VIX (Bouri et al., 2017, 2019), GPR (Aysan et al., 2019; Goodell et al., 2023), and economic policy uncertainty (Zhang et al., 2021). While these studies have established relationships between individual uncertainty measures and cryptocurrency performance, we extend this work by examining how multiple uncertainty indices differentially influence spillover dynamics across heterogeneous cryptocurrencies. Notably, we incorporate the World Uncertainty Index in spillover dynamics analysis for the first time, moving beyond its typical use as a control variable (Roche et al., 2025; Hodula, 2025). We also include climate-related risk factors (TRI, PRI), an area that remains largely understudied in cryptocurrency research despite growing concerns about the environmental implications of digital asset markets (Bua et al., 2021).

Building on these contributions, our research expands the dataset to include eight cryptocurrencies over an extended timeline and incorporates both economic and global factors. This expansion allows us to contribute to the ongoing debate about Bitcoin's status within the cryptocurrency ecosystem. While some studies maintain that Bitcoin remains the primary driver of volatility in the crypto market, others suggest a shift in this dynamic. Our analysis reveals that Ethereum has emerged as the dominant net transmitter of volatility across different volatility measures, challenging the traditional view of Bitcoin's central role in the cryptocurrency market. This aligns with recent studies (Bouri et al., 2022; Katsiampa, 2019). This finding is consistent across various risk metrics, including PRV, GV, and idiosyncratic risk measures. Notably, the Total Connectedness Index (TCI) varies significantly across different volatility measures, with higher connectedness observed in price-based volatility measures compared to idiosyncratic volatility measures. Our examination of global risk factors

reveals that traditional uncertainty measures, particularly Global Economic Policy Uncertainty (GEPU), VIX, and World Uncertainty Index (WUI), emerge as the dominant drivers of cryptocurrency spillover dynamics, collectively accounting for the majority of economically significant relationships across all cryptocurrencies examined. Importantly, while climate-related risk factors demonstrate high sensitivity to policy changes, their day-to-day economic impact remains limited. Furthermore, our staggered difference-in-differences analysis reveals that cryptocurrency markets exhibit heterogeneous responses to different types of shocks, with regulatory events (MiCA) demonstrating the largest and most persistent effects, followed by global crises like COVID-19, while geopolitical conflicts show more varied impacts potentially depending on their global economic implications. This comprehensive approach allows us to explore critical inflection points and the complex interplay between global events and cryptocurrency dynamics, offering valuable insights for investors, policymakers, and researchers navigating this rapidly evolving financial landscape.

The remaining sections are as follows: Section 2 reviews the related literature; Section 3 describes the data and econometric methodology; Section 4 presents the empirical analysis of the spillover across cryptocurrencies; Section 5 presents the analysis of spillover dynamics; Section 6 examines the impact of global events on spillover patterns; and finally, Section 7 concludes.

3.2 Prior Review and Hypotheses Development

3.2.1 Literature Review

The internal dynamics of cryptocurrency markets, particularly how they react to different types of exogenous shocks, remain an important area of examination. The extreme volatility observed in cryptocurrency returns stems from many factors such as intense speculative trading, sensitivity to online investor sentiment, regulations, macroeconomic, political climate, and global events. When extreme volatility occurs, it often manifests as a significant surge in

price variance, which can rapidly and intensely propagate from one cryptocurrency to others within the ecosystem (Bouri and Jalkh, 2023). To understand these market dynamics, researchers have undergone various approaches to measure and analyse volatility transmission patterns. These transmission patterns vary depending on the nature of the shock and understanding these varying responses has become crucial for market participants and regulators alike. The evolving nature of the cryptocurrency market necessitates robust methodological approaches to capture these dynamic relationships over time, particularly during periods of market stress. Furthermore, understanding how price-based volatility differs from idiosyncratic risk is particularly important, as it reveals whether market reactions to global factors affect the entire cryptocurrency ecosystem uniformly or impact individual assets differently. To shed light on these internal dynamics, we examine different approaches to measuring volatility, market interconnectedness, and the impact of various external factors on the cryptocurrency ecosystem.

Research examining cryptocurrency volatility has employed various methodological approaches, each offering distinct insights into market behaviour and risk transmission. The focus has been on identifying effective methods to capture the distinctive nature of this borderless market, characterised by 24-hour trading and extreme price movements. The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model is the most commonly employed model in research (Baur and Dimpfl, 2018; Bouri et al., 2017; Cheikhet et al., 2020; Katsiampa, et al., 2019; Panagiotidis et al., 2022). This method allows for the modelling of time-varying volatility by capturing past variances and innovations in returns. Building on this approach, researchers have also employed Multivariate GARCH (MGARCH) models, such as the BEKK or Dynamic Conditional Correlation (DCC) models (BenMabrouk et al., 2024). These models enable the examination of volatility spillovers and co-movements between multiple cryptocurrencies, providing insights into the interdependencies within the

market (Charfeddine et al., 2022). For instance, Aslanidis et al. (2019) applied a generalized DCC model to explore conditional correlations among cryptocurrencies, finding time-varying positive correlations with Monero showing the most stability over time. While GARCH-based models are widely used, they generally assume time-invariant shape and skewness parameters. To address this limitation, some researchers have employed the Autoregressive Conditional Density (ACD) model introduced by Hansen (1994). The ACD model extends GARCH-type dynamics to time-varying conditional higher-order moments, allowing for a more comprehensive analysis of cryptocurrency price dynamics. This approach enables the extraction of daily higher-order conditional moments—specifically, conditional volatility, conditional skewness, and conditional (excess) kurtosis—of major cryptocurrencies. Bouri and Jalkh (2023) employed the ACD model to analyse major cryptocurrencies, uncovering significant time-varying volatility patterns. Their findings reveal that cryptocurrencies are interconnected through volatility, with notable spikes during periods of market stress, such as the 2018 cryptocurrency crash and the early stages of the COVID-19 pandemic.

The Parkinson (1980) volatility estimator, while not as extensively utilized in cryptocurrency research as other measures, offers notable advantages due to its ability to capture daily intraday price fluctuations (Yi et al., 2018; Bourghelle et al., 2022; Sapkota, 2022). Unlike traditional close-to-close prices estimators, this method leverages daily high and low prices to estimate realized volatility, effectively capturing the range of price movements throughout a trading period. Smales (2022) highlights the limitations of close-to-close measures, arguing that such approaches often fail to account for significant price movements occurring within the trading day. The Parkinson estimator addresses this by incorporating the full price range, providing a more nuanced understanding of volatility, particularly in highly volatile and continuous trading environments such as cryptocurrencies. This makes it especially valuable in the cryptocurrency market, where the 24-hour trading cycle and

pronounced price fluctuations often result in substantial intraday movements. While the Parkinson measure does not account for trading volume or time-based weighting, its ability to reflect extreme price movements is an important distinction (Kulbhaskar and Subramaniam, 2022; Blasco et al., 2023). The Parkinson estimator offers these distinct advantages for analysing cryptocurrency volatility, but researchers have also explored other approaches to capture different aspects of market behaviour.

Similarly, the Garman-Klass (G-K; 1980) volatility proxy takes opening, high, low and closing prices into account. This proxy can capture not only minute-to-minute price changes but also the opening-closing price range, which is useful to capture different forms of price change and sources of volatility. Moreover, the G-K volatility measure is utilized for its efficiency in capturing price variability over a trading day, providing insights into the dynamic behaviour of different cryptocurrencies (Charfeddine et al., 2022; Bourghelle et al., 2022; Cheng et al., 2024; Cheraghali et al., 2024). Cheng et al. (2024) utilized G-K volatility as it was found to outperform close-price volatility in terms of accuracy for predictive models. This approach was particularly relevant in their examination of major cryptocurrencies' volatilities during periods of market turmoil, such as the COVID-19 pandemic and the Russia-Ukraine conflict, using machine learning techniques. Their findings also highlight Bitcoin's heightened sensitivity to external shocks such as regulations and media sentiment. In addition to these traditional econometric approaches, the Exponentially Weighted Moving Average (EWMA) method is often used for its ability to quickly adjust to recent price changes by giving more weight to recent data, thus offering a dynamic perspective on volatility (Wang et al., 2024).

As the cryptocurrency market continues to evolve, the application and comparison of idiosyncratic volatility with other volatility measures remain understudied but important for understanding individual cryptocurrency behaviour for informative investment and risk management strategies (Charfeddine et al., 2022). Liu et al. (2022) show that higher

idiosyncratic risk is associated with abnormal returns in specific crypto assets, suggesting that unsystematic risk may carry pricing information in these markets. We adopt their methodology by constructing two measures of idiosyncratic volatility using single- and multi-factor residuals from their crypto-specific asset pricing models. Zhang and Li (2020) further support this view by constructing a cryptocurrency market portfolio to calculate idiosyncratic volatility, revealing a positive correlation with cryptocurrency returns. Shen et al. (2024) employ an event study approach combined with a cryptocurrency CAPM to assess the impact of online message board activity on idiosyncratic volatility. Their findings show that idiosyncratic volatility significantly decreases after the opening of cryptocurrency-specific message boards, suggesting that increased information flow improves market efficiency by reducing asset-specific risk.

Musholombo (2023) uses the Granular Instrumental Variables (GIVs) approach and Local Projection models to demonstrate that while cryptocurrencies exhibit high idiosyncratic volatility, idiosyncratic shocks from the cryptocurrency market have minimal spillover effects on traditional stock markets, despite increasing correlations between assets like Bitcoin and the S&P 500. Borri (2019) provides important insights into the relationship between market-wide and idiosyncratic risks in cryptocurrency markets. While cryptocurrencies exhibit high correlation both unconditionally and conditionally among themselves, their idiosyncratic risks show distinct patterns, with cryptocurrency-specific variables and macro factors like VIX demonstrating different predictive power for future conditional tail-risk. This finding underscores the importance of employing multiple volatility measures to capture both market-wide movements and asset-specific risk characteristics. Particularly, they showed evidence that VIX maintains predictive power across all horizons while cryptocurrency-specific variables' predictability declines with time suggests that different risk measures might capture varying aspects of market behavior, especially during periods of external shocks. These diverse

findings underscore the complexity of idiosyncratic volatility in the cryptocurrency market and its importance in understanding overall market dynamics and risk. The purpose of employing multiple methods is to provide a more comprehensive understanding of volatility dynamics, as different methods may highlight various aspects of market behavior. This approach reduces the risk of biased conclusions and strengthens the generalizability of the findings by confirming that results are consistent across different volatility estimation techniques. Ultimately, it enhances the accuracy of risk assessments and informs more reliable investment and policy decisions (Bouri & Jalkh, 2023; Conlon et al., 2024; De La O González et al., 2021; Yi et al., 2018; Bourghelle et al., 2022). The application of multiple volatility measures has revealed how cryptocurrency markets respond differently to various types of external events. Furthermore, it is found that positive news impacts volatility differently than negative news, and the asymmetric nature of these responses becomes more pronounced as the market matures (Aharon et al., 2023; Ante, 2022; Dowling, 2022a, 2022b; Yousaf and Yarovaya, 2022; Zhang et al., 2021). The application of these various volatility measures has revealed complex patterns of interconnectedness in cryptocurrency markets at different time horizons.

This has led researchers to investigate the internal dynamics of cryptocurrency markets, particularly how volatility transmits between different crypto assets. Studies have documented internal transmission patterns between major cryptocurrencies, such as spillovers to smaller digital assets, and interactions with traditional financial markets. Understanding these transmission mechanisms has led to the development and application of various methodological approaches, each capturing different aspects of these relationships. The Diebold and Yilmaz (2012) methodology has emerged as a key approach for examining how shocks propagate through the cryptocurrency market to examine inter-crypto spillover effects in returns and volatility (Corbet et al., 2018; Koutmos, 2018; Yi et al., 2018; Ji et al., 2019; Walther et al., 2019; Fasanya et al., 2020; Kumar et al., 2022; Naeem et al., 2022). This

approach has been particularly influential in understanding the connectedness between different assets by decomposing forecast error variances into contributions from various sources, making it well-suited for analysing the interconnected nature of cryptocurrencies (Charfeddine et al., 2022). Recent studies have continued to implement this methodology in cryptocurrency market analysis (Khalfaoui et al., 2023; Umar et al., 2021; Bouri & Jalkh, 2023). Further developments of this framework, as presented in Diebold and Yilmaz (2014, 2015), have expanded its applications, providing more robust tools for examining the complex dynamics of cryptocurrency markets.

The Time-Varying Parameter Vector Autoregression (TVP-VAR) model allows researchers to capture the evolving relationships between assets, providing a more nuanced understanding of how interconnections shift over time in these rapidly changing markets. Unlike the Diebold and Yilmaz approach, which assumes constant parameters over the sample period, the TVP-VAR model allows coefficients to change with each observation, making it particularly suitable for analysing cryptocurrency dynamics. For instance, BenMabrouk et al. (2024) utilized the TVP-VAR approach to measure spillover effects between Non-Fungible Tokens (NFTs), Bitcoin, and the S&P500, providing insights into the relationships between these diverse digital and traditional assets. Similarly, Yousaf and Yarovaya (2022) applied the TVP-VAR model to examine the time-varying dynamics within cryptocurrency markets. Expanding the scope, Ha and Nham (2022) employed TVP-VAR to investigate the relationships between crude oil (WTI) prices, gold prices, the S&P500 index, and Bitcoin prices, offering a broader perspective on how cryptocurrencies interact with various financial and commodity markets. In the context of global events, Umar et al. (2021) used the TVP-VAR approach to measure the impact of COVID-19 news on return and volatility connectedness of leading cryptocurrencies and fiat currencies. Their findings revealed that

cryptocurrencies acted as net transmitters of shocks, while fiat currencies were net receivers, highlighting the unique role of digital assets during times of global uncertainty.

Research examining the internal dynamics of cryptocurrency markets reveals varying patterns of volatility transmission between different digital assets. While most studies agree on the presence of volatility spillovers, there is some debate about the degree to which different cryptocurrencies are affected. Empirical evidence suggests that major cryptocurrencies, particularly Bitcoin, play a central role in transmitting volatility across the cryptocurrency market (Bouri et al., 2021; Ji et al., 2019). For example, during the 2018 cryptocurrency crash, Mensi et al. (2020) used the Dynamic Conditional Correlation (DCC)--GJR--GARCH model to analyse volatility transmission patterns among Bitcoin (BTC), Ethereum (ETH), Litecoin (LTC), and Ripple (XRP). They found that not all cryptocurrencies react equally to market shocks, with BTC and ETH exhibiting higher volatility persistence, while LTC and XRP were more resilient. Naeem et al. (2022) find that Bitcoin is the main source of volatility spillovers in the market, with Ethereum following closely. Additionally, Binance Coin and Litecoin are strongly linked to both Bitcoin and Ethereum, contributing to notable volatility spillovers. Al-Shboul et al. (2022) show that Bitcoin and Ethereum are the most influential in return connectedness, with spillovers rising during COVID-19. Ethereum acted as both a value saver and risk diversifier, while Bitcoin remained a dominant risk hedge. Ripple served as a consistent value saver, and Litecoin functioned as a hedging asset, highlighting varied responses to market stress. Nguyen et al. (2023) employed a time-varying network analysis of 34 cryptocurrencies, examining both return and volatility time series with an additional noise and trend removal process. They found that Bitcoin and Ethereum were highly influential in the network before noise and trend removal, but their influence diminished after this process, with lower-ranking cryptocurrencies becoming more prominent. This finding aligns with Yi et al. (2018), who observed that while high market capitalization cryptocurrencies like Bitcoin,

Litecoin, and Dogecoin propagate large volatility shocks, some smaller cryptocurrencies also play significant roles in volatility transmission. Notably, they identified MAID as the largest emitter of volatility shocks, despite receiving less public attention. Beneki et al. (2019) further contributed to this discussion by demonstrating a time-varying correlation between Bitcoin and Ethereum's volatility spillovers and hedging abilities. Contrary to prevailing findings, Zieba et al. (2019) present evidence that price variations in Bitcoin neither significantly affect nor are affected by other cryptocurrencies, suggesting a lower level of interconnectedness than previously reported.

A strand of literature challenges Bitcoin's role as the volatility transmitter despite its market dominance, however, several studies have highlighted Ethereum's growing importance in the cryptocurrency ecosystem. Antonakakis et al. (2019) using a TVP-VAR model with generalized variance decompositions, found that while Bitcoin is the lead shock transmitter, Ethereum's dominance is increasing. Umar et al. (2021) apply the Diebold-Yilmaz framework to assess volatility and return spillovers between crypto and conventional markets across pandemic phases. Their results show that Ethereum and Bitcoin are consistently a major net transmitter of volatility, however, Ethereum's role intensified during the COVID period, highlighting its growing centrality in the evolving crypto-financial ecosystem. Elsayed et al. (2022) note that Bitcoin's dominance in the global cryptocurrency market has been steadily declining with the rise of altcoins (Elsayed et al., 2021; Ji et al., 2019; Shi et al., 2020; Yi et al., 2018; Ciaian et al., 2018; Corbet et al., 2018). Using a quantile regression framework to assess Bitcoin's risk transmission to traditional financial assets during the COVID-19 pandemic, they find that Bitcoin exhibits asymmetric transmission patterns, with stronger spillover effects during extreme market conditions. Shi et al. (2020) apply a multivariate factor stochastic volatility model (MFSVM) to analyse volatility co-movements among six cryptocurrencies. They find that Ethereum is significantly correlated with Ripple, Dash, and

Stellar, while Bitcoin is more tightly linked to Litecoin, indicating distinct clusters of volatility dynamics within the crypto ecosystem.

Research examining these transmission patterns shows how shocks propagate differently across assets, with varying responses to external events. Research revealed complex patterns of interconnectedness, both within the cryptocurrency ecosystem and with external markets where relationships vary in strength and direction depending on market conditions and external shocks. Some cryptocurrencies act as consistent transmitters of volatility while others primarily receive shocks. The literature highlights how external shocks have a pronounced impact on the volatility connectedness within the cryptocurrency market (Aharon et al., 2023). To examine the market response to an external shock, structural break analysis enables the identification of significant shifts in market behaviour and risk relationships, particularly when markets may initially underestimate the impact of unexpected news or shocks (Abakah et al., 2020; Bouri et al., 2019; Mensi et al., 2019; Aharon et al., 2023). Cheah and Fry (2016) applied an econophysics model to analyze the impact of exogenous shocks on cryptocurrency markets. Their findings suggest that not all exogenous shocks have equal effects. The collapse of Mt. Gox stood out as the most impactful event due to its lasting influence on market volatility and investor confidence. In contrast, the Silk Road shutdown and various regulatory actions primarily had temporary effects, though they contributed to overall market volatility. This differentiation in impact supports the idea that certain events exacerbate volatility more than others, highlighting the cryptocurrency market's resilience to some types of external disruptions.

COVID-19 is a crucial event in cryptocurrencies' analyses (Umar et al., 2021; Aharon et al., 2023; Al-Shboul et al., 2022; Bouri & Jalkh, 2023; Ha & Nham, 2022; De La O González et al., 2021; Mnif et al., 2020; Vidal-Tomás, 2021). Patel et al. (2024) observe increased connectedness between healthcare cryptocurrencies and traditional markets during global

economic shocks, such as the initial waves of COVID-19 and the Russia-Ukraine conflict, though this connectedness weakened following the development of COVID-19 vaccines. Bourghelle et al. (2022) found that sentiments have a significant impact on Bitcoin's volatility and analyzed the effects of exogenous shocks using Bai-Perron multiple breakpoint tests. They identified volatility spikes during major events such as the 2017 Bitcoin bubble and the COVID-19 pandemic, with Kumar et al. (2023) use TVP-VAR and Diebold-Yilmaz extensions to examine return spillovers between commodities, crypto, and G20 equity markets during major crises. They find that COVID-19 and the Russia–Ukraine war sharply increased global connectedness, with Bitcoin, gold, and oil acting as net receivers of volatility.the relationship between sentiment and volatility intensifying after each structural break. When examining wars, we find limited studies in the Gaza war whereas there are several studies concerning Russia-Ukraine (Abakah et al., 2023; Khalfaoui et al., 2023; Yousaf et al., 2022; Alexakis et al., 2023; Enilov and Mishra, 2023; Sakariyahu et al., 2024; Cheng et al., 2024). Zeinedini et al. (2024) and Kayani et al. (2024) are among the few studies to examine the impact of both the Russia–Ukraine and Gaza wars on crypto assets. Zeinedini et al. find that Bitcoin reacts to geopolitical shocks by aligning with gold in the short term, highlighting its temporary safe-haven behavior. Kayani et al., using a TVP-VAR approach, show that DeFi and NFT assets are particularly vulnerable to external volatility, while traditional assets like gold remain more resilient, emphasizing the asymmetric response of asset classes to global crises.

This highlights the importance of examining how global economic and political uncertainties are crucial drivers of asset prices, particularly in the volatile and emerging cryptocurrency market. Indicators such as the VIX, GPR and GEPU have been shown to significantly influence investor behavior and market dynamics (Sakariyahu et al., 2024; Patel et al., 2024). The VIX, often referred to as the "fear gauge," measures market expectations of near-term volatility and has been found to correlate with heightened risk aversion, leading to

increased volatility in cryptocurrencies during periods of global financial stress (Bouri et al., 2019; Sakariyahu et al., 2024). Osman et al. (2024) identify Tether and the Economic Sentiment Index as primary recipients of volatility shocks, with Ripple and Bitcoin emerging as dominant sources in the post-COVID era. The GPR Index captures the intensity of geopolitical risks, such as conflicts or diplomatic tensions, and its spikes often result in market turbulence, as investors seek refuge in more stable assets, though cryptocurrencies have shown mixed responses depending on the specific geopolitical context (Ji et al., 2019; Patel et al., 2024). The relationship between cryptocurrencies and geopolitical factors is complex and often contradictory, as evidenced by recent research. Kalyvas et al. (2020) found that Bitcoin's crash risk decreases during periods of high political uncertainty, suggesting its potential as a hedge against economic instability. However, Będowska-Sójka et al. (2024) present conflicting evidence, suggesting that while cryptocurrencies may hedge against uncertainties in equity, oil, and commodity markets, this is less evident for geopolitical risk or overall economic uncertainty. They observe weak and irregular transmission of shocks from risk indices to cryptocurrencies, contrasting with findings by Al-Yahyaee et al. (2019) and Aysan et al. (2019), who identify geopolitical risk as a predictive variable for Bitcoin's returns and volatility.

The Infectious Disease EMV Index (INFECT) was developed by Baker et al. (2020) to measure pandemic-induced uncertainty and market volatility specifically related to infectious diseases. Bampinas and Panagiotidis (2024) utilize this index to examine cross-market linkages between stock markets and Bitcoin and Ethereum during COVID-19 and the Russian-Ukrainian war, finding that high infectious disease uncertainty significantly increases dependency between these markets. Jiang et al. (2021) employ the INFECT index to analyse hedging properties of six cryptocurrencies (Bitcoin, Ethereum, Ripple, Litecoin, Stellar, and Monero) during COVID-19, demonstrating that Stellar (XLM) shows the best hedging

properties against EPU while their hedging capabilities diminish during extreme pandemic-induced financial market panic. Recent studies have documented the relationship between cryptocurrencies and traditional energy commodities, given the enormous energy requirements of crypto mining and transaction processes (Su et al., 2022; Zeng et al., 2020; Rehman and Kang, 2021; Ghabri et al., 2022). This is due to growing concerns about the economic and environmental impacts of cryptocurrencies particularly regarding their reliance on traditional energy sources and potential ecological damage. Naeem et al. (2023) found Ethereum to be a leading risk transmitter in the network of cryptocurrencies, energy metals, and clean energy markets, while Bitcoin, XRP, and various energy-related assets remained net risk receivers. Additionally, Pham et al. (2022) discovered that macroeconomic and financial indicators significantly influence the connectedness between carbon markets and both green and non-green cryptocurrencies.

The literature reveals several important gaps in our understanding of cryptocurrency market dynamics. While previous studies have employed various volatility measures, few have comprehensively compared price-based and idiosyncratic volatility measures to understand market connectedness. Furthermore, although research has documented the impact of different external shocks on cryptocurrency markets, the comparative effects of regulatory events versus geopolitical shocks remain understudied. The role of climate-related risks, despite growing environmental concerns about cryptocurrency operations, has received limited attention compared to traditional risk factors. Additionally, while studies have examined Bitcoin's dominance in volatility transmission, the evolution of Ethereum's role as a potential leading transmitter of volatility requires further investigation, particularly given the platform's growing importance in decentralized finance. These gaps in the literature lead us to formulate several hypotheses about the nature of volatility transmission and market responses to different types of external shocks in the cryptocurrency ecosystem.

3.2.2 Hypotheses Development

We utilise multiple volatility measures to capture the inner dynamics and risk profiles by comparing price-based volatility with idiosyncratic volatility within the cryptocurrency market. By isolating the asset-specific component of volatility, we can better understand the drivers of risk that are unique to each cryptocurrency, complementing traditional measures that focus on overall market volatility. In idiosyncratic risk analysis, we apply Liu et al.'s (2022) factors to construct a cryptocurrency-specific factor index. Studies show that idiosyncratic volatility significantly decreases after increased information flow, indicating improved market efficiency by reducing asset-specific risk (Shen et al., 2024). Idiosyncratic volatility measures capture risks unique to each cryptocurrency that cannot be explained by market movements, providing insights into individual digital asset risk profiles. The measures help distinguish between systematic market risks and firm-specific risks, enabling more targeted risk management strategies.

While the majority of cryptocurrency research uses different price-based volatility measures such as PRV (Parkinson, 1980), GARCH(1,1) volatility, and realized volatility, these measures capture overall market dynamics and price fluctuations (Yi et al., 2018; Bourghelle et al., 2022). However, when comparing both approaches, we believe that price-based volatility will reflect higher spillover than idiosyncratic risk because price-based volatility measures like PRV and GARCH are more sensitive to external market factors and broader market dynamics, leading to stronger connectedness across assets (Bourghelle et al., 2022). Price movements in major cryptocurrencies often lead to higher systemic volatility across the entire market, whereas idiosyncratic measures capture asset-specific risks that are less affected by broader market dynamics (Bouri et al., 2017; Ji et al., 2019). Therefore we hypothesize:

H1: *The total connectedness index (TCI) of the cryptocurrency market varies significantly across different volatility measures, with higher connectedness observed in price-based volatility measures compared to idiosyncratic volatility measures.*

Major cryptocurrencies, particularly Bitcoin and Ethereum, serve as key transmitters of volatility to the cryptocurrency system (Koutmos, 2018). Previous studies have highlighted Bitcoin as the dominant transmitter of volatility, but recent research suggests that Ethereum's role in volatility transmission is increasing, particularly as the cryptocurrency market matures. Several studies have documented Ethereum's growing importance in the cryptocurrency ecosystem, with empirical evidence showing that Ethereum's total return connectedness surpasses that of Bitcoin (Antonakakis et al., 2020; Elsayed et al., 2020; Adekoya and Oliyide, 2021). This finding is further supported by Bas et al. (2024), who identified Ethereum as the leading transmitter of volatility, and Kumar et al. (2022) supporting this view by showing that Ethereum consistently transmits shocks to other cryptocurrencies. Studies by Zieba et al. (2019), Yi et al. (2018), and Corbet et al. (2018) present evidence suggesting a more complex volatility transmission landscape, with Al-Shboul et al. (2022) noting that Bitcoin lost its position as a dominant "hedger" during the health crisis. Additionally, Shi et al. (2020) demonstrate Ethereum's broad market influence through its significant positive correlations with multiple cryptocurrencies including Dash, Ripple, and Stellar, suggesting a more diversified transmission network compared to Bitcoin's historically concentrated influence. Moreover, Ethereum's market maturity and liquidity allow it to exert greater influence on volatility transmission, particularly during times of market stress (Bouri et al., 2022; Corbet et al., 2018), showcasing its evolving role compared to altcoins. Therefore, we extend previous work by examining dynamics over an extended timeline that encompasses recent turbulent events including the Russia-Ukraine war, Gaza war, MiCA regulation, and COVID-19,

analysing these patterns at both the price-based and idiosyncratic levels for a comprehensive analysis.

H2: *Ethereum has emerged as the dominant net transmitter of volatility in the cryptocurrency market across different volatility measures, while altcoins tend to be net receivers of volatility shocks.*

Global risk factors (VIX, WUI, GPR, GEPU, TRI, PRI, INFECT) have shown varying degrees of influence on cryptocurrency volatility spillovers in the literature. The VIX has been extensively documented to significantly influence cryptocurrency market dynamics (Bouri et al., 2017; Fang et al., 2019; Sakariyahu et al., 2024; Będowska-Sójka et al., 2024). Bas et al. (2024) shows that VIX exhibits particularly strong spillover effects on major cryptocurrencies including BTC, ETH, and LTC, with its influence being especially pronounced during periods of heightened market uncertainty. The Geopolitical Risk Index (GPR) has become increasingly relevant given the politically tense environment of recent years, with studies demonstrating its impact on cryptocurrency markets (Ji et al., 2019; Patel et al., 2024; Wanidwaranan et al., 2025; Jana, 2024; Almeida et al., 2024). GEPU, while included in some cryptocurrency studies, has received relatively less comprehensive documentation compared to VIX and GPR (Zhang et al., 2021; Patel et al., 2024; Sakariyahu et al., 2024; Ozdamar et al., 2022). Our inclusion of WUI alongside climate-related risk factors TRI and PRI, recently developed climate risk indices (Bua et al., 2021), extends the analysis of global risk factors in cryptocurrency spillover research. The WUI provides a comprehensive measure of global uncertainty that complements traditional volatility indices, while climate risk factors address growing environmental concerns surrounding cryptocurrency mining and energy consumption. Additionally, we include the Infectious Disease EMV Tracker (INFECT) to capture disease-related market volatility effects that became particularly prominent during the COVID-19 pandemic.

Research has highlighted how different cryptocurrencies within the market react heterogeneously to external factors, with evolving inner market dynamics demonstrating different responses over time. The heterogeneous nature of cryptocurrency markets suggests that different digital assets may respond differently to various risk factors, reflecting their distinct characteristics, use cases, and investor bases. We have selected these risk factors because they encompass different major events from the last five years, including the COVID-19 pandemic, geopolitical conflicts, global uncertainty, and climate-related concerns. Understanding these differential responses is crucial for effective risk management, while the relative economic significance of uncertainty measures compared to climate-related factors requires empirical examination to understand how the current market responds. Therefore, we hypothesize:

H3A*: Different cryptocurrencies demonstrate heterogeneous responses to global uncertainty indices, with each uncertainty measure exhibiting varying degrees of impact across cryptocurrency types.*

H3B: *Global uncertainty factors (VIX, GEPU) demonstrate significantly greater economic impact than climate risk factors (TRI, PRI) in driving cryptocurrency spillover dynamics, while the novel World Uncertainty Index (WUI) reveals competitive significance that further reinforces uncertainty measures' dominance over environmental concerns.*

Global uncertainties and turbulence have been shown to affect cryptocurrencies. Several global factors under different global events exhibit significant impact, which is why we included four major events: CVOID-19, Russia-Ukraine and Gaza War, and MiCA to observe the different impacts of external shocks. The literature highlights how external shocks, such as the COVID-19 pandemic, have a pronounced impact on the volatility connectedness within the cryptocurrency market (Aharon et al., 2023). Patel et al. (2024) observe increased connectedness between healthcare cryptocurrencies and traditional markets during global

economic shocks, such as the initial waves of COVID-19 and the Russia-Ukraine conflict, though this connectedness weakened following the development of COVID-19 vaccines. Bourghelle et al. (2022) found that sentiments have a significant impact on Bitcoin's volatility and analyzed the effects of exogenous shocks using Bai-Perron multiple breakpoint tests, identifying volatility spikes during major events such as the 2017 Bitcoin bubble and the COVID-19 pandemic, with the relationship between sentiment and volatility intensifying after each structural break. Furthermore, Mnif et al. (2020) and Vidal-Tomás (2021) highlight market adaptation during the pandemic, supporting evidence of cryptocurrency market resilience following initial disruption. We incorporated two distinct wars to examine differential geopolitical impacts. The Russia-Ukraine War represents a large-scale conflict with broad global economic implications, including energy crises due to disruptions in oil and gas supplies and extensive international sanctions against Russia, which have heightened global economic uncertainty and influenced investor behaviour across financial markets, including cryptocurrencies (Iqbal et al., 2024; Będowska-Sójka et al., 2024; Long et al., 2022). In contrast, the Gaza War exhibits a more localized nature, primarily affecting a specific region without causing substantial disruptions to global economic systems. However, this understudied conflict occurs in a developing economy context, which warrants investigation into whether such localized conflicts in emerging markets generate comparatively different cryptocurrency risk patterns than globally impactful wars. Limited studies address the two wars simultaneously (Kayani et al, 2024 ; Zeinedini et al, 2024) However, we assume that a crypto-specific regulatory event would cause the most significant impact, even at the proposal level. Kennedy (2025) provides new evidence of fiscal policy transmission through cryptocurrency channels, documenting an overall increase in crypto outflows following US stimulus disbursement, with significantly higher impacts for flows to middle- and high-income countries respectively, demonstrating that different types of global shocks affect cryptocurrency markets

through distinct mechanisms and with varying magnitudes. The impact of regulatory changes on cryptocurrency markets is still growing (Auer and Claessens, 2018; Corbet et al., 2020a; Kennedy, 2025) but it is shown that regulation tends to have a profound and immediate effect on market volatility. Moreover, besides Conlon et al , (2024), MiCA's impact hasn't been examined further on cryptocurrencies. Therefore, while global economic and policy uncertainties are shown to greatly impact the crypto market, we hypothesize regulatory impact tailored towards cryptocurrencies has the greatest effect on its volatility.

H4: *Exogenous shocks, particularly regulatory events (such as the MiCA regulation), have a more pronounced effect on cryptocurrency volatility transmission dynamics compared to geopolitical events.*

3.3 Data and Econometric Methodology

3.3.1 Data

This study examines the connectedness and risk dynamics among eight major cryptocurrencies: Binance Coin (BNB), Bitcoin (BTC), Cardano (ADA), Dogecoin (DOGE), Ethereum (ETH), Monero (XMR), TRON (TRON), and Ripple (XRP). Stablecoins are excluded from this chapter, since their prices are pegged to a reference asset and their volatility therefore reflects deviations from the peg rather than the market-driven price dynamics that the spillover analysis is designed to capture. We use daily price data spanning from January 1, 2018, to July 12, 2024, obtained from Coinmarketcap.com, a comprehensive cryptocurrency data provider. Our sample period covers approximately six and a half years, allowing us to capture both short-term fluctuations and long-term trends in the cryptocurrency market, including periods of significant market events and structural changes (Aharon et al., 2023; Będowska-Sójka et al., 2024; Bouri & Jalkh, 2023; Caporale et al., 2021; Chen et al., 2024; Chowdhury et al., 2024; Conlon et al., 2024; Feng et al., 2024; Gonzalez et al., 2021; Kayani et al., 2023; Kumar et al.,

2022). It also allows us to examine the full sequence of events studied in this chapter, from the COVID-19 pandemic to the Gaza War. The study incorporates several key global risk indicators: the CBOE Volatility Index (VIX), World Uncertainty Index (WUI), Geopolitical Risk Index (GPR), and Global Economic Policy Uncertainty Index (GEPU). The VIX, often referred to as the "fear gauge," has been shown to significantly influence cryptocurrency market dynamics (Bouri et al., 2019; Sakariyahu et al., 2024). The WUI, developed by Ahir et al. (2018) using the methodology of Baker et al. (2016), provides a consistent measure of global uncertainty based on Economist Intelligence Unit country reports. To our knowledge, the WUI has not been previously used in cryptocurrency research, offering a novel perspective on global uncertainty impacts. The GPR, capturing geopolitical tensions, has been linked to cryptocurrency market turbulence (Ji et al., 2019; Patel et al., 2024). The GEPU, constructed by Baker, Bloom, and Davis, tracks global economic policy uncertainty and has been found to impact cryptocurrency volatility and trading volume (Zhang et al., 2021; Patel et al., 2024; Elsayed et al., 2022).

In addition to these traditional indicators, our study incorporates climate-related risk factors, specifically the Physical Risk Index (PRI) and Transition Risk Index (TRI). These indices, while relatively new in cryptocurrency research, are gaining importance due to the growing awareness of environmental impacts of cryptocurrency mining and transactions (Su et al., 2022; Naeem et al., 2023). To the best of our knowledge, these specific climate risk measures (PRI and TRI) have not been used in any other cryptocurrency research to date. The inclusion of these climate risk measures addresses a significant gap in the literature, as highlighted by Goodell et al. (2023), who emphasize the potential long-term impact of climate-related factors on cryptocurrency valuations and regulatory landscape. By examining these diverse factors, our study aims to provide a comprehensive understanding of the various forces shaping cryptocurrency market dynamics and spillover effects. These global risk measures are

collected at a daily frequency to match our cryptocurrency data, covering the same period from January 1, 2018, to July 31, 2024. This extensive dataset provides us with multiple major cryptocurrencies with a longer period to capture the latest market dynamics and the impact of recent global events on the cryptocurrency ecosystem as highlighted by the previous studies.

Next, we construct four risk measures since the main aim is to assess the dynamics and interdependencies across the top cryptocurrencies in the market.

3.3.2 Construction of Cryptocurrency Risk Factors

Following the methodology of Liu et al. (2022), we construct three cryptocurrency-specific risk factors: the cryptocurrency market factor (CMKT), the cryptocurrency size factor (CSMB), and the cryptocurrency momentum factor (CMOM). These factors are designed to capture the unique risks associated with the cryptocurrency market.

The Cryptocurrency Market Factor (CMKT) is constructed as a value-weighted index using daily closing prices of 1024 available cryptocurrencies. The CMKT is constructed as a value-weighted index using daily close prices of all 1024 available cryptocurrencies. The excess market return is calculated as:

$$CMKT_t = R_{m,t} - R_{f,t} \quad (1)$$

where $R_{m,t}$ is the cryptocurrency market return at time t and $R_{f,t}$ is the risk-free rate at time t. We use the 1-month US Treasury bill rate as a proxy for the risk-free rate.

Cryptocurrency Size Factor (CSMB) factor is constructed to capture the size effect in cryptocurrency returns. Each week, we sort the cryptocurrencies into three groups based on their market capitalization: Small (S): bottom 30%, Medium (M): middle 40%, and Big (B): top 30%. We then form value-weighted portfolios for each group. The CSMB is calculated as the return difference between the small and big size portfolios:

$$CSMB_t = R_{S,t} - R_{B,t} \quad (2)$$

where $R_{S,t}$ is the return of the small-size portfolio at time t and $R_{B,t}$ is the return of the big-size portfolio at time t.

Cryptocurrency Momentum Factor (CMOM) is designed to capture the momentum effect in cryptocurrency returns. We construct this factor based on 15-day past returns. The process involves the following steps: First, sort cryptocurrencies into two portfolios based on size. Within each size portfolio, form three momentum portfolios based on past 15-day returns: Low (L): bottom 30%, Medium (M): middle 40% and High (H): top 30%. Finally, calculate the momentum factor as:

$$CMOM_t = \frac{1}{2}\left(R_{S/H,t} + R_{B/H,t}\right) - \frac{1}{2}\left(R_{S/L,t} + R_{B/L,t}\right) \quad (3)$$

where $R_{S/H,t}$ and $R_{B/H,t}$ are the returns of the small-size/high-momentum and big-size/high-momentum portfolios at time t, respectively, and $R_{S/L,t}$ and $R_{B/L,t}$ are the returns of the small-size/low-momentum and big-size/low-momentum portfolios at time t, respectively.

3.3.3 Risk Measures

For each cryptocurrency, we compute four distinct measures of risk to provide a comprehensive view of the risk dynamics in the cryptocurrency market. To the best of our knowledge, this is the first study to employ these four risk measures simultaneously in the context of cryptocurrency markets:

Parkinson Range-Based Volatility (PRV):

Following Parkinson (1980) and as used in Diebold and Yilmaz (2012), we estimate the daily volatility using daily high and low prices. For each cryptocurrency *i* on day *t*, the annualized volatility is calculated as:

$$PRV_{it} = 100 \cdot \sqrt{365 \cdot 0.361 \cdot \left[\ln(P_{it}^{max}) - \ln\left(P_{it}^{min}\right)\right]^2} \quad (4)$$

Where P_{it}^{max} is the maximum (high) price of cryptocurrency *i* on day *t*, and P_{it}^{min} is the daily minimum (low) price.

GARCH(1,1) Volatility (GV):

We employ a GARCH(1,1) model to estimate the conditional volatility of each cryptocurrency. The model is specified as:

$$r_{it} = \mu_i + \varepsilon_{it}; \quad (5)$$

$$\varepsilon_{it} = \sigma_{it} z_{it};\ z_{it} \sim N(0,1)$$

$$\sigma_{it}^2 = \omega_i + \alpha_i \varepsilon_{it-1}^2 + \beta_i \sigma_{it-1}^2 \quad (6)$$

where r_t is the daily return, σ_t^2 is the conditional variance, and ω, α, and β are parameters to be estimated. The conditional mean is specified by a constant, μ. We use the estimated time varying standard deviation obtained from equation 3. Therefore, the second measure is defined as:

$$GV_{it} = \sqrt{\sigma_{it}^2} \quad (7)$$

Idiosyncratic Risk:

Idiosyncratic risk represents the residual risk that cannot be explained by movements in market returns. We compute idiosyncratic risk using two approaches: a one-factor model and a three-factor model.

One-Factor Model Idiosyncratic Risk (IR1F):

Following Dunbar and Owusu-Amoako (2022) and Shen et al., (2024), we estimate idiosyncratic risk using a one-factor model:

$$r_{it} = \alpha_i + \beta_i CMKT_t + \varepsilon_{it} \quad (8)$$

where r_{it} is the return of cryptocurrency i, $CMKT_t$ is the cryptocurrency market return, and ε_{it} is the residual.

Three-Factor Model Idiosyncratic Risk (IR3F):

We extend the one-factor model to a three-factor model, incorporating size and momentum factors following Liu et al. (2022):

$$r_{it} = \alpha_i + \beta_{1i} CMKT_t + \beta_{2i} CSMB_t + \beta_{3i} CMOM_t + \varepsilon_{it} \quad (9)$$

where $CMKT_t$ is the cryptocurrency market factor, $CSMB_t$ is the size factor, and $CMOM_t$ is the momentum factor.

For both models, we compute a relative measure of idiosyncratic risk, following Ferreira and Laux (2007), Luo and Bhattacharya (2009), and Shen et al. (2024). For each asset i and day t, we calculate:

$$IVOL_{it} = \ln\left(\frac{1-R_{it}^2}{R_{it}^2}\right) \quad (10)$$

where R_{it}^2 is the coefficient of determination from the respective regression model. This logistic transformation of $1 - R^2$ captures the total volatility not explained by the model factors. Because the measure is expressed as $\ln[(1 - R^2)/R^2]$, it can take negative values when $R^2 > 0.5$; these values reflect a relatively low share of idiosyncratic risk rather than negative risk.

3.3.4 Econometric Models

Our econometric methodology consists of two stages. The first stage consists of estimating the spillover index, both total spillover and pairwise spillover indices, between cryptocurrencies. The second stage aims to examine the determinants of these spillovers using global economic and financial risk indices to attempt linking. For the aims of this paper, we therefore apply spillover approach based on Diebold and Yilmaz (2012; 2014) approach and regression analysis. This multi-measure, multi-asset approach serves as an inherent robustness mechanism, as consistent findings across different volatility specifications and cryptocurrency types strengthen confidence in our results.

Spillover Index

This study employs a Vector Autoregressive (VAR) framework to analyse the interconnectedness between the cryptocurrencies. The VAR model allows for the examination of dynamic relationships among multiple time series variables, accounting for potential feedback effects and lagged interactions.

The general form of the VAR model is specified as follows:

$$Y_t = c + \sum_{i=1}^{p} \Phi_i Y_{t-i} + u_t \quad (11)$$

where $\boldsymbol{Y_t}$ is an $n \times 1$ vector of endogenous variables at time t, including all the eight cryptocurrencies in this study. The term $\boldsymbol{c}$ is an $n \times 1$ vector of constants, $\Phi_{\boldsymbol{i}}$ represents $n \times n$ coefficient matrices for $i = 1, 2, \ldots, p$, where p is the optimal lag length. The error term $\boldsymbol{u_t}$ is an $n \times 1$ vector with zero mean and a variance-covariance matrix Σ, which is an $n \times n$ symmetric and possibly non-diagonal matrix.

To address potential non-stationarity issues, we employ the Toda and Yamamoto (1995) approach, which allows for the estimation of VARs in levels, even in the presence of integrated or cointegrated processes. This method involves estimating a $(k + d_{max})$th-order VAR model, where k is the optimal lag length determined by information criteria, and d_{max} is the maximal order of integration suspected in the system.

To measure the interconnectedness among variables, we adopt the generalized variance decomposition approach proposed by Diebold and Yilmaz (2012), which builds upon the work of Pesaran and Shin (1998). This method allows for correlated shocks and is invariant to the ordering of variables in the VAR system. The h-step generalized variance decomposition is given by:

$$d_{ij,t}^{gH} = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(\boldsymbol{e_i'} \boldsymbol{\Theta_{h,t}} \Sigma_t \boldsymbol{e_j}\right)^2}{\sum_{h=0}^{H-1} \left(\boldsymbol{e_i'} \boldsymbol{\Theta_{h,t}} \Sigma_t \boldsymbol{\Theta_{h,t}'} \boldsymbol{e_i}\right)} \quad (12)$$

where σ_{jj} is the jth diagonal element of the error variance-covariance matrix Σ, $\boldsymbol{e_i}$ is a selection vector with unity as its ith element and zeros elsewhere, and $\boldsymbol{\Theta_h}$ represents the coefficient

matrix multiplying the h-lagged shock vector in the infinite moving average representation of the VAR model.

To ensure that the spillover indices are comparable across variables, we normalize the elements of the variance decomposition matrix as follows:

$$\widetilde{d_{ij,t}^{gH}} = \frac{d_{ij,t}^{gH}}{\sum_{j=1}^{N} d_{ij,t}^{gH}} \tag{13}$$

Using these normalized elements, we compute several measures of connectedness:

1. Total Connectedness Index (TCI):

$$C_t^{gH} = \frac{\sum_{i,j=1,i\neq j}^{N} \widetilde{d_{ij,t}^{gH}}}{\sum_{i,j=1}^{N} \widetilde{d_{ij,t}^{gH}}} \times 100 \tag{14}$$

2. Directional spillover from all variables j to variable i:

$$C_{i\leftarrow j}^{gH} = \frac{\sum_{j=1,j\neq i}^{N} \widetilde{d_{ij,t}^{gH}}}{\sum_{i=1}^{N} \widetilde{d_{ij,t}^{gH}}} \times 100 \tag{15}$$

3. Directional spillover from all variables i to variable j:

$$C_{i\rightarrow j}^{gH} = \frac{\sum_{j=1,j\neq i}^{N} \widetilde{d_{ji,t}^{gH}}}{\sum_{i=1}^{N} \widetilde{d_{ji,t}^{gH}}} \times 100 \tag{16}$$

To address the challenges posed by high-dimensional data and perform effective variable selection, we employ the adaptive elastic net estimation technique. This method combines the benefits of both lasso and ridge regression, allowing for both sparsity and shrinkage effects. The estimation procedure involves minimizing the following objective function:

$$\hat{\beta} = argmin_{\beta} \left\{ \frac{1}{T} \sum_{t=1}^{T} |\boldsymbol{Y_t} - \boldsymbol{X_t}\beta|^2 + \lambda_1 \sum_{j=1}^{k} |\beta_j| + \lambda_2 \sum_{j=1}^{k} |\beta_j|^2 \right\} \tag{17}$$

where $\hat{\beta}$ represents the estimated coefficient matrix, $\boldsymbol{Y_t}$ and $\boldsymbol{X_t}$ denote the vector of endogenous variables and the design matrix consisting of lagged variables, respectively. The terms λ_1 and λ_2 are tuning parameters that control the level of regularization, with λ_1 promoting sparsity (lasso) and λ_2 encouraging shrinkage (ridge).

3.4 Empirical Analysis of the Spillover across Cryptocurrencies

3.4.1 Descriptive Analysis

Before presenting the connectedness analysis, we first summarize the descriptive statistics and pairwise correlations of the four volatility measures (Tables 1–6) to provide an overview of risk dynamics across cryptocurrencies. Table 1 presents the descriptive statistics for the four risk measures across all cryptocurrencies in our sample. The Parkinson Range-Based Volatility (PRV) exhibits the highest mean value of 72.418, indicating substantial price fluctuations in the cryptocurrency market. In contrast, the GARCH(1,1) Volatility (GV) shows a lower mean of 0.052, reflecting the model's focus on conditional volatility. The one-factor idiosyncratic volatility (IVOL1F) displays a positive mean of 0.531, while the three-factor idiosyncratic volatility (IVOL3F) presents a negative mean of -0.868. This disparity suggests that the additional factors in the three-factor model explain more of the variation in cryptocurrency returns, resulting in lower idiosyncratic risk estimates.

[Table 3.1 about here]

Table 3.2 provides a more granular view by breaking down the risk measures for each individual cryptocurrency. Bitcoin demonstrates the lowest mean PRV (51.595) and GV (0.045), suggesting it may be the least volatile among the cryptocurrencies studied. In contrast, Dogecoin exhibits the highest mean PRV (85.264) and GV (0.057), indicating potentially higher volatility. Notably, Bitcoin has the lowest mean IVOL1F (-2.275) and IVOL3F (-3.339), implying that its returns are best explained by the market and factor models. Conversely, Ripple shows the highest mean IVOL1F (1.71), while Dogecoin has the highest mean IVOL3F (0.198), suggesting these cryptocurrencies have the most idiosyncratic risk relative to the factor models.

[Table 3.2 about here]

Figures 3.1-3.8 offer visual representations of the four risk measures for each cryptocurrency over time, revealing several key patterns and characteristics. A prominent feature observed

across all cryptocurrencies is the presence of volatility clustering, where periods of high volatility are followed by periods of relative calm. This phenomenon is particularly evident in the PRV and GV plots, aligning with established financial literature on volatility dynamics in traditional asset classes. Three further patterns are visible. First, the price-based measures spike at similar dates across all eight cryptocurrencies, most clearly in March 2020 and during 2021, indicating that extreme volatility episodes are largely market-wide rather than coin-specific. Second, the idiosyncratic measures behave differently from the price-based measures, moving slowly and shifting between persistent levels rather than spiking and reverting, which suggests that coin-specific risk evolves through regime-like changes. Third, the level of idiosyncratic risk differs markedly across cryptocurrencies, with Ethereum's falling sharply early in the sample and remaining low, consistent with its price being increasingly explained by market-wide factors.

[Figures 3.1 – 3.8 about here]

The figures also highlight the occurrence of extreme events, manifested as sharp spikes in volatility across all cryptocurrencies. These spikes likely correspond to major market events or significant news, such as the notable increase in volatility observed across most cryptocurrencies in March 2020, coinciding with the global market turmoil at the onset of the COVID-19 pandemic. This observation underscores the sensitivity of cryptocurrency markets to global economic shocks and the potential for contagion effects. The IVOL1F and IVOL3F measures exhibit considerable variation over time, suggesting that the proportion of cryptocurrency returns unexplained by market or common factors fluctuates substantially. This temporal variation in idiosyncratic risk highlights the dynamic nature of cryptocurrency-specific factors and the challenges in consistently explaining their returns using standard factor models.

While there are similarities in the overall patterns, each cryptocurrency displays distinct risk characteristics. For instance, Bitcoin's volatility measures appear more stable compared to newer or smaller-cap cryptocurrencies like Dogecoin or Cardano. This observation may reflect Bitcoin's status as the largest and most established cryptocurrency, potentially benefiting from greater market depth and liquidity. The difference between IVOL1F and IVOL3F varies across cryptocurrencies, with some showing larger gaps than others. This divergence suggests that the additional factors in the three-factor model have varying degrees of explanatory power for different cryptocurrencies, pointing to the heterogeneity in risk drivers across the cryptocurrency market. Some cryptocurrencies exhibit noticeable trends in their risk measures over time. For example, Ethereum's volatility measures seem to decrease over the sample period, possibly indicating increasing market maturity or changes in its underlying fundamentals and use cases. While the four risk measures often move in tandem, there are periods where they diverge, highlighting the importance of considering multiple risk metrics for a comprehensive understanding of cryptocurrency risk dynamics. This observation emphasizes the complex nature of cryptocurrency risks and the potential limitations of relying on a single risk measure. The pairwise correlation matrices presented in Tables 3.3-3.6 offer valuable insights into the interconnectedness of risk measures across the eight major cryptocurrencies in our sample. These correlations provide an initial understanding of the risk dynamics and potential spillover effects within the cryptocurrency market.

[Tables 3.3 – 3.6 about here]

Table 3.3 presents the correlations for the Parkinson Range-Based Volatility (PRV) measure. We observe strong positive correlations across all cryptocurrency pairs, with coefficients ranging from 0.461 (between Dogecoin and TRON) to 0.847 (between Bitcoin and Ethereum). This high degree of positive correlation suggests that volatility shocks in one cryptocurrency are likely to coincide with volatility increases in others. The particularly strong

correlation between Bitcoin and Ethereum (0.847) is noteworthy, potentially reflecting their status as the two largest cryptocurrencies by market capitalization and their role as benchmarks for the broader crypto market. The GARCH(1,1) Volatility (GV) correlations in Table 3.4 exhibit a similar pattern of positive relationships, albeit with slightly lower magnitudes compared to the PRV measure. The correlations range from 0.334 (between Dogecoin and TRON) to 0.817 (between Bitcoin and Ethereum). This consistency across different volatility measures reinforces the notion of strong volatility co-movements in the cryptocurrency market.

Tables 3.5 and 3.6, which present correlations for the one-factor (IVOL1F) and three-factor (IVOL3F) idiosyncratic volatility measures, respectively, reveal more nuanced relationships. For IVOL1F, we observe generally positive correlations, with coefficients ranging from 0.152 (between Bitcoin and Monero) to 0.943 (between Cardano and Ethereum). The lower correlation involving Bitcoin might suggest that its idiosyncratic risk is less closely linked to that of other cryptocurrencies, possibly due to its unique position in the market. The IVOL3F correlations in Table 3.6 show a more diverse pattern, including some negative correlations. For instance, Dogecoin exhibits negative correlations with Bitcoin (-0.130) and TRON (-0.062). This divergence in idiosyncratic risk patterns when accounting for additional factors highlights the complexity of risk dynamics in the cryptocurrency market and suggests that different cryptocurrencies may have distinct risk drivers beyond common market factors.

While these correlation analyses provide valuable initial insights, it is crucial to acknowledge their limitations. Firstly, correlation is a linear measure of association and may not capture non-linear relationships that could exist between cryptocurrency risks. The cryptocurrency market, known for its complexity and rapid evolution, may exhibit non-linear dependencies that are not reflected in simple correlation coefficients. Secondly, correlation does not imply causation. High correlations between two cryptocurrencies' risk measures do not necessarily indicate a causal relationship or the direction of influence. External factors or

market-wide events could drive concurrent changes in multiple cryptocurrencies without direct causality between them. Thirdly, correlations are static measures that represent average relationships over the entire sample period. They do not capture potential time-varying dynamics in the relationships between cryptocurrencies. Given the rapidly evolving nature of the cryptocurrency market, these relationships may change significantly over time, particularly during periods of market stress or in response to regulatory developments. Furthermore, outliers or extreme events can significantly influence correlation coefficients, potentially leading to biased interpretations. The cryptocurrency market is prone to sudden price swings and periods of extreme volatility, which could disproportionately affect correlation estimates. Lastly, the use of daily data in our analysis may obscure intraday dynamics and lead to potential aggregation bias. High-frequency trading and rapid information flows in cryptocurrency markets might result in important risk interactions that are not captured at the daily level.

3.4.2 Analysis of the Spillovers Across Crypto Assets

The empirical analysis of spillovers and networks in the cryptocurrency market reveals a complex structure of interconnections and risk transmission patterns among the eight major cryptocurrencies examined: Binance Coin, Bitcoin, Cardano, Dogecoin, Ethereum, Monero, TRON, and Ripple. This comprehensive investigation employs four distinct risk measures: Parkinson Range-Based Volatility (PRV), GARCH(1,1) Volatility (GV), 1-Factor Idiosyncratic Volatility (IVOL1F), and 3-Factor Idiosyncratic Volatility (IVOL3F). The primary results are derived from the elastic net estimation method, with ridge and lasso estimations serving as robustness checks, following the methodological approach of Diebold and Yilmaz (2012) and building upon recent studies in cryptocurrency markets such as Yi et al. (2018), Koutmos (2018) and Bas et al (2024).

[Table 3.7 about here]

The analysis of Parkinson Range-Based Volatility (PRV) spillovers, presented in Table 3.7, reveals a total connectedness index (TCI) of 67%, indicating a high degree of interconnectedness among the studied cryptocurrencies. This finding aligns with the work of Corbet et al. (2018), who documented significant interdependencies in cryptocurrency markets. Ethereum emerges as the largest net transmitter of volatility (NET = 20.54), followed by Cardano (NET = 16.68) and Bitcoin (NET = 3.25). This result extends the findings of Antonakakis et al. (2019), who identified Bitcoin as a significant transmitter of shocks, by highlighting the growing importance of Ethereum in the cryptocurrency ecosystem. Conversely, Ripple is observed to be the largest net receiver (NET = -22.64), followed by Dogecoin (NET = -20.82), suggesting these cryptocurrencies are more susceptible to volatility shocks originating from other market participants. The strong spillovers observed under the PRV measure echo the early evidence of high market interdependence reported by Corbet et

al. (2018) and Ji et al. (2019), reinforcing that systemic volatility in crypto markets is primarily driven by the major assets rather than isolated shocks.

[Table 3.8 about here]

The GARCH(1,1) Volatility (GV) spillover analysis, presented in Table 3.8, corroborates the high level of interconnectedness with a similar TCI of 67%. However, the net transmission patterns exhibit some variations compared to the PRV analysis. Ethereum maintains its position as the largest net transmitter (NET = 22.61), but Bitcoin's role as a transmitter is more pronounced (NET = 10.60). This finding is consistent with the work of Katsiampa et al. (2019), who emphasized the central role of Bitcoin in volatility transmission. Interestingly, Cardano's net transmission is reduced (NET = 6.02) in the GV analysis, highlighting the sensitivity of spillover effects to the choice of volatility measure. Similar to Bouri and Jalkh (2023), the persistence of high TCI values across conditional volatility models suggests that common information flows dominate market dynamics, indicating that broader market forces rather than coin-specific factors drive volatility behaviour.

The analysis of 1-Factor Idiosyncratic Volatility (IVOL1F) spillovers, presented in Table 3.9, reveals a lower TCI of 48%, suggesting that idiosyncratic risks are less interconnected than overall volatility. This finding extends the work of Liu et al. (2022) on cryptocurrency-specific risk factors by quantifying the degree of interconnectedness in idiosyncratic risks. Binance Coin emerges as the largest net transmitter (NET = 13.53), followed by TRON (NET = 12.35), while Ripple remains the largest net receiver (NET = -12.33). The generally smaller magnitudes of net spillovers in IVOL1F compared to PRV and GV measures suggest that cryptocurrency-specific risks are less prone to transmission across the market. This pattern supports the argument in Liu et al. (2022) that once systemic influences are accounted for, idiosyncratic components exhibit limited spillover capacity across cryptocurrencies.

[Table 3.9 about here]

The 3-Factor Idiosyncratic Volatility (IVOL3F) analysis, presented in Table 3.10, exhibits the lowest TCI at 43%, indicating that when accounting for additional factors, the idiosyncratic risks become even less interconnected. This result underscores the importance of considering multiple risk factors in cryptocurrency analysis, as advocated by Liu et al. (2022). Ethereum regains its position as the largest net transmitter (NET = 10.62), while Monero becomes the largest net receiver (NET = -6.20), demonstrating how the consideration of additional factors can alter the perceived risk transmission dynamics in the cryptocurrency market. The further decline in connectedness aligns with Antonakakis et al. (2019), highlighting that more granular volatility models capture narrower, asset-specific linkages rather than broad market-wide effects, supporting the view in Liu et al. (2022) that idiosyncratic components retain limited spillover capacity once systemic influences are filtered out. The substantially lower TCI values for idiosyncratic risk measures (IVOL1F: 48%, IVOL3F: 43%) compared to price-based measures (PRV and GV: 67%) suggest meaningful diversification opportunities within cryptocurrency portfolios, consistent with the portfolio optimization findings of Platanakis and Urquhart (2019) and the risk decomposition framework of Bouri et al. (2019). This distinction between systematic and idiosyncratic risk transmission channels has important implications for the safe-haven debate (Conlon et al., 2020; Dyhrberg, 2016).

[Table 3.10 about here]

The network representations in Figure 3.9 provide a visual corroboration of these spillover effects, offering insights into the topological structure of risk transmission in the cryptocurrency market. For PRV and GV, we observe dense networks with strong connections between most cryptocurrencies, confirming the high TCI values. Ethereum and Bitcoin appear as central nodes, reflecting their roles as major transmitters of volatility. This network structure aligns with the findings of Ji et al. (2019), who identified a core periphery pattern in which a

few dominant cryptocurrencies such as Bitcoin and Ethereum act as central hubs transmitting shocks to the broader market.

[Figure 3.9 about here]

Consistent with the IVOL1F spillover results, IVOL1F network exhibits a less dense structure, with Binance Coin and TRON occupying more prominent positions. This aligns with their roles as primary transmitters of idiosyncratic risk under the 1-factor model and suggests that the network structure of idiosyncratic risks differs substantially from that of overall volatility. The IVOL3F network displays the sparsest structure among all four measures, with Ethereum maintaining a central position but overall connectivity reduced. This observation is consistent with the lower TCI observed in the spillover analysis and suggests that as more factors are accounted for, the apparent interconnectedness of cryptocurrency-specific risks diminishes.

The analysis of volatility spillovers across various risk measures in the cryptocurrency market supports two hypotheses. H1 is supported by the significantly higher TCI observed in price-based volatility measures (PRV and GV) compared to idiosyncratic measures, consistent with the findings of Corbet et al. (2018) and Ji et al. (2019), who documented extensive interdependencies in cryptocurrency markets. H2 is also supported, as Ethereum consistently emerges as the dominant net transmitter of volatility, overtaking Bitcoin across all specifications. This finding contrasts with earlier studies by Corbet et al. (2018) and Ji et al. (2019), which identified Bitcoin as the dominant force in cryptocurrency markets, but aligns with more recent work by Patel et al. (2024) and Bourghelle et al. (2022), suggesting a structural shift in cryptocurrency market leadership that reflects Ethereum's expanding role in decentralized finance and smart contract applications.

Price-based volatility measures, such as PRV and GV, both exhibit a TCI of 67%, indicating high interconnectedness. This finding aligns with Antonakakis et al. (2019) and

Kumar et al. (2023), who documented elevated spillovers during crisis periods, and extends the cryptocurrency contagion literature (Corbet et al., 2020a; Bouri et al., 2021) by showing that market-wide volatility measures capture substantially more interconnectedness than asset-specific risk factors. These measures capture overall market volatility, reflecting how price fluctuations in one cryptocurrency rapidly spread to others. In contrast, idiosyncratic volatility measures, such as IVOL1F and IVOL3F, show lower TCIs of 48% and 43% respectively. These measures capture risks unique to each cryptocurrency and are less likely to propagate across the market, suggesting potential diversification benefits. This substantial gap between price-based (67%) and idiosyncratic (43-48%) connectedness represents a key empirical finding that resolves apparent contradictions in prior literature: studies using market-wide volatility measures (Corbet et al., 2020a; Kumar et al., 2023) consistently report high interdependence, while those examining asset-specific risks (Musholombo, 2023; Borri, 2019) find weaker transmission. Our parallel analysis of both measure types demonstrates that these findings are complementary rather than contradictory. Cryptocurrency markets exhibit strong systematic connections but retain meaningful idiosyncratic components that offer diversification potential.

The implications of these findings are important for both academic research and practical applications in cryptocurrency markets. The high Total Connectedness Index (TCI) values observed for Parkinson Range-Based Volatility (PRV) and GARCH(1,1) Volatility (GV) indicate a highly integrated cryptocurrency market, characterized by rapid shock transmission from one currency to others. This level of integration presents challenges for portfolio diversification, as highlighted by Platanakis and Urquhart (2019) and Brauneis and Mestel (2019), who showed that diversification benefits within cryptocurrency portfolios diminish as interdependence increases. It also underscores the potential for systemic risk within the cryptocurrency ecosystem, consistent with Corbet et al. (2020), who identified strong

contagion channels between major cryptocurrencies during stress episodes. From a regulatory perspective, these findings emphasize the importance of coordinated oversight and intervention strategies that reflect the dense interdependencies among cryptocurrencies, echoing Conlon et al. (2024), who argue that regulatory coordination is essential given the cross-market transmission of volatility under policy uncertainty. For investors and traders, the high degree of market integration highlights the need to monitor a broad set of assets, since volatility in even the less dominant cryptocurrencies may propagate across the market.

Ethereum consistently emerges as the dominant net transmitter of volatility across all four volatility measures, with net transmission values of 20.54 in the PRV model and 22.61 in the GV model, while maintaining significance in idiosyncratic volatility models. Bitcoin also plays a notable, though secondary, role as a transmitter, particularly in the GV model. This dominance underscores their pivotal roles in the cryptocurrency ecosystem, extending the work of Corbet et al. (2018) and suggesting they function as key indicators for the broader market. In contrast, other cryptocurrencies like Ripple, Dogecoin, and Monero generally act as net receivers of volatility across the different measures. In the PRV model, Ripple (NET = -22.64) and Dogecoin (NET = -20.82) are the largest receivers, indicating their susceptibility to volatility shocks transmitted from major cryptocurrencies. Interestingly, the analysis uncovers notable findings related to Binance Coin and TRON. In the IVOL1F model, Binance Coin emerges as the largest net transmitter of idiosyncratic risk (NET = 13.53), followed closely by TRON (NET = 12.35). This suggests they play a significant role in spreading risks unique to the cryptocurrencies themselves, independent of broader market trends.

The lower TCIs for IVOL1F and IVOL3F indicate that cryptocurrency-specific risks are less interconnected, suggesting potential diversification benefits for investors who can isolate and exploit these idiosyncratic risk components. This finding contributes to the ongoing debate on the diversification benefits of cryptocurrencies, as discussed by Brauneis and Mestel

(2019), and offers a new perspective on risk management in cryptocurrency portfolios. The identification of net transmitters and receivers of risk can provide more informative risk management strategies. Portfolios heavily weighted towards net receivers like Ripple and Dogecoin may be more vulnerable to market-wide shocks, while those concentrated in net transmitters like Ethereum and Bitcoin may be more resilient but could also contribute more significantly to systemic risk.

3.5 The Analysis of Spillover Dynamics

Having established cryptocurrency spillover networks in Section 4, this section observes their external drivers. We examine how external global risk factors: VIX, WUI, GEPU, GPR, TRI, PRI, and INFECT, systematically influence cryptocurrency market interconnectedness. Recent literature documents that cryptocurrency volatility responds to broader macro-financial uncertainty (Bouri et al., 2017; Corbet et al., 2019), with emerging evidence highlighting the dominant role of policy uncertainty (Zhang et al., 2021; Patel et al., 2024) and potential climate risk channels (Engle et al., 2020; Goodell et al., 2023). This two-stage approach follows Bostancı and Yılmaz (2020), who first estimated connectedness networks then used secondary regression analysis to identify their determinants in sovereign credit markets. We extend their methodology to cryptocurrency spillovers by incorporating economic significance analysis, which quantifies not merely statistical significance but the practical magnitude of each global risk factor's impact. This extension allows us to assess whether cryptocurrency responses to global uncertainty are homogeneous or exhibit significant heterogeneity across different digital assets.

3.5.1 Descriptive Statistics

Table 3.11 presents the descriptive statistics of the global risk variables used in our analysis. The VIX index, a measure of market volatility, shows a mean of 2.96 with a standard deviation

of 0.326, indicating moderate variability in market uncertainty over the sample period. The World Uncertainty Index (WUI) exhibits a higher mean of 10.08 and a standard deviation of 0.404, suggesting substantial global uncertainty based on news coverage. The Geopolitical Risk Index (GPR) has a mean of 4.514 and a standard deviation of 0.566, reflecting significant geopolitical tensions during the sample period.

[Table 3.11 about here]

The Transition Risk Index (TRI) and Physical Risk Index (PRI), both related to climate risks, show means close to zero (-0.006 and -0.005 respectively) with standard deviations of 0.025 and 0.024. The Global Economic Policy Uncertainty Index (GEPU) has a mean of 5.569 and a standard deviation of 0.191, further emphasizing the persistent economic policy uncertainty globally. Lastly, the Infectious Disease EMV Tracker shows the highest variability with a mean of 10.354 and a standard deviation of 12.032, reflecting high variability in infectious disease-related uncertainty during the sample period.

3.5.2 Regression Model Specification

For each cryptocurrency i and volatility measure j, we estimate the following model:

$$NS_{(ij,t)} = \alpha + \beta_1 VIX_t + \beta_2 WUI_t + \beta_3 GPR_t + \beta_4 TRI_t + \beta_5 PRI_t + \beta_6 GEPU_t + \beta_7 INFECT_t + \varepsilon_{(ij,t)} \quad (18)$$

where $NS_{(ij,t)}$ represents the net spillover contribution for cryptocurrency i under volatility measure j at time t. We include the full set of global risk factors to capture their individual contributions whilst controlling for potential interactions. The comprehensive specification ensures that we can isolate the individual effects of each risk factor on spillover dynamics, providing a robust framework for testing our theoretical predictions.

3.5.3 Economic Significance Analysis

To assess the economic importance of each risk factor, we calculate the economic significance (ES) using the following formula:

$$ES_{(k,i)} = \beta_{(k,i)} \times \sigma_k \quad (19)$$

where $\beta_{(k,i)}$ represents the coefficient of risk factor k for cryptocurrency i, and σ_k denotes the standard deviation of risk factor k. This measure captures the expected change in net spillovers from a one-standard-deviation change in each risk factor, providing a standardised comparison across variables with different scales and units of measurement.

The economic significance measure is particularly valuable in our context because it addresses the challenge of comparing coefficients across variables with vastly different scales. For instance, climate risk indices (TRI and PRI) have much smaller standard deviations than measures such as the Infectious Disease EMV Tracker (INFECT), making direct coefficient comparison misleading. By standardising through the product of coefficient and standard deviation, we obtain a measure that reflects the practical importance of each variable in driving spillover dynamics.

[Tables 3.13-3.20 about here]

[Table 3.21 about here]

3.5.4 Key Findings and Hypothesis Testing

Our regression analysis, presented in Tables 13-20, reveals several important patterns that provide strong support for hypotheses H3A and H3B and offer new insights into cryptocurrency market dynamics. The findings demonstrate clear heterogeneity in how

different cryptocurrencies respond to global risk factors. The analysis confirms that established global uncertainty measures maintain the strongest economic influence on cryptocurrency spillovers. As evidenced in Table 21, Global Economic Policy Uncertainty (GEPU) emerges as the dominant factor, showing the highest economic significance for ten out of thirty-two cases across all cryptocurrencies and volatility measures examined. This finding suggests that cryptocurrency markets are particularly sensitive to policy uncertainty at the global level, reflecting their evolving regulatory landscape and the continued uncertainty surrounding digital asset governance frameworks. Notably, GEPU demonstrates particularly strong economic significance for Bitcoin (-2.94), Dogecoin (-4.02 in GV measure), and Ripple (4.40 in IVOL1F measure), indicating that policy uncertainty affects both established and alternative cryptocurrencies, albeit with varying magnitudes and directions. The prominence of GEPU in driving spillover dynamics aligns with the theoretical expectation that cryptocurrency markets, being relatively nascent and subject to regulatory uncertainty, would be highly responsive to shifts in global policy environments. This finding is consistent with Zhang et al. (2021) and Patel et al. (2024), who documented the significant impact of GEPU on cryptocurrency volatility and trading volume. Despite previous literature acknowledging the importance of global economic policy uncertainty in cryptocurrency markets (Zhang et al., 2021; Patel et al., 2024), this factor remains relatively understudied compared to VIX and GPR, which dominate the cryptocurrency-uncertainty literature (Aysan et al., 2019; Bouri et al., 2017)**.** Our findings reveal this represents a significant research gap, as GEPU emerges as the most economically significant factor across diverse cryptocurrency types, accounting for the highest economic significance in 10 of 32 cases examined. Our findings suggest this represents a significant research gap, as evidenced by GEPU emerging as the most economically significant factor across diverse cryptocurrency types. The fact that GEPU dominates across diverse cryptocurrency types suggests that policy uncertainty represents a systematic risk factor that

cannot be diversified away within the cryptocurrency ecosystem. This finding is particularly evident when examining the regression results across Tables 3.13-3.20, where GEPU coefficients consistently demonstrate statistical significance and substantial magnitudes across different model specifications.

VIX demonstrates particular importance for major market players, as shown in Table 3.21, ranking as the most economically significant factor for Binance (2.20 in PRV measure) and Ethereum (-2.95 in PRV measure). Given these cryptocurrencies' roles as key market transmitters, as established in Section 4.2, this finding indicates that traditional market fear measures continue to drive the behaviour of leading cryptocurrencies. The relationship between VIX and major cryptocurrency spillovers suggests that these assets have not decoupled from traditional financial markets as some proponents have argued, but rather remain sensitive to broader market sentiment and risk appetite. This relationship is particularly pronounced in the results presented in Tables 3.13 and 3.17, where VIX coefficients for Binance and Ethereum consistently show strong statistical significance across different volatility measures.

The strong VIX sensitivity observed in major market players aligns with hypothesis H3B regarding differential cryptocurrency responses to global risk factors. The evidence indicates that leading cryptocurrencies exhibit heightened correlation with traditional market sentiment, with this integration being most pronounced among cryptocurrencies that serve as primary volatility transmitters within the cryptocurrency ecosystem (Ji et al., 2019). These findings have implications for portfolio diversification strategies, as the maintained predictive power of VIX over cryptocurrency market leaders challenges previous assertions about cryptocurrencies' hedging capabilities against traditional market volatility (Dyhrberg, 2016; Bouri et al., 2017) and suggests that the diversification benefits traditionally attributed to cryptocurrencies may be limited during periods of elevated traditional market volatility. Recent work by Bas et al. (2024) corroborates this finding, documenting VIX's pronounced spillover

effects on BTC and ETH, while Sakariyahu et al. (2024) demonstrate that this influence has intensified during market stress. Our economic significance analysis (Table 3.21) quantifies this relationship, revealing VIX as the dominant factor for Binance (2.20) and Ethereum (-2.95), establishing that integration with traditional markets has strengthened rather than weakened as cryptocurrency markets have matured.

Equally compelling is the consistent influence of the World Uncertainty Index (WUI) across all cryptocurrencies. Table 3.21 reveals that WUI shows remarkably consistent economic impact, achieving the highest ranking for Monero (2.49 in GV measure) and maintaining substantial significance for Bitcoin (1.55 in GV measure), Dogecoin, and others. This finding challenges conventional frameworks and suggests WUI deserves recognition alongside VIX and GEPU as a core driver of cryptocurrency market dynamics. The consistent influence of WUI across different cryptocurrency types indicates that global uncertainty, measured through news-based metrics, captures aspects of market sentiment that are not fully reflected in traditional financial volatility measures.

This pattern supports a refined interpretation whereby cryptocurrency markets exhibit extreme sensitivity to climate policy changes, but these events occur infrequently. When climate-related policy shifts do occur, they generate substantial market responses, reflecting the environmental concerns surrounding cryptocurrency mining and energy consumption. However, as demonstrated in Table 3.21, their day-to-day economic impact on spillover dynamics remains minimal because such policy changes represent discrete events rather than continuous market forces. The low economic significance of climate risk factors does not diminish their potential importance for long-term market dynamics but rather suggests that whilst cryptocurrency markets are prepared to respond dramatically to climate policy announcements, the relative stability of climate policy frameworks means that such responses are infrequent. The regression results across Tables 3.13-3.20 reveal distinct response patterns

across different types of cryptocurrencies, providing evidence for market segmentation within the broader cryptocurrency ecosystem. Major cryptocurrencies, including Bitcoin and Ethereum, show strong sensitivity to traditional uncertainty measures, with the economic significance analysis in Table 3.21 revealing that Bitcoin is particularly responsive to GEPU (-2.94) whilst Ethereum shows the highest VIX sensitivity (-2.95). This pattern suggests that established cryptocurrencies have become more integrated with traditional financial markets and are increasingly viewed by investors as alternative assets subject to similar risk factors.

In contrast, Dogecoin, Monero, and Ripple, display more varied responses across risk factors, suggesting greater idiosyncratic behaviour within this segment. Table 3.21 shows that Dogecoin exhibits extreme GEPU sensitivity (-4.02 in GV measure), reflecting its speculative nature and sensitivity to regulatory announcements that might affect its viability. Meanwhile, Monero presents a unique case, being dominated by WUI with an economic significance of 2.49, which may reflect its association with privacy concerns and the particular sensitivity to global uncertainty that characterises privacy-focused cryptocurrencies. Ripple demonstrates interesting heterogeneity across volatility measures, with WUI showing economic significance ranging from -1.79 in GV measure to 7.11 in IVOL3F measure, indicating that different aspects of its risk profile respond differently to global uncertainty. Binance Coin exhibits strong VIX sensitivity with an economic significance of 2.20 in the PRV measure, alongside moderate sensitivity to policy uncertainty measures as shown across Tables 3.13 and 3.21. This pattern likely reflects its dual nature as both a cryptocurrency and a token associated with a major exchange platform, making it simultaneously exposed to broader cryptocurrency market dynamics and the specific business risks of cryptocurrency exchange operations.

These findings provide compelling support for hypothesis H3A, confirming that different cryptocurrencies demonstrate heterogeneous responses to global uncertainty indices, with each uncertainty measure exhibiting varying degrees of impact across cryptocurrency

types. This aligns with previous studies highlighting the changing linkages between cryptocurrencies over time (Boako et al., 2019; Ji et al., 2019; Yi et al., 2018; Katsiampa, 2019; Antonakakis et al., 2019) and extends our understanding of how these differential responses manifest across various uncertainty measures. Our analysis also provides strong support for hypothesis H3B, revealing that global uncertainty factors (VIX, GEPU, WUI) demonstrate significantly greater economic impact than climate risk factors (TRI, PRI) in driving cryptocurrency spillover dynamics. Traditional uncertainty measures collectively account for 68.8% of the dominant positions across all cryptocurrencies and volatility measures, establishing their clear superiority over climate-related factors. The novel World Uncertainty Index reveals competitive significance that further reinforces uncertainty measures' dominance over environmental concerns.

Furthermore, our analysis reveals a striking pattern for climate-related risk factors (TRI and PRI) that warrants careful interpretation. Whilst these variables often exhibit large coefficients across Tables 3.13-3.20, with TRI showing coefficients as high as 38.087 for Binance, their economic significance remains consistently low in Table 3.21, typically ranging from 0.1 to 0.6, due to their small standard deviations. This finding contributes to understanding the mixed evidence in the literature: while some studies report strong climate policy impacts (Goodell et al., 2023), others find minimal effects (Corbet et al., 2020a). Our distinction between statistical sensitivity and economic significance suggests that cryptocurrency markets may exhibit high sensitivity to climate policy changes when they occur, yet the infrequency of such policy events could explain their limited day-to-day economic significance. The distinction between sensitivity and economic significance, clearly illustrated through the comparison between the raw coefficients in Tables 3.13-3.20 and the standardised measures in Table 3.21, proves crucial for understanding how different types of risks affect cryptocurrency markets. This finding extends the work of Engle et al. (2020) and

Goodell et al. (2023) on climate risks in financial markets to the cryptocurrency domain, while demonstrating that traditional uncertainty measures, particularly those capturing market volatility and policy uncertainty, maintain dominant predictive power over emerging climate factors, consistent with Bouri et al. (2017) and Corbet et al. (2019), who documented that macroeconomic and market-based uncertainty remain the primary drivers of cryptocurrency dynamics. An important methodological finding is that the results often vary depending on the volatility measure used (PRV, GV, IVOL1F, IVOL3F), extending the work of Katsiampa (2017) and confirming that the choice of volatility measure can significantly influence conclusions about cryptocurrency market behaviour. Having established the continuous drivers of spillover dynamics, we now turn to examining how specific global events impact cryptocurrency interconnectedness.

3.6 Impact of Global Events on Cryptocurrency Spillovers

3.6.1 Structural Break Identification

We first confirm these events caused structural changes, then analyse their dynamic effects. The Chow break point test results presented in Table 3.12 provide statistical confirmation of significant structural breaks corresponding to major global events. The test reveals highly significant breaks (all at the 1% level) for the COVID-19 pandemic declaration, the commencement of the Russia-Ukraine war, the approval of the MiCA framework, and the outbreak of the Gaza war. These findings corroborate the graphical evidence from Figure 3.10 and underscore the profound impact of regulatory developments and geopolitical conflicts on cryptocurrency market dynamics.

[Table 3.12 about here]

The exceptionally high Wald statistics for the MiCA framework approval and the Gaza war highlight the particular sensitivity of the cryptocurrency market to regulatory changes and

geopolitical tensions. The MiCA finding is particularly novel: whilst prior literature has extensively examined pandemic impacts (Umar et al., 2021; Aharon et al., 2023) and geopolitical conflicts (Khalfaoui et al., 2023; Sakariyahu et al., 2024), comprehensive crypto-specific regulatory frameworks remain largely unexplored. To our knowledge, only Conlon et al. (2024) have examined MiCA's effects, making our analysis among the first to compare regulatory structural breaks directly against other major event types. The substantially higher Wald statistics for MiCA (680.05*** for GV) compared to COVID-19 (98.11***) and Russia-Ukraine (253.99***) challenge the prevailing assumption in the literature that health and geopolitical crises represent the most significant external shocks to cryptocurrency markets.

3.6.2 Staggered Difference-in-Differences Specification

The analysis of cryptocurrency market dynamics and their relationship to global events presents unique methodological challenges. While net spillover measures, as conceptualized in the Diebold and Yilmaz (2012; 2014) framework, inherently capture interdependence among cryptocurrencies, our focus on event impacts necessitates an approach that can handle treatment timing differences. The staggered difference-in-differences (DiD) methodology is particularly suitable as it allows us to examine how net spillovers change around specific events while accounting for both anticipatory effects and post-event market reactions.

Our empirical strategy utilizes the Interaction Weighted (IW) estimator to analyse four major events: the COVID-19 pandemic declaration, the Russia-Ukraine War, the MiCA regulation implementation, and the Gaza War. The IW estimator addresses potential biases from treatment effect heterogeneity documented by Baker et al., (2022), who demonstrate that standard two-way fixed effects estimators can be biased in staggered DiD designs. Therefore, for each event, we examine a window of ten days before and after the event date, allowing us to capture both anticipatory effects and post-event market reactions. The specification follows:

$$NS_{i,t} = \alpha + \sum_{k=-10}^{10} \beta_k (Event_k)_{it} + \gamma X_{it} + \varepsilon_{it} \quad (20)$$

where $NS_{i,t}$ represents the net spillover contribution for cryptocurrency i at time t, $(Event_k)_{it}$ are dummy variables for each day in the event window (k ranging from -10 to +10, with 0 being the event day), X_{it} is a vector of time-varying covariates including global risk factors, and ε_{it} is the error term. The sample comprises 17,072 observations, with all specifications including relevant covariates to control for time-varying factors. This granular analysis enables identification of both immediate market reactions and potential anticipatory effects, while accounting for the complex dynamics inherent in cryptocurrency markets.

In this context, we capture four global events occurred during the period 2018 – 2024. This includes: a global pandemic event (COVID-19), geopolitical and armed conflicts (Russian-Ukraine and Gaza wars) and policy initiatives (the introduction of MiCA). These dummy variables allow for the examination of structural breaks and regime shifts in cryptocurrency spillover dynamics, as suggested by the work of Guesmi et al. (2019) on cryptocurrency market regimes. Our staggered DiD approach offers methodological advancement over single-event studies that dominate the cryptocurrency literature. Whilst Shen et al. (2024) applied similar methodology to online message board effects, and broader event study designs follow Callaway and Sant'Anna (2021) and Sun and Abraham (2021), we extend this approach to compare multiple heterogeneous external shocks within a unified framework. This comparative design allows us to assess not merely whether events impact cryptocurrency spillovers, but which event types exert the strongest influence which is a question that cannot be addressed through isolated single-event analyses.

3.6.3 Examining Global Events Impact

Tables 3.22 through 3.25 present the results of the staggered DID estimation using the IW estimator for the impact of global events on the net spillover contributions among

cryptocurrencies. These results offer several key insights into the complex dynamics of cryptocurrency market spillovers.

[Tables 3.22 – 3.25 about here]

The impact of global events exhibits substantial heterogeneity across different types of shocks. For instance, the COVID-19 pandemic shows significant negative pre-trends in net spillovers, with coefficients ranging from -12.939 to -15.049 before the event, followed by a notable reduction in magnitude post-event (around -5.8 to -6.0). This pattern aligns with the findings of Aharon et al. (2023) and Bourghelle et al. (2022), who documented significant initial market disruption followed by increased resilience in cryptocurrency markets during the pandemic. The reduction in magnitude post-COVID announcement supports Mnif et al. (2020) and Vidal-Tomás (2021), highlighting market adaptation during the pandemic, while Kumar et al. (2022) found that cryptocurrency markets demonstrated evolving spillover patterns in response to major global shocks. The COVID-19 results align with the extensive pandemic-cryptocurrency literature (Umar et al., 2021; Elsayed et al., 2022; Ha and Nham, 2022), but our net spillover focus extends these findings beyond simple volatility or return effects. By examining how COVID-19 altered transmission dynamics rather than absolute volatility levels, we show that the pandemic not only increased individual cryptocurrency volatility, as widely documented, but fundamentally restructured inter-cryptocurrency relationships.

The MiCA regulation, representing a major regulatory event, shows the largest magnitude effects with pre-event coefficients ranging from -14.9 to -15.5 and sustained post-event effects around -14.2 to -15.0. Notably, MiCA is the only cryptocurrency-specific event among those examined, and we selected the proposal date directly from official EU institutional sources, ensuring precision in capturing the regulatory announcement's market impact. This approach is particularly important given that cryptocurrency market participants are likely to closely monitor and scan official regulatory channels for crypto-specific policy developments,

making the timing of formal announcements from institutional sources especially relevant for market reactions. The persistence and magnitude of these effects, notably larger than those observed for other events, support the findings of Auer and Claessens (2018) regarding the substantial impact of regulatory announcements on cryptocurrency markets. The fact that this crypto-specific regulatory event generated the strongest market response underscores the particular sensitivity of digital asset markets to targeted regulatory developments. This provides strong support for H4, highlighting that regulatory uncertainty specifically designed for cryptocurrencies has more immediate and substantial impact on volatility transmission dynamics than broader geopolitical events.

The staggered difference-in-differences estimation reveals varying patterns in cryptocurrency market responses across different types of exogenous shocks. The Russia-Ukraine War shows substantial negative effects on net spillover contributions, with pre-event coefficients around -11.5 escalating to -12.6 post-event. This significant market reaction aligns with the conflict's broad global impact, including energy crises due to disruptions in oil and gas supplies and extensive international sanctions against Russia. These factors have heightened global economic uncertainty, influencing investor behaviour across financial markets, including cryptocurrencies. This observation supports Hypothesis H4, emphasizing that exogenous shocks with significant global economic implications have a more pronounced effect on cryptocurrency volatility transmission dynamics.

In contrast, the Gaza War exhibits notably smaller and statistically insignificant effects on net spillover contributions, with coefficients ranging from -2.2 to -3.2. The more localized nature of the Gaza War, primarily affecting a specific region without causing substantial disruptions to global economic systems, likely explains the limited market response. This finding is consistent with Kayani et al. (2024) and Zeinedini et al. (2024), who found that localized geopolitical conflicts have markedly different cryptocurrency market impacts

compared to globally significant events. This disparity in market responses underscores the importance of the scale and economic implications of geopolitical events in determining their impact on cryptocurrency markets. Russia-Ukraine disrupted global energy markets and triggered widespread sanctions, while Gaza remained largely regional. This difference in global economic reach is a plausible explanation for the contrasting responses. The Russia-Ukraine war also had a direct financial channel to cryptocurrency markets through sanctions, which drew attention to cryptocurrencies as an alternative means of cross-border payment, whereas the Gaza War involved no comparable channel. In addition, the Gaza War occurred when geopolitical risk was already elevated, so part of its risk may already have been reflected in prices. This finding aligns with the literature suggesting that the magnitude of market reactions to geopolitical risks is proportional to the perceived global economic impact of the events (Będowska-Sójka et al., 2024; Ji et al., 2019).

3.7 Conclusion

This study provides the first comprehensive comparison of price-based volatility and idiosyncratic volatility measures in cryptocurrency markets while simultaneously examining connectedness patterns and exogenous shocks. By integrating these dimensions within a unified framework, we demonstrate that apparent contradictions in prior literature can be reconciled once volatility measure choice and market conditions are properly accounted for. Our results strongly support all four hypotheses, revealing: (1) significant variation in total connectedness index (TCI) across different volatility measures, with higher connectedness in price-based measures; (2) Ethereum's emergence as a dominant net transmitter of volatility; (3) differential impacts of global risk factors on cryptocurrency spillovers, with traditional uncertainty measures demonstrating greater economic significance than climate-related

factors; and (4) more pronounced effects of regulatory events compared to geopolitical events on volatility transmission dynamics.

Our study offers several novel contributions. First, we provide the first systematic comparison of price-based and idiosyncratic volatility in cryptocurrency spillover analysis, revealing that the substantial gap between price-based (67%) and idiosyncratic (43-48%) connectedness resolves apparent contradictions in prior literature where some studies report high interdependence while others find weaker transmission. Second, we are among the first to examine the structural impact of MiCA regulation on cryptocurrency markets, with only Conlon et al. (2024) having previously analysed this landmark regulatory framework. Our finding that MiCA produces stronger structural breaks than major geopolitical conflicts including the Russia-Ukraine War challenges the prevailing assumption that health and geopolitical crises represent the most significant external shocks to cryptocurrency markets. Third, our novel inclusion of the World Uncertainty Index in spillover dynamics analysis, beyond its typical use as a control variable, reveals that this news-based measure captures market sentiment aspects not fully reflected in traditional financial volatility indicators.

The timeliness of this research is particularly relevant. By extending our analysis to 2024, we capture the cryptocurrency market's response to unprecedented regulatory transformation within the EU, ongoing geopolitical tensions, and the post-pandemic market maturation characterised by increased institutional participation. Most existing studies rely on data up to late 2022, limiting their ability to capture these recent structural shifts. Our extended timeline reveals that the cryptocurrency market has fundamentally evolved, with Ethereum displacing Bitcoin as the dominant volatility transmitter and regulatory events now exerting stronger influence than traditional macroeconomic shocks.

Our findings carry important implications for market participants and policymakers. For investors, the high interconnectedness in price-based volatility (67% TCI) suggests limited

diversification benefits during market stress when systematic risk dominates. However, the substantially lower connectedness in idiosyncratic measures (43-48%) indicates that cryptocurrency-specific risks remain relatively isolated, offering potential diversification opportunities for investors who can identify and exploit these idiosyncratic components. The heterogeneous responses across cryptocurrencies to different uncertainty indices further suggest that portfolio construction should account for individual cryptocurrency sensitivities rather than treating digital assets as a homogeneous class.

For policymakers, our results demonstrate that crypto-specific regulation exerts measurable and persistent effects on market structure. The pronounced structural break associated with MiCA implementation indicates that regulatory frameworks can fundamentally reshape cryptocurrency market dynamics, providing empirical support for coordinated regulatory approaches. The differential impact of geopolitical events, with globally significant conflicts (Russia-Ukraine) producing stronger effects than regionally contained ones (Gaza), suggests that cryptocurrency markets have become sufficiently integrated with the global financial system to respond systematically to macroeconomic disruptions with broad economic implications.

Future research should continue to monitor how cryptocurrency market dynamics evolve as regulatory frameworks mature globally, particularly as jurisdictions beyond the EU implement comprehensive crypto-asset regulations. The methodology developed here, combining spillover analysis with economic significance assessment and staggered difference-in-differences, provides a template for examining how future shocks reshape digital asset markets. As the cryptocurrency ecosystem continues to integrate with traditional finance, understanding these transmission mechanisms will be crucial for effective risk management, portfolio construction, and regulatory design.

Tables

Table 3.1: Descriptive Statistics of Measures of Risk (All Cryptocurrencies)

Variable	Obs	Mean	Std. Dev.	Min	Max
PRV	19080	72.418	67.171	4.074	1763.981
GV	19080	.052	.026	.033	.783
$IVOL_{1F}$	18560	.531	1.563	-3.608	17.738
$IVOL_{3F}$	18560	-.868	1.232	-4.488	2.42

Notes: This table reports the descriptive statistics of the full sample including all cryptocurrencies. PRV is Parkinson Range-Based Volatility. GV is GARCH(1,1) Based Volatility. $IVOL_{1F}$ is 1 – Factor Idiosyncratic Volatility. $IVOL_{3F}$ is 3 – Factor idiosyncratic Volatility. The sample covers the period 2018 – 2024. The measures $IVOL_{1F}$ and $IVOL_{3F}$ are based on one year rolling windows leading to smaller sample size compared to the other measures.

Table 3.2: Descriptive Statistics of Measures of Risk by Cryptocurrency

	Obs	Mean	Std. Dev.	Min	Max
Binance					
PRV	2385	71.14	63.776	5.917	725.578
GV	2385	.051	.025	.033	.304
$IVOL_{1F}$	2320	.643	.75	-1.017	2.38
$IVOL_{3F}$	2320	-.508	.777	-2.229	1.161
Bitcoin					
PRV	2385	51.595	40.631	4.12	561.812
GV	2385	.045	.013	.033	.242
$IVOL_{1F}$	2320	-2.275	.515	-3.608	-1.323
$IVOL_{3F}$	2320	-3.339	.392	-4.488	-2.182
Cardano					
PRV	2385	83.803	62.713	10.198	779.934
GV	2385	.055	.021	.033	.264
$IVOL_{1F}$	2320	1.048	1.32	-.798	10.072
$IVOL_{3F}$	2320	-.771	.661	-2.186	.953
Dogecoin					
PRV	2385	85.264	95.67	8.719	1763.981
GV	2385	.057	.042	.033	.783
$IVOL_{1F}$	2320	1.182	.784	-.618	3.257
$IVOL_{3F}$	2320	.198	.707	-.974	1.954
Ethereum					
PRV	2385	66.73	50.734	4.074	649.454
GV	2385	.05	.018	.033	.288
$IVOL_{1F}$	2320	.28	1.159	-1.082	17.738
$IVOL_{3F}$	2320	-1.436	.444	-2.388	.08
Monero					
PRV	2385	72.564	56.021	6.655	930.878
GV	2385	.051	.021	.033	.293
$IVOL_{1F}$	2320	.598	.896	-.937	4.439
$IVOL_{3F}$	2320	-.445	.819	-1.662	2.42
TRON					
PRV	2385	73.005	73.756	5.107	949.75
GV	2385	.053	.028	.033	.446
$IVOL_{1F}$	2320	1.062	.794	-.814	3.37
$IVOL_{3F}$	2320	-.253	.732	-1.924	1.277
Ripple					
PRV	2385	75.245	73.36	6.455	832.354
GV	2385	.053	.027	.033	.294
$IVOL_{1F}$	2320	1.71	1.811	-.601	11.514
$IVOL_{3F}$	2320	-.388	.747	-1.679	1.09

Notes: This table reports the descriptive statistics of the full sample including all cryptocurrencies. PRV is Parkinson Range-Based Volatility. GV is GARCH(1,1) Based Volatility. $IVOL_{1F}$ is 1 – Factor Idiosyncratic Volatility. $IVOL_{3F}$ is 3 – Factor idiosyncratic Volatility. The sample covers the period 2018 – 2024. The measures $IVOL_{1F}$ and $IVOL_{3F}$ are based on one year rolling windows leading to smaller sample size compared to the other measures.

Table 3.3: Pairwise Correlation Matrix of PRV Risk Measure across Cryptocurrencies

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Binance	1.000							
(2) Bitcoin	0.694***	1.000						
(3) Cardano	0.717***	0.735***	1.000					
(4) Dogecoin	0.489***	0.518***	0.542***	1.000				
(5) Ethereum	0.727***	0.847***	0.795***	0.525***	1.000			
(6) Monero	0.718***	0.757***	0.726***	0.522***	0.781***	1.000		
(7) TRON	0.694***	0.622***	0.692***	0.461***	0.666***	0.654***	1.000	
(8) Ripple	0.594***	0.602***	0.708***	0.543***	0.659***	0.609***	0.617***	1.000

Notes: This table reports pairwise correlations of Parkinson Range-Based Volatility (PRV) across eight cryptocurrencies over the full sample period (January 2018–December 2024). PRV is constructed from daily high and low prices. All correlations are positive and statistically significant at the 1% level, indicating broad systematic co-movement in range-based volatility across the market. *** p<0.01.

Table 3.4: Pairwise Correlation Matrix of GV Risk Measure across Cryptocurrencies

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Binance	1.000							
(2) Bitcoin	0.644***	1.000						
(3) Cardano	0.656***	0.710***	1.000					
(4) Dogecoin	0.366***	0.360***	0.405***	1.000				
(5) Ethereum	0.639***	0.817***	0.756***	0.369***	1.000			
(6) Monero	0.646***	0.715***	0.651***	0.346***	0.728***	1.000		
(7) TRON	0.723***	0.615***	0.671***	0.334***	0.619***	0.604***	1.000	
(8) Ripple	0.516***	0.493***	0.630***	0.495***	0.557***	0.489***	0.587***	1.000

Notes: This table reports pairwise correlations of GARCH(1,1) Volatility (GV) across eight cryptocurrencies over the full sample period January 2018–December 2024). GV is estimated from a standard GARCH(1,1) model applied to daily returns. All correlations are positive and significant at the 1% level, consistent with PRV, though at slightly lower magnitudes, reflecting the conditional rather than range-based nature of this volatility measure. *** p<0.01.

Table 3.5: Pairwise Correlation Matrix of $IVOL_{1F}$ Risk Measure across Cryptocurrencies

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Binance	1.000							
(2) Bitcoin	0.352***	1.000						
(3) Cardano	0.634***	0.526***	1.000					
(4) Dogecoin	0.758***	0.502***	0.555***	1.000				
(5) Ethereum	0.582***	0.554***	0.943***	0.504***	1.000			
(6) Monero	0.665***	0.152***	0.726***	0.420***	0.653***	1.000		
(7) TRON	0.835***	0.389***	0.775***	0.660***	0.677***	0.810***	1.000	
(8) Ripple	0.585***	0.535***	0.780***	0.495***	0.661***	0.599***	0.752***	1.000

Notes: This table reports pairwise correlations of 1-Factor Idiosyncratic Volatility (IVOL1F) across eight cryptocurrencies over the full sample period January 2018–December 2024). IVOL1F is the residual from a one-factor cryptocurrency asset pricing model following Liu et al. (2022), capturing volatility unexplained by the common market factor. Correlations are generally lower than those for price-based measures, consistent with idiosyncratic components being less systematically connected than total volatility. *** p<0.01.

Table 3.6: Pairwise Correlation Matrix of $IVOL_{3F}$ Risk Measure across Cryptocurrencies

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Binance	1.000							
(2) Bitcoin	0.081***	1.000						
(3) Cardano	0.586***	0.243***	1.000					
(4) Dogecoin	0.371***	-0.130***	0.119***	1.000				
(5) Ethereum	0.776***	0.207***	0.850***	0.203***	1.000			
(6) Monero	0.505***	-0.118***	0.548***	0.075***	0.736***	1.000		
(7) TRON	0.612***	0.342***	0.650***	-0.062***	0.784***	0.665***	1.000	
(8) Ripple	0.718***	0.242***	0.682***	0.319***	0.795***	0.690***	0.685***	1.000

Notes: This table reports pairwise correlations of 3-Factor Idiosyncratic Volatility (IVOL3F) across eight cryptocurrencies over the full sample period January 2018–December 2024). IVOL3F is the residual from a three-factor model following Liu et al. (2022), incorporating market, size, and momentum factors. Controlling for additional systematic factors produces a more heterogeneous correlation structure, including negative correlations for several pairs, indicating that once common factors are removed, residual idiosyncratic risk components move in opposite directions for some assets. *** p<0.01.

Table 3.7: PRV Risk Measure Spillover Table, Stock Risk Using Net Elastic Estimator

	Binance	Bitcoin	Cardano	Dogecoin	Ethereum	Monero	TRON	Ripple	From
Binance	27.82	13.3	13.86	1.93	15.47	13.64	10.1	3.89	72.18
Bitcoin	12.46	26.37	13.53	1.94	19.96	12.09	10.36	3.29	73.63
Cardano	11.85	12.37	24	3.03	16.6	14.77	10.96	6.4	76
Dogecoin	3.97	4.38	7.44	60.04	6.06	8.63	5.49	4	39.96
Ethereum	12.49	17.15	15.66	2.33	22.7	14.69	10.83	4.15	77.3
Monero	12.37	11.71	15.68	3.68	16.53	25.59	10.05	4.4	74.41
TRON	10.87	11.89	13.78	2.84	14.42	11.94	29.57	4.71	70.43
Ripple	6.63	6.09	12.73	3.4	8.81	8.35	7.47	46.51	53.49
To	70.64	76.88	92.68	19.15	97.84	84.12	65.26	30.84	537.4
Inc.Own	98.46	103.25	116.68	79.18	120.54	109.7	94.83	77.36	cTCI/TCI
NET	-1.54	3.25	16.68	-20.82	20.54	9.7	-5.17	-22.64	76.77/67
NPT	3	4	6	0	7	5	2	1	

Notes: Table 3.7 presents the Spillover Table for PRV risk measure Net Elastic Estimator. The "FROM" column represents the total spillover received by each variable from all other variables in the network. The "TO" row represents the total spillover transmitted by each variable to all other variables in the network. The "Inc.Own" row represents the incremental own-variable spillover, which measures the spillover from a variable to itself. The "NET" row represents the net spillover effect, calculated as the difference between the "TO" and "FROM" values. Positive values indicate that the variable is a net transmitter of spillovers, while negative values indicate that the variable is a net receiver of spillovers. The "NPT" row represents the number of pairwise transmissions, which counts the number of significant pairwise spillovers between variables. The table also includes the TCI, which measures the overall connectedness or interdependence among the variables, and the Conditional Total Connectedness Index (cTCI), which measures the connectedness after controlling for other factors or variables. The ratio of cTCI to TCI (cTCI/TCI) is provided to assess the relative importance of direct connections between variables compared to the overall connectedness of the network

Table 3.8: GV Risk Measure Spillover Table, Stock Risk Using Net Elastic Estimator

	Binance	Bitcoin	Cardano	Dogecoin	Ethereum	Monero	TRON	Ripple	From
Binance	27.95	12.73	10.82	3.22	14.36	11.98	12.98	5.96	72.05
Bitcoin	11.31	26.57	12.54	2.67	18.56	12.18	10.83	5.35	73.43
Cardano	10.07	13.16	27.29	3.42	16.13	9.94	10.87	9.12	72.71
Dogecoin	3.74	6.79	5.66	61.48	6.94	5.35	4.27	5.76	38.52
Ethereum	11.18	16.5	13.54	2.52	25.8	12.16	11.47	6.83	74.2
Monero	10.87	14.12	11.2	2.72	14.72	29.29	11.47	5.61	70.71
TRON	11.8	12.45	12.04	2.28	14.4	10.69	28.34	8	71.66
Ripple	7.2	8.28	12.94	5.84	11.71	7.39	11.25	35.39	64.61
To	66.16	84.03	78.73	22.66	96.81	69.7	73.15	46.64	537.89
Inc.Own	94.12	110.6	106.02	84.14	122.61	98.99	101.49	82.03	cTCI/TCI
NET	-5.88	10.6	6.02	-15.86	22.61	-1.01	1.49	-17.97	76.84/67
NPT	2	6	5	1	7	3	4	0	

Notes: Table 3.8 presents the Spillover Table for GV risk measure Net Elastic Estimator. The "FROM" column represents the total spillover received by each variable from all other variables in the network. The "TO" row represents the total spillover transmitted by each variable to all other variables in the network. The "Inc.Own" row represents the incremental own-variable spillover, which measures the spillover from a variable to itself. The "NET" row represents the net spillover effect, calculated as the difference between the "TO" and "FROM" values. Positive values indicate that the variable is a net transmitter of spillovers, while negative values indicate that the variable is a net receiver of spillovers. The "NPT" row represents the number of pairwise transmissions, which counts the number of significant pairwise spillovers between variables. The table also includes the TCI, which measures the overall connectedness or interdependence among the variables, and the Conditional Total Connectedness Index (cTCI), which measures the connectedness after controlling for other factors or variables. The ratio of cTCI to TCI (cTCI/TCI) is provided to assess the relative importance of direct connections between variables compared to the overall connectedness of the network.

Table 3.9: $IVOL_{1F}$ Risk Measure Spillover Table, Stock Risk Using Net Elastic Estimator

	Binance	Bitcoin	Cardano	Dogecoin	Ethereum	Monero	TRON	Ripple	From
Binance	43.48	5.65	8.63	9.62	8.23	7.73	13.94	2.72	56.52
Bitcoin	6.28	55.24	6.28	6.44	7.32	4.93	10.58	2.94	44.76
Cardano	10.98	6.2	44.97	6.61	11.61	6.3	9.07	4.26	55.03
Dogecoin	12.14	6.55	6.52	55.75	4.28	5.16	7.26	2.35	44.25
Ethereum	11.07	7.77	11.35	5.01	45.69	5.98	8.92	4.21	54.31
Monero	10.49	6.16	7.38	5.81	5.95	52.86	9.39	1.96	47.14
TRON	13.51	8.6	8	6.07	6.87	6.97	46.39	3.6	53.61
Ripple	5.59	4.63	5.24	3.92	5.34	2.85	6.8	65.63	34.37
To	70.05	45.54	53.4	43.48	49.59	39.94	65.95	22.03	389.98
Inc.Own	113.53	100.78	98.37	99.23	95.29	92.8	112.35	87.67	cTCI/TCI
NET	13.53	0.78	-1.63	-0.77	-4.71	-7.2	12.35	-12.33	55.71/48
NPT	6	4	3	4	2	2	7	0	

Notes: Table 3.9 presents the Spillover Table for $IVOL_{1F}$ risk measure Net Elastic Estimator. The "FROM" column represents the total spillover received by each variable from all other variables in the network. The "TO" row represents the total spillover transmitted by each variable to all other variables in the network. The "Inc.Own" row represents the incremental own-variable spillover, which measures the spillover from a variable to itself. The "NET" row represents the net spillover effect, calculated as the difference between the "TO" and "FROM" values. Positive values indicate that the variable is a net transmitter of spillovers, while negative values indicate that the variable is a net receiver of spillovers. The "NPT" row represents the number of pairwise transmissions, which counts the number of significant pairwise spillovers between variables. The table also includes the TCI, which measures the overall connectedness or interdependence among the variables, and the Conditional Total Connectedness Index (cTCI), which measures the connectedness after controlling for other factors or variables. The ratio of cTCI to TCI (cTCI/TCI) is provided to assess the relative importance of direct connections between variables compared to the overall connectedness of the network.

Table 3.10: $IVOL_{3F}$ Risk Measure Spillover Table, Stock Risk Using Net Elastic Estimator

	Binance	Bitcoin	Cardano	Dogecoin	Ethereum	Monero	TRON	Ripple	From
Binance	50.43	4.43	8.11	5.65	11.01	5.19	7.75	7.43	49.57
Bitcoin	4.42	59.23	7.46	4.29	9.99	4.17	2.25	8.18	40.77
Cardano	8.82	8.51	52.02	5.51	7.48	5.15	2.85	9.65	47.98
Dogecoin	6.07	4.62	5.48	63.5	9.15	4.59	2.94	3.64	36.5
Ethereum	9.49	9.38	5.8	7.44	46.8	6.48	5.62	8.98	53.2
Monero	6.83	4.6	5.95	4.87	8.56	61.44	2.84	4.92	38.56
TRON	8.55	2.64	3.3	2.96	7.55	2.54	66.47	5.99	33.53
Ripple	7.77	9.6	9.05	4.05	10.07	4.24	5.26	49.98	50.02
To	51.95	43.78	45.14	34.77	63.81	32.36	29.52	48.79	350.13
Inc.Own	102.38	103.01	97.16	98.27	110.62	93.8	95.99	98.77	cTCI/TCI
NET	2.38	3.01	-2.84	-1.73	10.62	-6.2	-4.01	-1.23	50.02/43
NPT	5	6	2	4	7	0	1	3	

Notes: Table 3.10 presents the Spillover Table for $IVOL_{3F}$ risk measure Net Elastic Estimator. The "FROM" column represents the total spillover received by each variable from all other variables in the network. The "TO" row represents the total spillover transmitted by each variable to all other variables in the network. The "Inc.Own" row represents the incremental own-variable spillover, which measures the spillover from a variable to itself. The "NET" row represents the net spillover effect, calculated as the difference between the "TO" and "FROM" values. Positive values indicate that the variable is a net transmitter of spillovers, while negative values indicate that the variable is a net receiver of spillovers. The "NPT" row represents the number of pairwise transmissions, which counts the number of significant pairwise spillovers between variables. The table also includes the TCI, which measures the overall connectedness or interdependence among the variables, and the Conditional Total Connectedness Index (cTCI), which measures the connectedness after controlling for other factors or variables. The ratio of cTCI to TCI (cTCI/TCI) is provided to assess the relative importance of direct connections between variables compared to the overall connectedness of the network.

Table 3.11: Descriptive Statistics of Global Risk Variables

Variable	Obs	Mean	Std. Dev.	Min	Max
VIX	2134	2.96	.326	2.446	4.415
WUI	2134	10.08	.404	9.111	10.96
GPR	2134	4.514	.566	1.271	6.293
TRI	2134	-.006	.025	-.075	.101
PRI	2134	-.005	.024	-.056	.123
GEPU	2134	5.569	.191	5.212	6.08
INFECT	2134	10.354	12.032	0	113.81

Notes: This table reports descriptive statistics for the seven global risk variables over 2,134 daily observations covering January 2018 to July 2024. VIX, WUI, GPR, and GEPU are expressed in natural logarithm; their low standard deviations relative to their means reflect the smoothing effect of this transformation. TRI and PRI are daily returns of climate-related risk indices and are centred near zero with small standard deviations, consistent with their low day-to-day variability and limited economic significance in continuous market dynamics. INFECT exhibits the highest absolute variability (standard deviation of 12.032), with a minimum of zero during non-epidemic periods and a maximum of 113.81 during the peak of the COVID-19 pandemic. VIX: CBOE Volatility Index, expressed in natural logarithm. WUI: World Uncertainty Index, expressed in natural logarithm. GPR: Geopolitical Risk Index, expressed in natural logarithm. TRI: Transition Risk Index (daily returns). PRI: Physical Risk Index (daily returns). GEPU: Global Economic Policy Uncertainty Index, expressed in natural logarithm. INFECT: Infectious Disease Equity Market Volatility Tracker.

Table 3.12: Chow Structural Break Tests Results

Event	**Date**	**PRV**	**GV**	**$IVOL_{1F}$**	**$IVOL_{3F}$**
COVID-19	11 March 2020	67.95^{***}	98.11^{***}	0.0002	115.57^{***}
Russia-Ukraine War	24 February 2022	35.51^{***}	253.99^{***}	369.85^{***}	828.52^{***}
MiCA	20 April 2023	508.14^{***}	680.05^{***}	60.14^{***}	80.52^{***}
Gaza War	7 October 2023	454.51^{***}	987.13^{***}	12.06^{***}	12.22^{***}

Notes: This table reports Wald test statistics from Chow structural break tests conducted at each of the four event dates. The null hypothesis states no structural break at the specified date; the alternative states the presence of a structural break. Each column reports the test statistic for the corresponding volatility measure. PRV: Parkinson Range-Based Volatility. GV: GARCH(1,1) Volatility. IVOL1F: 1-Factor Idiosyncratic Volatility. IVOL3F: 3-Factor Idiosyncratic Volatility. *** $p<0.01$.

Table 3.13: Robust OLS Regression Estimates of Global Events on Binance Net Spillovers Contribution

	(1)	(2)	(3)	(4)	(5)	(6)
PRV Risk Measure						
VIX	15.235***	3.852***	18.97***	18.092***	13.004***	6.763***
WUI	-3.56***	-.024	.304	-2.372***	-4.714***	2.111***
GPR	3.775***	4.192***	-1.477***	2.984***	4.643***	-.144
TRI	38.087***	14.213	51.95***	45.608***	24.048**	9.506
PRI	16.135	3.847	43.95***	24.384**	3.362	15.048**
GEPU	10.465***	11.641***	3.852***	10.161***	10.784***	5.078***
INFECT	.064**	.009	.065***	.038	.086***	.04**
COVID		12.108***				10.606***
RUWAR			14.386***			14.849***
MICA				4.328***		2.962***
GWAR					-5.02***	-9.699***
Intercept	-87.223***	-103.759***	-82.325***	-102.946***	-74.412***	-82.661***
T	2134	2134	2134	2134	2134	2134
R-squared	.342	.462	.592	.354	.353	.733
GV Risk Measure						
VIX	16.645***	3.414***	18.952***	16.375***	15.776***	6.028***
WUI	-2.842***	1.268**	-.455	-2.954***	-3.291***	4.162***
GPR	2.702***	3.187***	-.541	2.777***	3.041***	-.089
TRI	8.996	-18.753*	17.558*	8.285	3.527	-8.107
PRI	10.084	-4.199	27.263***	9.304	5.108	14.966*
GEPU	6.303***	7.67***	2.219*	6.332***	6.428***	3.904***
INFECT	.067**	.003	.068**	.07**	.076***	-.011
COVID		14.073***				14.781***
RUWAR			8.885***			8.041***
MICA				-.409		1.325
GWAR					-1.956**	.712
Intercept	-72.323***	-91.543***	-69.298***	-70.836***	-67.332***	-96.401***
T	2134	2134	2134	2134	2134	2134
R-squared	.3	.458	.393	.3	.302	.549
$IVOL_{1F}$ Risk Measure						
VIX	11.298***	-2.275	12.048***	8.338***	-.066	-3.575***
WUI	-4.861***	-.336	-3.988***	-6.069***	-10.766***	-3.276***
GPR	-4.495***	-4.042***	-5.768***	-3.649***	.375	-1.982***
TRI	105.701***	79.413***	107.835***	99.037***	37.848***	25.26**
PRI	91.183***	78.515***	96.987***	83.39***	27.758**	34.315***
GEPU	-10.572***	-9.161***	-12.174***	-10.26***	-8.897***	-9.445***
INFECT	-.096***	-.169***	-.094***	-.068**	.018	-.117***
COVID		14.89***				13.036***
RUWAR			3.524***			2.309***
MICA				-4.747***		16.405***
GWAR					-29.473***	-35.556***
Intercept	98.65***	75.731***	100.922***	114.612***	162.003***	101.333***
T	2069	2069	2069	2069	2069	2069
R-squared	.141	.256	.151	.151	.347	.463
$IVOL_{3F}$ Risk Measure						
VIX	2.379**	5.163***	.594	-1.434	1.087	2.91**
WUI	-2.652***	-3.58***	-4.73***	-4.208***	-3.323***	-6.346***
GPR	-3.11***	-3.203***	-.08	-2.02***	-2.557***	-.208
TRI	-26.332**	-20.94*	-31.411***	-34.918***	-34.045***	-26.617**
PRI	23.601*	26.199*	9.789	13.56	16.391	11.387
GEPU	14.443***	14.154***	18.254***	14.845***	14.633***	17.445***
INFECT	-.076***	-.061**	-.08***	-.04*	-.063***	-.043*
COVID		-3.054***				-4.126***
RUWAR			-8.387***			-7.083***
MICA				-6.116***		-3.02***
GWAR					-3.35***	.417
Intercept	-55.822***	-51.121***	-61.227***	-35.257***	-48.621***	-44.776***
T	2069	2069	2069	2069	2069	2069
R-squared	.08	.088	.172	.106	.084	.182

Table 3.13: Robust OLS Regression Estimates of Global Events on Binance Net Spillovers Contribution. This table reports robust OLS estimates of the impact of global risk factors and events on Binance's net spillovers contribution, using four different risk measures: PRV (Price Range-based Volatility), GV (GARCH Volatility), IVOL1F (1-Factor Idiosyncratic Volatility), and IVOL3F (3-Factor Idiosyncratic Volatility). Model Specifications: (1) Baseline model including all risk factors, (2) Baseline model plus COVID-19 dummy, (3) Baseline model plus Russia-Ukraine War dummy, (4) Baseline model plus MiCA regulation dummy, (5) Baseline model plus Gaza War dummy, (6) Full model including all risk factors and event dummies, VIX: CBOE Volatility Index expressed in natural logarithm. WUI: World Uncertainty Index expressed in natural logarithm. GPR: Geopolitical Risk Index expressed in natural logarithm. TRI: Transition Risk Index. PRI: Physical Risk Index. GEPU: Global Economic Policy Uncertainty Index expressed in natural logarithm. INFECT: Infectious Disease EMV Tracker. Robust standard errors are used in all regressions. Dummy variables: COVID: COVID-19 pandemic period (March 11, 2020 - May 5, 2023), RUWAR: Russia-Ukraine War period (from February 24, 2022), MICA: Period following MiCA regulation implementation (from April 20, 2023), GWAR: Gaza War period (from October 7, 2023). *** p<.01, ** p<.05, * p<.1. T represents the number of observations.

Table 3.14: Robust OLS Regression Estimates of Global Events on Bitcoin Net Spillovers Contribution

	(1)	(2)	(3)	(4)	(5)	(6)
PRV Risk Measure						
VIX	5.878***	1.701***	6.25***	3.641***	4.605***	1.531**
WUI	-.15	1.147***	.235	-1.08***	-.808**	-.018
GPR	-.645***	-.492**	-1.169***	-.026	-.15	-.976***
TRI	3.155	-5.606	4.537	-2.733	-4.856	-6.238
PRI	-9.821	-14.33**	-7.049	-16.278***	-17.11***	-14.616**
GEPU	-14.219***	-13.788***	-14.878***	-13.981***	-14.037***	-15.367***
INFECT	-.02	-.04***	-.02	0	-.008	.002
COVID		4.444***				1.966***
RUWAR			1.434***			3.714***
MICA				-3.389***		-5.254***
GWAR					-2.865***	.012
Intercept	69.913***	63.845***	70.402***	82.222***	77.224***	87.546***
T	2134	2134	2134	2134	2134	2134
R-squared	.139	.201	.148	.168	.152	.236
GV Risk Measure						
VIX	3.6***	-2.268**	6.733***	4.011***	3.66***	-.539
WUI	3.149***	4.972***	6.392***	3.32***	3.181***	3.831***
GPR	2.79***	3.005***	-1.617***	2.676***	2.766***	-1.336***
TRI	1.629	-10.677	13.261	2.712	2.01	-4.038
PRI	-13.553	-19.887*	9.785	-12.366	-13.207	-4.614
GEPU	3.459***	4.065***	-2.09	3.415***	3.45***	-4.141***
INFECT	-.164***	-.193***	-.164***	-.168***	-.165***	-.071***
COVID		6.241***				-.877
RUWAR			12.071***			18.603***
MICA				.623		-15.023***
GWAR					.136	.279
Intercept	-66.571***	-75.095***	-62.461***	-68.834***	-66.918***	-5.181
T	2134	2134	2134	2134	2134	2134
R-squared	.088	.133	.336	.089	.088	.456
$IVOL_{1F}$ Risk Measure						
VIX	-4.429***	-1.01	-7.098***	-8.791***	-2.371	-2.723*
WUI	-8.481***	-9.621***	-11.589***	-10.261***	-7.412***	-9.967***
GPR	-.682	-.796	3.849***	.564	-1.564**	2.391***
TRI	23.971	30.593**	16.375	14.148	36.255**	46.445***
PRI	15.804	18.995	-4.852	4.317	27.287*	20.296
GEPU	-6.397***	-6.752***	-.697	-5.937***	-6.7***	-.831
INFECT	-.054*	-.036	-.061**	-.014	-.075**	-.097***
COVID		-3.75***				-.848
RUWAR			-12.544***			-13.838***
MICA				-6.997***		-2.677**
GWAR					5.336***	14.383***
Intercept	136.897***	142.67***	128.814***	160.426***	125.428***	107.371***
T	2069	2069	2069	2069	2069	2069
R-squared	.093	.1	.213	.113	.1	.253
$IVOL_{3F}$ Risk Measure						
VIX	6.307***	-6.872***	1.033	-7.409***	.281	-10.72***
WUI	-10.043***	-5.648***	-16.183***	-15.64***	-13.174***	-6.05***
GPR	-3.164***	-2.725***	5.788***	.756	-.582	5.938***
TRI	51.722**	26.196	36.716**	20.837	15.739	20.97
PRI	79.231***	66.93***	38.424**	43.113**	45.596**	39.382**
GEPU	-10.1***	-8.73***	1.16	-8.652***	-9.212***	5.85**
INFECT	.205***	.134***	.193***	.333***	.266***	-.039
COVID		14.458***				23.82***
RUWAR			-24.78***			-32.973***
MICA				-21.999***		16.65***
GWAR					-15.63***	3.429**
Intercept	164.496***	142.241***	148.527***	238.473***	198.091***	43.223***
T	2069	2069	2069	2069	2069	2069
R-squared	.101	.159	.351	.207	.132	.443

Table 3.14: Robust OLS Regression Estimates of Global Events on Bitcoin Net Spillovers Contribution. This table reports robust OLS estimates of the impact of global risk factors and events on Bitcoin 's net spillovers contribution, using four different risk measures: PRV (Price Range-based Volatility), GV (GARCH Volatility), IVOL1F (1-Factor Idiosyncratic Volatility), and IVOL3F (3-Factor Idiosyncratic Volatility). Model Specifications: (1) Baseline model including all risk factors, (2) Baseline model plus COVID-19 dummy, (3) Baseline model plus Russia-Ukraine War dummy, (4) Baseline model plus MiCA regulation dummy, (5) Baseline model plus Gaza War dummy, (6) Full model including all risk factors and event dummies, VIX: CBOE Volatility Index expressed in natural logarithm. WUI: World Uncertainty Index expressed in natural logarithm. GPR: Geopolitical Risk Index expressed in natural logarithm. TRI: Transition Risk Index. PRI: Physical Risk Index. GEPU: Global Economic Policy Uncertainty Index expressed in natural logarithm. INFECT: Infectious Disease EMV Tracker. Robust standard errors are used in all regressions. Dummy variables: COVID: COVID-19 pandemic period (March 11, 2020 - May 5, 2023), RUWAR: Russia-Ukraine War period (from February 24, 2022), MICA: Period following MiCA regulation implementation (from April 20, 2023), GWAR: Gaza War period (from October 7, 2023). *** p<.01, ** p<.05, * p<.1. T represents the number of observations.

Table 3.15: Robust OLS Regression Estimates of Global Events on Cardano Net Spillovers Contribution

	(1)	(2)	(3)	(4)	(5)	(6)
PRV Risk Measure						
VIX	-7.167***	-3.802***	-8.807***	-10.316***	-8.701***	-6.104***
WUI	6.503***	5.458***	4.806***	5.193***	5.71***	2.262***
GPR	-1.406***	-1.529***	.901***	-.534**	-.809***	.903***
TRI	11.458*	18.514***	5.369	3.166	1.804	8.202
PRI	20.903***	24.535***	8.687	11.809	12.12	7.627
GEPU	.12	-.228	3.024***	.455	.339	1.865**
INFECT	-.091***	-.074***	-.091***	-.062***	-.076***	-.034**
COVID		-3.579***				-5.785***
RUWAR			-6.318***			-4.216***
MICA				-4.772***		-4.16***
GWAR					-3.452***	-1.206
Intercept	-29.197***	-24.309***	-31.348***	-11.864**	-20.388***	-4.545
T	2134	2134	2134	2134	2134	2134
R-squared	.267	.292	.382	.303	.279	.419
GV Risk Measure						
VIX	-20.365***	-4.541***	-20.419***	-14.967***	-18.186***	-5.466***
WUI	8.042***	3.126***	7.985***	10.286***	9.168***	1.151*
GPR	-.514	-1.094***	-.438	-2.008***	-1.362***	-.568**
TRI	-11.644	21.544***	-11.846	2.564	2.065	9.795
PRI	-9.471	7.611	-9.876	6.112	3.001	-3.66
GEPU	14.259***	12.625***	14.355***	13.685***	13.947***	12.02***
INFECT	-.09***	-.013	-.09***	-.139***	-.111***	.033**
COVID		-16.831***				-19.245***
RUWAR			-.21			1.842***
MICA				8.177***		-1.996**
GWAR					4.902***	-5.298***
Intercept	-93.587***	-70.6***	-93.658***	-123.29***	-106.095***	-45.906***
T	2134	2134	2134	2134	2134	2134
R-squared	.387	.646	.387	.436	.398	.659
$IVOL_{1F}$ Risk Measure						
VIX	-20.365***	-4.541***	-20.419***	-14.967***	-18.186***	-5.466***
WUI	8.042***	3.126***	7.985***	10.286***	9.168***	1.151*
GPR	-.514	-1.094***	-.438	-2.008***	-1.362***	-.568**
TRI	-11.644	21.544***	-11.846	2.564	2.065	9.795
PRI	-9.471	7.611	-9.876	6.112	3.001	-3.66
GEPU	14.259***	12.625***	14.355***	13.685***	13.947***	12.02***
INFECT	-.09***	-.013	-.09***	-.139***	-.111***	.033**
COVID		-16.831***				-19.245***
RUWAR			-.21			1.842***
MICA				8.177***		-1.996**
GWAR					4.902***	-5.298***
Intercept	-93.587***	-70.6***	-93.658***	-123.29***	-106.095***	-45.906***
T	2134	2134	2134	2134	2134	2134
R-squared	.387	.646	.387	.436	.398	.659
$IVOL_{3F}$ Risk Measure						
VIX	7.268***	5.171***	6.977***	3.915***	1.826*	2.998***
WUI	6.801***	7.5***	6.461***	5.432***	3.973***	2.967***
GPR	-1.816***	-1.746***	-1.322***	-.858**	.516	.209
TRI	38.503***	34.441***	37.674***	30.954***	6.01	6.438
PRI	32.637***	30.681***	30.384***	23.81**	2.265	2.235
GEPU	-21.523***	-21.305***	-20.901***	-21.169***	-20.72***	-21.745***
INFECT	.062***	.051**	.062***	.094***	.117***	.147***
COVID		2.3***				-2.628***
RUWAR			-1.369**			2.139***
MICA				-5.377***		-1.948
GWAR					-14.114***	-15.318***
Intercept	32.959***	29.419***	32.077***	51.041***	63.297***	77.86***
T	2069	2069	2069	2069	2069	2069
R-squared	.126	.131	.129	.148	.212	.218

Table 3.15: Robust OLS Regression Estimates of Global Events on Cardano Net Spillovers Contribution. This table reports robust OLS estimates of the impact of global risk factors and events on Cardano's net spillovers contribution, using four different risk measures: PRV (Price Range-based Volatility), GV (GARCH Volatility), IVOL1F (1-Factor Idiosyncratic Volatility), and IVOL3F (3-Factor Idiosyncratic Volatility). Model Specifications: (1) Baseline model including all risk factors, (2) Baseline model plus COVID-19 dummy, (3) Baseline model plus Russia-Ukraine War dummy, (4) Baseline model plus MiCA regulation dummy, (5) Baseline model plus Gaza War dummy, (6) Full model including all risk factors and event dummies, VIX: CBOE Volatility Index expressed in natural logarithm. WUI: World Uncertainty Index expressed in natural logarithm. GPR: Geopolitical Risk Index expressed in natural logarithm. TRI: Transition Risk Index. PRI: Physical Risk Index. GEPU: Global Economic Policy Uncertainty Index expressed in natural logarithm. INFECT: Infectious Disease EMV Tracker. Robust standard errors are used in all regressions. Dummy variables: COVID: COVID-19 pandemic period (March 11, 2020 - May 5, 2023), RUWAR: Russia-Ukraine War period (from February 24, 2022), MICA: Period following MiCA regulation implementation (from April 20, 2023), GWAR: Gaza War period (from October 7, 2023). *** p<.01, ** p<.05, * p<.1. T represents the number of observations.

Table 3.16: Robust OLS Regression Estimates of Global Events on Dogecoin Net Spillovers Contribution

	(1)	(2)	(3)	(4)	(5)	(6)
PRV Risk Measure						
VIX	-6.789***	3.671***	-6.116***	-1.067	1.066	5.819***
WUI	-8.008***	-11.257***	-7.311***	-5.629***	-3.949***	-8.268***
GPR	2.608***	2.225***	1.661***	1.025***	-.448	-.155
TRI	-59.714***	-37.774***	-57.214***	-44.652***	-10.297	-5.689
PRI	-56.266***	-44.973***	-51.251***	-39.747***	-11.306	-14.068
GEPU	3.194**	2.114	2.002	2.586*	2.071	.635
INFECT	.004	.055**	.004	-.048*	-.072***	.017
COVID		-11.127***				-9.61***
RUWAR			2.594***			2.303***
MICA				8.669***		-5.853***
GWAR					17.671***	15.387***
Intercept	57.044***	72.24***	57.927***	25.557***	11.951*	52.952***
T	2134	2134	2134	2134	2134	2134
R-squared	.206	.328	.216	.266	.36	.414
GV Risk Measure						
VIX	-1.692*	.022	-.51	3.43***	3.847***	3.09***
WUI	-10.335***	-10.867***	-9.112***	-8.205***	-7.472***	-5.733***
GPR	3.505***	3.442***	1.844***	2.088***	1.35***	.75*
TRI	-29.995***	-26.4**	-25.61**	-16.512	4.851	1.868
PRI	-44.028***	-42.177***	-35.228***	-29.239***	-12.324	-10.68
GEPU	-20.024***	-20.201***	-22.116***	-20.569***	-20.816***	-21.056***
INFECT	.185***	.193***	.185***	.138***	.131***	.102***
COVID		-1.823***				2.932***
RUWAR			4.551***			.785
MICA				7.76***		3.832***
GWAR					12.461***	10.811***
Intercept	188.5***	190.99***	190.05***	160.311***	156.703***	143.258***
T	2134	2134	2134	2134	2134	2134
R-squared	.382	.385	.408	.423	.448	.46
$IVOL_{1F}$ Risk Measure						
VIX	5.105***	19.897***	6.072***	12.847***	8.569***	20.556***
WUI	4.527***	-.405	5.652***	7.686***	6.327***	-.402
GPR	2.877***	2.384***	1.236**	.665	1.393***	.964**
TRI	-17.699	10.95	-14.948	-.267	2.984	7.684
PRI	-28.61**	-14.805	-21.13	-8.225	-9.278	-13.056
GEPU	-31.476***	-33.013***	-33.54***	-32.293***	-31.986***	-35.598***
INFECT	-.148***	-.068**	-.145***	-.22***	-.182***	-.037
COVID		-16.227***				-17.815***
RUWAR			4.542***			5.96***
MICA				12.416***		-1.123
GWAR					8.984***	-3.52***
Intercept	92.806***	117.783***	95.733***	51.053***	73.496***	135.41***
T	2069	2069	2069	2069	2069	2069
R-squared	.184	.346	.202	.258	.206	.371
$IVOL_{3F}$ Risk Measure						
VIX	-29.633***	-.625	-25.009***	-5.203**	-13.485***	6.383***
WUI	-7.698***	-17.371***	-2.315	2.271	.692	-8.167***
GPR	8.672***	7.704***	.823	1.689**	1.752**	-1.757**
TRI	-72.323***	-16.139	-59.167***	-17.312	24.093	24.132
PRI	-119.849***	-92.774***	-84.071***	-55.517**	-29.725	-30.86*
GEPU	-9.641***	-12.656***	-19.513***	-12.219***	-12.021***	-21.915***
INFECT	-.256***	-.099*	-.245***	-.484***	-.418***	-.173***
COVID		-31.824***				-27.93***
RUWAR			21.726***			19.165***
MICA				39.184***		1.355
GWAR					41.88***	14.612***
Intercept	189.32***	238.305***	203.32***	57.554***	99.3***	208.698***
T	2069	2069	2069	2069	2069	2069
R-squared	.3	.468	.415	.5	.434	.602

Table 3.16: Robust OLS Regression Estimates of Global Events on Dogecoin Net Spillovers Contribution. This table reports robust OLS estimates of the impact of global risk factors and events on Dogecoin net spillovers contribution, using four different risk measures: PRV (Price Range-based Volatility), GV (GARCH Volatility), IVOL1F (1-Factor Idiosyncratic Volatility), and IVOL3F (3-Factor Idiosyncratic Volatility). Model Specifications: (1) Baseline model including all risk factors, (2) Baseline model plus COVID-19 dummy, (3) Baseline model plus Russia-Ukraine War dummy, (4) Baseline model plus MiCA regulation dummy, (5) Baseline model plus Gaza War dummy, (6) Full model including all risk factors and event dummies, VIX: CBOE Volatility Index expressed in natural logarithm. WUI: World Uncertainty Index expressed in natural logarithm. GPR: Geopolitical Risk Index expressed in natural logarithm. TRI: Transition Risk Index. PRI: Physical Risk Index. GEPU: Global Economic Policy Uncertainty Index expressed in natural logarithm. INFECT: Infectious Disease EMV Tracker. Robust standard errors are used in all regressions. Dummy variables: COVID: COVID-19 pandemic period (March 11, 2020 - May 5, 2023), RUWAR: Russia-Ukraine War period (from February 24, 2022), MICA: Period following MiCA regulation implementation (from April 20, 2023), GWAR: Gaza War period (from October 7, 2023). *** p<.01, ** p<.05, * p<.1. T represents the number of observations.

Table 3.17: Robust OLS Regression Estimates of Global Events on Ethereum Net Spillovers Contribution

	(1)	(2)	(3)	(4)	(5)	(6)
PRV Risk Measure						
VIX	-12.63***	-8.696***	-12.504***	-10.794***	-12.953***	-9.037***
WUI	2.89***	1.668***	3.021***	3.654***	2.723***	1.013***
GPR	-.852***	-.996***	-1.03***	-1.36***	-.726***	-.724***
TRI	-5.516	2.736	-5.048	-.683	-7.551	-6.543
PRI	5.915	10.162*	6.854	11.216*	4.063	2.601
GEPU	.122	-.284	-.101	-.073	.169	-.47
INFECT	-.049***	-.03***	-.049***	-.066***	-.046***	-.016
COVID		-4.185***				-4.769***
RUWAR			.486*			.711*
MICA				2.782***		1.802***
GWAR					-.728	-5.094***
Intercept	23.925***	29.64***	24.09***	13.821***	25.782***	37.135***
T	2134	2134	2134	2134	2134	2134
R-squared	.379	.418	.379	.392	.379	.437
GV Risk Measure						
VIX	-9.801***	-4.423***	-9.221***	-7.899***	-13.345***	-6***
WUI	7.275***	5.604***	7.875***	8.066***	5.444***	1.929***
GPR	-.752**	-.949***	-1.567***	-1.278***	.627**	-.207
TRI	33.428***	44.709***	35.581***	38.435***	11.135	12.094*
PRI	26.611***	32.417***	30.93***	32.102***	6.328	5.01
GEPU	10.234***	9.679***	9.207***	10.032***	10.741***	7.815***
INFECT	-.088***	-.061***	-.087***	-.105***	-.053**	.03*
COVID		-5.721***				-10.289***
RUWAR			2.234***			5.374***
MICA				2.882***		.45
GWAR					-7.972***	-17.015***
Intercept	-81.012***	-73.199***	-80.251***	-91.479***	-60.669***	-23.346***
T	2134	2134	2134	2134	2134	2134
R-squared	.289	.336	.3	.299	.335	.499
$IVOL_{1F}$ Risk Measure						
VIX	-6.724***	-6.189***	-5.605***	-3.187***	-6.083***	-4.882***
WUI	-9.655***	-9.834***	-8.353***	-8.212***	-9.322***	-8.233***
GPR	-2.063***	-2.081***	-3.961***	-3.074***	-2.338***	-3.689***
TRI	34.527***	35.563***	37.709***	42.492***	38.355***	34.34***
PRI	6.648	7.146	15.3	15.961	10.225	12.424
GEPU	-6.209***	-6.264***	-8.596***	-6.582***	-6.303***	-8.124***
INFECT	-.065**	-.062**	-.063**	-.098***	-.072**	-.074**
COVID		-.586				.233
RUWAR			5.254***			4.112***
MICA				5.673***		4.011***
GWAR					1.663	-3.43***
Intercept	176.382***	177.285***	179.768***	157.306***	172.809***	172.558***
T	2069	2069	2069	2069	2069	2069
R-squared	.179	.18	.208	.197	.18	.212
$IVOL_{3F}$ Risk Measure						
VIX	-8.609***	-15.414***	-9.025***	-13.117***	-12.827***	-16.731***
WUI	-2.874***	-.605	-3.357***	-4.713***	-5.065***	-2.958**
GPR	-4.32***	-4.093***	-3.616***	-3.032***	-2.513***	-2.662***
TRI	50.196***	37.016**	49.014***	40.046**	25.013	23.081
PRI	9.052	2.701	5.84	-2.817	-14.487	-12.811
GEPU	16.473***	17.18***	17.359***	16.948***	17.094***	17.697***
INFECT	.26***	.224***	.259***	.302***	.302***	.264***
COVID		7.465***				5.379***
RUWAR			-1.951**			-.6
MICA				-7.229***		-.517
GWAR					-10.939***	-7.179***
Intercept	-15.175	-26.666*	-16.432	9.136	8.338	-6.669
T	2069	2069	2069	2069	2069	2069
R-squared	.087	.112	.09	.105	.112	.123

Table 3.17: Robust OLS Regression Estimates of Global Events on Ethereum Net Spillovers Contribution. This table reports robust OLS estimates of the impact of global risk factors and events on Ethereum's net spillovers contribution, using four different risk measures: PRV (Price Range-based Volatility), GV (GARCH Volatility), IVOL1F (1-Factor Idiosyncratic Volatility), and IVOL3F (3-Factor Idiosyncratic Volatility). Model Specifications: (1) Baseline model including all risk factors, (2) Baseline model plus COVID-19 dummy, (3) Baseline model plus Russia-Ukraine War dummy, (4) Baseline model plus MiCA regulation dummy, (5) Baseline model plus Gaza War dummy, (6) Full model including all risk factors and event dummies, VIX: CBOE Volatility Index expressed in natural logarithm. WUI: World Uncertainty Index expressed in natural logarithm. GPR: Geopolitical Risk Index expressed in natural logarithm. TRI: Transition Risk Index. PRI: Physical Risk Index. GEPU: Global Economic Policy Uncertainty Index expressed in natural logarithm. INFECT: Infectious Disease EMV Tracker. Robust standard errors are used in all regressions. Dummy variables: COVID: COVID-19 pandemic period (March 11, 2020 - May 5, 2023), RUWAR: Russia-Ukraine War period (from February 24, 2022), MICA: Period following MiCA regulation implementation (from April 20, 2023), GWAR: Gaza War period (from October 7, 2023). *** p<.01, ** p<.05, * p<.1. T represents the number of observations.

Table 3.18: Robust OLS Regression Estimates of Global Events on Monero Net Spillovers Contribution

	(1)	(2)	(3)	(4)	(5)	(6)
PRV Risk Measure						
VIX	-3.355***	-3.364***	-4.49***	-4.103***	-6.284***	-4.658***
WUI	2.339***	2.342***	1.165***	2.028***	.826**	1.834***
GPR	-2.582***	-2.582***	-.986***	-2.375***	-1.443***	-.232
TRI	39.876***	39.857***	35.662***	37.907***	21.451***	21.548***
PRI	34.53***	34.521***	26.076***	32.37***	17.767**	15.377**
GEPU	-8.392***	-8.391***	-6.382***	-8.312***	-7.973***	-5.064***
INFECT	-.036**	-.036**	-.037**	-.03*	-.008	-.069***
COVID		.009				2.286***
RUWAR			-4.372***			-7.07***
MICA				-1.133***		9.887***
GWAR					-6.589***	-8.649***
Intercept	50.874***	50.861***	49.385***	54.991***	67.687***	31.502***
T	2134	2134	2134	2134	2134	2134
R-squared	.194	.194	.257	.196	.243	.34
GV Risk Measure						
VIX	.721	-2.118*	-2.11**	-7.909***	-5.935***	-6.555***
WUI	11.327***	12.209***	8.398***	7.739***	7.887***	6.15***
GPR	-5.575***	-5.471***	-1.595***	-3.187***	-2.985***	-.661
TRI	30.131***	24.177**	19.624**	7.414	-11.745	-5.596
PRI	38.503***	35.438***	17.421	13.588	.404	-3.916
GEPU	-17.23***	-16.937***	-12.218***	-16.312***	-16.277***	-12.917***
INFECT	-.175***	-.188***	-.175***	-.096***	-.11***	-.116***
COVID		3.02***				-.735
RUWAR			-10.904***			-7.861***
MICA				-13.074***		-3.182***
GWAR					-14.975***	-8.609***
Intercept	13.37	9.245	9.657	60.861***	51.581***	45.22***
T	2134	2134	2134	2134	2134	2134
R-squared	.264	.272	.402	.372	.353	.439
$IVOL_{1F}$ Risk Measure						
VIX	4.267***	-1.44	3.81***	2.614**	.155	-1.979*
WUI	-2.088***	-.186	-2.62***	-2.763***	-4.225***	-.094
GPR	-4.033***	-3.842***	-3.258***	-3.56***	-2.271***	-2.012***
TRI	7.568	-3.484	6.27	3.848	-16.984*	-21.151**
PRI	4.213	-1.113	.684	-.138	-18.737*	-17.6*
GEPU	7.173***	7.766***	8.147***	7.348***	7.779***	10.323***
INFECT	.168***	.137***	.167***	.183***	.209***	.098***
COVID		6.26***				8.73***
RUWAR			-2.143***			-5.366***
MICA				-2.65***		11.687***
GWAR					-10.665***	-11.496***
Intercept	-21.146***	-30.782***	-22.527***	-12.235	1.778	-52.633***
T	2069	2069	2069	2069	2069	2069
R-squared	.195	.238	.202	.201	.252	.307
$IVOL_{3F}$ Risk Measure						
VIX	3.73***	7.678***	4.548***	9.334***	9.593***	10.381***
WUI	-2.697***	-4.013***	-1.744**	-.41	.35	1.078
GPR	1.864***	1.732***	.474	.262	-.649	-.904
TRI	-67.537***	-59.89***	-65.209***	-54.918***	-32.528**	-34.072***
PRI	-14.289	-10.604	-7.957	.468	18.436	18.858
GEPU	12.12***	11.709***	10.372***	11.528***	11.256***	11.226***
INFECT	-.059**	-.038	-.057**	-.111***	-.117***	-.135***
COVID		-4.331***				.766
RUWAR			3.845***			-.035
MICA				8.988***		3.92***
GWAR					15.207***	12.743***
Intercept	-55.027***	-48.359***	-52.549***	-85.253***	-87.714***	-96.801***
T	2069	2069	2069	2069	2069	2069
R-squared	.065	.078	.08	.11	.14	.145

Table 3.18: Robust OLS Regression Estimates of Global Events on Monero Net Spillovers Contribution. This table reports robust OLS estimates of the impact of global risk factors and events on Monero's net spillovers contribution, using four different risk measures: PRV (Price Range-based Volatility), GV (GARCH Volatility), IVOL1F (1-Factor Idiosyncratic Volatility), and IVOL3F (3-Factor Idiosyncratic Volatility). Model Specifications: (1) Baseline model including all risk factors, (2) Baseline model plus COVID-19 dummy, (3) Baseline model plus Russia-Ukraine War dummy, (4) Baseline model plus MiCA regulation dummy, (5) Baseline model plus Gaza War dummy, (6) Full model including all risk factors and event dummies, VIX: CBOE Volatility Index expressed in natural logarithm. WUI: World Uncertainty Index expressed in natural logarithm. GPR: Geopolitical Risk Index expressed in natural logarithm. TRI: Transition Risk Index. PRI: Physical Risk Index. GEPU: Global Economic Policy Uncertainty Index expressed in natural logarithm. INFECT: Infectious Disease EMV Tracker. Robust standard errors are used in all regressions. Dummy variables: COVID: COVID-19 pandemic period (March 11, 2020 - May 5, 2023), RUWAR: Russia-Ukraine War period (from February 24, 2022), MICA: Period following MiCA regulation implementation (from April 20, 2023), GWAR: Gaza War period (from October 7, 2023). *** p<.01, ** p<.05, * p<.1. T represents the number of observations.

Table 3.19: Robust OLS Regression Estimates of Global Events on TRON Net Spillovers Contribution

	(1)	(2)	(3)	(4)	(5)	(6)
PRV Risk Measure						
VIX	5.878***	1.701***	6.25***	3.641***	4.605***	1.531**
WUI	-.15	1.147***	.235	-1.08***	-.808**	-.018
GPR	-.645***	-.492**	-1.169***	-.026	-.15	-.976***
TRI	3.155	-5.606	4.537	-2.733	-4.856	-6.238
PRI	-9.821	-14.33**	-7.049	-16.278***	-17.11***	-14.616**
GEPU	-14.219***	-13.788***	-14.878***	-13.981***	-14.037***	-15.367***
INFECT	-.02	-.04***	-.02	0	-.008	.002
COVID		4.444***				1.966***
RUWAR			1.434***			3.714***
MICA				-3.389***		-5.254***
GWAR					-2.865***	.012
Intercept	69.913***	63.845***	70.402***	82.222***	77.224***	87.546***
T	2134	2134	2134	2134	2134	2134
R-squared	.139	.201	.148	.168	.152	.236
GV Risk Measure						
VIX	3.6***	-2.268**	6.733***	4.011***	3.66***	-.539
WUI	3.149***	4.972***	6.392***	3.32***	3.181***	3.831***
GPR	2.79***	3.005***	-1.617***	2.676***	2.766***	-1.336***
TRI	1.629	-10.677	13.261	2.712	2.01	-4.038
PRI	-13.553	-19.887*	9.785	-12.366	-13.207	-4.614
GEPU	3.459***	4.065***	-2.09	3.415***	3.45***	-4.141***
INFECT	-.164***	-.193***	-.164***	-.168***	-.165***	-.071***
COVID		6.241***				-.877
RUWAR			12.071***			18.603***
MICA				.623		-15.023***
GWAR					.136	.279
Intercept	-66.571***	-75.095***	-62.461***	-68.834***	-66.918***	-5.181
T	2134	2134	2134	2134	2134	2134
R-squared	.088	.133	.336	.089	.088	.456
$IVOL_{1F}$ Risk Measure						
VIX	-4.429***	-1.01	-7.098***	-8.791***	-2.371	-2.723*
WUI	-8.481***	-9.621***	-11.589***	-10.261***	-7.412***	-9.967***
GPR	-.682	-.796	3.849***	.564	-1.564**	2.391***
TRI	23.971	30.593**	16.375	14.148	36.255**	46.445***
PRI	15.804	18.995	-4.852	4.317	27.287*	20.296
GEPU	-6.397***	-6.752***	-.697	-5.937***	-6.7***	-.831
INFECT	-.054*	-.036	-.061**	-.014	-.075**	-.097***
COVID		-3.75***				-.848
RUWAR			-12.544***			-13.838***
MICA				-6.997***		-2.677**
GWAR					5.336***	14.383***
Intercept	136.897***	142.67***	128.814***	160.426***	125.428***	107.371***
T	2069	2069	2069	2069	2069	2069
R-squared	.093	.1	.213	.113	.1	.253
$IVOL_{3F}$ Risk Measure						
VIX	-2.151**	-2.315**	.55	2.132*	-2.446**	-.803
WUI	2.475***	2.529***	5.62***	4.223***	2.322***	1.904***
GPR	4.343***	4.349***	-.242	3.119***	4.47***	.575
TRI	32.762***	32.446***	40.449***	42.407***	31.005**	24.307**
PRI	-19.151	-19.303	1.754	-7.871	-20.793	-14.965
GEPU	-11.847***	-11.83***	-17.615***	-12.299***	-11.804***	-19.067***
INFECT	-.117***	-.118***	-.111***	-.157***	-.114***	-.017
COVID		.179				-5.101***
RUWAR			12.694***			16.718***
MICA				6.87***		-5.767***
GWAR					-.763	-8.465***
Intercept	18.434*	18.158*	26.614***	-4.669	20.074*	74.646***
T	2069	2069	2069	2069	2069	2069
R-squared	.116	.116	.284	.142	.116	.317

Table 3.19: Robust OLS Regression Estimates of Global Events on TRON Net Spillovers Contribution. This table reports robust OLS estimates of the impact of global risk factors and events on TRON's net spillovers contribution, using four different risk measures: PRV (Price Range-based Volatility), GV (GARCH Volatility), IVOL1F (1-Factor Idiosyncratic Volatility), and IVOL3F (3-Factor Idiosyncratic Volatility). Model Specifications: (1) Baseline model including all risk factors, (2) Baseline model plus COVID-19 dummy, (3) Baseline model plus Russia-Ukraine War dummy, (4) Baseline model plus MiCA regulation dummy, (5) Baseline model plus Gaza War dummy, (6) Full model including all risk factors and event dummies, VIX: CBOE Volatility Index expressed in natural logarithm. WUI: World Uncertainty Index expressed in natural logarithm. GPR: Geopolitical Risk Index expressed in natural logarithm. TRI: Transition Risk Index. PRI: Physical Risk Index. GEPU: Global Economic Policy Uncertainty Index expressed in natural logarithm. INFECT: Infectious Disease EMV Tracker. Robust standard errors are used in all regressions. Dummy variables: COVID: COVID-19 pandemic period (March 11, 2020 - May 5, 2023), RUWAR: Russia-Ukraine War period (from February 24, 2022), MICA: Period following MiCA regulation implementation (from April 20, 2023), GWAR: Gaza War period (from October 7, 2023). *** p<.01, ** p<.05, * p<.1. T represents the number of observations.

Table 3.20: Robust OLS Regression Estimates of Global Events on Ripple Net Spillovers Contribution

	(1)	(2)	(3)	(4)	(5)	(6)
PRV Risk Measure						
VIX	5.017***	5.469***	5.373***	6.082***	6.978***	6.359***
WUI	-1.786***	-1.926***	-1.418***	-1.343***	-.772**	-.665*
GPR	.896***	.88***	.397	.602**	.133	-.078
TRI	-27.015***	-26.067***	-25.695***	-24.213***	-14.679**	-14.961**
PRI	-31.435***	-30.947***	-28.787***	-28.361***	-20.212***	-19.641***
GEPU	13.231***	13.184***	12.601***	13.117***	12.95***	12.571***
INFECT	.054***	.056***	.054***	.044***	.035**	.039**
COVID		-.481				.26
RUWAR			1.369***			1.007**
MICA				1.613***		-1.352**
GWAR					4.411***	4.987***
Intercept	-82.791***	-82.134***	-82.324***	-88.649***	-94.047***	-90.614***
T	2134	2134	2134	2134	2134	2134
R-squared	.285	.285	.29	.289	.305	.308
GV Risk Measure						
VIX	-.885	-.66	-2.836***	-.748	3.408***	.445
WUI	-9.487***	-9.557***	-11.505***	-9.43***	-7.268***	-4.438***
GPR	.065	.057	2.807***	.027	-1.606***	1.318***
TRI	-39.012***	-38.539***	-46.251***	-38.651***	-12.003	-10.124
PRI	-23.349**	-23.106**	-37.875***	-22.953*	1.224	-2.538
GEPU	10.522***	10.499***	13.976***	10.507***	9.908***	16.667***
INFECT	.22***	.221***	.219***	.218***	.178***	.047**
COVID		-.24				9.146***
RUWAR			-7.513***			-15.193***
MICA				.208		10.647***
GWAR					9.658***	15.399***
Intercept	29.176***	29.504***	26.618***	28.422***	4.531	-66.456***
T	2134	2134	2134	2134	2134	2134
R-squared	.202	.202	.277	.202	.244	.422
IVOL$_{1F}$ Risk Measure						
VIX	-8.049***	-7.806***	-5.967***	1.49	-.919	-2.654*
WUI	6.649***	6.568***	9.073***	10.542***	10.354***	15.973***
GPR	4.576***	4.568***	1.042	1.85***	1.521**	-.225
TRI	-87.152***	-86.682***	-81.229***	-65.674***	-44.583***	-54.208***
PRI	-68.023***	-67.796***	-51.915***	-42.906***	-28.232*	-23.553
GEPU	24.423***	24.398***	19.978***	23.416***	23.372***	23.059***
INFECT	.169***	.171***	.174***	.08**	.098**	-.007
COVID		-.267				9.423***
RUWAR			9.782***			1.342
MICA				15.298***		14.242***
GWAR					18.491***	12.498***
Intercept	-208.448***	-208.038***	-202.145***	-259.894***	-248.194***	-296.844***
T	2069	2069	2069	2069	2069	2069
R-squared	.144	.144	.199	.216	.205	.259
IVOL$_{3F}$ Risk Measure						
VIX	20.71***	7.213***	20.331***	11.781***	15.971***	5.581***
WUI	16.688***	21.188***	16.247***	13.044***	14.226***	17.571***
GPR	-2.467***	-2.017***	-1.825***	.085	-.436	-1.192**
TRI	-6.989	-33.13**	-8.066	-27.095*	-35.286**	-38.241***
PRI	8.767	-3.829	5.838	-14.745	-17.683	-13.226
GEPU	10.075***	11.478***	10.884***	11.017***	10.774***	10.509***
INFECT	-.02	-.093*	-.02	.064	.028	-.004
COVID		14.806***				9.82***
RUWAR			-1.779**			2.668***
MICA				-14.321***		-10.672***
GWAR					-12.291***	-.238
Intercept	-279.185***	-301.976***	-280.332***	-231.026***	-252.765***	-256.181***
T	2069	2069	2069	2069	2069	2069
R-squared	.35	.429	.352	.408	.375	.444

Table 3.20: Robust OLS Regression Estimates of Global Events on Ripple Net Spillovers Contribution. This table reports robust OLS estimates of the impact of global risk factors and events on Ripple's net spillovers contribution, using four different risk measures: PRV (Price Range-based Volatility), GV (GARCH Volatility), IVOL1F (1-Factor Idiosyncratic Volatility), and IVOL3F (3-Factor Idiosyncratic Volatility). Model Specifications: (1) Baseline model including all risk factors, (2) Baseline model plus COVID-19 dummy, (3) Baseline model plus Russia-Ukraine War dummy, (4) Baseline model plus MiCA regulation dummy, (5) Baseline model plus Gaza War dummy, (6) Full model including all risk factors and event dummies, VIX: CBOE Volatility Index expressed in natural logarithm. WUI: World Uncertainty Index expressed in natural logarithm. GPR: Geopolitical Risk Index expressed in natural logarithm. TRI: Transition Risk Index. PRI: Physical Risk Index. GEPU: Global Economic Policy Uncertainty Index expressed in natural logarithm. INFECT: Infectious Disease EMV Tracker. Robust standard errors are used in all regressions. Dummy variables: COVID: COVID-19 pandemic period (March 11, 2020 - May 5, 2023), RUWAR: Russia-Ukraine War period (from February 24, 2022), MICA: Period following MiCA regulation implementation (from April 20, 2023), GWAR: Gaza War period (from October 7, 2023). *** p<.01, ** p<.05, * p<.1. T represents the number of observations.

Table 3.21: Events Economic Significance Analysis

Cryptocurrency	VIX	WUI	GPR	TRI	PRI	GEPU	INFECT	Top 3 Factors
Binance								
PRV	2.20	0.85	-0.08	0.24	0.36	0.97	0.48	VIX > GEPU > WUI
GV	1.96	1.68	-0.05	-0.20	0.36	0.75	-0.13	VIX > WUI > GEPU
IVOL1F	-1.17	-1.32	-0.51	0.63	0.82	-1.81	-1.41	GEPU > INFECT > WUI
IVOL3F	0.95	-2.57	-0.12	-0.67	0.27	3.34	-0.52	GEPU > WUI > VIX
Bitcoin								
PRV	0.50	-0.01	-0.55	-0.16	-0.35	-2.94	0.02	GEPU > GPR > PRI
GV	-0.18	1.55	-0.76	-0.10	-0.11	-0.79	-0.85	WUI > INFECT > GEPU
IVOL1F	-0.89	-4.03	1.35	1.16	0.49	-0.16	-1.17	WUI > INFECT > VIX
IVOL3F	-3.49	-2.44	3.36	0.52	0.94	1.12	-0.47	VIX > GPR > WUI
Cardano								
PRV	-1.99	0.91	0.51	0.21	0.18	0.36	-0.41	VIX > WUI > GPR
GV	-1.78	0.47	-0.32	0.24	-0.09	2.30	0.40	GEPU > VIX > WUI
IVOL1F	0.81	0.81	-1.00	0.48	0.20	2.65	0.69	GEPU > GPR > VIX
IVOL3F	0.98	1.20	0.12	0.16	0.05	-4.16	1.77	GEPU > INFECT > WUI
Dogecoin								
PRV	1.90	-3.34	-0.09	-0.14	-0.34	0.12	0.20	WUI > VIX > PRI
GV	1.01	-2.32	0.42	0.05	-0.26	-4.02	1.23	GEPU > WUI > INFECT
IVOL1F	6.71	-0.16	0.55	0.19	-0.31	-6.81	-0.45	GEPU > VIX > GEPU
IVOL3F	2.08	-3.30	-0.99	0.60	-0.74	-4.19	-2.08	GEPU > WUI > VIX
Ethereum								
PRV	-2.95	0.41	-0.41	-0.16	0.06	-0.09	-0.19	VIX > WUI > GPR
GV	-1.96	0.78	-0.12	0.30	0.12	1.49	0.36	VIX > GEPU > WUI
IVOL1F	-1.59	-3.33	-2.09	0.86	0.30	-1.55	-0.89	WUI > GPR > VIX
IVOL3F	-5.45	-1.19	-1.51	0.58	-0.31	3.38	3.18	VIX > GEPU > INFECT
Monero								
PRV	-1.52	0.74	-0.13	0.54	0.37	-0.97	-0.83	VIX > GEPU > INFECT
GV	-2.14	2.49	-0.37	-0.14	-0.09	-2.47	-1.40	WUI > GEPU > VIX
IVOL1F	-0.64	-0.04	-1.14	-0.53	-0.42	1.97	1.18	GEPU > INFECT > GPR
IVOL3F	3.38	0.44	-0.51	-0.85	0.45	2.14	-1.62	VIX > GEPU > INFECT
TRON								
PRV	0.50	-0.01	-0.55	-0.16	-0.35	-2.94	0.02	GEPU > GPR > PRI
GV	-0.18	1.55	-0.76	-0.10	-0.11	-0.79	-0.85	WUI > INFECT > GEPU
IVOL1F	-0.89	-4.03	1.35	1.16	0.49	-0.16	-1.17	WUI > INFECT > VIX
IVOL3F	-0.26	0.77	0.33	0.61	-0.36	-3.64	-0.20	GEPU > WUI > TRI
Ripple								
PRV	2.07	-0.27	-0.04	-0.37	-0.47	2.40	0.47	GEPU > VIX > INFECT
GV	0.15	-1.79	0.75	-0.25	-0.06	3.18	0.57	GEPU > WUI > GPR
IVOL1F	-0.87	6.46	-0.13	-1.35	-0.57	4.40	-0.08	WUI > GEPU > PRI
IVOL3F	1.82	7.11	-0.68	-0.96	-0.32	2.01	-0.05	WUI > VIX > GEPU

Summary Rankings by Economic Significance

Cryptocurrency	PRV Risk	GV Risk	IVOL1F Risk	IVOL3F Risk
Binance	VIX	VIX	GEPU	GEPU
Bitcoin	GEPU	WUI	WUI	VIX
Cardano	VIX	GEPU	GEPU	GEPU
Dogecoin	WUI	GEPU	GEPU	GEPU
Ethereum	VIX	VIX	WUI	VIX
Monero	VIX	WUI	GEPU	VIX
TRON	GEPU	WUI	WUI	GEPU
Ripple	GEPU	GEPU	WUI	WUI

Notes: Economic significance calculated as coefficient × standard deviation of explanatory variable using Equation (20). All results are based exclusively on Model 6 (full model specification) from the robust OLS regressions reported in Tables 13-20, which includes all global risk factors and event dummy variables simultaneously. PRV = Parkinson Range-Based Volatility; GV = GARCH(1,1) Volatility; IVOL1F = 1-Factor Idiosyncratic Volatility; IVOL3F = 3-Factor Idiosyncratic Volatility. Positive values indicate positive economic impact; negative values indicate negative economic impact. The magnitude represents the expected change in net spillovers from a one-standard-deviation change in the risk factor, holding all other variables constant

Table 3.22: Staggered Difference-in-Differences Estimates Using the Interaction Weighted (IW) Estimator – COVID-19 Pandemic Declaration

	Coef.	Std.Err.	t
covid_pre1	-12.939	2.985	-4.340
covid_pre2	-13.051	2.974	-4.390
covid_pre3	-14.112	2.607	-5.410
covid_pre4	-14.642	2.617	-5.600
covid_pre5	-14.855	2.612	-5.690
covid_pre6	-14.869	2.621	-5.670
covid_pre7	-15.049	2.600	-5.790
covid_pre8	-14.297	2.690	-5.320
covid_pre9	-14.281	2.676	-5.340
covid_pre10	-13.051	2.709	-4.820
covid_0	-12.945	2.979	-4.350
covid_post1	-6.067	2.134	-2.840
covid_post2	-5.833	2.366	-2.460
covid_post3	-5.831	2.366	-2.460
covid_post4	-5.834	2.370	-2.460
covid_post5	-5.899	2.388	-2.470
covid_post6	-5.886	2.388	-2.460
covid_post7	-5.887	2.387	-2.470
covid_post8	-5.891	2.398	-2.460
covid_post9	-5.789	2.400	-2.410
covid_post10	-5.797	2.398	-2.420
Sample Size		17,072	
R-squared		0.4776	
Covariates		Yes	

Notes: This table presents results from staggered difference-in-differences estimation for the COVID-19 pandemic declaration (11 March 2020), using an event window of ten days before and after the event date. The outcome variable is the net spillover contribution (NS) for each cryptocurrency, as defined in Equation (20), measuring the difference between the total volatility transmitted to and received from all other cryptocurrencies in the network at each point in time. Estimates are obtained using the Interaction Weighted (IW) estimator of Sun and Abraham (2021), which accounts for heterogeneous treatment effects across time and units and is robust to staggered treatment timing. Rows labelled covid_pre1 through covid_pre10 report dynamic effects for the ten days preceding the event and serve as placebo tests of the parallel trends assumption. covid_0 reports the contemporaneous effect on the event date. Rows labelled covid_post1 through covid_post10 report post-treatment dynamic effects for the ten days following the event. All specifications include global risk factor covariates as defined in Equation (18). Standard errors and t-statistics are reported for each estimate.

Table 3.23: Staggered Difference-in-Differences Estimates Using the Interaction Weighted (IW) Estimator – Russia-Ukraine War

	Coef.	Std.Err.	t
ru_pre1	-11.598	2.291	-5.060
ru_pre2	-11.650	2.318	-5.030
ru_pre3	-11.637	2.313	-5.030
ru_pre4	-11.573	2.309	-5.010
ru_pre5	-11.573	2.309	-5.010
ru_pre6	-11.556	2.320	-4.980
ru_pre7	-11.511	2.317	-4.970
ru_pre8	-11.490	2.318	-4.960
ru_pre9	-11.518	2.323	-4.960
ru_pre10	-11.555	2.315	-4.990
ru_0	-11.830	2.245	-5.270
ru_post1	-11.830	2.228	-5.310
ru_post2	-11.844	2.227	-5.320
ru_post3	-11.901	2.236	-5.320
ru_post4	-12.419	2.171	-5.720
ru_post5	-12.394	2.169	-5.720
ru_post6	-12.383	2.165	-5.720
ru_post7	-12.414	2.165	-5.730
ru_post8	-12.481	2.088	-5.980
ru_post9	-12.482	2.084	-5.990
ru_post10	-12.604	2.074	-6.080
Sample Size		17,072	
R-squared		0.4771	
Covariates		Yes	

Notes: This table presents results from staggered difference-in-differences estimation for the Russia-Ukraine War onset (24 February 2022), using an event window of ten days before and after the event date. The outcome variable is the net spillover contribution (NS) for each cryptocurrency, as defined in Equation (20), measuring the difference between the total volatility transmitted to and received from all other cryptocurrencies in the network at each point in time. Estimates are obtained using the Interaction Weighted (IW) estimator of Sun and Abraham (2021), which accounts for heterogeneous treatment effects across time and units and is robust to staggered treatment timing. Rows labelled ru_pre1 through ru_pre10 report dynamic effects for the ten days preceding the event and serve as placebo tests of the parallel trends assumption. ru_0 reports the contemporaneous effect on the event date. Rows labelled ru_post1 through ru_post10 report post-treatment dynamic effects for the ten days following the event. All specifications include global risk factor covariates as defined in Equation (18). Standard errors and t-statistics are reported for each estimate.

Table 3.24: Staggered Difference-in-Differences Estimates Using the Interaction Weighted (IW) Estimator – MiCA Regulation

	Coef.	Std.Err.	t
mica_pre1	-15.118	2.915	-5.190
mica_pre2	-15.039	2.896	-5.190
mica_pre3	-15.356	2.957	-5.190
mica_pre4	-15.183	2.903	-5.230
mica_pre5	-15.419	2.891	-5.330
mica_pre6	-15.194	2.837	-5.360
mica_pre7	-15.497	2.909	-5.330
mica_pre8	-14.923	2.845	-5.250
mica_pre9	-14.986	2.863	-5.230
mica_pre10	-15.009	2.843	-5.280
mica_0	-15.164	2.939	-5.160
mica_post1	-15.040	2.867	-5.250
mica_post2	-14.930	2.869	-5.200
mica_post3	-15.009	2.885	-5.200
mica_post4	-14.930	2.864	-5.210
mica_post5	-14.802	2.932	-5.050
mica_post6	-15.295	2.970	-5.150
mica_post7	-14.343	2.984	-4.810
mica_post8	-14.757	2.928	-5.040
mica_post9	-14.647	2.996	-4.890
mica_post10	-14.239	2.995	-4.750
Sample Size		17,072	
R-squared		0.4792	
Covariates		Yes	

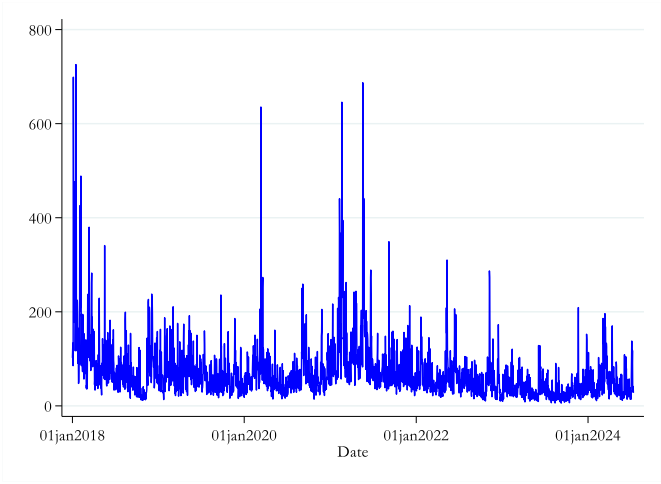
Notes: This table presents results from staggered difference-in-differences estimation for the MiCA framework approval (20 April 2023), using an event window of ten days before and after the event date. The outcome variable is the net spillover contribution (NS) for each cryptocurrency, as defined in Equation (20), measuring the difference between the total volatility transmitted to and received from all other cryptocurrencies in the network at each point in time. Estimates are obtained using the Interaction Weighted (IW) estimator of Sun and Abraham (2021), which accounts for heterogeneous treatment effects across time and units and is robust to staggered treatment timing. Rows labelled mica_pre1 through mica_pre10 report dynamic effects for the ten days preceding the event and serve as placebo tests of the parallel trends assumption. mica_0 reports the contemporaneous effect on the event date. Rows labelled mica_post1 through mica_post10 report post-treatment dynamic effects for the ten days following the event. All specifications include global risk factor covariates as defined in Equation (18). Standard errors and t-statistics are reported for each estimate.

Table 3.25: Staggered Difference-in-Differences Estimates Using the Interaction Weighted (IW) Estimator – Gaza War

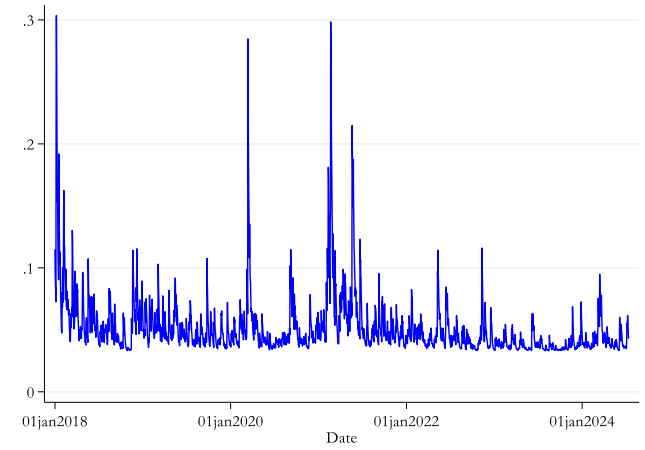
	Coef.	Std.Err.	t
gaza_pre1	-2.281	2.000	-1.140
gaza_pre2	-2.329	2.015	-1.160
gaza_pre3	-2.328	2.012	-1.160
gaza_pre4	-2.589	2.027	-1.280
gaza_pre5	-3.226	1.996	-1.620
gaza_pre6	-3.247	1.975	-1.640
gaza_pre7	0.077	2.023	0.040
gaza_pre8	0.186	2.022	0.090
gaza_pre9	0.086	1.991	0.040
gaza_pre10	0.071	1.979	0.040
gaza_0	-2.329	2.023	-1.150
gaza_post1	-2.333	2.036	-1.150
gaza_post2	-2.362	2.034	-1.160
gaza_post3	-2.356	2.037	-1.160
gaza_post4	-2.240	2.107	-1.060
gaza_post5	-2.257	2.111	-1.070
gaza_post6	-2.247	2.122	-1.060
gaza_post7	-2.280	2.125	-1.070
gaza_post8	-2.271	2.135	-1.060
gaza_post9	-2.507	2.177	-1.150
gaza_post10	-2.495	2.178	-1.150
Sample Size		17,072	
R-squared		0.4757	
Covariates		Yes	

Notes: This table presents results from staggered difference-in-differences estimation for the Gaza War outbreak (7 October 2023), using an event window of ten days before and after the event date. The outcome variable is the net spillover contribution (NS) for each cryptocurrency, as defined in Equation (20), measuring the difference between the total volatility transmitted to and received from all other cryptocurrencies in the network at each point in time. Estimates are obtained using the Interaction Weighted (IW) estimator of Sun and Abraham (2021), which accounts for heterogeneous treatment effects across time and units and is robust to staggered treatment timing. Rows labelled *gaza_pre1* through *gaza_pre10* report dynamic effects for the ten days preceding the event and serve as placebo tests of the parallel trends assumption. *gaza_0* reports the contemporaneous effect on the event date. Rows labelled *gaza_post1* through *gaza_post10* report post-treatment dynamic effects for the ten days following the event. All specifications include global risk factor covariates as defined in Equation (18). Standard errors and t-statistics are reported for each estimate.

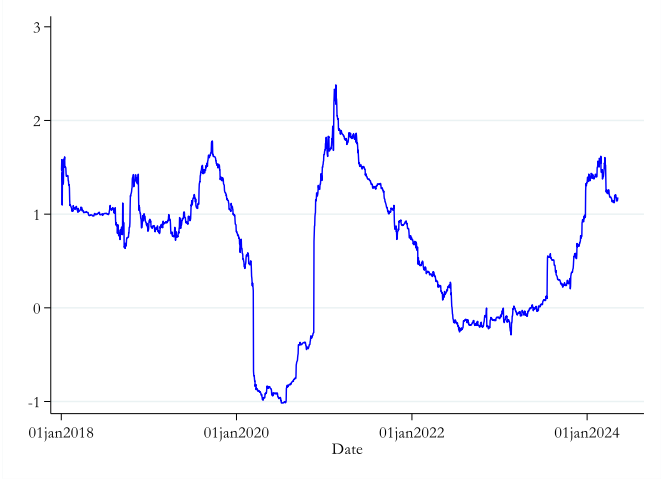
Figures



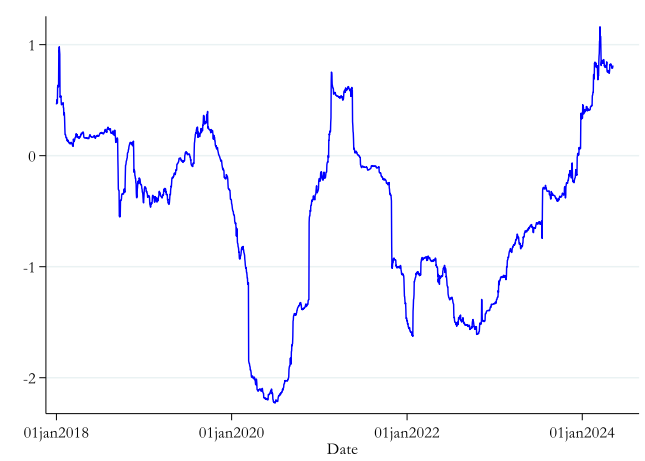
Parkinson Range-Based Volatility (Annualised)



GARCH (1,1) Volatility



1 Factor Idiosyncratic Risk



3 Factor Idiosyncratic Risk

Figure 3.1: Binance Risk Measures

This figure plots the daily time series of four volatility measures for Binance Coin over the sample period January 2018 to July 2024. The upper two panels display price-based measures: Parkinson Range-Based Volatility (PRV, annualised, upper left) and GARCH(1,1) Volatility (GV, upper right). The lower two panels display idiosyncratic volatility

measures: 1-Factor Idiosyncratic Volatility (IVOL1F, lower left) and 3-Factor Idiosyncratic Volatility (IVOL3F, lower right), estimated as residuals from one- and three-factor cryptocurrency asset pricing models following Liu et al. (2022). The x-axis represents the date and the y-axis represents the value of the respective measure.

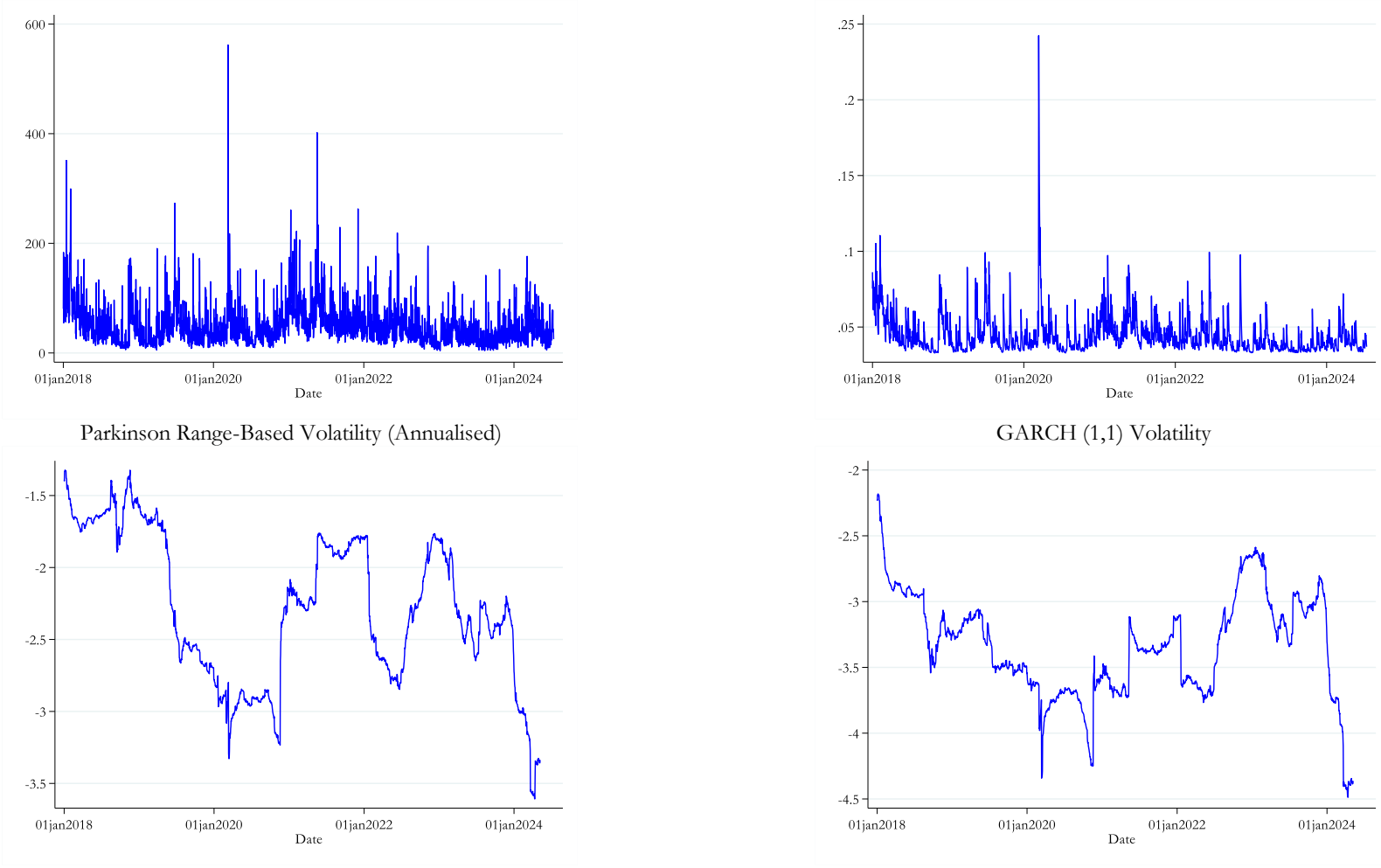


Figure 3.2: Bitcoin Risk Measures

This figure plots the daily time series of four volatility measures for Bitcoin over the sample period January 2018 to July 2024. The upper two panels display price-based measures: Parkinson Range-Based Volatility (PRV, annualised, upper left) and GARCH(1,1) Volatility (GV, upper right). The lower two panels display idiosyncratic volatility measures: 1-Factor Idiosyncratic Volatility (IVOL1F, lower left) and 3-Factor Idiosyncratic Volatility (IVOL3F, lower right), estimated as residuals from one- and three-factor cryptocurrency asset pricing models following Liu et al. (2022). The x-axis represents the date and the y-axis represents the value of the respective measure.

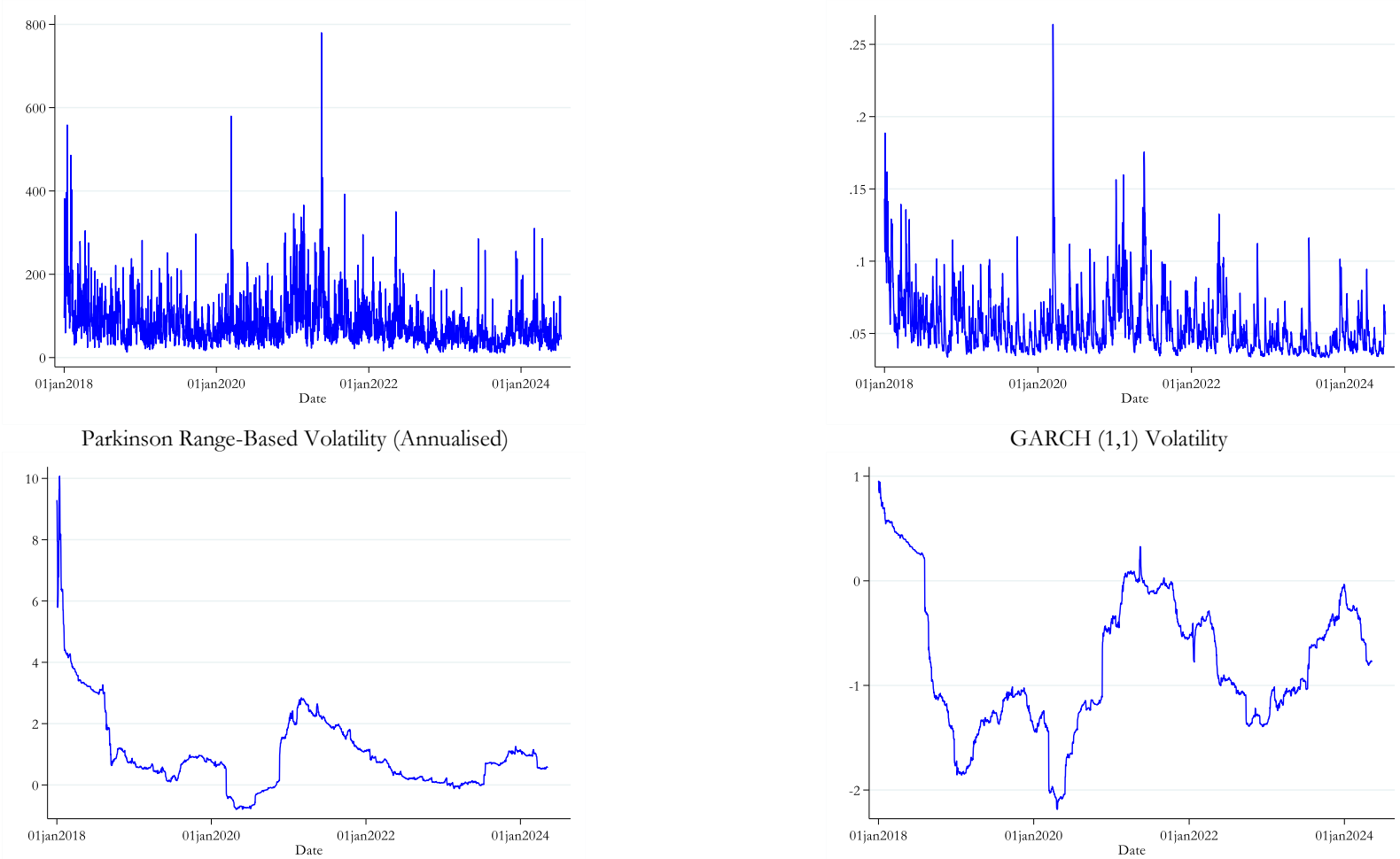
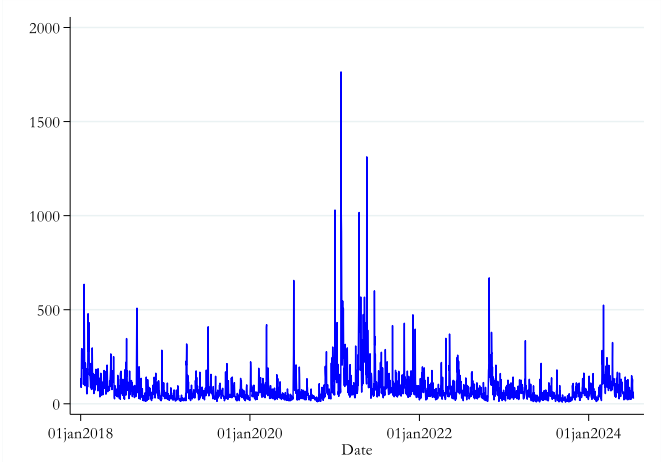
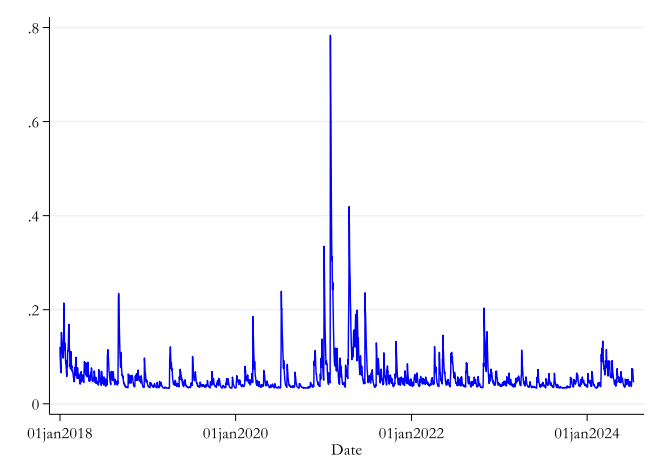


Figure 3.3: Cardano Risk Measures

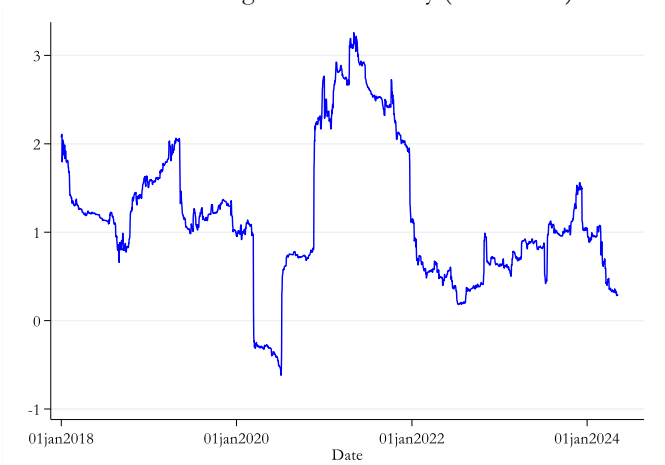
This figure plots the daily time series of four volatility measures for Cardano over the sample period January 2018 to July 2024. The upper two panels display price-based measures: Parkinson Range-Based Volatility (PRV, annualised, upper left) and GARCH(1,1) Volatility (GV, upper right). The lower two panels display idiosyncratic volatility measures: 1-Factor Idiosyncratic Volatility (IVOL1F, lower left) and 3-Factor Idiosyncratic Volatility (IVOL3F, lower right), estimated as residuals from one- and three-factor cryptocurrency asset pricing models following Liu et al. (2022). The x-axis represents the date and the y-axis represents the value of the respective measure.



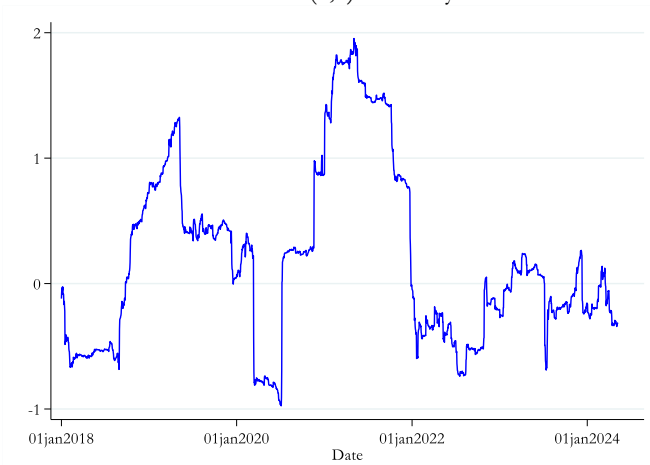
Parkinson Range-Based Volatility (Annualised)



GARCH (1,1) Volatility



1 Factor Idiosyncratic Risk



3 Factor Idiosyncratic Risk

Figure 3.4: Dogecoin Risk Measures

This figure plots the daily time series of four volatility measures for Dogecoin over the sample period January 2018 to July 2024. The upper two panels display price-based measures: Parkinson Range-Based Volatility (PRV, annualised, upper left) and GARCH(1,1) Volatility (GV, upper right). The lower two panels display idiosyncratic volatility measures: 1-Factor Idiosyncratic Volatility (IVOL1F, lower left) and 3-Factor Idiosyncratic Volatility (IVOL3F, lower right), estimated as residuals from one- and three-factor cryptocurrency asset pricing models following Liu et al. (2022). The x-axis represents the date and the y-axis represents the value of the respective measure.

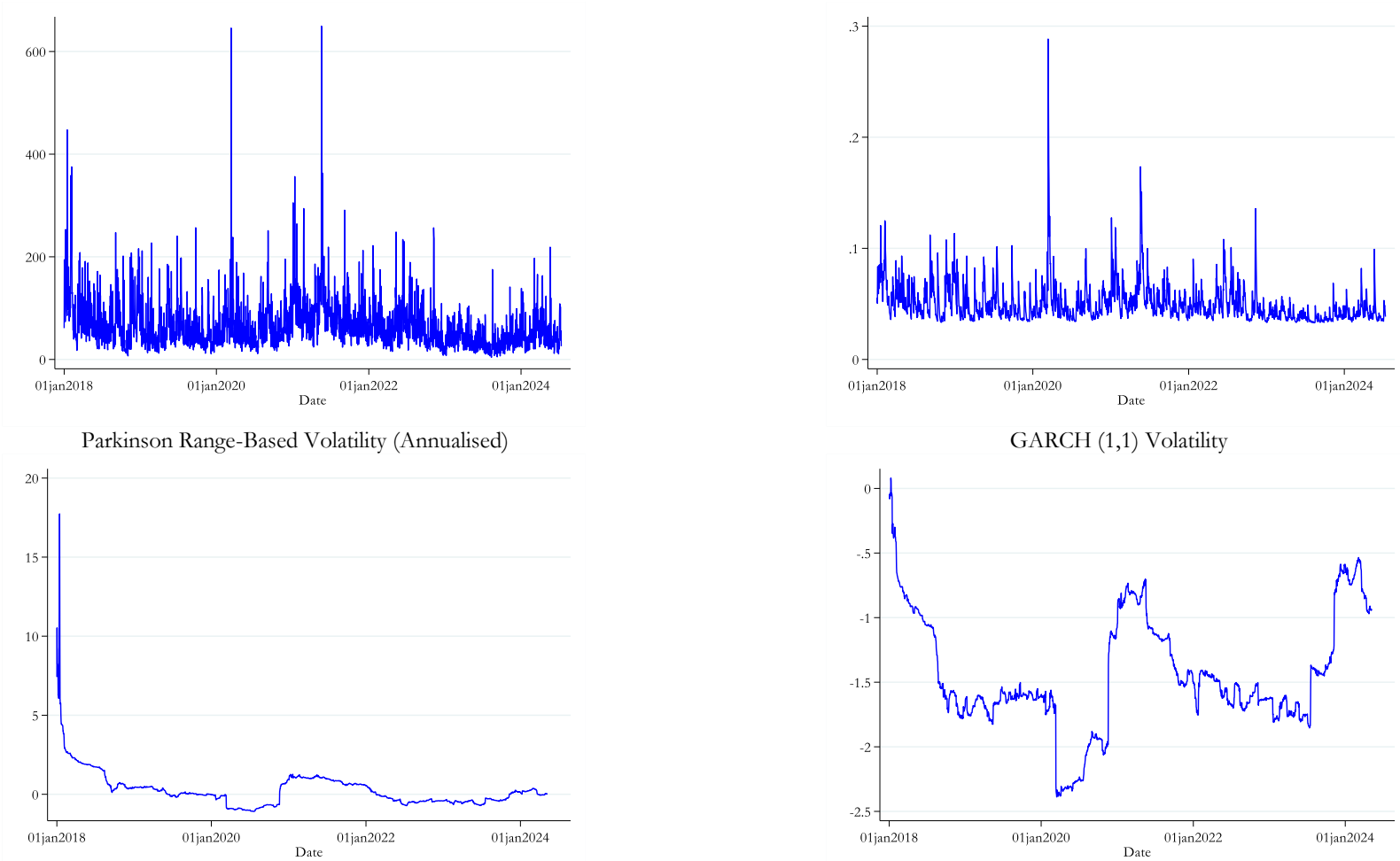
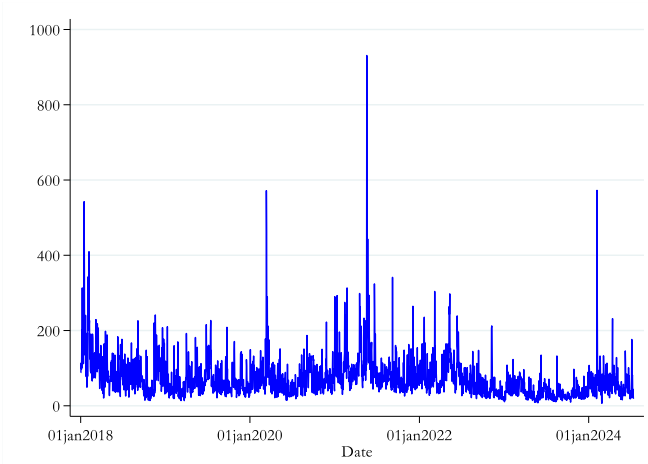
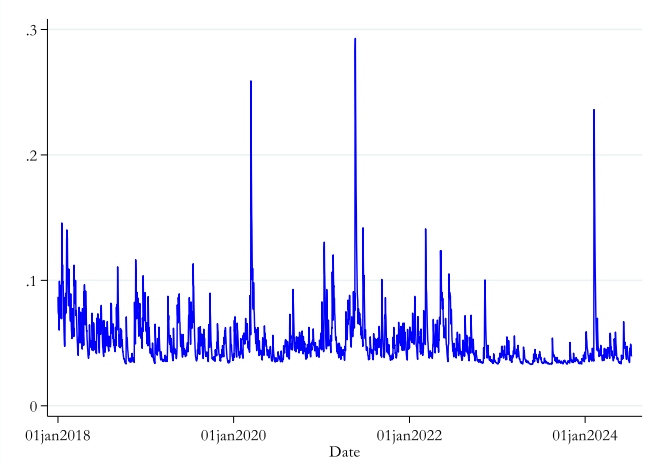


Figure 3.5: Ethereum Risk Measures

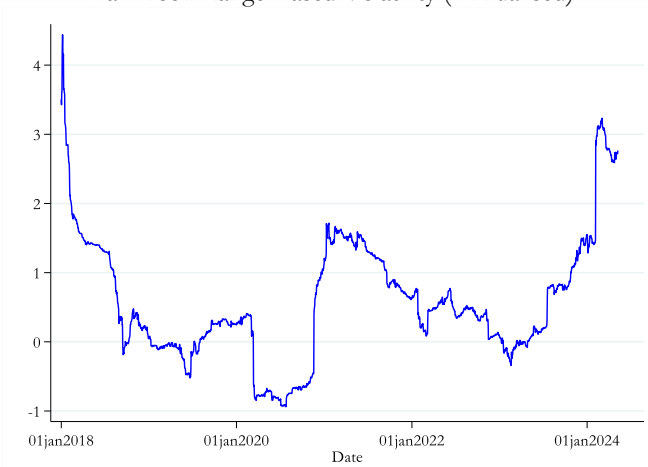
This figure plots the daily time series of four volatility measures for Ethereum over the sample period January 2018 to July 2024. The upper two panels display price-based measures: Parkinson Range-Based Volatility (PRV, annualised, upper left) and GARCH(1,1) Volatility (GV, upper right). The lower two panels display idiosyncratic volatility measures: 1-Factor Idiosyncratic Volatility (IVOL1F, lower left) and 3-Factor Idiosyncratic Volatility (IVOL3F, lower right), estimated as residuals from one- and three-factor cryptocurrency asset pricing models following Liu et al. (2022). The x-axis represents the date and the y-axis represents the value of the respective measure.



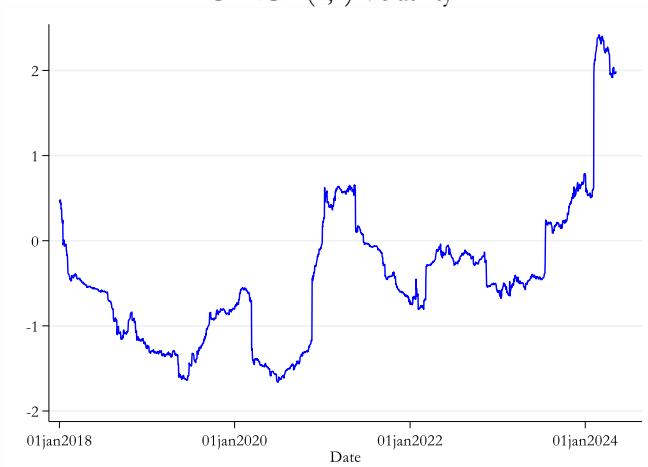
Parkinson Range-Based Volatility (Annualised)



GARCH (1,1) Volatility



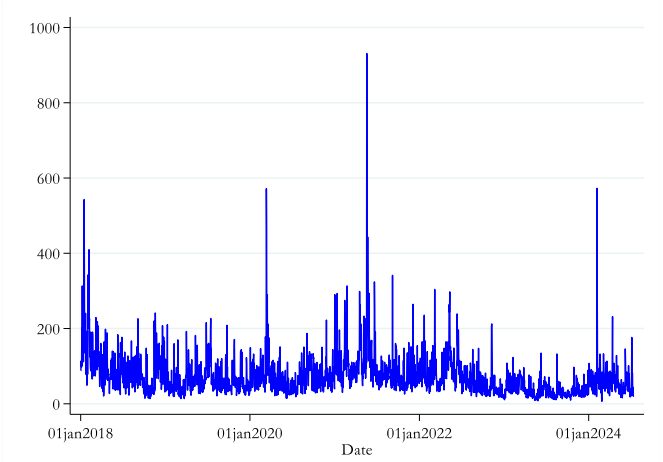
1 Factor Idiosyncratic Risk



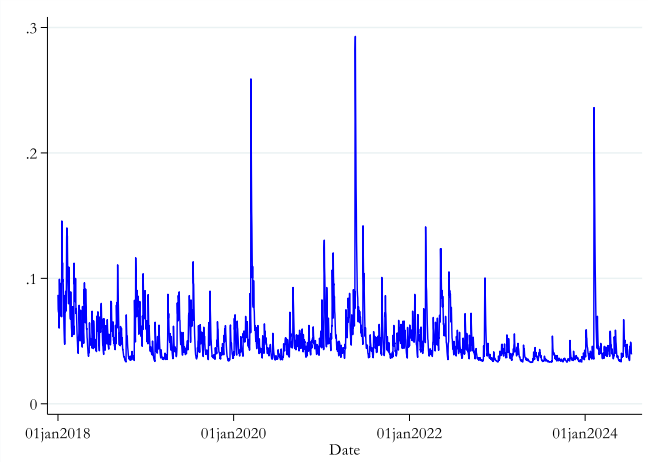
3 Factor Idiosyncratic Risk

Figure 3.6: Monero Risk Measures

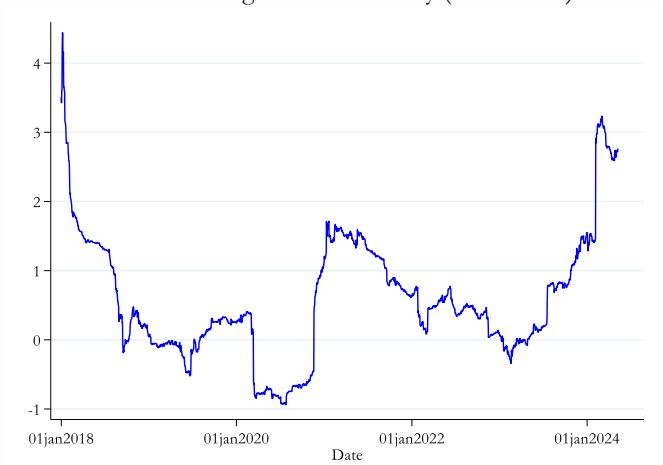
This figure plots the daily time series of four volatility measures for Monero over the sample period January 2018 to July 2024. The upper two panels display price-based measures: Parkinson Range-Based Volatility (PRV, annualised, upper left) and GARCH(1,1) Volatility (GV, upper right). The lower two panels display idiosyncratic volatility measures: 1-Factor Idiosyncratic Volatility (IVOL1F, lower left) and 3-Factor Idiosyncratic Volatility (IVOL3F, lower right), estimated as residuals from one- and three-factor cryptocurrency asset pricing models following Liu et al. (2022). The x-axis represents the date and the y-axis represents the value of the respective measure.



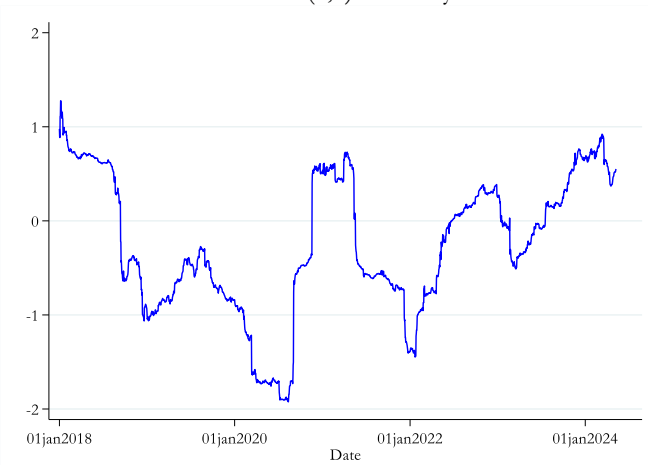
Parkinson Range-Based Volatility (Annualised)



GARCH (1,1) Volatility



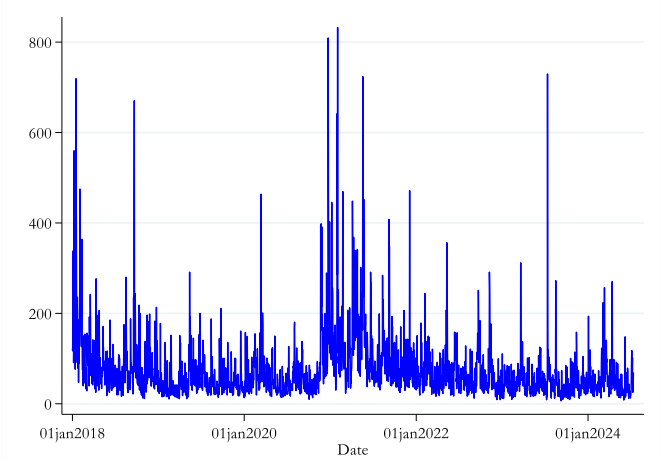
1 Factor Idiosyncratic Risk



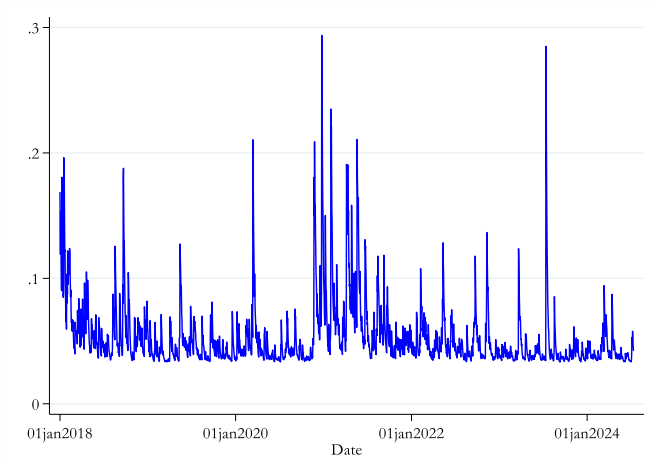
3 Factor Idiosyncratic Risk

Figure 3.7: TRON Risk Measures

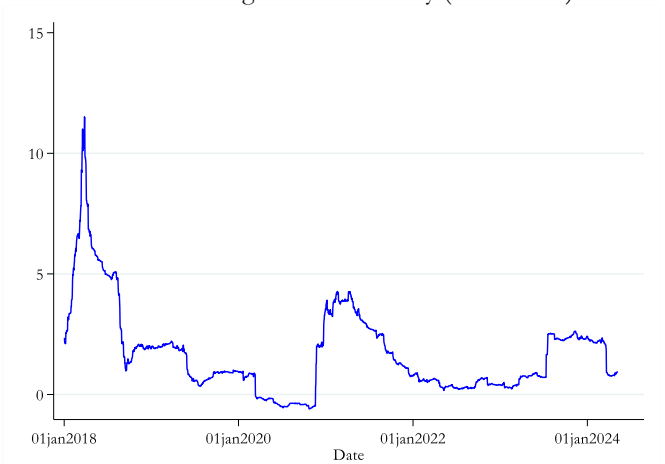
This figure plots the daily time series of four volatility measures for TRON over the sample period January 2018 to July 2024. The upper two panels display price-based measures: Parkinson Range-Based Volatility (PRV, annualised, upper left) and GARCH(1,1) Volatility (GV, upper right). The lower two panels display idiosyncratic volatility measures: 1-Factor Idiosyncratic Volatility (IVOL1F, lower left) and 3-Factor Idiosyncratic Volatility (IVOL3F, lower right), estimated as residuals from one- and three-factor cryptocurrency asset pricing models following Liu et al. (2022). The x-axis represents the date and the y-axis represents the value of the respective measure.



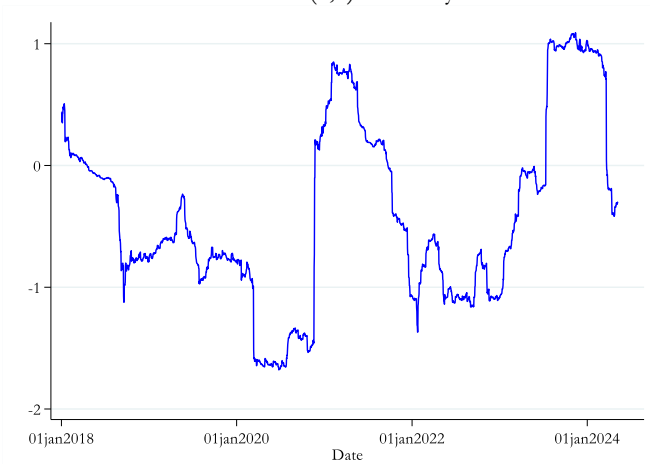
Parkinson Range-Based Volatility (Annualised)



GARCH (1,1) Volatility



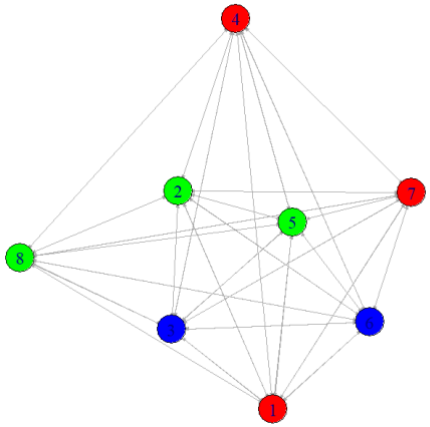
1 Factor Idiosyncratic Risk



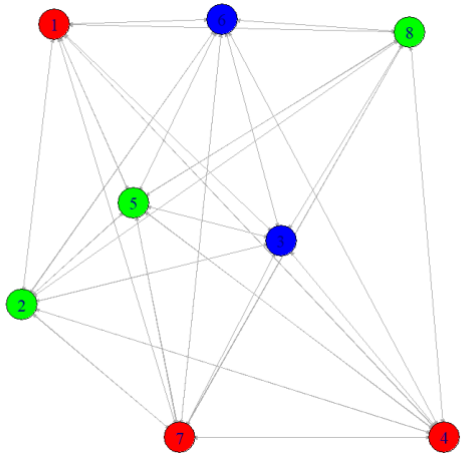
3 Factor Idiosyncratic Risk

Figure 3.8: Ripple Risk Measures

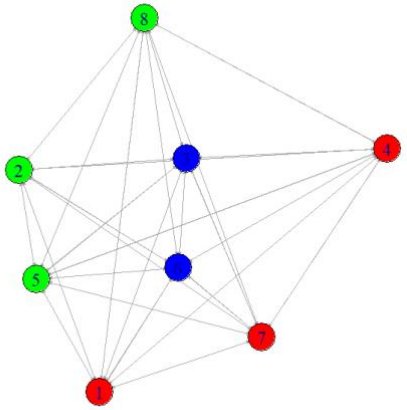
This figure plots the daily time series of four volatility measures for Ripple over the sample period January 2018 to July 2024. The upper two panels display price-based measures: Parkinson Range-Based Volatility (PRV, annualised, upper left) and GARCH(1,1) Volatility (GV, upper right). The lower two panels display idiosyncratic volatility measures: 1-Factor Idiosyncratic Volatility (IVOL1F, lower left) and 3-Factor Idiosyncratic Volatility (IVOL3F, lower right), estimated as residuals from one- and three-factor cryptocurrency asset pricing models following Liu et al. (2022). The x-axis represents the date and the y-axis represents the value of the respective measure.



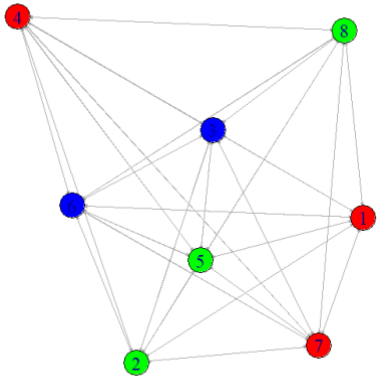
Parkinson Range-Based Volatility



GARCH (1,1) Volatility



1 Factor Idiosyncratic Risk



3 Factor Idiosyncratic Risk

(1) Binance, (2) Bitcoin, (3) Cardano, (4) Dogecoin, (5) Ethereum, (6) Monero, (7) TRON, (8) Ripple.

Figure 3.9: Network Representation of Estimated Connectedness

Each panel displays the network representation of estimated pairwise volatility spillovers for the respective risk measure: PRV, GV, IVOL1F, and IVOL3F. Nodes represent the eight cryptocurrencies; edges represent significant pairwise spillover transmissions constructed from Tables 3.7–3.10 using the Net Elastic Estimator. Node colour indicates net role: green nodes are net transmitters, red nodes are net receivers, and blue nodes are approximately neutral. Denser connectivity in the PRV and GV panels reflects higher total connectedness relative to the sparser IVOL1F and IVOL3F panels. (1) Binance, (2) Bitcoin, (3) Cardano, (4) Dogecoin, (5) Ethereum, (6) Monero, (7) TRON, (8) Ripple.

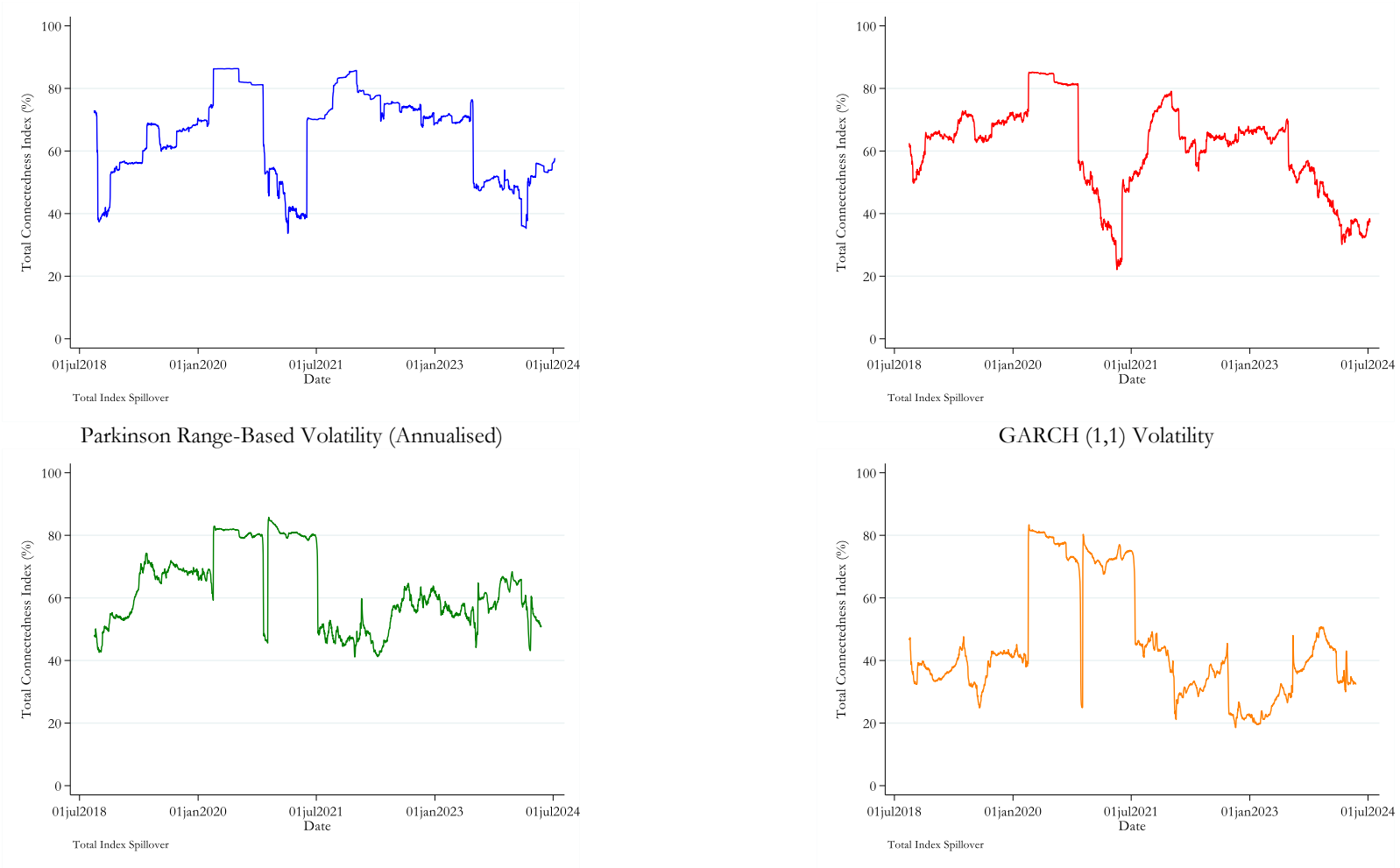


Figure 3.10: Total Spillover Index

Each panel displays the time-varying Total Connectedness Index (TCI) for the respective volatility measure, PRV (blue), GV (red), IVOL1F (green), and IVOL3F (orange), over the sample period January 2018 to July 2024. The TCI is derived from the Diebold-Yilmaz spillover framework and measures the share of forecast error variance attributable to cross-asset spillovers at each point in time. Price-based measures (PRV and GV) fluctuate in a higher range than idiosyncratic measures (IVOL1F and IVOL3F), consistent with the static spillover results in Tables 3.7–3.10.

Appendix 3:A The Staggered Difference-in-Differences Framework

This chapter examines four external shocks that occur at different dates between 2018 and 2024: the COVID-19 pandemic, the Russia-Ukraine war, the introduction of MiCA, and the Gaza war. Because these shocks arrive at different dates, the analysis uses a staggered difference-in-differences framework that takes the timing of each event into account and lets the response differ across cryptocurrencies and across the event window. This appendix sets out that framework and the estimator used in Section 3.6.2.

The starting point is the standard two-way fixed effects estimator, written as

$$NS_{i,t} = \alpha_i + \lambda_t + \beta D_{i,t} + \varepsilon_{i,t} \quad (3.A.1)$$

where $\alpha_i$is a unit fixed effect, λ_t a time fixed effect, $D_{i,t}$ an indicator equal to one once unit i is treated, and β the coefficient of interest. Under staggered timing, and when treatment effects differ across units and over time, β is a weighted average of the underlying effects rather than a single average effect, and units treated earlier can act as controls for units treated later. Baker et al. (2022) document this property in applied finance settings. This is why the chapter uses a heterogeneity-robust estimator instead.

That estimator is the interaction-weighted estimator of Sun and Abraham (2021). It estimates treatment effects separately for each cohort and each point in event time, then combines them using weights equal to each cohort's share of the sample. The resulting estimates stay interpretable when treatment effects differ across cohorts and over time, and they do not rely on comparisons between units treated at different times. The chapter uses this estimator for its direct event-time reading.

The framework is applied to each of the four events. The specification, which corresponds to equation (20), is

$$NS_{i,t} = \alpha + \Sigma_{k=-10}^{+10} \beta_k Event_{k,i,t} + \gamma X_{i,t} + \varepsilon_{i,t} \quad (3.A.2)$$

where $NS_{i,t}$ is the net spillover contribution of cryptocurrency i at time t, and $Event_{k,i,t}$ marks

each day in the window of ten days before and after the event date, with $k = 0$ the event day. The coefficients β_k trace the response across the event window. $X_{i,t}$ holds time-varying covariates, including the global risk factors used in the main analysis. Estimation uses the interaction-weighted estimator, and the results for the four events appear in Tables 3.22 to 3.25.

CHAPTER 4

4. Centralised and Decentralised Exchanges Under Regulatory Pressure: Liquidity Evidence Across Three Jurisdictions

4.1 Introduction

Cryptocurrency markets have grown into a broad and highly traded asset class, and with that expansion has come greater demand for oversight, particularly directed at centralised exchanges. The ecosystem has developed two fundamentally different types of trading venues. Centralised exchanges (CEX) rely on identifiable intermediaries, custody arrangements, and concentrated pools of liquidity, and their visible infrastructure has placed them at the centre of regulatory attention. Decentralised exchanges (DEX), part of the broader decentralised finance (DeFi) ecosystem, operate through smart contracts without a central intermediary and have grown in parallel while remaining comparatively outside the scope of many developing regulatory frameworks. This uneven regulatory reach is the starting point for this chapter. The effects of unequal regulation across exchanges are visible in liquidity. It reflects not just whether a market is active but whether participants can trade efficiently, at what cost, and with what price impact, making it a sensitive indicator of how regulatory pressure reshapes market conditions across venue types (Huang, 2024; Bianchi et al., 2022). While prior research has documented how regulatory shocks affect aggregate crypto market quality, the venue-specific dimension of that response remains largely unexamined (Griffith and Clancey-Shang, 2023; Aspris et al., 2021). We examine three regulatory announcements across three distinct

jurisdictions, each placing a different form of burden on centralised exchange infrastructure and ask whether that pressure produces measurable responses in DEX liquidity and trading activity.

This chapter is motivated by the idea that centralised and decentralised crypto markets are interconnected rather than isolated. DEXs are a core part of crypto-market infrastructure because they provide a trading and liquidity layer for blockchain-based assets without relying on centralised intermediaries. As regulatory scrutiny increasingly targets centralised exchanges, it is therefore important to examine whether decentralised market liquidity also changes, even when DEXs are not the direct object of regulation. The three events examined here differ deliberately in regulatory design, allowing us to observe whether that association holds across events that differ in regulatory design and jurisdiction, rather than assuming it applies uniformly. The first is the European policy shock, introduced through the Markets in Crypto Assets (MiCA) proposal announced in September 2020, which marked the first major attempt to establish a comprehensive regulatory framework for crypto markets within a large jurisdiction. MiCA governs crypto assets with identifiable issuers and Crypto Asset Service Providers, requiring authorisation, capital requirements, and compliance with investor protection obligations, while services provided in a fully decentralised manner were excluded from its initial scope.

The second is the Chinese policy shock announced in May 2021, which prohibited cryptocurrency trading and mining outright, effectively shutting down centralised exchange activity within Chinese jurisdiction, while decentralised protocols operating beyond direct territorial reach remained comparatively less exposed (Griffith and Clancey-Shang, 2023). The third is the American policy shock, defined by the GENIUS Act first announced in February 2025, which brings payment stablecoins into the formal regulatory perimeter by extending

federal supervision to stablecoin issuers and providing legal standing, consumer protections, and insolvency priority rights. Unlike the first two events, this measure does not restrict centralised crypto activity but integrates it further into the formal financial system. MiCA treats stablecoins as crypto assets within the crypto ecosystem, requiring issuers to obtain authorisation, maintain reserves, and comply with crypto-specific rules. The GENIUS Act takes a different approach, treating stablecoin issuers more like regulated financial institutions subject to federal supervision, capital requirements, and insolvency protections, effectively pulling stablecoins out of the crypto-only regulatory perimeter and into the broader federal financial architecture. Both frameworks impose regulatory burden on a core component of centralised exchange infrastructure, but through different institutional logics and with different implications for how that burden is felt across the ecosystem. Stablecoins are directly implicated in both MiCA and the GENIUS Act but are excluded from the token sample because their liquidity is governed by peg maintenance, redemption mechanisms, and fiat settlement infrastructure rather than the same price-discovery process that governs CEX-linked and DEX-linked tokens (Liang, 2026; Dunbar et al., 2026). The chapter therefore treats them as part of the infrastructure through which regulatory shocks transmit rather than as outcome assets in the comparison.

Understanding how regulatory pressure on centralised infrastructure is associated with decentralised exchange activity matters beyond the immediate empirical setting. Regulatory decisions affecting CEXs are not contained within the centralised ecosystem. Prior evidence shows that regulatory pressure reshapes where activity flows rather than simply reducing it, and that participants respond to changes in the relative accessibility and attractiveness of different venues (Cong et al., 2023; Foley et al., 2019). At the same time, DEX participation is not driven by a fixed preference for decentralisation but by incentives, institutional conditions, and the financial environment in which participants operate (Cornelli et al., 2025; Nguyen and

Nguyen, 2024). This means that the response of decentralised venues to regulatory pressure on centralised infrastructure is genuinely uncertain, and for regulators, understanding whether oversight of CEX infrastructure is associated with shifts toward effectively unregulated decentralised venues has direct implications for how regulatory frameworks are designed and where their boundaries are drawn. For market participants, it speaks to whether decentralised venues offer a genuine alternative under regulatory pressure or whether the two ecosystems are too connected for that substitution to materialise cleanly. Prior research on cryptocurrency liquidity and regulation provides the background for this study, but it has not examined how CEX and DEX markets respond differently when regulatory pressure targets centralised infrastructure. How decentralised exchange liquidity and trading activity respond in light of the growing global regulatory attention directed at centralised exchanges therefore remains largely unexamined (Griffith and Clancey-Shang, 2023; Aspris et al., 2021; Giménez Roche et al., 2025). This is what motivates the present study, as the continued integration of crypto asset markets into the broader financial system makes understanding these exchange-level dynamics increasingly relevant.

The literature on cryptocurrency liquidity and regulatory shocks provides the foundation for this chapter, though it does not directly address the venue-level question at its centre. Bianchi et al. (2022) establish that liquidity variation across digital assets carries meaningful implications for returns, showing that less liquid and more volatile cryptocurrency pairs require greater compensation for liquidity provision, confirming that liquidity is a core dimension of crypto market quality rather than a secondary concern. Huang (2024) takes this further by applying depth, tightness, and resilience measures simultaneously to cryptocurrency markets, showing that liquidity dimensions do not always respond uniformly to the same conditions, an approach increasingly adopted across cryptocurrency liquidity research (Augustin et al., 2023; Bianchi et al., 2022). This multidimensional view is central to the

present study because a regulatory shock may affect trading activity without affecting price impact, or improve price quality on one venue without changing transaction costs on another. Makarov and Schoar (2020) document substantial segmentation across exchanges and jurisdictions, showing why venue-level analysis remains meaningful in cryptocurrency markets. Griffith and Clancey-Shang (2023) provide the most direct regulatory evidence, showing that the 2021 Chinese ban was associated with measurable deterioration in crypto market quality including liquidity, though their analysis treats the market as a whole without distinguishing between centralised and decentralised venue responses. Giménez Roche et al. (2025) note that the literature has largely focused on centralised exchange activity and that regulation does not reach CEXs and DEXs evenly, pointing directly to the gap this chapter addresses. The closest empirical precedent is Aspris et al. (2021), who show that a structural change in CEX accessibility, specifically a token obtaining a CEX listing, is associated with a sharp decline in DEX trading activity while total activity rises. Farag et al. (2025) further show that decentralised exchange conditions on Uniswap are associated with liquidity provision conditions in centralised cryptocurrency markets, reinforcing the view that CEX and DEX markets are connected rather than isolated. What remains unexamined is whether regulatory announcements produce a comparable venue-level response, and whether that response differs across regulatory designs. This chapter contributes to a growing but still limited literature on venue-specific liquidity dynamics in cryptocurrency markets by providing the first examination of how regulatory announcements across distinct jurisdictions and regulatory designs are associated with differential liquidity and trading activity responses across CEX-linked and DEX-linked token ecosystems.

To examine this, we construct two token indices, one linked to centralised exchanges (CEXs) and one linked to decentralised exchanges (DEXs) following the aggregation approach adopted in prior work on cryptocurrency markets (Makarov and Schoar, 2020; Aspris et al.,

2021). Each group contains the largest tokens by market value and is classified based on the ecosystem it mainly belongs to and is traded. This classification reflects the reality that many DeFi-associated tokens trade across multiple venues while remaining constitutively tied to the decentralised ecosystem in terms of governance and utility. Liquidity is measured across three dimensions: Amihud Illiquidity capturing price impact, Roll's Measure capturing transaction costs, and Turnover capturing trading intensity. The empirical framework is a two-way fixed effects panel regression with an interaction term between venue type and post-announcement period, estimated separately for each of the three regulatory events. This design absorbs time-invariant differences across tokens and common time trends affecting both groups, allowing us to observe whether the post-announcement change in liquidity differs between CEX-linked and DEX-linked assets. Event window specifications of one, three, five, and thirty days around each announcement date complement the baseline results. Narrow windows isolate the immediate market reaction at announcement, while the thirty day window captures whether any initial response persists or reverses over a longer horizon, a distinction that matters given that announcement-period and post-period responses need not point in the same direction, as the baseline and event window results in this chapter demonstrate (Aspris et al., 2021). Specifically, the analysis focuses on announcement dates to capture how markets absorb and respond to regulatory news, rather than the effects of implemented or enforced regulation. This announcement-date approach is consistent with prior crypto studies that treat regulatory announcements or structural market events as information shocks, including Griffith and Clancey-Shang (2023), Chokor and Alfieri (2021), Aspris et al. (2021), and Augustin et al. (2023).

After all three regulatory events, DEX trading activity declined relative to CEX in the sustained post-announcement period regardless of the intensity or form of the shock, suggesting that regulatory pressure on centralised exchange infrastructure is not associated with a

sustained shift toward decentralised trading. The event windows around the announcement period tells a more nuanced story. Both events placing a heavier burden on centralised exchange infrastructure were associated with a temporary relative increase in DEX trading activity around the announcement date. The American shock produced no such pattern, instead showing a gradual and progressive decline in relative DEX activity across the five- and thirty-day windows. The market therefore differentiates across regulatory designs at announcement even when the longer-run direction converges. Alongside the trading activity results, DEX price-impact liquidity improved relative to CEX at the baseline in two of the three events, despite the concurrent decline in relative trading activity. This decoupling between where activity is concentrated and how efficiently prices absorb volume suggests that trading activity and price-impact liquidity respond through different channels rather than moving together as a single liquidity outcome. Taken together, these patterns show that regulatory pressure directed at centralised infrastructure does transmit to decentralised markets, but not uniformly across liquidity dimensions. DEX trading activity declined relative to CEX in the sustained post-announcement period across all three events, while DEX-linked assets showed relative improvement in price-impact liquidity under two of the three events. Trading activity and price-impact liquidity therefore respond through different channels, and that divergence is itself informative about how interconnected crypto markets absorb regulatory pressure. These findings have implications for how regulators approach the boundaries of crypto oversight and for market participants who may assume that decentralised venues operate independently from regulatory developments directed at centralised infrastructure.

The remainder of this chapter is structured as follows. Section 2 reviews the relevant literature and develops the hypotheses. Section 3 describes the data and empirical methodology. Section 4 presents and discusses the empirical findings. Section 5 concludes.

4.2 Literature Review and Hypotheses Development

4.2.1 Literature Review

Regulatory Shocks and Cryptocurrency Market

Regulatory shocks do not affect cryptocurrency markets uniformly, and policies of different designs produce different market outcomes. Prior studies show bans produce outright market deterioration, while compliance-based frameworks generate more heterogeneous responses depending on asset characteristics, information environment, and the scope of entities covered (Auer and Claessens, 2018; Chokor and Alfieri, 2021). The evidence on volume is consistent: regulatory announcements are associated with meaningful declines in trading activity, with institutional participants driving the largest share of that reduction (Copestake et al., 2023). Price effects follow a similar pattern, with negative abnormal returns documented around regulatory announcements and their magnitude varying with asset liquidity and information asymmetry (Chokor and Alfieri, 2021; Koenraadt and Leung, 2022). Single-country actions do not stay contained. Borri and Shakhnov (2020) and Shanaev et al. (2020) show that restrictions in one jurisdiction redirect activity internationally and produce portfolio-level declines across global crypto holdings, while Griffith and Clancey-Shang (2023) demonstrate that the 2021 Chinese ban produced measurable deterioration in market quality including liquidity. Regulatory pressure does not simply reduce activity, it reshapes where it flows. Increased tax scrutiny shifts crypto investor behaviour toward tax planning strategies and affects traders' preference across exchange venues, while participants seeking anonymity and lighter oversight migrate toward more obscure and less regulated assets as mainstream cryptocurrencies attract greater regulatory visibility (Cong et al., 2023; Foley et al., 2019). This chapter extends this line of inquiry by examining three regulatory events across three distinct jurisdictions, asking whether CEX-linked and DEX-linked assets respond differently to the same shock. DEXs and DeFis are a natural point of comparison precisely because they remain largely outside the

regulatory perimeter this literature documents, making them a relevant alternative when centralised infrastructure comes under pressure.

Regulation difference between CEXs and DEXs

While both are part of the same crypto ecosystem, their underlying architecture, liquidity mechanics, and exposure to oversight differ in ways that matter for how regulation reaches them. CEXs are identifiable intermediaries with legal presence, custody arrangements, and concentrated liquidity pools. That visibility places them directly in the path of compliance obligations, registration requirements, enforcement actions, and operational restrictions. DEXs operate through smart contracts on a blockchain without a central intermediary, which means most current regulatory frameworks do not reach them in the same way. Compliance obligations, custody rules, and institutional restrictions fall on identifiable platforms, not on code (Giménez Roche et al., 2025). This asymmetry in regulatory exposure is the reason the same shock may land differently across venue types.

The mechanics of how DEX liquidity works deepen that distinction. Unlike CEXs, which rely on order books maintained by professional market makers who can withdraw when uncertainty rises, DEXs use automated market makers where liquidity providers deposit assets into pools and a trading function determines execution prices. AMM liquidity is pre-funded through liquidity pools and therefore differs from CEX order-book liquidity, which depends on continuously updated quotes. However, this does not mean DEX liquidity is fixed or immune to withdrawal. Liquidity providers can still remove capital from pools, and execution costs remain sensitive to pool depth, trade size, exchange rates, and arbitrage incentives (Fabi and Prat, 2025; Cartea et al., 2025). The assets traded on DEX venues also behave differently from mainstream cryptocurrencies. DeFi-linked tokens are sensitive to news and sentiment shocks, and smaller DeFi coins appear especially exposed, with negative sentiment having a

disproportionately strong effect on returns (Akyildirim et al., 2025). DeFi participation itself is shaped by yield-seeking, speculation, and governance motives rather than a fixed preference for decentralisation, meaning activity on DEX venues is responsive to changing conditions and can adjust after a shock (Cornelli et al., 2025). That adjustment is not always uniform, evidence from DeFi lending shows that users tend to remain active after adverse events but scale back the intensity of their positions, with larger participants showing the most pronounced reduction in activity scale (Gadzinski and Liuzzi, 2025). Wealth concentration within DeFi means that DEX liquidity and governance token activity are disproportionately driven by a small number of large participants, so when those participants adjust their positions in response to a shock, the effect on the broader ecosystem is amplified rather than diffuse (Sapkota, 2025). Whether DEX trading activity and liquidity improve after a regulatory shock targeting CEX infrastructure therefore depends on whether liquidity providers and traders find it worthwhile to stay or move, not simply on which venue the regulation nominally targets.

CEX and DEX venues are also not isolated from each other, and that interdependence shapes how a shock to one venue transmits to the other. Aspris et al. (2021) provide the clearest evidence of this: when DEX-traded tokens obtain CEX listings, DEX trading activity declines sharply while total activity across both venues rises, showing that changes in the relative attractiveness of centralised platforms produce measurable and directional consequences for decentralised venue activity. The mechanism runs both ways. Farag et al. (2025) show that Uniswap liquidity conditions, trading volume, and transaction count are associated with liquidity provision premiums in centralised cryptocurrency markets, meaning that what happens on DEX venues feeds back into CEX conditions rather than the two operating in parallel. Cartea et al. (2025) show that Binance rates lead Uniswap rates and that arbitrage activity aligns AMM prices with centralised exchange reference prices, confirming that DEX liquidity and pricing remain connected to CEX market conditions rather than operating as fully

independent alternatives. DeFi more broadly remains connected to traditional financial conditions through stablecoins, collateral, and settlement infrastructure in ways that limit how independently decentralised venues can move. Federal funds rate changes produce statistically significant counter-cyclical effects on DeFi lending rates and asset growth, with increases in policy rates reducing DeFi activity, a pattern Dunbar et al. (2026) describe as a decentralisation illusion. Liang (2026) reinforces this point by showing that monetary policy shocks pass through to DeFi stablecoin yields with a structural delay driven by fiat settlement frictions, confirming that even algorithmically governed protocols remain constrained by off-chain infrastructure. Sapkota (2025) adds a further qualification: wealth concentration within DeFi is substantial, particularly in governance and DAO tokens, meaning the ecosystem carries its own internal vulnerabilities that sit alongside, rather than replace, the risks associated with centralised exchange infrastructure.

Liquidity has distinct dimensions that do not always move together, and that distinction matters for how you read market quality around a shock. Huang (2024) applies three liquidity measures simultaneously to cryptocurrency markets, treating price impact, transaction costs, and market resilience as separate dimensions that respond differently to the same conditions. The depth dimension, captured by Amihud Illiquidity, reflects whether a market can absorb trading volume without large price movements. The tightness dimension, captured by Roll's Measure, reflects the cost of executing a trade through the implied bid-ask spread. The activity dimension, captured by Turnover, reflects how intensively a market is being used. Bianchi et al. (2022) show that these dimensions carry different information about market quality, with Amihud Illiquidity predicting returns in cryptocurrency markets in ways that volume-based measures alone do not. Aspris et al. (2021) use Turnover as their primary measure when examining venue-level activity shifts, showing that trading intensity is the most direct observable signal of where participants choose to trade. Examining only one dimension risks

missing the full picture, because a regulatory shock may shift where participants trade without immediately changing price impact, or may improve price quality on one venue without any corresponding change in transaction costs. This chapter uses all three measures precisely because the venue-level response to a regulatory shock may not be uniform across dimensions, and observing where the response appears and where it does not is itself informative.

4.2.2 Hypotheses Development

The first measure in our multi-dimensional liquidity analysis is examine whether regulatory announcements are associated with shifts in DEX assets relative to CEX assets in trading activity. We use Turnover to capture the intensity of trading to provide a direct way to observe whether regulatory pressure on centralised exchange infrastructure is associated with a relative change in DEX. Bianchi et al. (2022) support the use of trading activity as a liquidity-relevant outcome by showing that trading volume is closely related to liquidity provision in cryptocurrency markets. Their results indicate that lower-volume, less liquid, and more volatile crypto pairs require greater compensation for liquidity provision, suggesting that trading activity contains information about market quality. Augustin et al. (2023) show that trading volume is an important component of the liquidity response to a major structural event in cryptocurrency markets. In their analysis of the introduction of Bitcoin futures, they find that changes in market structure are associated with improvements in liquidity conditions and adjustments in trading activity. Galati (2024) examines trading activity as a distinct liquidity-relevant channel in cryptocurrency markets. The study analyses Binance's zero-fee trading experiment, where maker–taker fees were removed for selected Bitcoin trading pairs. To capture trading activity, Galati (2024) uses turnover alongside related activity variables such as trading volume, number of trades, number of quotes, fill rate, and average trade size. He finds that the removal of trading fees increased investors' willingness to trade and raised trading

activity. Importantly, however, this increase in activity did not translate into an unambiguous improvement in market quality. Galati (2024) shows that even as trading activity rose, bid–ask spreads widened, market depth deteriorated, and total transaction costs increased for customers. This distinction is relevant to the present study, as we treat trading activity as a separate dimension of liquidity rather than a proxy for overall market quality, consistent with the multidimensional framework applied throughout this chapter.

Prior research provides direct evidence that trading activity across CEX and DEX venues responds to changes in venue conditions. Giménez Roche et al. (2025) show that regulatory constraints reach CEXs and DEXs asymmetrically, with direct obligations falling on centralised platforms while decentralised venues remain comparatively less exposed. This asymmetry means that when regulatory pressure targets centralised infrastructure, trading conditions across the two venue types may adjust differently, making the relative trading activity response of DEX-linked assets an empirical question worth examining. Aspris et al. (2021) show that after DEX-traded tokens obtain CEX listings, DEX trades, DEX volume, and unique DEX traders decline sharply, while total trading activity increases. This indicates that the CEX listing does not simply add another venue for DeFis, but it changes where activity is concentrated. Their findings establish that changes in the relative attractiveness of centralised venues can be directly reflected in decentralised trading activity, and that CEX and DEX activity are connected rather than isolated. While Aspris et al. (2021) examine DeFi listing in CEXs, we build on their study on the basis CEXs and DEXs are not isolated markets but shifts can occur due to changes in one venue from another. Farag et al. (2025) provide evidence that decentralized exchange activity affects liquidity provision in centralized cryptocurrency markets. Using Uniswap V2 data, they show that increases in DEX liquidity, trading volume, and transaction count reduce the liquidity provision premium in centralized cryptocurrency markets, while withdrawals, gas fees, and impermanent loss increase it. This suggests that

decentralized and centralized exchanges are not isolated markets. Instead, active and liquid DEX conditions reduce the compensation required by CEX liquidity providers, whereas DEX stress increases liquidity provision costs. While Farag et al. (2025), who use trading volume and transaction count as measures of trading activity, our study uses turnover to capture trading intensity relative to market size. However, none of these studies examine trading activity in light of regulatory announcements. We extend this line of research by asking whether regulatory announcements that place a heavier burden on centralised exchange infrastructure are associated with a relative shift in trading activity toward DEX-linked assets. If such announcements increase the compliance or operational burden on centralised platforms without placing equivalent requirements on decentralised venues, market participants may redirect their trading activity toward DEX-linked assets as the comparatively less constrained alternative. The hypothesis tests whether DEX assets experience higher trading activity relative to CEX assets in the post-announcement period.

H1: *Regulatory announcements that burden CEX infrastructure are associated with higher DEX trading activity relative to CEX in the post-announcement period.*

The second measure in our liquidity framework is Amihud Illiquidity, which captures the price-impact dimension of market quality. Following Amihud (2002), the measure relates absolute price movements to trading volume, where higher values indicate that a given amount of trading produces a larger price movement. In this sense, Amihud captures whether market depth is sufficient to absorb trades without large price changes. This makes it distinct from Turnover, which captures the intensity of trading activity, and from Roll's Measure, which captures price-reversal and transaction-cost dynamics. Bianchi et al. (2022) use Amihud Illiquidity to rank cryptocurrency pairs by price-impact liquidity and show that assets with higher Amihud values behave differently from more liquid assets in liquidity-provision

strategies. Their results indicate that Amihud captures the extent to which trading volume translates into price movement, making it a meaningful proxy for price-impact risk in crypto markets rather than simply a general liquidity label. Huang (2024) uses Amihud Illiquidity to measure the depth component of crypto liquidity and finds that depth-based liquidity risk is sensitive to broader market conditions. In the paper's dynamic model, liquidity shocks from equity markets increase crypto liquidity risk in the depth dimension by approximately 20–36%, showing that Amihud captures a market-quality channel that is sensitive to external shocks and cross-market conditions. Augustin et al. (2023) include Amihud Illiquidity within an aggregate illiquidity index that combines price-impact, spread-based, and trading-activity measures, finding that aggregate illiquidity declines after the introduction of Bitcoin futures. While their setting concerns futures introduction rather than regulatory announcements, their evidence shows that Amihud-based liquidity can change around major structural events in cryptocurrency markets.

Griffith and Clancey-Shang (2023) examine the 2021 Chinese cryptocurrency ban as a regulatory shock to crypto market quality. Using Amihud Illiquidity alongside other market-quality proxies, they find evidence of liquidity deterioration after the ban, with the Amihud effect especially visible among less actively traded cryptocurrencies. While Griffith and Clancey-Shang (2023) establish that regulatory intervention can weaken aggregate crypto-market liquidity, their framework does not distinguish between centralised and decentralised venue-linked assets. This chapter extends their setting by examining whether the Amihud response differs between CEX- and DEX-linked assets after regulatory announcements. If regulatory announcements place a heavier compliance or operational burden on centralised exchange infrastructure without placing equivalent requirements on decentralised venues, the price impact of trading may deteriorate on the centralised. Under such conditions, DEX-linked

assets should experience lower Amihud Illiquidity relative to CEX-linked assets, reflecting a relative improvement in market depth on the less directly burdened venue type.

Therefore, we hypothesise:

H2: *Regulatory announcements that burden CEX infrastructure are associated with lower price impact for DEX relative to CEX in the post-announcement period.*

Our third liquidity measure is Roll's Measure, which captures the transaction-cost and price-reversal dimension of liquidity. Roll's Measure is based on the covariance of consecutive price changes and reflects the degree of price reversal between adjacent trading periods. It is commonly interpreted as a proxy for the effective bid-ask spread and the cost of transacting in a given market. Unlike Amihud Illiquidity, which captures price impact, and Turnover, which captures trading activity, Roll's Measure captures liquidity through the effective spread implied by price reversals. Although Roll's Measure is used less frequently in cryptocurrency research than Amihud-based or volume-based measures, recent studies increasingly incorporate it into multidimensional liquidity frameworks. Augustin et al. (2023), for example, use Roll's Measure as an illiquidity measure alongside Amihud Illiquidity, bid-ask spread proxies, trading volume, and volatility when examining Bitcoin spot-market quality. Their findings show that BTC–USD became more liquid relative to other Bitcoin–fiat pairs after the futures introduction, and their individual illiquidity measures are qualitatively consistent with the aggregate illiquidity index. Importantly, they attribute this improvement to a reduction in arbitrage frictions, including short-sale constraints, block-confirmation risk, and market segmentation. This suggests that when a market shock reduces trading frictions and improves market integration, Roll-implied illiquidity should decrease; by contrast, shocks that increase segmentation or intermediary constraints should raise Roll-implied transaction costs.

Huang (2024) similarly incorporates Roll into a multidimensional crypto-liquidity framework, using Amihud Illiquidity to capture liquidity depth, Relative Spread to capture liquidity tightness, and Roll's Measure to capture liquidity resilience. Their study shows that crypto liquidity dynamics differ across liquidity dimensions and across geographic markets, indicating that resilience does not necessarily move in the same direction as other liquidity channels. Huang (2024) also finds bidirectional liquidity-risk transmission between crypto and equity markets, suggesting that crypto liquidity is sensitive to shocks and external market conditions. This supports the use of Roll to test whether regulatory announcements affect the resilience and transaction-cost component of liquidity differently from price-impact or trading-activity channels. Together, these studies provide the mechanism for our CEX–DEX comparison under regulatory shocks. Shocks that increase segmentation or intermediary constraints should raise Roll-implied transaction costs, while shocks that improve market integration should lower them. Huang (2024) further shows that the resilience component captured by Roll may respond differently from price-impact or trading-activity channels. In our study, regulatory announcements that place greater compliance or operational burdens on centralised platforms may worsen trading conditions on CEXs, leaving DEX platforms comparatively less affected because they are not explicitly targeted by the announcements. Therefore, regulatory announcements that burden CEX infrastructure should be associated with a relative decline in Roll-based illiquidity for DEXs in the post-announcement period.

We therefore hypothesise:

H3: *Regulatory announcements that burden CEX infrastructure are associated with lower transaction costs for DEX relative to CEX in the post-announcement period.*

4.3 Data and Econometric Methodology

4.3.1 Data

The empirical analysis uses daily cryptocurrency price and trading data from 1 January 2020 to 31 October 2025, covering the three regulatory events examined in this study. Event dates are defined using the first official public announcement or proposal date associated with each regulatory intervention, cross-checked against official institutional releases and major financial news coverage. Accordingly, the European policy shock is dated to 24 September 2020, corresponding to the MiCA proposal announcement; the Chinese policy shock is dated to 18 May 2021, corresponding to the first major official ban announcement; and the American policy shock is dated to 4 February 2025, corresponding to the first announcement of the GENIUS Act.

To examine differential responses across market environments, cryptocurrencies in the sample are classified as either CEX-linked or DEX-linked based on their primary trading venue. After excluding tokens without consistent daily data over the sample period, the final CEX-linked index comprises 15 tokens and the DEX-linked index comprises 12 tokens. Daily data on price, trading volume, and market capitalisation are obtained through academic API access from Coin Metrics. The resulting indices therefore capture the aggregate behaviour of DEX-linked and CEX-linked token ecosystems under regulatory shocks, rather than venue-specific trading mechanics in the strict sense. To construct these indices, we cross-checked CoinMarketCap classifications to identify the leading assets in each category. The token sample is restricted to non-pegged cryptoassets, as stablecoins exhibit fundamentally different price dynamics and liquidity behaviour by design. Their pegged structure suppresses the price impact and spread variation that Amihud Illiquidity and Roll's Measure are constructed to capture, which would undermine the internal consistency of the sample. This restriction follows directly from the research focus. This study examines how regulatory shocks transmit into the

liquidity of CEX-linked and DEX-linked token ecosystems, where the regulatory burden falls on centralised exchange infrastructure and its participants. Stablecoins form part of the centralised ecosystem in the sense that they circulate primarily through CEX venues and their issuers are subject to regulatory oversight, but their pricing mechanism is constitutively different from non-pegged assets and they do not respond to regulatory shocks through price impact or spread channels in the way that market-determined assets do. This is consistent with evidence that stablecoin yields and liquidity are governed by peg maintenance, fiat settlement infrastructure, and monetary policy transmission rather than the speculative price-discovery process that governs non-pegged crypto assets (Liang, 2026; Dunbar et al., 2026). Under the American policy shock, however, stablecoins remain relevant as infrastructure rather than as a subject of direct measurement. The GENIUS Act regulates stablecoin issuers as part of the settlement and liquidity infrastructure underpinning centralised exchange activity, and the American event is therefore interpreted through this infrastructural channel rather than through stablecoin price behaviour itself.

While prior studies use different methods to proxy exchange-level or venue-related dynamics in cryptocurrency markets, aggregation remains common given the fragmented structure of crypto trading and the limited availability of broad, consistent daily venue-specific data. Makarov and Schoar (2020), for example, aggregate across exchanges and regions to study arbitrage and price dispersion, while Aspris et al. (2021) examine DEX-CEX interaction through trading activity around cross-listings. Our design differs from both: unlike Aspris et al. (2021), who examine individual token cross-listings, we group tokens by ecosystem character to capture market-level responses to regulatory shocks. CEX-linked tokens comprise established layer-1 blockchains and payment-oriented assets whose primary price discovery and trading activity occur on centralised venues. DEX-linked tokens comprise protocol-native DeFi assets, including governance tokens, lending protocols, and infrastructure tokens, whose

utility and governance are constitutively tied to the decentralised ecosystem. This classification reflects ecosystem character rather than venue exclusivity. This approach is consistent with prior work that distinguishes crypto assets by their functional character and ecosystem role rather than treating the market as homogeneous (Corbet et al., 2020a; Makarov and Schoar, 2020). Restricting the analysis to isolated on-chain DEX trading would capture only a narrow slice of market activity, since DeFi-associated tokens are actively traded across multiple venues. The aggregate price and volume data from Coin Metrics therefore provides a more complete and representative picture of each token ecosystem's response to regulatory shocks than venue-specific data alone would allow.

4.3.2 Measures

Liquidity Measures

The analysis employs three liquidity measures as dependent variables, each capturing a distinct dimension of market quality. Following Kyle (1985) and Harris (2003), liquidity is conceptualised as a multidimensional construct encompassing depth (the ability to trade without moving prices), tightness (the cost of immediate execution), and resilience (the speed at which prices recover following trades). The three measures employed capture these dimensions respectively: Amihud illiquidity (depth), Roll measure (tightness/resilience), and turnover (trading activity). The formulas for constructing each measure are presented below.

The Amihud (2002) measure captures price impact per unit of trading volume, representing the price change associated with one dollar of trading volume. For cryptocurrency *i* on date *t*, the measure is computed as:

$$Amihud_{it} = |Return_{it}|/(Volume_{it}/1{,}000{,}000) \quad (1)$$

where $|Return_{it}|$ represents the absolute value of the daily return (computed as the logarithmic price change from day *t*-1 to day *t*), and $Volume_{it}$ represents daily trading volume measured in US dollars. The denominator is scaled by one million to produce coefficients of convenient

magnitude. Higher values indicate greater price impact from a given volume of trades, hence greater illiquidity.

Amihud is included because it directly measures the price impact of trading volume and is well established in both the broader liquidity literature and recent work on cryptocurrency markets. Bianchi et al. (2022) show that Amihud illiquidity predicts cryptocurrency returns, while Huang (2024) confirms its usefulness as a depth measure in crypto markets. It is also practical for the present setting, since it requires only price and volume data. This makes it particularly suitable for examining whether regulatory shocks change market depth across CEX- and DEX-linked assets.

The Roll (1984) measure estimates the effective bid-ask spread from the serial covariance of returns, capturing both spread costs and price resilience. Following Huang (2024), the measure is calculated as:

$$Roll_{it} = 2\sqrt{\left(-Cov(Return_{it}, Return_{it-1})\right)} \quad (2)$$

where $Cov(Return_{it}, Return_{it-1})$ represents the covariance between returns on day t and returns on day t-1, estimated using a 30-day rolling window. The square root is taken of the negative covariance under the assumption that serial covariance is negative due to bid-ask bounce which is the tendency of transaction prices to alternate between bid and ask quotes, inducing negative autocorrelation in returns (Roll, 1984). When the estimated covariance is positive (indicating return momentum rather than bid-ask bounce), the Roll measure is set to zero, as the underlying model assumes negative serial dependence. Lower values indicate tighter effective spreads and faster price recovery following trades, hence better market quality. The 30-day rolling window provides sufficient observations for stable covariance estimation whilst allowing the measure to adapt to time-varying market conditions. Huang (2024)

validates the Roll measure in cryptocurrency markets specifically, finding that it exhibits expected relationships with other liquidity proxies and responds predictably to market stress events. Regulatory shocks may affect resilience by changing the composition of market participants: if regulation drives informed traders away from CEX platforms, bid-ask spreads and price reversals may decrease on DEX platforms relative to CEX platforms, manifesting as differential changes in the Roll measure.

Turnover measures trading activity normalised by market capitalisation, capturing the intensity of trading relative to the total value of outstanding coins. The measure is computed as:

$$Turnover_{it} = Volume_{it} / MarketCap_{it} \quad (3)$$

where $MarketCap_{it}$ represents the market capitalisation (price multiplied by circulating supply) at the end of day *t*. The ratio measures the fraction of outstanding supply that trades each day. Higher values indicate more active markets with greater investor participation. Turnover provides a direct measure of trading activity that complements the price-based liquidity proxies (Amihud and Roll). Whilst Amihud and Roll infer liquidity from price dynamics, turnover directly observes market activity intensity, providing convergent validity when all three measures respond consistently to treatment.

Turnover is a direct measure of trading activity intensity identified as a fundamental dimension of liquidity distinct from depth and resilience. Aspris et al. (2021) use turnover as their primary liquidity measure in comparing DEX and CEX markets, finding systematic differences in trading activity patterns across venues. The measure is particularly relevant for this setting because regulatory compliance costs may directly affect trading volumes: if regulation increases transaction costs or reduces market access for certain participants, trading activity should decline on regulated platforms relative to unregulated alternatives. Unlike the

Amihud and Roll measures, which estimate latent liquidity characteristics from price dynamics, turnover provides a direct observation of market activity. This complementarity strengthens inference: if all three measures respond consistently to regulatory shocks, this provides convergent evidence of liquidity effects that is robust to measurement choices. Together, these three measures provide a comprehensive assessment of liquidity across its key dimensions.

Controls

To control for broader market conditions that may affect cryptocurrency liquidity independently of the regulatory events, the analysis includes three uncertainty measures. The VIX, sourced from CBOE, is used as a proxy for global risk sentiment and reflects the market's expectation of 30-day forward-looking volatility derived from S&P 500 option prices (Cornelli et al., 2025, Griffith and Clancey-Shang, 2023). The Global Economic Policy Uncertainty index, obtained from policyuncertainty.com, captures global policy-related uncertainty as a GDP-weighted average of national EPU indices. The World Uncertainty Index, obtained from worlduncertaintyindex.com, captures broader global uncertainty by text mining Economist Intelligence Unit country reports and is available for 143 countries (Giménez Roche et al., 2025).

4.3.3 Econometric Framework

Regulatory Events

This study examines three regulatory announcements that reflect distinct regulatory approaches: the China cryptocurrency ban announced on 18 May 2021, the European Union MiCA proposal announced on 24 September 2020, and the United States GENIUS Act proposed on 4 February 2025. The analysis focuses exclusively on these proposal dates to isolate the immediate market response at the point of announcement. By doing so, the study captures how investors adjust trading activity and liquidity across centralised and decentralised

venues in direct response to new regulatory information, without conflating these effects with implementation dynamics or subsequent policy developments. This design allows observation of the initial differentiation in market behaviour across regulatory frameworks.

Econometric Model

The primary empirical specification is a panel regression model that compares liquidity changes for DEX-linked cryptocurrencies to CEX-linked cryptocurrencies before and after regulatory events. The panel framework is appropriate because it accounts for time-invariant differences between DEX-linked and CEX-linked groups and common time trends affecting both groups, under the assumption that the three regulatory announcements represent genuine external shocks to the CEX ecosystem. DEX-linked cryptocurrencies are assigned a group indicator of one (treated = 1) and CEX-linked cryptocurrencies are assigned a group indicator of zero (treated = 0), with classification determined by each token's primary trading venue at sample entry and held fixed throughout the sample period.

Following Griffith and Clancey-Shang (2023) who examine the Chinese cryptocurrency ban using panel regression methods, and consistent with panel approaches used to examine venue-level activity differences in cryptocurrency markets (Aspris et al., 2021), the baseline specification is:

$$Liquidity_{it} = \beta_0 + \beta_1 \cdot Treated_i + \beta_2 \cdot Post_t + \beta_D \cdot (Treated_i \times Post_t) + \gamma' X_{it} + \alpha_i + \delta_t + \varepsilon_{it} \quad (4)$$

where $Liquidity_{it}$ represents one of the three liquidity measures (Amihud, Roll, Turnover) for cryptocurrency i on date t, $Treated_i$ is an indicator equal to one for DEX-linked cryptocurrencies, $Post_t$ is an indicator equal to one for observations after the regulatory event, and X_{it} is a vector of control variables including lagged returns, lagged log market capitalisation, lagged log trading volume, and lagged macroeconomic uncertainty measures

(VIX, WUI, GEPU). The coefficient of interest is β_D, which captures the differential change in liquidity for DEX-linked tokens relative to CEX-linked tokens following the regulatory shock. β_D captures the differential association between the regulatory shock and liquidity outcomes for DEX-linked cryptocurrencies relative to CEX-linked cryptocurrencies.

Event Window Analysis

To trace the dynamic evolution of treatment effects around regulatory announcements and to test whether effects are concentrated around event dates (as would be expected under market efficiency), the analysis employs event window specifications that restrict the estimation sample to discrete windows around each event date. This approach identifies the timing of liquidity responses, distinguishing immediate reactions at announcement from gradual adjustments in the weeks that follow. Four window sizes are examined: ±1 day, ±3 days, ±5 days, and ±30 days around each event. These windows span from immediate responses (1-day window) to medium-term adjustments (30-day window), allowing assessment of both announcement effects and post-announcement period.

The event window specification replaces the post-period indicator with a window-specific indicator:

$$Liquidity_{it} = \beta_0 + \beta_1 \cdot Treated_i + \beta_2 \cdot Window_t + \beta_w \cdot (Treated_i \times Window_t) + \gamma' X_{it} + \alpha_i + \delta_t + \varepsilon_{it} \quad (5)$$

where $Window_t$ equals one for observations falling within the specified number of days after the event date and zero otherwise. The coefficient β_w captures the differential change in liquidity for DEX-linked tokens relative to CEX-linked tokens within the narrow window around the event, isolating short-term reactions from longer-run adjustments. Each event window specification is estimated under all four fixed effects structures, providing 16 estimates per liquidity measure per event (4 windows × 4 fixed effects specifications). This

comprehensive approach allows identification of both immediate market responses and the persistence of regulatory effects whilst maintaining robustness to alternative identifying assumptions.

4.4 Empirical Findings

4.4.1 Descriptive Statistics and Pairwise Correlations

Table 4.1 presents descriptive statistics for all three measures alongside control variables. The Amihud measure exhibits substantial variation, ranging from near-zero to 0.067, with a mean of 0.0023. The Roll measure similarly shows wide variation, reflecting heterogeneity in effective spreads across cryptocurrencies and time periods. Turnover ranges from zero to 8.91, with a mean of 0.052, indicating that on average approximately 5.2% of outstanding supply trades daily, though with substantial cross-sectional and time-series variation.

[Table 4.1 about here]

Table 4.2 presents pairwise correlations between the three liquidity measures and the control variables. The correlations between the dependent variables are moderate and directionally consistent with their theoretical interpretations. Turnover and Amihud Illiquidity are negatively correlated (−0.066), consistent with the depth interpretation of Amihud: assets that trade more actively tend to absorb volume with less price impact. Turnover and Roll Measure are positively correlated (0.185), reflecting the tendency for more actively traded assets to exhibit greater short-run price reversals, which Roll's covariance estimator captures as a proxy for transaction costs. The positive correlation between Amihud and Roll (0.111) suggests that the depth and tightness dimensions of illiquidity co-move to some degree, though the modest magnitude confirms they capture meaningfully distinct aspects of liquidity.

Among the control variables, log trading volume and log market capitalisation are highly correlated (0.880), reflecting the tendency for larger assets to attract more trading activity. This is consistent with Bianchi et al. (2022) and is common in cryptocurrency liquidity studies. Both

variables are retained as controls given that the fixed effects structure absorbs time-invariant cross-sectional variation, reducing the practical impact of their collinearity. Among the uncertainty indices, GEPU and WUI are correlated (0.669), but are retained as they capture conceptually distinct sources of uncertainty and because the daily time fixed effects in the most demanding specifications absorb common time variation, limiting the risk of unstable estimates.

[Table 4.2 about here]

4.4.2 Empirical Results by Regulatory Event

European Policy Shock

Table 4.3 reports the baseline Turnover results for the European Shock. The baseline DEX × Post coefficient is negative and significant across all four specifications, ranging from −0.0775 ($p < 0.10$) to −0.0894 ($p < 0.05$), indicating that the DEX index experienced a relative decline in trading activity compared to the CEX index over the full post-announcement period. This result does not support H1 in the sustained post-period. Instead, it suggests that although the European Shock placed a heavier compliance burden on centralised exchange infrastructure, the longer-run trading activity response did not favour DEX-linked assets. Over the full post-period, the CEX index showed relatively higher trading activity than the DEX index.

Tables 4.6 and 4.7 present the event-window results for Turnover. In contrast to the baseline result, the DEX × Post interaction is positive and significant across every announcement window. In the 1-day window, the interaction is positive and significant at approximately 0.11 ($p < 0.10$) across all four specifications, and the significance strengthens in the 3-day and 5-day windows ($p < 0.05$). The positive and significant interaction remains present in the 30-day window, where coefficients range from 0.1179 to 0.1212 ($p < 0.05$). These results are directionally consistent with H1, showing that the DEX index experienced

higher trading activity relative to the CEX index around the European Shock announcement. Notably, the coefficient magnitude at the 30-day window is larger than at the 1-day window, suggesting that the event-window response does not weaken over longer horizons but becomes more pronounced. The contrast between the positive event-window results and the negative baseline result reflects a distinction between the immediate announcement-period response and the sustained post-period average. It suggests that the European Shock produced two different Turnover patterns depending on the horizon examined. Around the announcement itself, the DEX index showed higher trading activity relative to the CEX index, consistent with the expectation that regulatory announcements placing heavier burdens on centralised infrastructure are associated with a relative change in trading activity across venue types. However, this window-period response did not translate into a sustained post-period advantage. Once the broader post-announcement period is considered, the direction reverses, with the DEX index showing lower trading activity relative to the CEX index. This indicates that H1 is supported in the announcement windows but not in the baseline post-period. Furthermore, the event-window coefficients are larger in absolute magnitude than the baseline coefficient, ranging from approximately 0.11 to 0.12 across windows compared to −0.0775 to −0.0894 in the baseline. This suggests that the announcement-period response is stronger in magnitude than the sustained post-period differential, indicating that the immediate market response to the European Shock was more pronounced than the longer-run reallocation captured by the baseline. The 30-day window produces the largest event-window coefficient, at 0.1179 to 0.1212, suggesting that the announcement-period response strengthens rather than fades as the window extends.

This finding extends Aspris et al. (2021) by showing that venue-level trading activity is not only sensitive to listing-related changes in CEX accessibility, but also to regulatory announcements. Aspris et al. show that when DEX-traded tokens obtain CEX listings, DEX

activity declines sharply while total activity rises, demonstrating that changes in venue attractiveness are reflected in trading activity. The present study extends this logic to a regulatory setting. The positive event-window coefficients suggest that regulatory pressure on centralised infrastructure is associated with a short-run increase in DEX-relative activity. However, the negative baseline result also qualifies a simple DEX-benefit interpretation: over the longer post-period, the CEX index shows relatively higher trading activity than the DEX index. The result is also consistent with Farag et al. (2025), who show that CEX and DEX liquidity conditions are interrelated rather than isolated. The European Shock window results suggest that a regulatory announcement directed primarily at centralised crypto infrastructure is associated with a measurable change in relative DEX activity, supporting the view that shocks to one venue type can be reflected in the other. At the same time, the reversal in the baseline result suggests that this relationship is dynamic rather than one-directional. The DEX index shows higher relative activity around the announcement, but this does not necessarily persist once market participants adjust to the regulatory framework.

Table 4.4 reports the baseline Amihud Illiquidity results for the European Shock. The baseline DEX × Post coefficient is negative and statistically significant across all four specifications, ranging from −0.0101 ($p < 0.10$) to −0.0124 ($p < 0.05$). The estimate is stable across all four specifications. Since higher Amihud values indicate greater price impact, the negative coefficient shows that the DEX index experienced lower price-impact illiquidity relative to the CEX index over the full post-announcement period. This supports H2. However, the event-window Amihud results in Tables 4.8 and 4.9 are weaker. The DEX × Post coefficients are not consistently significant across the 1-day, 3-day, 5-day, or 30-day windows. The Amihud effect therefore appears mainly in the broader baseline post-announcement period rather than in the announcement windows.

Table 4.5 reports the baseline Roll Measure results for the European Shock. The baseline DEX × Post coefficients are negative across all four specifications, but none reach statistical significance. This does not support H3. The Roll coefficients also do not strengthen or reach significance as the event windows extend, suggesting that the persistence observed for the European Shock is a Turnover pattern rather than a Roll pattern.

These results should be read alongside the Turnover baseline result. While H1 predicts higher DEX trading activity relative to CEX, the baseline Turnover result does not support this in the sustained post-period. The Amihud result, however, moves in the expected direction. Taken together, the Amihud and Roll results help identify the channel through which the European Shock operates. Huang (2024) shows that depth-based liquidity is sensitive to broader market conditions and dynamic cross-market transmission, which helps explain why the Amihud effect appears as a broader post-period difference rather than a narrow announcement-window response. Huang (2024) further shows that Roll-based resilience does not necessarily move with depth-based liquidity, with the transaction-cost and resilience dimensions behaving differently from price-impact channels across crypto markets. The European Shock follows this pattern: price-impact liquidity improves for the DEX index relative to the CEX index, but Roll does not respond. This suggests that the liquidity response to the European Shock is concentrated in the price-impact dimension rather than in transaction-cost or price-reversal dynamics.

Griffith and Clancey-Shang (2023) show that the 2021 Chinese cryptocurrency ban weakened aggregate crypto market quality, including Amihud-based liquidity. Their setting is an outright prohibition, whereas the European Shock operates through compliance-based formalisation. MiCA places authorisation, disclosure, governance, and operational requirements on identifiable centralised intermediaries, but it also introduces investor

protection and institutional legitimacy across a large jurisdiction in which crypto activity had previously operated with greater regulatory freedom. Although MiCA burdens CEX infrastructure more directly than decentralised protocols, it may also increase the credibility of regulated centralised venues rather than simply redirecting activity toward DEX. The DEX index experienced lower price impact relative to the CEX index over the post-announcement period, indicating that the price-impact response was not uniform across venue types. This qualifies the aggregate-market evidence in Griffith and Clancey-Shang by showing that regulatory design matters: a prohibition shock and a compliance-formalisation shock may both affect liquidity, but they need not produce the same venue-level response.

Overall, the European Shock provides partial support for H1, supports H2, and does not support H3. The main implication is that the European Shock affected venue use and price-impact liquidity differently. The DEX index showed higher trading activity relative to the CEX index around the announcement, but lower relative trading activity over the full post-announcement period. At the same time, the Amihud results show lower price-impact illiquidity for the DEX index relative to the CEX index in the baseline post-period, while the event-window Amihud results are not consistently significant. This indicates that Turnover and Amihud follow different timing patterns: the trading-activity response appears in the event windows, whereas the price-impact response appears mainly in the broader post-period. This pattern is consistent with Galati (2024), who shows that increased trading activity does not necessarily imply an improvement in market quality, reinforcing the interpretation that Turnover should be read as a venue-use response rather than as a complete measure of liquidity improvement.

[Tables 4.3-4.11 about here]

Chinese Policy Shock

Table 4.12 presents the Turnover results for the Chinese cryptocurrency ban. The DEX × Post interaction coefficient is negative and significant across all four specifications, ranging from −0.0669 ($p < 0.05$) to −0.0763 ($p < 0.05$). This indicates that DEX-linked assets experienced lower trading activity relative to CEX-linked assets over the full post-announcement period following the ban. The direction and magnitude are broadly comparable to the MiCA Turnover result, suggesting that both shocks are associated with a similar sustained pattern of relative DEX trading activity decline. This result does not support H1 in the sustained post-period. Despite the Chinese ban placing a heavy and direct burden on centralised exchange infrastructure, the longer-run trading activity response did not favour DEX-linked assets over the full post-period. Tables 4.15 and 4.16 report the Turnover event windows. Interestingly, the 1-day window produces a positive and marginally significant DEX interaction of approximately 0.068 ($p < 0.10$) across all four specifications, indicating a brief increase in relative DEX trading activity immediately following the announcement. This effect dissipates rapidly by the 3-day window, the interaction is insignificant and remains so across the 5-day and 30-day horizons. This short-lived activity response is consistent with Aspris et al. (2021), who show that changes in venue attractiveness can be reflected in DEX trading activity, but it also shows that such responses need not persist. This provides directional support for H1 in the immediate announcement window, but the effect does not persist. The China pattern therefore shares a structural resemblance with the European shock at announcement, where both produced an initial positive DEX Turnover spike, but the two diverge sharply in duration. Under the European shock, the positive DEX interaction remained significant across all windows including the 30-day horizon. Under the Chinese ban, the spike was confined to a single day.

Table 4.13 presents the Amihud Illiquidity results. The DEX × Post interaction coefficient is small and insignificant in columns (1) and (2), but achieves significance when

we add individual and time effects in columns (3) and (4), yielding coefficients of −0.0038 ($p < 0.10$) and −0.0042 ($p < 0.05$) respectively. The emergence of significance upon inclusion of both crypto-specific and time fixed effects indicates that the differential price impact association for DEX-linked assets relative to CEX-linked assets becomes detectable only once asset-level heterogeneity and time-related variation are jointly controlled for. This pattern is consistent with H2, which predicts that restrictive regulatory shocks are associated with lower Amihud Illiquidity for DEX relative to CEX, though the evidence is weaker than in the European case where the negative coefficient was significant across all four specifications. Griffith and Clancey-Shang (2023) show that the Chinese ban deteriorated market quality at the aggregate level, while our design differs by comparing DEX-linked and CEX-linked tokens directly, finding that the effects of the ban were not uniform across venue types. The event windows in Tables 4.17 and 4.18 produce no significant DEX interaction across any horizon for Amihud. The price-impact improvement associated with the Chinese ban therefore appears only in the broader post-period once time-related variation is controlled for, and is not visible in the narrow windows around the announcement itself. This contrasts with the European shock, where Amihud showed a marginally significant positive interaction in the 1-day window. The absence of any announcement-window Amihud response under the Chinese ban suggests that the price-impact channel responded differently under prohibition than under compliance-based regulation.

Table 4.14 presents the Roll Measure results. The DEX × Post interaction coefficient is negative across all four specifications, reaching significance in columns (3) and (4) at −0.0092 ($p < 0.10$) and −0.0109 ($p < 0.05$) respectively. This makes the Chinese ban the only event across the three regulatory shocks for which Roll reaches statistical significance, and it does so only in specifications that absorb broader time-related variation. This is consistent with H3, which predicts that CEX-burdening announcements are associated with lower transaction costs

for DEX relative to CEX, though the evidence depends on the inclusion of time fixed effects and does not hold for the European shock. This potentially could be due to the extremity of China's complete ban on traditional cryptocurrencies as opposed to MiCA which subjects them to regulation. Huang (2024) applies the Roll measure to cryptocurrency markets and finds that the transaction-cost dimension of liquidity does not always respond uniformly to conditions that affect price impact, which is consistent with the pattern observed here since Roll responds under the most severe restrictive shock while remaining silent under the compliance-based European shock. The result suggests that the most severe regulatory intervention may be required before transaction-cost differentials between DEX and CEX venues become detectable. The event windows in Tables 4.19 and 4.20 produce no significant DEX interaction for Roll across any horizon, indicating that the transaction-cost response is a broader post-period phenomenon rather than an announcement-concentrated effect, mirroring the Amihud pattern.

While we expected outright prohibition to generate a stronger and more persistent DEX response relative to CEX, the results show that the immediate venue-level effect was limited. We find an increase in relative DEX trading activity in the 1-day window, but this disappears by the 3-day window and does not persist across longer windows. Interestingly, however, the baseline results reveal a more sustained post-period pattern: DEX-linked assets are associated with lower trading activity relative to CEX-linked assets, but also with lower price impact and lower Roll-based transaction costs in the more controlled specifications. Despite the severity of the Chinese ban, the venue-level trading response is short-lived: the DEX Turnover increase appears only in the 1-day window and disappears by the 3-day window.Griffith and Clancey-Shang (2023) similarly document that the ban produced sharp but transitory market-quality effects. Yang et al. (2025) show that Chinese cryptocurrency restrictions increased return, volatility, and extreme-risk spillovers, suggesting that the ban operated through broader

market-risk conditions rather than only immediate trading relocation. This is consistent with our finding that liquidity-quality effects emerge in the baseline specifications that absorb time-related variation, while the immediate DEX activity response proved short-lived. Giménez Roche et al. (2025) argue that outright bans affect centralised platforms more directly and decentralised protocols more indirectly. The 1-day DEX Turnover spike is consistent with this asymmetry, but its rapid disappearance suggests that the market quickly absorbed the announcement. Makarov and Schoar (2020) show that cryptocurrency markets are segmented across exchanges and jurisdictions, which helps explain why a territorially concentrated prohibition may produce a sharp but short-lived venue response rather than a persistent global reallocation toward DEX.

[Tables 4.12-4.20 about here]

American Policy Shock

Table 4.21 presents the Turnover results for the GENIUS Act. The DEX × Post interaction coefficient is negative and significant across all four specifications, ranging from −0.0204 ($p < 0.05$) to −0.0251 ($p < 0.01$). This indicates that DEX-linked assets experienced lower trading activity relative to CEX-linked assets over the full post-announcement period. The direction is consistent with the baseline Turnover results observed under both the European and Chinese shocks where DEX-linked trading activity declines relative to CEX-linked activity in the sustained post-period. Tables 4.24 and 4.25 report the Turnover event windows. The 1-day and 3-day window interactions are small and statistically indistinguishable from zero. A negative and significant DEX interaction emerges at the 5-day horizon, approximately −0.0125 ($p < 0.05$), and strengthens at the 30-day horizon to approximately −0.0193 ($p < 0.01$). This progressive pattern is distinct from the European and Chinese results, which each produced a

positive DEX interaction at the 1-day window. Under the GENIUS Act, there is no announcement-day activity response in either direction.

Table 4.22 presents the Amihud Illiquidity results. The DEX × Post interaction coefficient is small and statistically insignificant across all four specifications, indicating no sustained differential shift in price impact between DEX-linked and CEX-linked assets over the full post-announcement period. The event windows in Tables 4.26 and 4.27 reveal a concentrated announcement-day response.The 1-day window produces a negative and highly significant DEX interaction of approximately −0.0022 ($p < 0.01$), indicating a brief relative improvement in DEX price-impact liquidity on the announcement day. This effect is short-lived and disappears by the 3-day window, with the 5-day and 30-day interactions also insignificant. Notably, the 1-day Amihud interaction under the GENIUS Act is one of the strongest price-impact results across the three regulatory events, reaching the highest significance level despite the absence of a sustained baseline effect. Although the coefficient is negative and highly significant, the effect disappears by the 3-day window and is absent in the baseline specification. This indicates a brief announcement-day price-impact response rather than a sustained improvement in relative DEX liquidity. In contrast to the European and Chinese shocks, where Amihud effects appear in the broader post-period, the GENIUS Act leaves no lasting price-impact imprint. The American Shock therefore appears to operate mainly through trading activity, as reflected in the progressive decline in DEX Turnover, rather than through a sustained improvement in price-impact liquidity.

Table 4.23 presents the Roll Measure results. The DEX × Post interaction coefficient is small and insignificant across all four specifications, and the event windows in Tables 4.28 and 4.29 produce no significant DEX interaction across any horizon. Roll remains silent under the GENIUS Act at every horizon, suggesting that the policy did not produce a detectable response in the Roll-based transaction-cost, price-reversal, or resilience dimension of liquidity. Huang

(2024) finds that the transaction-cost dimension of liquidity does not always respond to the same conditions that affect price impact, and the divergence between the significant 1-day Amihud result and the null Roll result here is consistent with that observation.

The overall pattern under the GENIUS Act is that price-quality measures produce no sustained post-period differential, while Turnover shows a progressive negative effect beginning at the 5-day window and strengthening by the 30-day window. Unlike the European and Chinese shocks, the GENIUS Act does not produce an announcement-period increase in DEX trading activity. Instead, the results show a gradual decline in DEX trading activity relative to CEX, suggesting that the main response to the Act appears through venue use rather than through sustained changes in price-impact or Roll-based liquidity. Vidal-Tomás (2025) emphasises the central role of stablecoins in cryptocurrency trading activity and centralised exchange infrastructure. The progressive decline in DEX Turnover relative to CEX is therefore consistent with the view that regulatory formalisation of stablecoin infrastructure may strengthen the relative position of centralised venues.

[Tables 4.21-4.29 about here]

Cross-Event Regulatory Impact Analysis

The three regulatory events examined in this chapter originate from three of the largest economies in the world, the United States, the European Union, and China, where each send a regulatory signal into what was an effectively unregulated global market. Each had their distinct approach to governing cryptocurrency markets and despite their differences in design, scope, and jurisdiction, all three share a common feature: they are directed at the centralised layer of the cryptocurrency market. The patterns documented across all three events reflect announcement-period market reactions, capturing how participants adjusted liquidity and trading activity in response to regulatory news rather than to fully implemented regulatory frameworks. This is consistent with prior crypto studies that use announcement dates to isolate

the informational content of regulatory shocks before implementation dynamics unfold (Griffith and Clancey-Shang, 2023; Chokor and Alfieri, 2021; Aspris et al., 2021). The DEX protocols are less directly exposed to each policy examined here. This disproportionateness is consistent with Giménez Roche et al. (2025), who argue that regulatory obligations and prohibitions fall more directly on centralised platforms while affecting decentralised protocols more indirectly. This brings us to the central theme of our chapter, where we examine when regulations lands on the centralised layer, does the decentralised layer benefit from its unregulated status or perhaps regulations are not as negatively perceived? Our baseline results contribute to the latter. The shared characteristic of every single event across every baseline specification we find Turnover results are significant. Across all three events, DEX-linked assets lost relative trading activity to CEX-linked assets in the sustained post-period. This is the only outcome that is consistently significant at baseline across all three events, and the direction is the same every time. Table 4.30 summarises these patterns, collating the key interaction coefficients from Tables 4.3 to 4.29 across the three events, liquidity measures and event windows.

[Table 4.30 about here]

Aspris et al. (2021) provide the closest empirical foundation for our study. They show that when DEX-traded tokens obtain CEX listings, DEX activity declines sharply while total trading activity increases, implying that traders prefer the liquidity, convenience, and market depth of centralised exchanges over the anonymity and non-custodial benefits of decentralised venues. We observed the same pattern in our results, even though the premise is fundamentally different. The implication of their study could be in line with our findings. We extend their logic from listing events to regulatory events, we find that policy shocks directed at centralised infrastructure produce a reduction in DEX trading activity. Farag et al. (2025) further show that liquidity and activity conditions in decentralised exchanges are linked to liquidity provision

conditions in centralised crypto markets, supporting the view that CEX and DEX venues should be analysed jointly rather than as isolated markets. Regardless of whether the regulatory signal came from prohibition, compliance governance, or institutional formalisation, and regardless of its origin, trading activity became relatively more concentrated in the regulated and institutionally recognised layer over time. This consistency across structurally different events, different jurisdictions, and different periods tells us there is more than regulated vs unregulated markets but perhaps an increase in legitimacy in crypto markets. This perspective is supported by the increase of institutional and corporate investment within the centralised ecosystem which benefit from increased oversight (Auer et al., 2022; Huang et al., 2022; Cong et al., 2023; Fisch & Momtaz, 2020).

Moreover, under the European and Chinese events, the baseline negative Turnover direction reversed at the 1-day window, producing a brief positive DEX interaction at announcement. This suggests an initial search for less constrained venues immediately following each announcement. But the two events diverge sharply in how long this response lasted. Under the European shock, the positive DEX Turnover interaction remained significant across all subsequent windows including the 30-day horizon, with the announcement-period coefficient of approximately +0.12 exceeding the baseline coefficient of approximately −0.08 in absolute magnitude. Interestingly, the short-run DEX activity elevation was not just a sign reversal but it was stronger in magnitude than the sustained post-period decline. Under the Chinese ban, the positive interaction appeared only in the 1-day window and was gone by the 3-day window. Griffith and Clancey-Shang (2023) document that the Chinese ban produced sharp but transitory market-quality effects that wore off within approximately eight days, which is consistent with this pattern. Makarov and Schoar (2020) show that cryptocurrency markets are segmented across exchanges and jurisdictions, which helps interpret the difference between the Chinese and European event-window patterns. Although China is a major force in global

cryptocurrency markets, the Chinese ban was issued by a single national authority and directly targeted activity within Chinese jurisdiction. Its international effects were therefore consequential but potentially more geographically contained than those of the European Shock. By contrast, the European framework applied across a supranational market and affected centralised service providers operating across multiple jurisdictions. This difference in regulatory scope may help explain why the Chinese DEX Turnover response was sharp but short-lived, while the European response persisted across longer event windows.

Across the three events, the Chinese ban is the most prohibitive, yet it produces the shortest-lived DEX-relative Turnover response. Griffith and Clancey-Shang (2023) document that the Chinese ban produced sharp but transitory market-quality effects that wore off within approximately eight days, which is consistent with this pattern. However, their analysis treats the cryptocurrency market as a whole and does not distinguish between centralised and decentralised trading venues. We extend their framework by examining DEX-linked assets relative to CEX-linked assets, allowing us to ask not only whether the ban affected market quality but whether its effects were distributed equally across venue types. Our results show they were not. The transitory nature of the DEX Turnover spike under the Chinese ban, compared to the sustained response under the European shock, suggests that the reach and design of a regulatory intervention shapes how venue-level responses propagate and dissipate, a dimension that aggregate-level studies cannot capture. This is potentially explained by Yang et al. (2025), who show that Chinese cryptocurrency restrictions increased return, volatility, and extreme-risk spillovers between cryptocurrencies and China's financial markets, suggesting that the ban operated through broader market-risk conditions rather than only immediate trading relocation. Their findings are notable in that the restrictions were associated with increased connectedness and risk transmission rather than a simple reduction in activity, which further supports the interpretation that the ban's effects operated through systemic

channels rather than direct venue-level reallocation. Examining the DEX ecosystem relative to CEX, we find a pattern consistent with this interpretation: rather than the sustained increase in DEX trading activity that outright prohibition might be expected to generate, the venue-level response was brief and quickly absorbed.

Under the American Shock, there was no announcement-day DEX activity spike. The 1-day and 3-day Turnover interactions are insignificant. The negative effect emerges only from the 5-day window and strengthens at 30 days. This reaction isn't paralleled neither in the European or Chinese shocks. Rather than triggering an immediate venue-level search for unregulated alternatives, the regulatory signal of formal stablecoin integration appears to have initiated a gradual reorientation of activity toward centralised venues as market participants absorbed its implications over the weeks following the announcement. Vidal-Tomás (2025) documents that stablecoins account for the majority of total cryptocurrency trading activity and serve as the primary liquidity and settlement infrastructure of centralised exchange trading. The proposed formal integration of stablecoin issuers into the federal regulatory perimeter may have strengthened the institutional credibility of the CEX ecosystem more broadly, producing a progressive rather than immediate decline in relative DEX activity.

Turning to the price-quality measures, the picture is more varied. Amihud provides the clearest evidence of price-impact differences across venue types, while Roll is largely silent. The baseline Amihud result is significant across all four specifications under the European Shock and in the more controlled specifications under the Chinese Shock, indicating that both restrictive events are associated with lower DEX price-impact illiquidity relative to CEX over the full post-period. This is important because both events also show negative baseline Turnover coefficients. DEX-linked assets therefore lose relative trading activity over the sustained post-period, but they do not necessarily become worse trading environments in price-impact terms. Following Bianchi et al. (2022), Amihud reflects the price-impact cost of trading

rather than trading activity itself. The baseline results therefore show that venue use and price-impact liquidity are separate outcomes: fewer trades are concentrated in DEX-linked assets relative to CEX-linked assets, but the trades that do occur are associated with lower relative price impact.

The American Shock differs from this pattern. Its baseline Amihud coefficient is insignificant, meaning that the GENIUS Act produces no sustained differential price-impact effect between DEX- and CEX-linked assets. Under the GENIUS Act, the 1-day Amihud interaction is negative and significant at $p < 0.01$, making it one of the strongest price-impact results across the three events, reaching the highest significance level despite the absence of a sustained baseline effect. This matters because the American Shock produces a progressive decline in DEX Turnover relative to CEX, but no lasting price-impact effect. The response therefore appears mainly through relative trading activity rather than through sustained price-impact liquidity.

Our final measure, Roll, is largely silent throughout except for one shock, China. The baseline Roll coefficient reaches significance only under the Chinese ban, and only in the two most controlled specifications. No event window across any of the three events produces a significant Roll interaction, including the Chinese Shock. This absence of significance is meaningful because it shows the limits of the regulatory response. Whatever venue-level reallocation is documented here, it rarely operates through transaction-cost or price-reversal dynamics. Activity is shifting, and price impact is shifting in some cases, but the cost-of-trading dimension measured by Roll is largely unaffected across the board. This is consistent with Huang (2024), who shows that Roll-based liquidity does not always respond to the same conditions that affect price-impact liquidity. It also extends the use of Roll in recent crypto-liquidity work such as Augustin et al. (2023), where Roll is included as part of a broader market-quality framework. In our setting, Roll helps show that the regulatory response is not a

general liquidity response across all dimensions. Instead, regulatory announcements appear more visible in Turnover and, in some cases, Amihud, while Roll remains mostly unchanged.

The contribution here is not simply that Amihud responds to regulatory announcements, but that it reveals a different layer of the CEX–DEX response than Turnover. If only trading activity were examined, the baseline results would suggest that DEX-linked assets weaken relative to CEX-linked assets across the post-period. The Amihud results qualify this interpretation. Under the European and Chinese shocks, DEX-linked assets lose relative trading activity but show lower relative price impact, meaning that the venue receiving less activity is not necessarily the venue with weaker price-impact liquidity. This is consistent with Galati (2024), who shows that trading activity and price-impact quality are separable dimensions of market liquidity that do not always move together, and with Bianchi et al. (2022), who treat Amihud as an economically meaningful price-impact measure rather than a proxy for trading volume. Huang (2024) further shows that liquidity dimensions do not move uniformly, which is consistent with the divergence between Amihud and Turnover documented here. The American shock further sharpens this point. It produces the clearest sustained Turnover movement toward CEX-linked assets, but no sustained Amihud effect. This means that the relative concentration of trading activity can change without a corresponding lasting shift in price-impact liquidity. The implication is that regulatory announcements affect venue activity and liquidity quality through different channels, and these channels should not be collapsed into a single liquidity outcome.

The cross-event differences in DEX activity responses are not only a function of regulatory design, but also of the broader institutional environments in which market participants operate. Nguyen and Nguyen (2024) show that DeFi adoption is conditioned by country-level social, economic, and cultural factors, indicating that decentralised market participation is embedded in broader institutional environments rather than being driven solely

by technological preference. Their cross-country evidence establishes that institutional context shapes how participants engage with decentralised markets. This chapter extends that insight from adoption patterns to regulatory responses: by examining three major regulatory jurisdictions with distinct legal, institutional, and geographic characteristics, we show that regulatory announcements affecting centralised exchange infrastructure produce different venue-level responses across countries, liquidity dimensions, and time horizons. The Chinese ban, the European compliance framework, and the American stablecoin proposal each reached different participant bases operating under different institutional and geographic conditions, and the venue-level responses reflect that heterogeneity. This suggests that the institutional environment is not only a determinant of DeFi adoption, as Nguyen and Nguyen (2024) document, but also a determinant of how markets respond when regulation arrives.

Taken together, the results allow us to return to the central question posed at the outset of this chapter: does the decentralised layer benefit from its less regulated status when regulation lands on the centralised layer? The evidence suggests that both forces appear, but on different horizons. Around the European and Chinese announcements, DEX-linked assets experience brief increases in relative trading activity, consistent with an initial search for less constrained venues. However, this response does not translate into a durable DEX advantage. Across all three events, DEX-linked assets lose relative trading activity to CEX-linked assets in the sustained post-period. The American Shock provides the clearest version of this pattern, producing no announcement-period DEX spike and instead showing a progressively stronger decline in DEX Turnover relative to CEX. While the analysis does not directly observe the motives of individual traders, the observed venue-level pattern suggests that regulatory formalisation does not simply push activity toward decentralised alternatives. Instead, it is associated with sustained relative strength in CEX-linked trading activity. This points to the continuing strength of established CEX infrastructure, consistent with Vidal-Tomás (2025),

who argues that centralised exchanges remain important because they provide trust, custodial structure, solvency safeguards, and institutional credibility.

Across all three events, Turnover is more consistently significant at baseline than Amihud or Roll, suggesting that the main regulatory response operates through behavioural adjustment in where participants trade rather than through uniform changes in price quality. This is consistent with Galati (2024), who shows that activity and market quality are separable dimensions of liquidity. The broader implication is that regulation affects CEX–DEX dynamics primarily through venue activity, while price-impact and transaction-cost channels respond more selectively.

To our knowledge, this chapter is the first to examine the CEX and DEX liquidity relationship through a regulatory-shock framework, comparing venue-level responses across three major policy events originating from three of the world's largest regulatory jurisdictions. Prior studies such as Griffith and Clancey-Shang (2023), Yang et al. (2025), and Aspris et al. (2021) each provide important evidence on regulatory effects and venue dynamics in cryptocurrency markets, but none examine whether regulatory shocks produce differential liquidity and trading-activity responses across centralised and decentralised venue types simultaneously. This chapter addresses that gap directly. While we find behaviours that are consistent with patterns documented in the existing literature, including transitory market-quality effects, venue-migration logic, and the separability of activity and price-impact dimensions, we observe them in a different context: one in which the regulatory status of cryptocurrency markets is being actively reshaped. The three events examined here are not isolated policy episodes. They represent a broader structural transition in which a market that previously operated under fragmented and uneven regulatory oversight is being brought more directly within the institutional perimeter of major economies. The venue-level responses documented here show how markets are navigating that transition. The results suggest that the

appeal of operating outside the regulatory perimeter does not automatically translate into a flourishing of decentralised alternatives. Instead, two things appear to be happening at once. Trading activity in DEX-linked assets declines relative to CEX-linked assets in the sustained post-period across all three events. Yet under two of the three events, DEX-linked assets show relative improvement in price-impact liquidity. We find this consistently across three major regulatory events, three jurisdictions, and multiple measurement horizons. What these results collectively show is not what drives the CEX–DEX relationship, but how it responds to regulation: trading activity and liquidity quality move differently under regulatory shocks, and the direction depends on which dimension you examine and when.

4.5 Robustness

To examine whether the interaction coefficients in the main specification reflect movement in one venue type or both, the baseline and event-window regressions are estimated separately for DEX-linked and CEX-linked subsamples. These results are reported in Appendix 3.A1–3.A9 for DEX only subsample and Tables 3.A10-3.A18 for the CEX only subsample. For Turnover, the baseline decline under all three events is present in the DEX subsample but absent in the CEX subsample. The 1-day Turnover spike under both restrictive shocks appears in both subsamples, with larger coefficients for DEX tokens. For Amihud, the baseline improvement under the European shock is present in the DEX subsample only; under the Chinese shock, the DEX subsample shows a significant baseline improvement while the CEX subsample produces no significant response at any horizon; under the American shock, the DEX subsample shows a significant baseline decline alongside positive and significant window coefficients, while the CEX subsample response is limited. For Roll, both subsamples show similar directional movements under the same events, consistent with the null interaction coefficients in the main specification.

4.6 Conclusion

Decentralised exchanges are an integral part of the crypto ecosystem, yet their response to regulatory pressure directed at centralised infrastructure remains largely unexamined. This chapter examines whether regulatory announcements targeting centralised exchange infrastructure are associated with measurable changes in decentralised exchange liquidity and trading activity, using three events that differ in jurisdiction and regulatory design and three liquidity measures that capture distinct dimensions of market quality. Liquidity captures whether a market can support trading smoothly and comparing it across centralised and decentralised venues reveals whether regulatory pressure transmits differently depending on where and how that liquidity is organised. The analysis focuses on announcement dates to capture market responses at the point when regulatory information first reaches participants, consistent with prior crypto studies that use announcement dates to isolate the informational content of regulatory shocks before later implementation dynamics unfold (Griffith and Clancey-Shang, 2023; Chokor and Alfieri, 2021). Our central finding is that DEX trading activity declined relative to CEX in the sustained post-announcement period across all three events, suggesting that regulatory pressure on centralised exchange infrastructure is not associated with a sustained benefit for decentralised venue trading activity.

Turnover proved the most robust and persistent signal across all three events, while Amihud Illiquidity showed improvement for DEX-linked assets in two of the three events and Roll's Measure produced limited results, confirming that the venue-level response operates primarily through shifts in trading behaviour rather than immediate changes in price impact or transaction costs. The observed windows reveal a more differentiated picture. The European shock and the Chinese ban were both associated with a temporary relative increase in DEX trading activity around the announcement date, but this did not persist beyond the event windows, with the Chinese ban dissipating within a single day while the European shock

sustained the elevated DEX response across all event windows. The American shock produced a qualitatively different pattern entirely, with no announcement period spike and instead a gradual and progressive decline in relative DEX activity from the fifth day onward through the thirty-day window, consistent with how integrative regulation that legitimises centralised infrastructure may transmit a different market signal from outright restriction. The market therefore differentiates across regulatory designs at announcement even when the longer run direction converges. The sustained decline in relative DEX trading activity means that H1 is not supported in the post-announcement period, with the Turnover interaction negative and significant across all three events; support for H1 is confined to the event windows following the European shock and, briefly, the Chinese ban. The price impact results differ. Consistent with H2, Amihud Illiquidity fell for DEX-linked assets relative to CEX following the European shock and the Chinese ban, although not following the American shock. H3 receives limited support, with the Roll interaction significant only following the Chinese ban and only in two of the four specifications. The liquidity response to regulatory pressure on centralised infrastructure therefore operates through price impact rather than through trading activity or transaction costs.

Two strands of literature motivate examining CEX and DEX markets jointly rather than in isolation. The first is the venue-interconnection literature. Aspris et al. (2021) show that when DEX-traded tokens obtain CEX listings, DEX trading activity declines while total trading activity rises, demonstrating that activity responds to changes in relative venue conditions. The second is the regulatory-pressure literature, which shows that crypto activity can move across jurisdictions, assets, and trading environments when regulatory burden rises in one segment (Borri and Shakhnov, 2020; Cong et al., 2023; Foley et al., 2019). At the same time, recent DeFi research shows that decentralised markets are not fully insulated from centralised and traditional financial infrastructure. AMM liquidity remains linked to external prices through

arbitrage, DeFi stablecoin yields respond to monetary policy and fiat settlement frictions, and DeFi participation is shaped by incentives rather than by a fixed preference for decentralisation (Cartea et al., 2025; Liang, 2026; Gadzinski and Liuzzi, 2025). The results contribute to the literature at the intersection of these two strands by showing that regulatory pressure on CEX infrastructure is associated with changes in the relative liquidity and trading activity of DEX-linked assets. Across three jurisdictions and three regulatory designs, the results show that DEX-linked assets do not experience a durable trading activity advantage relative to CEX-linked assets. However, price-impact liquidity tells a different story, improving for DEX-linked assets in two of the three events. Trading activity and price-impact liquidity therefore do not move together, and that divergence is itself informative about how regulatory announcements are reflected across venue types.

The three jurisdictions examined in this study are institutionally strong and carry significant weight in global crypto markets. Each approached regulation differently, yet the sustained post-period result is consistent: CEX retained its relative trading activity position across all three events. This suggests that even under different regulatory designs from influential jurisdictions, the fundamental structure of where activity is concentrated did not shift dramatically. Regulators could benefit from this analysis by recognising that these dynamics do not operate uniformly and that the effects of targeting centralised infrastructure transmit across the broader ecosystem. Indeed, DEX trading activity declined across all three events despite not being the direct target of any of the regulatory interventions examined. Aspris et al. (2021) show that DEXs perform an important price discovery and on-ramping function in the broader crypto ecosystem, and Giménez Roche et al. (2025) demonstrate that decentralised venues serve a genuine and distinct role for market participants. The weakening of DEX activity under regulatory pressure directed elsewhere is therefore a finding that warrants attention in its own right. Importantly, the exemption of decentralised venues from

regulatory frameworks such as MiCA did not produce a sustained increase in DEX trading activity, suggesting that the exemption status did not create a backdoor for participants in activity terms. However, price impact liquidity improved for DEX-linked assets under two of the three events, meaning the exemption is not neutral in its effects and operates through market quality channels that policymakers should account for when drawing the boundaries of regulatory oversight. Policymakers should therefore monitor both CEX and DEX dynamics throughout the implementation and transition process, not just at the announcement stage, as the longer-run effects remain an open question.

Future research should examine whether the patterns documented here represent a genuine regime change, meaning a durable shift in market participation, activity concentration, or dominance between venue types, as regulatory frameworks move from announcement to implementation and enforcement. A related question is whether regulatory scrutiny of centralised exchanges may, under some conditions, reinforce rather than undermine their market position, given that the sustained CEX trading activity advantage observed here held across events that differed considerably in design and intent. Both questions need to be examined at two levels: at the exchange level, both individually and in aggregate, and at the coin level, since major cryptocurrencies hold the bulk of market activity and their response to regulation may differ from the broader token ecosystem examined here. The primary limitation of this study that future work should address is data availability at the exchange level. This study examines venue-level dynamics through token-level ecosystem proxies, an approach consistent with prior work given the limited availability of granular exchange-level data, but direct access to order book and liquidity pool data across specific exchanges would allow the questions raised here to be examined with greater precision.

Tables

Table 4.1: Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Turnover	73484	.052	.105	0	8.911
Amihud	62996	.002	.008	0	.067
Returns	62964	0	.059	-.88	1.407
Market Cap	73444	21.556	2.171	15.019	28.543
Volume	76000	17.923	2.315	-.414	25.038
VIX	76309	20.337	6.872	11.86	82.69
WUI	76309	32060.758	23852.771	11888.73	106862.2
GEPU	76309	266.945	88.25	170.414	628.115

Table 4.2: Pairwise correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) Turnover	1.000								
(2) Amihud Illiquidity	-0.066*	1.000							
(3) Roll Measure	0.185*	0.111*	1.000						
(4) Returns	0.070*	-0.015*	-0.023*	1.000					
(5) Market Cap	-0.171*	-0.370*	-0.112*	0.021*	1.000				
(6) Volume	0.086*	-0.512*	-0.048*	0.034*	0.880*	1.000			
(7) VIX	0.079*	0.127*	0.218*	-0.066*	-0.080*	-0.055*	1.000		
(8) WUI	-0.055*	0.024*	-0.072*	-0.014*	-0.017*	-0.031*	0.037*	1.000	
(9) GEPU	0.012*	0.049*	0.027*	0.001	-0.059*	-0.045*	0.337*	0.669*	1.000

***Note**: This table reports pairwise Pearson correlations between all variables used in the analysis. The sample covers daily observations from 1 January 2020 to 31 October 2025 for CEX-linked and DEX-linked cryptocurrency indices. Turnover, Amihud Illiquidity, and Roll Measure are the three dependent liquidity variables. Returns, log market capitalisation, and log trading volume are lagged by one period. VIX, WUI, and GEPU are also lagged by one period. * denotes statistical significance at the 10% level ($p < 0.10$); all marked correlations are also significant at $p < 0.01$.*

Table 4.3: European Policy Shock - Turnover

	(1)	(2)	(3)	(4)
DEX × Post	-0.0775*	-0.0932**	-0.0907*	-0.0894**
	(0.0427)	(0.0454)	(0.0448)	(0.0417)
DEX	0.0752			
	(0.0448)			
Post	0.0006	0.0115	0.0276*	
	(0.0075)	(0.0085)	(0.0156)	
Returns	0.0849***	0.0861***	0.0840***	0.1195**
	(0.0265)	(0.0258)	(0.0260)	(0.0470)
Market Cap	-0.0517***	-0.0557***	-0.0531***	-0.0538***
	(0.0077)	(0.0093)	(0.0089)	(0.0102)
Volume	0.0483***	0.0473***	0.0452***	0.0466***
	(0.0072)	(0.0071)	(0.0067)	(0.0078)
VIX	0.0004***	0.0003*	0.0003**	
	(0.0001)	(0.0001)	(0.0001)	
WUI	-0.0000***	-0.0000**	-0.0000	
	(0.0000)	(0.0000)	(0.0000)	
Observations	61814	61814	61814	61814
Adj. R-squared	0.367	0.405	0.410	0.459
Individual FE	NO	YES	YES	YES
Year FE	NO	NO	YES	NO
Time FE	NO	NO	NO	YES

Note: *This table reports difference-in-differences estimates of the effect of the MiCA proposal announcement (September 24, 2020) on cryptocurrency market liquidity. The dependent variable is Turnover. The coefficient of interest, DiD (DEX × Post), captures the differential change in Turnover for DEX-linked tokens relative to CEX-linked tokens following the proposal announcement. Treated (DEX) is a time-invariant indicator equal to one for cryptocurrencies classified as DEX-linked and zero for CEX-linked cryptocurrencies; this indicator is absorbed by the cryptocurrency fixed effect in columns (2)–(4). Post-MiCA is an indicator equal to one for observations after September 24, 2020 and zero otherwise; this indicator is absorbed by the daily time fixed effect in column (4) only. Column (1) includes no fixed effects; column (2) includes cryptocurrency fixed effects; column (3) includes cryptocurrency and year fixed effects; column (4) includes cryptocurrency and daily time fixed effects. Controls include one-period lagged returns, lagged log market capitalisation, lagged log trading volume, VIX, and WUI. All specifications are estimated using a difference-in-differences framework with two-way fixed effects. Standard errors are clustered by cryptocurrency. Standard errors in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.*

Table 4.4: European Policy Shock - Amihud Illiquidity

	(1)	(2)	(3)	(4)
DEX × Post	-0.0101*	-0.0126**	-0.0127**	-0.0124**
	(0.0051)	(0.0049)	(0.0048)	(0.0050)
DEX	0.0098*			
	(0.0055)			
Post	-0.0033	-0.0013	-0.0008	0.0000
	(0.0029)	(0.0027)	(0.0018)	(.)
Returns	0.0009	0.0006	0.0004	0.0107**
	(0.0011)	(0.0011)	(0.0009)	(0.0039)
Market Cap	0.0015**	0.0001	0.0001	0.0012
	(0.0006)	(0.0004)	(0.0005)	(0.0008)
Volume	-0.0030***	-0.0025***	-0.0031***	-0.0044***
	(0.0008)	(0.0008)	(0.0009)	(0.0013)
VIX	0.0001***	0.0000**	0.0000*	0.0000
	(0.0000)	(0.0000)	(0.0000)	(.)
WUI	-0.0000	-0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(.)
Observations	61815	61815	61815	61815
Adj. R-squared	0.351	0.423	0.457	0.501
Individual FE	NO	YES	YES	YES
Year FE	NO	NO	YES	NO
Time FE	NO	NO	NO	YES

Note: *This table reports difference-in-differences estimates of the effect of the MiCA proposal announcement (September 24, 2020) on cryptocurrency market liquidity. The dependent variable is Amihud Illiquidity. The coefficient of interest, DiD (DEX × Post), captures the differential change in Amihud Illiquidity for DEX-linked tokens relative to CEX-linked tokens following the proposal announcement. Treated (DEX) is a time-invariant indicator equal to one for cryptocurrencies classified as DEX-linked and zero for CEX-linked cryptocurrencies; this indicator is absorbed by the cryptocurrency fixed effect in columns (2)–(4). Post-MiCA is an indicator equal to one for observations after September 24, 2020 and zero otherwise; this indicator is absorbed by the daily time fixed effect in column (4) only. Column (1) includes no fixed effects; column (2) includes cryptocurrency fixed effects; column (3) includes cryptocurrency and year fixed effects; column (4) includes cryptocurrency and daily time fixed effects. Controls include one-period lagged returns, lagged log market capitalisation, lagged log trading volume, VIX, and WUI. All specifications are estimated using a difference-in-differences framework with two-way fixed effects. Standard errors are clustered by cryptocurrency. Standard errors in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.*

Table 4.5: European Policy Shock - Roll Measure

	(1)	(2)	(3)	(4)
DEX × Post	-0.0161	-0.0163	-0.0168	-0.0175
	(0.0142)	(0.0144)	(0.0142)	(0.0127)
DEX	0.0166	0.0000	0.0000	0.0000
	(0.0145)	(.)	(.)	(.)
Post	-0.0126***	-0.0145***	-0.0150***	0.0000
	(0.0027)	(0.0029)	(0.0035)	(.)
Returns	-0.0111*	-0.0120**	-0.0126**	-0.0165
	(0.0055)	(0.0055)	(0.0056)	(0.0108)
Market Cap	-0.0041***	-0.0038***	-0.0038***	-0.0027*
	(0.0009)	(0.0013)	(0.0010)	(0.0014)
Volume	0.0034***	0.0042***	0.0030***	0.0022*
	(0.0011)	(0.0010)	(0.0009)	(0.0011)
VIX	0.0007***	0.0007***	0.0009***	0.0000
	(0.0001)	(0.0001)	(0.0001)	(.)
WUI	-0.0000***	-0.0000***	-0.0000**	0.0000
	(0.0000)	(0.0000)	(0.0000)	(.)
Observations	61787	61787	61787	61787
Adj. R-squared	0.090	0.102	0.122	0.457
Individual FE	NO	YES	YES	YES
Year FE	NO	NO	YES	NO
Time FE	NO	NO	NO	YES

Note: *This table reports difference-in-differences estimates of the effect of the MiCA proposal announcement (September 24, 2020) on cryptocurrency market liquidity. The dependent variable is Roll Measure. The coefficient of interest, DiD (DEX × Post), captures the differential change in Roll Measure for DEX-linked tokens relative to CEX-linked tokens following the proposal announcement. Treated (DEX) is a time-invariant indicator equal to one for cryptocurrencies classified as DEX-linked and zero for CEX-linked cryptocurrencies; this indicator is absorbed by the cryptocurrency fixed effect in columns (2)–(4). Post-MiCA is an indicator equal to one for observations after September 24, 2020 and zero otherwise; this indicator is absorbed by the daily time fixed effect in column (4) only. Column (1) includes no fixed effects; column (2) includes cryptocurrency fixed effects; column (3) includes cryptocurrency and year fixed effects; column (4) includes cryptocurrency and daily time fixed effects. Controls include one-period lagged returns, lagged log market capitalisation, lagged log trading volume, VIX, and WUI. All specifications are estimated using a difference-in-differences framework with two-way fixed effects. Standard errors are clustered by cryptocurrency. Standard errors in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.*

Table 4.6: European Policy Shock - Event Windows– Part 1: Turnover

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1-Day Window × DEX	0.1120*	0.1119*	0.1110*	0.1105*				
	(0.0568)	(0.0552)	(0.0563)	(0.0574)				
3-Day Window × DEX					0.1060**	0.1061**	0.1051**	0.1047*
					(0.0511)	(0.0496)	(0.0506)	(0.0517)
DEX	-0.0000				-0.0001			
	(0.0067)				(0.0067)			
1-Day Window	-0.0084	-0.0146	-0.0230*					
	(0.0088)	(0.0109)	(0.0124)					
3-Day Window					-0.0102	-0.0164*	-0.0250**	0.0000
					(0.0072)	(0.0094)	(0.0113)	(.)
Returns	0.0864***	0.0866***	0.0832***	0.1250**	0.0868***	0.0870***	0.0835***	0.1254**
	(0.0267)	(0.0261)	(0.0264)	(0.0474)	(0.0266)	(0.0260)	(0.0264)	(0.0473)
Market Cap	-0.0508***	-0.0534***	-0.0496***	-0.0494***	-0.0508***	-0.0534***	-0.0497***	-0.0495***
	(0.0074)	(0.0089)	(0.0083)	(0.0093)	(0.0074)	(0.0088)	(0.0083)	(0.0093)
Volume	0.0472***	0.0457***	0.0437***	0.0440***	0.0472***	0.0457***	0.0437***	0.0439***
	(0.0069)	(0.0069)	(0.0065)	(0.0072)	(0.0068)	(0.0069)	(0.0065)	(0.0072)
VIX	0.0005***	0.0004*	0.0003*		0.0005***	0.0004*	0.0003*	
	(0.0002)	(0.0002)	(0.0002)		(0.0002)	(0.0002)	(0.0002)	
WUI	-0.0000***	-0.0000***	-0.0000*		-0.0000***	-0.0000***	-0.0000*	
	(0.0000)	(0.0000)	(0.0000)		(0.0000)	(0.0000)	(0.0000)	
Observations	61814	61814	61814	61814	61814	61814	61814	61814
Adj. R-squared	0.359	0.395	0.401	0.451	0.359	0.396	0.401	0.451
Individual FE	NO	YES	YES	YES	NO	YES	YES	YES
Year FE	NO	NO	YES	NO	NO	NO	YES	NO
Time FE	NO	NO	NO	YES	NO	NO	NO	YES

Note: *This table reports difference-in-differences estimates of the effect of the MiCA proposal announcement (September 24, 2020) on cryptocurrency market liquidity within discrete event windows. The dependent variable is Turnover. The coefficient of interest, [1-Day and 3-Day] × DEX respectively, captures the differential change in Turnover for DEX-linked tokens relative to CEX-linked tokens within the specified post-announcement window. Treated (DEX) is a time-invariant indicator equal to one for cryptocurrencies classified as DEX-linked and zero for CEX-linked cryptocurrencies; this indicator is absorbed by the cryptocurrency fixed effect in columns (2), (3), (4), (6), (7), and (8). The window indicator, 1-Day and 3-Day Window, are an indicator equal to one for observations falling within the specified number of trading days after the announcement date and zero otherwise; this indicator is absorbed by the daily time fixed effect in columns (4) and (8) only. Within each window, column (1) includes no fixed effects; column (2) includes cryptocurrency fixed effects; column (3) includes cryptocurrency and year fixed effects; column (4) includes cryptocurrency and daily time fixed effects. Controls include one-period lagged returns, lagged log market capitalisation, lagged log trading volume, VIX, and WUI. All specifications are estimated using a difference-in-differences framework with two-way fixed effects. Standard errors are clustered by cryptocurrency. Standard errors in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.*

Table 4.7: European Policy Shock - Event Windows– Part 2: Turnover

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
5-Day Window × DEX	0.1056**	0.1059**	0.1048**	0.1048**				
	(0.0488)	(0.0472)	(0.0481)	(0.0491)				
30-Day Window × DEX					0.1179**	0.1197**	0.1193**	0.1212**
					(0.0533)	(0.0508)	(0.0507)	(0.0530)
DEX	-0.0002				-0.0019			
	(0.0067)				(0.0065)			
5-Day Window	-0.0116*	-0.0178*	-0.0265**					
	(0.0066)	(0.0091)	(0.0110)					
30-Day Window					-0.0121**	-0.0183**	-0.0251**	
					(0.0053)	(0.0079)	(0.0094)	
Returns	0.0872***	0.0874***	0.0839***	0.1263**	0.0897***	0.0899***	0.0869***	0.1325***
	(0.0267)	(0.0260)	(0.0264)	(0.0473)	(0.0260)	(0.0254)	(0.0256)	(0.0459)
Market Cap	-0.0507***	-0.0533***	-0.0497***	-0.0495***	-0.0502***	-0.0529***	-0.0504***	-0.0501***
	(0.0074)	(0.0088)	(0.0083)	(0.0093)	(0.0070)	(0.0085)	(0.0082)	(0.0092)
Volume	0.0471***	0.0457***	0.0436***	0.0438***	0.0467***	0.0452***	0.0433***	0.0433***
	(0.0068)	(0.0068)	(0.0065)	(0.0071)	(0.0065)	(0.0065)	(0.0062)	(0.0067)
VIX	0.0005***	0.0004*	0.0003*		0.0005***	0.0003*	0.0003*	
	(0.0002)	(0.0002)	(0.0002)		(0.0002)	(0.0002)	(0.0001)	
WUI	-0.0000***	-0.0000***	-0.0000*		-0.0000***	-0.0000***	-0.0000**	
	(0.0000)	(0.0000)	(0.0000)		(0.0000)	(0.0000)	(0.0000)	
Observations	61814	61814	61814	61814	61814	61814	61814	61814
Adj. R-squared	0.360	0.396	0.402	0.452	0.369	0.406	0.410	0.460
Individual FE	NO	YES	YES	YES	NO	YES	YES	YES
Year FE	NO	NO	YES	NO	NO	NO	YES	NO
Time FE	NO	NO	NO	YES	NO	NO	NO	YES

Note: *This table reports difference-in-differences estimates of the effect of the MiCA proposal announcement (September 24, 2020) on cryptocurrency market liquidity within discrete event windows. The dependent variable is Turnover. The coefficient of interest, [5-Day and 30-Day] × DEX respectively, captures the differential change in Turnover for DEX-linked tokens relative to CEX-linked tokens within the specified post-announcement window. Treated (DEX) is a time-invariant indicator equal to one for cryptocurrencies classified as DEX-linked and zero for CEX-linked cryptocurrencies; this indicator is absorbed by the cryptocurrency fixed effect in columns (2), (3), (4), (6), (7), and (8). The window indicator, 5-Day and 30-Day Window, are an indicator equal to one for observations falling within the specified number of trading days after the announcement date and zero otherwise; this indicator is absorbed by the daily time fixed effect in columns (4) and (8) only. Within each window, column (1) includes no fixed effects; column (2) includes cryptocurrency fixed effects; column (3) includes cryptocurrency and year fixed effects; column (4) includes cryptocurrency and daily time fixed effects. Controls include one-period lagged returns, lagged log market capitalisation, lagged log trading volume, VIX, and WUI. All specifications are estimated using a difference-in-differences framework with two-way fixed effects. Standard errors are clustered by cryptocurrency. Standard errors in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.*

Table 4.8: European Policy Shock - Event Windows -Part 1: Amihud Illiquidity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1-Day Window × DEX	0.0009	0.0018	0.0022	0.0033*				
	(0.0018)	(0.0017)	(0.0018)	(0.0017)				
3-Day Window × DEX					0.0003	0.0012	0.0016	0.0026
					(0.0021)	(0.0019)	(0.0021)	(0.0020)
DEX	-0.0004				-0.0004			
	(0.0012)				(0.0012)			
1-Day Window	0.0013	-0.0003	-0.0015					
	(0.0018)	(0.0014)	(0.0010)					
3-Day Window					0.0012	-0.0004	-0.0017	
					(0.0021)	(0.0018)	(0.0012)	
Returns	0.0016	0.0010	0.0004	0.0114***	0.0016	0.0010	0.0004	0.0114***
	(0.0013)	(0.0013)	(0.0010)	(0.0037)	(0.0014)	(0.0013)	(0.0010)	(0.0037)
Market Cap	0.0015***	0.0000	0.0006	0.0018**	0.0016***	0.0000	0.0006	0.0018**
	(0.0006)	(0.0004)	(0.0005)	(0.0007)	(0.0006)	(0.0004)	(0.0005)	(0.0007)
Volume	-0.0032***	-0.0027***	-0.0034***	-0.0048***	-0.0032***	-0.0027***	-0.0034***	-0.0048***
	(0.0008)	(0.0008)	(0.0009)	(0.0012)	(0.0008)	(0.0008)	(0.0009)	(0.0012)
VIX	0.0001***	0.0001**	0.0000*		0.0001***	0.0001**	0.0000*	
	(0.0001)	(0.0000)	(0.0000)		(0.0001)	(0.0000)	(0.0000)	
WUI	-0.0000	-0.0000	0.0000		-0.0000	-0.0000	0.0000	
	(0.0000)	(0.0000)	(0.0000)		(0.0000)	(0.0000)	(0.0000)	
Observations	61815	61815	61815	61815	61815	61815	61815	61815
Adj. R-squared	0.313	0.390	0.431	0.481	0.313	0.390	0.431	0.481
Individual FE	NO	YES	YES	YES	NO	YES	YES	YES
Year FE	NO	NO	YES	NO	NO	NO	YES	NO
Time FE	NO	NO	NO	YES	NO	NO	NO	YES

Note: *This table reports difference-in-differences estimates of the effect of the MiCA proposal announcement (September 24, 2020) on cryptocurrency market liquidity within discrete event windows. The dependent variable is Amihud Illiquidity. The coefficient of interest, [1-Day and 3-Day] × DEX respectively, captures the differential change in Amihud Illiquidity for DEX-linked tokens relative to CEX-linked tokens within the specified post-announcement window. Treated (DEX) is a time-invariant indicator equal to one for cryptocurrencies classified as DEX-linked and zero for CEX-linked cryptocurrencies; this indicator is absorbed by the cryptocurrency fixed effect in columns (2), (3), (4), (6), (7), and (8). The window indicator, 1-Day and 3-Day Window, are an indicator equal to one for observations falling within the specified number of trading days after the announcement date and zero otherwise; this indicator is absorbed by the daily time fixed effect in columns (4) and (8) only. Within each window, column (1) includes no fixed effects; column (2) includes cryptocurrency fixed effects; column (3) includes cryptocurrency and year fixed effects; column (4) includes cryptocurrency and daily time fixed effects. Controls include one-period lagged returns, lagged log market capitalisation, lagged log trading volume, VIX, and WUI. All specifications are estimated using a difference-in-differences framework with two-way fixed effects. Standard errors are clustered by cryptocurrency. Standard errors in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.*

Table 4.9: European Policy Shock - Event Windows - Part 2: Amihud Illiquidity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
5-Day Window × DEX	-0.0000	0.0009	0.0013	0.0025				
	(0.0019)	(0.0018)	(0.0019)	(0.0019)				
30-Day Window × DEX					-0.0009	0.0000	0.0002	0.0012
					(0.0021)	(0.0019)	(0.0021)	(0.0020)
DEX	-0.0004				-0.0004			
	(0.0012)				(0.0012)			
5-Day Window	0.0009	-0.0007	-0.0021*					
	(0.0020)	(0.0016)	(0.0011)					
30-Day Window					0.0011	-0.0005	-0.0021*	
					(0.0020)	(0.0017)	(0.0012)	
Returns	0.0016	0.0010	0.0004	0.0115***	0.0016	0.0010	0.0003	0.0115***
	(0.0014)	(0.0013)	(0.0009)	(0.0037)	(0.0013)	(0.0013)	(0.0009)	(0.0036)
Market Cap	0.0016***	0.0000	0.0006	0.0018**	0.0016***	0.0000	0.0006	0.0018**
	(0.0006)	(0.0004)	(0.0005)	(0.0007)	(0.0006)	(0.0004)	(0.0005)	(0.0007)
Volume	-0.0032***	-0.0027***	-0.0034***	-0.0048***	-0.0032***	-0.0027***	-0.0034***	-0.0048***
	(0.0008)	(0.0008)	(0.0009)	(0.0012)	(0.0008)	(0.0008)	(0.0009)	(0.0012)
VIX	0.0001***	0.0001**	0.0000*		0.0001***	0.0001**	0.0000*	
	(0.0001)	(0.0000)	(0.0000)		(0.0000)	(0.0000)	(0.0000)	
WUI	-0.0000	-0.0000	0.0000		-0.0000	-0.0000	0.0000	
	(0.0000)	(0.0000)	(0.0000)		(0.0000)	(0.0000)	(0.0000)	
Observations	61815	61815	61815	61815	61815	61815	61815	61815
Adj. R-squared	0.313	0.390	0.431	0.481	0.313	0.390	0.432	0.481
Individual FE	NO	YES	YES	YES	NO	YES	YES	YES
Year FE	NO	NO	YES	NO	NO	NO	YES	NO
Time FE	NO	NO	NO	YES	NO	NO	NO	YES

Note: *This table reports difference-in-differences estimates of the effect of the MiCA proposal announcement (September 24, 2020) on cryptocurrency market liquidity within discrete event windows. The dependent variable is Amihud Illiquidity. The coefficient of interest, [5-Day and 30-Day] × DEX respectively, captures the differential change in Amihud Illiquidity for DEX-linked tokens relative to CEX-linked tokens within the specified post-announcement window. Treated (DEX) is a time-invariant indicator equal to one for cryptocurrencies classified as DEX-linked and zero for CEX-linked cryptocurrencies; this indicator is absorbed by the cryptocurrency fixed effect in columns (2), (3), (4), (6), (7), and (8). The window indicator, 5-Day and 30-Day Window, are an indicator equal to one for observations falling within the specified number of trading days after the announcement date and zero otherwise; this indicator is absorbed by the daily time fixed effect in columns (4) and (8) only. Within each window, column (1) includes no fixed effects; column (2) includes cryptocurrency fixed effects; column (3) includes cryptocurrency and year fixed effects; column (4) includes cryptocurrency and daily time fixed effects. Controls include one-period lagged returns, lagged log market capitalisation, lagged log trading volume, VIX, and WUI. All specifications are estimated using a difference-in-differences framework with two-way fixed effects. Standard errors are clustered by cryptocurrency. Standard errors in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.*

Table 4.10: European Policy Shock - Event Windows – Part 1: Roll's Measure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1-Day Window × DEX	0.0149	0.0140	0.0144	0.0137				
	(0.0341)	(0.0338)	(0.0333)	(0.0337)				
3-Day Window × DEX					0.0195	0.0185	0.0188	0.0179
					(0.0331)	(0.0327)	(0.0322)	(0.0326)
DEX	-0.0008				-0.0008			
	(0.0019)				(0.0019)			
1-Day Window	0.0187**	0.0182**	0.0141*					
	(0.0077)	(0.0074)	(0.0077)					
3-Day Window					0.0155**	0.0150**	0.0110	
					(0.0074)	(0.0071)	(0.0074)	
Returns	-0.0089	-0.0099*	-0.0122**	-0.0154	-0.0086	-0.0096*	-0.0119**	-0.0153
	(0.0055)	(0.0054)	(0.0057)	(0.0103)	(0.0054)	(0.0053)	(0.0055)	(0.0101)
Market Cap	-0.0042***	-0.0053***	-0.0032***	-0.0018	-0.0041***	-0.0052***	-0.0032***	-0.0018
	(0.0009)	(0.0012)	(0.0011)	(0.0015)	(0.0009)	(0.0012)	(0.0011)	(0.0015)
Volume	0.0030***	0.0040***	0.0024***	0.0017*	0.0030***	0.0040***	0.0024***	0.0016*
	(0.0010)	(0.0010)	(0.0008)	(0.0010)	(0.0010)	(0.0010)	(0.0008)	(0.0009)
VIX	0.0009***	0.0009***	0.0009***		0.0009***	0.0009***	0.0009***	
	(0.0001)	(0.0001)	(0.0001)		(0.0001)	(0.0001)	(0.0001)	
WUI	-0.0000***	-0.0000***	-0.0000		-0.0000***	-0.0000***	-0.0000	
	(0.0000)	(0.0000)	(0.0000)		(0.0000)	(0.0000)	(0.0000)	
Observations	61787	61787	61787	61787	61787	61787	61787	61787
Adj. R-squared	0.075	0.086	0.112	0.455	0.075	0.086	0.112	0.455
Individual FE	NO	YES	YES	YES	NO	YES	YES	YES
Year FE	NO	NO	YES	NO	NO	NO	YES	NO
Time FE	NO	NO	NO	YES	NO	NO	NO	YES

Note: *This table reports difference-in-differences estimates of the effect of the MiCA proposal announcement (September 24, 2020) on cryptocurrency market liquidity within discrete event windows. The dependent variable is Roll Measure. The coefficient of interest, [1-Day and 3-Day] × DEX respectively, captures the differential change in Roll Measure for DEX-linked tokens relative to CEX-linked tokens within the specified post-announcement window. Treated (DEX) is a time-invariant indicator equal to one for cryptocurrencies classified as DEX-linked and zero for CEX-linked cryptocurrencies; this indicator is absorbed by the cryptocurrency fixed effect in columns (2), (3), (4), (6), (7), and (8). The window indicator, 1-Day and 3-Day Window, are an indicator equal to one for observations falling within the specified number of trading days after the announcement date and zero otherwise; this indicator is absorbed by the daily time fixed effect in columns (4) and (8) only. Within each window, column (1) includes no fixed effects; column (2) includes cryptocurrency fixed effects; column (3) includes cryptocurrency and year fixed effects; column (4) includes cryptocurrency and daily time fixed effects. Controls include one-period lagged returns, lagged log market capitalisation, lagged log trading volume, VIX, and WUI. All specifications are estimated using a difference-in-differences framework with two-way fixed effects. Standard errors are clustered by cryptocurrency. Standard errors in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.*

Table 4.11: European Policy Shock - Event Windows– Part 2: Roll's Measure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
5-Day Window × DEX	0.0209	0.0200	0.0203	0.0195				
	(0.0335)	(0.0331)	(0.0327)	(0.0330)				
30-Day Window × DEX					0.0237	0.0235	0.0239	0.0239
					(0.0238)	(0.0236)	(0.0235)	(0.0238)
DEX	-0.0007				-0.0009			
	(0.0019)				(0.0019)			
5-Day Window	0.0165**	0.0161**	0.0122					
	(0.0075)	(0.0072)	(0.0076)					
30-Day Window					0.0081	0.0079	0.0054	
					(0.0060)	(0.0058)	(0.0064)	
Returns	-0.0085	-0.0095*	-0.0117**	-0.0151	-0.0079	-0.0088*	-0.0107**	-0.0140
	(0.0053)	(0.0052)	(0.0054)	(0.0100)	(0.0048)	(0.0046)	(0.0046)	(0.0087)
Market Cap	-0.0041***	-0.0052***	-0.0032***	-0.0018	-0.0039***	-0.0048***	-0.0034***	-0.0019
	(0.0009)	(0.0012)	(0.0011)	(0.0015)	(0.0008)	(0.0011)	(0.0011)	(0.0015)
Volume	0.0030***	0.0039***	0.0023***	0.0016*	0.0028***	0.0038***	0.0022***	0.0015*
	(0.0010)	(0.0010)	(0.0008)	(0.0009)	(0.0009)	(0.0009)	(0.0008)	(0.0009)
VIX	0.0009***	0.0009***	0.0009***		0.0009***	0.0008***	0.0009***	
	(0.0001)	(0.0001)	(0.0001)		(0.0001)	(0.0001)	(0.0001)	
WUI	-0.0000***	-0.0000***	-0.0000		-0.0000***	-0.0000***	-0.0000	
	(0.0000)	(0.0000)	(0.0000)		(0.0000)	(0.0000)	(0.0000)	
Observations	61787	61787	61787	61787	61787	61787	61787	61787
Adj. R-squared	0.077	0.088	0.113	0.455	0.082	0.093	0.117	0.458
Individual FE	NO	YES	YES	YES	NO	YES	YES	YES
Year FE	NO	NO	YES	NO	NO	NO	YES	NO
Time FE	NO	NO	NO	YES	NO	NO	NO	YES

Note: *This table reports difference-in-differences estimates of the effect of the MiCA proposal announcement (September 24, 2020) on cryptocurrency market liquidity within discrete event windows. The dependent variable is Roll Measure. The coefficient of interest, [5-Day and 30-Day] × DEX respectively, captures the differential change in Roll Measure for DEX-linked tokens relative to CEX-linked tokens within the specified post-announcement window. Treated (DEX) is a time-invariant indicator equal to one for cryptocurrencies classified as DEX-linked and zero for CEX-linked cryptocurrencies; this indicator is absorbed by the cryptocurrency fixed effect in columns (2), (3), (4), (6), (7), and (8). The window indicator, 5-Day and 30-Day Window, are an indicator equal to one for observations falling within the specified number of trading days after the announcement date and zero otherwise; this indicator is absorbed by the daily time fixed effect in columns (4) and (8) only. Within each window, column (1) includes no fixed effects; column (2) includes cryptocurrency fixed effects; column (3) includes cryptocurrency and year fixed effects; column (4) includes cryptocurrency and daily time fixed effects. Controls include one-period lagged returns, lagged log market capitalisation, lagged log trading volume, VIX, and WUI. All specifications are estimated using a difference-in-differences framework with two-way fixed effects. Standard errors are clustered by cryptocurrency. Standard errors in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.*

Table 4.12: Chinese Policy Shock- Turnover

	(1)	(2)	(3)	(4)
DEX × Post	-0.0669**	-0.0760**	-0.0762**	-0.0763**
	(0.0285)	(0.0302)	(0.0307)	(0.0301)
DEX	0.0590**			
	(0.0281)			
Post	-0.0031	0.0034	0.0052	
	(0.0067)	(0.0089)	(0.0134)	
Returns	0.0778***	0.0802***	0.0807***	0.1249**
	(0.0262)	(0.0258)	(0.0258)	(0.0473)
Markt Cap	-0.0495***	-0.0527***	-0.0532***	-0.0559***
	(0.0071)	(0.0093)	(0.0092)	(0.0103)
Volume	0.0459***	0.0443***	0.0439***	0.0460***
	(0.0063)	(0.0062)	(0.0063)	(0.0072)
VIX	0.0002	0.0001	0.0002	
	(0.0001)	(0.0001)	(0.0002)	
WUI	-0.0000	-0.0000	-0.0000	
	(0.0000)	(0.0000)	(0.0000)	
Observations	61814	61814	61814	61814
Adj. R-squared	0.387	0.425	0.426	0.472
Individual FE	NO	YES	YES	YES
Year FE	NO	NO	YES	NO
Time FE	NO	NO	NO	YES

Note: *This table reports difference-in-differences estimates of the effect of the Chinese cryptocurrency ban proposal (May 18, 2021) on cryptocurrency market liquidity. The dependent variable is Turnover. The coefficient of interest, DiD (DEX × Post), captures the differential change in Turnover for DEX-linked tokens relative to CEX-linked tokens following the proposal announcement. Treated (DEX) is a time-invariant indicator equal to one for cryptocurrencies classified as DEX-linked and zero for CEX-linked cryptocurrencies; this indicator is absorbed by the cryptocurrency fixed effect in columns (2)–(4). Post-China is an indicator equal to one for observations after May 18, 2021 and zero otherwise; this indicator is absorbed by the daily time fixed effect in column (4) only. Column (1) includes no fixed effects; column (2) includes cryptocurrency fixed effects; column (3) includes cryptocurrency and year fixed effects; column (4) includes cryptocurrency and daily time fixed effects. Controls include one-period lagged returns, lagged log market capitalisation, lagged log trading volume, VIX, and WUI. All specifications are estimated using a difference-in-differences framework with two-way fixed effects. Standard errors are clustered by cryptocurrency. Standard errors in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.*

Table 4.13: Chinese Policy Shock- Amihud Illiquidity

	(1)	(2)	(3)	(4)
DEX × Post	-0.0017	-0.0034	-0.0038*	-0.0042**
	(0.0023)	(0.0024)	(0.0022)	(0.0020)
DEX	0.0018			
	(0.0025)			
Post	-0.0036	-0.0021	0.0005	
	(0.0022)	(0.0021)	(0.0013)	
Returns	-0.0000	-0.0000	0.0004	0.0114***
	(0.0008)	(0.0008)	(0.0008)	(0.0037)
Market Cap	0.0019***	0.0006	0.0004	0.0014*
	(0.0006)	(0.0005)	(0.0005)	(0.0008)
Volume	-0.0035***	-0.0030***	-0.0034***	-0.0047***
	(0.0008)	(0.0009)	(0.0009)	(0.0012)
VIX	0.0001***	0.0000**	0.0000*	
	(0.0000)	(0.0000)	(0.0000)	
WUI	0.0000	0.0000	0.0000	
	(0.0000)	(0.0000)	(0.0000)	
Observations	61815	61815	61815	61815
Adj. R-squared	0.346	0.413	0.438	0.488
Individual FE	NO	YES	YES	YES
Year FE	NO	NO	YES	NO
Time FE	NO	NO	NO	YES

Note: *This table reports difference-in-differences estimates of the effect of the Chinese cryptocurrency ban proposal (May 18, 2021) on cryptocurrency market liquidity. The dependent variable is Amihud Illiquidity. The coefficient of interest, DiD (DEX × Post), captures the differential change in Amihud Illiquidity for DEX-linked tokens relative to CEX-linked tokens following the proposal announcement. Treated (DEX) is a time-invariant indicator equal to one for cryptocurrencies classified as DEX-linked and zero for CEX-linked cryptocurrencies; this indicator is absorbed by the cryptocurrency fixed effect in columns (2)–(4). Post-China is an indicator equal to one for observations after May 18, 2021 and zero otherwise; this indicator is absorbed by the daily time fixed effect in column (4) only. Column (1) includes no fixed effects; column (2) includes cryptocurrency fixed effects; column (3) includes cryptocurrency and year fixed effects; column (4) includes cryptocurrency and daily time fixed effects. Controls include one-period lagged returns, lagged log market capitalisation, lagged log trading volume, VIX, and WUI. All specifications are estimated using a difference-in-differences framework with two-way fixed effects. Standard errors are clustered by cryptocurrency. Standard errors in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.*

Table 4.14: Chinese Policy Shock- Roll Measure

	(1)	(2)	(3)	(4)
DEX × Post	-0.0075	-0.0076	-0.0092*	-0.0109**
	(0.0053)	(0.0052)	(0.0052)	(0.0052)
DEX	0.0068			
	(0.0054)			
Post	-0.0053***	-0.0053***	0.0081***	
	(0.0018)	(0.0018)	(0.0029)	
Returns	-0.0118**	-0.0124**	-0.0111*	-0.0154
	(0.0056)	(0.0056)	(0.0056)	(0.0101)
Market Cap	-0.0036***	-0.0039***	-0.0041***	-0.0027**
	(0.0008)	(0.0012)	(0.0010)	(0.0013)
Volume	0.0026***	0.0033***	0.0027***	0.0020*
	(0.0009)	(0.0009)	(0.0009)	(0.0010)
VIX	0.0008***	0.0008***	0.0009***	
	(0.0001)	(0.0001)	(0.0001)	
WUI	-0.0000***	-0.0000***	-0.0000	
	(0.0000)	(0.0000)	(0.0000)	
Observations	61787	61787	61787	61787
Adj. R-squared	0.083	0.094	0.114	0.458
Individual FE	NO	YES	YES	YES
Year FE	NO	NO	YES	NO
Time FE	NO	NO	NO	YES

Note: *This table reports difference-in-differences estimates of the effect of the Chinese cryptocurrency ban proposal (May 18, 2021) on cryptocurrency market liquidity. The dependent variable is Roll Measure. The coefficient of interest, DiD (DEX × Post), captures the differential change in Roll Measure for DEX-linked tokens relative to CEX-linked tokens following the proposal announcement. Treated (DEX) is a time-invariant indicator equal to one for cryptocurrencies classified as DEX-linked and zero for CEX-linked cryptocurrencies; this indicator is absorbed by the cryptocurrency fixed effect in columns (2)–(4). Post-China is an indicator equal to one for observations after May 18, 2021 and zero otherwise; this indicator is absorbed by the daily time fixed effect in column (4) only. Column (1) includes no fixed effects; column (2) includes cryptocurrency fixed effects; column (3) includes cryptocurrency and year fixed effects; column (4) includes cryptocurrency and daily time fixed effects. Controls include one-period lagged returns, lagged log market capitalisation, lagged log trading volume, VIX, and WUI. All specifications are estimated using a difference-in-differences framework with two-way fixed effects. Standard errors are clustered by cryptocurrency. Standard errors in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.*

Table 4.15: Chinese Policy Shock- Event Windows – Part 1: Turnover

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*
1-Day Window × DEX	0.0683*	0.0677*	0.0661*	0.0658*				
	(0.0382)	(0.0386)	(0.0377)	(0.0383)				
3-Day Window × DEX					0.0425	0.0419	0.0402	0.0408
					(0.0270)	(0.0273)	(0.0265)	(0.0271)
DEX	-0.0001				-0.0001			
	(0.0067)				(0.0067)			
1-Day Window	0.0551***	0.0603***	0.0539***					
	(0.0115)	(0.0114)	(0.0110)					
3-Day Window					0.0320***	0.0374***	0.0314***	
					(0.0106)	(0.0102)	(0.0096)	
Returns	0.0866***	0.0868***	0.0834***	0.1246**	0.0885***	0.0890***	0.0853***	0.1249**
	(0.0268)	(0.0262)	(0.0265)	(0.0475)	(0.0267)	(0.0261)	(0.0264)	(0.0475)
Market Cap	-0.0508***	-0.0534***	-0.0496***	-0.0495***	-0.0507***	-0.0533***	-0.0496***	-0.0495***
	(0.0075)	(0.0089)	(0.0083)	(0.0094)	(0.0075)	(0.0089)	(0.0083)	(0.0094)
Volume	0.0471***	0.0456***	0.0436***	0.0440***	0.0470***	0.0455***	0.0436***	0.0440***
	(0.0069)	(0.0069)	(0.0065)	(0.0072)	(0.0069)	(0.0069)	(0.0065)	(0.0072)
VIX	0.0005***	0.0004*	0.0003*		0.0005***	0.0004*	0.0003*	
	(0.0002)	(0.0002)	(0.0002)		(0.0002)	(0.0002)	(0.0002)	
WUI	-0.0000***	-0.0000***	-0.0000*		-0.0000***	-0.0000***	-0.0000*	
	(0.0000)	(0.0000)	(0.0000)		(0.0000)	(0.0000)	(0.0000)	
Observations	61814	61814	61814	61814	61814	61814	61814	61814
Adj. R-squared	0.360	0.397	0.402	0.451	0.359	0.396	0.401	0.451
Individual FE	NO	YES	YES	YES	NO	YES	YES	YES
Year FE	NO	NO	YES	NO	NO	NO	YES	NO
Time FE	NO	NO	NO	YES	NO	NO	NO	YES

Note: *This table reports difference-in-differences estimates of the effect of the Chinese cryptocurrency ban proposal (May 18, 2021) on cryptocurrency market liquidity within discrete event windows. The dependent variable is Turnover. The coefficient of interest, [1-Day and 3-Day] × DEX, captures the differential change in Turnover for DEX-linked tokens relative to CEX-linked tokens within the specified post-announcement window. Treated (DEX) is a time-invariant indicator equal to one for cryptocurrencies classified as DEX-linked and zero for CEX-linked cryptocurrencies; this indicator is absorbed by the cryptocurrency fixed effect in columns (2), (3), (4), (6), (7), and (8). The window indicator, 1-Day and 3-Day Window, is an indicator equal to one for observations falling within the specified number of trading days after the announcement date and zero otherwise; this indicator is absorbed by the daily time fixed effect in columns (4) and (8) only. Within each window, column (1) includes no fixed effects; column (2) includes cryptocurrency fixed effects; column (3) includes cryptocurrency and year fixed effects; column (4) includes cryptocurrency and daily time fixed effects. Controls include one-period lagged returns, lagged log market capitalisation, lagged log trading volume, VIX, and WUI. All specifications are estimated using a difference-in-differences framework with two-way fixed effects. Standard errors are clustered by cryptocurrency. Standard errors in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.*

Table 4.16: Chinese Policy Shock- Event Windows – Part 2: Turnover

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
5-Day Window × DEX	0.0454	0.0449	0.0433	0.0439				
	(0.0277)	(0.0280)	(0.0271)	(0.0278)				
30-Day Window × DEX					0.0181	0.0170	0.0153	0.0164
					(0.0121)	(0.0125)	(0.0118)	(0.0123)
DEX	-0.0003				-0.0005			
	(0.0067)				(0.0066)			
5-Day Window	0.0269**	0.0324***	0.0266***					
	(0.0107)	(0.0102)	(0.0094)					
30-Day Window					0.0034	0.0075	0.0005	
					(0.0078)	(0.0073)	(0.0069)	
Returns	0.0905***	0.0913***	0.0873***	0.1250**	0.0879***	0.0886***	0.0843***	0.1251**
	(0.0268)	(0.0261)	(0.0264)	(0.0475)	(0.0269)	(0.0262)	(0.0265)	(0.0474)
Market Cap	-0.0506***	-0.0532***	-0.0495***	-0.0495***	-0.0507***	-0.0533***	-0.0496***	-0.0495***
	(0.0075)	(0.0088)	(0.0083)	(0.0094)	(0.0075)	(0.0089)	(0.0083)	(0.0094)
Volume	0.0469***	0.0453***	0.0434***	0.0440***	0.0470***	0.0453***	0.0437***	0.0441***
	(0.0068)	(0.0069)	(0.0065)	(0.0072)	(0.0069)	(0.0069)	(0.0066)	(0.0072)
VIX	0.0005***	0.0004*	0.0003*		0.0006***	0.0004**	0.0003*	
	(0.0002)	(0.0002)	(0.0002)		(0.0002)	(0.0002)	(0.0002)	
WUI	-0.0000***	-0.0000**	-0.0000*		-0.0000***	-0.0000**	-0.0000*	
	(0.0000)	(0.0000)	(0.0000)		(0.0000)	(0.0000)	(0.0000)	
Observations	61814	61814	61814	61814	61814	61814	61814	61814
Adj. R-squared	0.360	0.397	0.402	0.451	0.359	0.396	0.401	0.451
Individual FE	NO	YES	YES	YES	NO	YES	YES	YES
Year FE	NO	NO	YES	NO	NO	NO	YES	NO
Time FE	NO	NO	NO	YES	NO	NO	NO	YES

Note: *This table reports difference-in-differences estimates of the effect of the Chinese cryptocurrency ban proposal (May 18, 2021) on cryptocurrency market liquidity within discrete event windows. The dependent variable is Turnover. The coefficient of interest, [5-Day and 30-Day] × DEX, captures the differential change in Turnover for DEX-linked tokens relative to CEX-linked tokens within the specified post-announcement window. Treated (DEX) is a time-invariant indicator equal to one for cryptocurrencies classified as DEX-linked and zero for CEX-linked cryptocurrencies; this indicator is absorbed by the cryptocurrency fixed effect in columns (2), (3), (4), (6), (7), and (8). The window indicator, 5-Day and 30-Day Window, is an indicator equal to one for observations falling within the specified number of trading days after the announcement date and zero otherwise; this indicator is absorbed by the daily time fixed effect in columns (4) and (8) only. Within each window, column (1) includes no fixed effects; column (2) includes cryptocurrency fixed effects; column (3) includes cryptocurrency and year fixed effects; column (4) includes cryptocurrency and daily time fixed effects. Controls include one-period lagged returns, lagged log market capitalisation, lagged log trading volume, VIX, and WUI. All specifications are estimated using a difference-in-differences framework with two-way fixed effects. Standard errors are clustered by cryptocurrency. Standard errors in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.*

Table 4.17: Chinese Policy Shock- Event Windows – Part 1: Amihud Illiquidity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1-Day Window × DEX	-0.0005	0.0000	-0.0002	-0.0006				
	(0.0020)	(0.0018)	(0.0018)	(0.0019)				
3-Day Window × DEX					-0.0005	0.0000	-0.0002	-0.0004
					(0.0019)	(0.0017)	(0.0017)	(0.0017)
DEX	-0.0004				-0.0004			
	(0.0012)				(0.0012)			
1-Day Window	0.0051***	0.0054***	0.0033***					
	(0.0014)	(0.0016)	(0.0011)					
3-Day Window					0.0055***	0.0057***	0.0037***	
					(0.0014)	(0.0017)	(0.0011)	
Returns	0.0016	0.0011	0.0005	0.0114***	0.0018	0.0013	0.0006	0.0114***
	(0.0013)	(0.0013)	(0.0010)	(0.0037)	(0.0014)	(0.0013)	(0.0010)	(0.0037)
Market Cap	0.0016***	0.0000	0.0006	0.0018**	0.0016***	0.0000	0.0006	0.0018**
	(0.0006)	(0.0004)	(0.0005)	(0.0007)	(0.0006)	(0.0004)	(0.0005)	(0.0007)
Volume	-0.0032***	-0.0027***	-0.0034***	-0.0048***	-0.0032***	-0.0028***	-0.0034***	-0.0048***
	(0.0008)	(0.0008)	(0.0009)	(0.0012)	(0.0008)	(0.0008)	(0.0009)	(0.0012)
VIX	0.0001***	0.0001**	0.0000*	0.0000	0.0001***	0.0001**	0.0000*	
	(0.0001)	(0.0000)	(0.0000)	(.)	(0.0001)	(0.0000)	(0.0000)	
WUI	-0.0000	-0.0000	0.0000	0.0000	-0.0000	-0.0000	0.0000	
	(0.0000)	(0.0000)	(0.0000)	(.)	(0.0000)	(0.0000)	(0.0000)	
Observations	61815	61815	61815	61815	61815	61815	61815	61815
Adj. R-squared	0.313	0.390	0.431	0.480	0.314	0.391	0.432	0.480
Individual FE	NO	YES	YES	YES	NO	YES	YES	YES
Year FE	NO	NO	YES	NO	NO	NO	YES	NO
Time FE	NO	NO	NO	YES	NO	NO	NO	YES

Note: *This table reports difference-in-differences estimates of the effect of the Chinese cryptocurrency ban proposal (May 18, 2021) on cryptocurrency market liquidity within discrete event windows. The dependent variable is Amihud Illiquidity. The coefficient of interest, [1-Day and 3-Day] × DEX, captures the differential change in Amihud Illiquidity for DEX-linked tokens relative to CEX-linked tokens within the specified post-announcement window. Treated (DEX) is a time-invariant indicator equal to one for cryptocurrencies classified as DEX-linked and zero for CEX-linked cryptocurrencies; this indicator is absorbed by the cryptocurrency fixed effect in columns (2), (3), (4), (6), (7), and (8). The window indicator, 1-Day and 3-Day Window, is an indicator equal to one for observations falling within the specified number of trading days after the announcement date and zero otherwise; this indicator is absorbed by the daily time fixed effect in columns (4) and (8) only. Within each window, column (1) includes no fixed effects; column (2) includes cryptocurrency fixed effects; column (3) includes cryptocurrency and year fixed effects; column (4) includes cryptocurrency and daily time fixed effects. Controls include one-period lagged returns, lagged log market capitalisation, lagged log trading volume, VIX, and WUI. All specifications are estimated using a difference-in-differences framework with two-way fixed effects. Standard errors are clustered by cryptocurrency. Standard errors in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.*

Table 4.18: Chinese Policy Shock- Event Windows – Part 2: Amihud Illiquidity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
5-Day Window × DEX	-0.0002	0.0003	0.0001	0.0000				
	(0.0021)	(0.0018)	(0.0019)	(0.0019)				
30-Day Window × DEX					-0.0001	0.0003	0.0000	-0.0003
					(0.0017)	(0.0016)	(0.0016)	(0.0017)
DEX	-0.0004				-0.0004			
	(0.0012)				(0.0012)			
5-Day Window	0.0056***	0.0058***	0.0039***	0.0000				
	(0.0016)	(0.0018)	(0.0013)	(.)				
30-Day Window					0.0044***	0.0046***	0.0023**	
					(0.0011)	(0.0013)	(0.0009)	
Returns	0.0021	0.0016	0.0008	0.0114***	0.0021	0.0016	0.0007	0.0114***
	(0.0014)	(0.0014)	(0.0010)	(0.0037)	(0.0014)	(0.0013)	(0.0010)	(0.0037)
Market Cap	0.0016***	0.0001	0.0006	0.0018**	0.0016***	0.0001	0.0006	0.0018**
	(0.0006)	(0.0004)	(0.0005)	(0.0007)	(0.0006)	(0.0004)	(0.0005)	(0.0007)
Volume	-0.0032***	-0.0028***	-0.0034***	-0.0048***	-0.0033***	-0.0029***	-0.0034***	-0.0048***
	(0.0008)	(0.0008)	(0.0009)	(0.0012)	(0.0008)	(0.0009)	(0.0009)	(0.0012)
VIX	0.0001***	0.0001**	0.0000*		0.0002***	0.0001**	0.0000*	
	(0.0001)	(0.0000)	(0.0000)		(0.0001)	(0.0000)	(0.0000)	
WUI	-0.0000	-0.0000	0.0000		-0.0000	0.0000	0.0000	
	(0.0000)	(0.0000)	(0.0000)		(0.0000)	(0.0000)	(0.0000)	
Observations	61815	61815	61815	61815	61815	61815	61815	61815
Adj. R-squared	0.315	0.392	0.432	0.480	0.321	0.399	0.433	0.480
Individual FE	NO	YES	YES	YES	NO	YES	YES	YES
Year FE	NO	NO	YES	NO	NO	NO	YES	NO
Time FE	NO	NO	NO	YES	NO	NO	NO	YES

Note: *This table reports difference-in-differences estimates of the effect of the Chinese cryptocurrency ban proposal (May 18, 2021) on cryptocurrency market liquidity within discrete event windows. The dependent variable is Amihud Illiquidity. The coefficient of interest, [5-Day and 30-Day] × DEX, captures the differential change in Amihud Illiquidity for DEX-linked tokens relative to CEX-linked tokens within the specified post-announcement window. Treated (DEX) is a time-invariant indicator equal to one for cryptocurrencies classified as DEX-linked and zero for CEX-linked cryptocurrencies; this indicator is absorbed by the cryptocurrency fixed effect in columns (2), (3), (4), (6), (7), and (8). The window indicator, 5-Day and 30-Day Window, is an indicator equal to one for observations falling within the specified number of trading days after the announcement date and zero otherwise; this indicator is absorbed by the daily time fixed effect in columns (4) and (8) only. Within each window, column (1) includes no fixed effects; column (2) includes cryptocurrency fixed effects; column (3) includes cryptocurrency and year fixed effects; column (4) includes cryptocurrency and daily time fixed effects. Controls include one-period lagged returns, lagged log market capitalisation, lagged log trading volume, VIX, and WUI. All specifications are estimated using a difference-in-differences framework with two-way fixed effects. Standard errors are clustered by cryptocurrency. Standard errors in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.*

Table 4.19: Chinese Policy Shock- Event Windows – Part 1: Roll's Measure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1-Day Window × DEX	-0.0062	-0.0056	-0.0064	-0.0071				
	(0.0103)	(0.0102)	(0.0102)	(0.0103)				
3-Day Window × DEX					-0.0068	-0.0062	-0.0071	-0.0078
					(0.0095)	(0.0095)	(0.0094)	(0.0094)
DEX	-0.0008				-0.0008			
	(0.0019)				(0.0019)			
1-Day Window	0.0283***	0.0273***	0.0206***					
	(0.0049)	(0.0051)	(0.0047)					
3-Day Window					0.0417***	0.0406***	0.0342***	
					(0.0049)	(0.0050)	(0.0046)	
Returns	-0.0087	-0.0097*	-0.0120**	-0.0153	-0.0072	-0.0083	-0.0108*	-0.0154
	(0.0055)	(0.0054)	(0.0057)	(0.0103)	(0.0055)	(0.0054)	(0.0057)	(0.0103)
Market Cap	-0.0042***	-0.0053***	-0.0032***	-0.0018	-0.0041***	-0.0052***	-0.0032***	-0.0018
	(0.0009)	(0.0012)	(0.0011)	(0.0015)	(0.0009)	(0.0012)	(0.0011)	(0.0015)
Volume	0.0030***	0.0040***	0.0024***	0.0017*	0.0028***	0.0038***	0.0023**	0.0017*
	(0.0010)	(0.0010)	(0.0008)	(0.0010)	(0.0010)	(0.0010)	(0.0008)	(0.0010)
VIX	0.0009***	0.0009***	0.0009***		0.0009***	0.0009***	0.0009***	
	(0.0001)	(0.0001)	(0.0001)		(0.0001)	(0.0001)	(0.0001)	
WUI	-0.0000***	-0.0000***	-0.0000		-0.0000***	-0.0000***	-0.0000	
	(0.0000)	(0.0000)	(0.0000)		(0.0000)	(0.0000)	(0.0000)	
Observations	61787	61787	61787	61787	61787	61787	61787	61787
Adj. R-squared	0.075	0.086	0.112	0.455	0.079	0.090	0.115	0.455
Individual FE	NO	YES	YES	YES	NO	YES	YES	YES
Year FE	NO	NO	YES	NO	NO	NO	YES	NO
Time FE	NO	NO	NO	YES	NO	NO	NO	YES

Note: *This table reports difference-in-differences estimates of the effect of the Chinese cryptocurrency ban proposal (May 18, 2021) on cryptocurrency market liquidity within discrete event windows. The dependent variable is Roll Measure. The coefficient of interest, [1-Day and 3-Day] × DEX, captures the differential change in Roll Measure for DEX-linked tokens relative to CEX-linked tokens within the specified post-announcement window. Treated (DEX) is a time-invariant indicator equal to one for cryptocurrencies classified as DEX-linked and zero for CEX-linked cryptocurrencies; this indicator is absorbed by the cryptocurrency fixed effect in columns (2), (3), (4), (6), (7), and (8). The window indicator, 1-Day and 3-Day Window, is an indicator equal to one for observations falling within the specified number of trading days after the announcement date and zero otherwise; this indicator is absorbed by the daily time fixed effect in columns (4) and (8) only. Within each window, column (1) includes no fixed effects; column (2) includes cryptocurrency fixed effects; column (3) includes cryptocurrency and year fixed effects; column (4) includes cryptocurrency and daily time fixed effects. Controls include one-period lagged returns, lagged log market capitalisation, lagged log trading volume, VIX, and WUI. All specifications are estimated using a difference-in-differences framework with two-way fixed effects. Standard errors are clustered by cryptocurrency. Standard errors in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.*

Table 4.20: Chinese Policy Shock- Event Windows – Part 2: Roll's Measure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
5-Day Window × DEX	-0.0091	-0.0086	-0.0094	-0.0101				
	(0.0086)	(0.0085)	(0.0085)	(0.0085)				
30-Day Window × DEX					-0.0013	-0.0007	-0.0015	-0.0030
					(0.0068)	(0.0068)	(0.0066)	(0.0067)
DEX	-0.0008				-0.0011			
	(0.0019)				(0.0017)			
5-Day Window	0.0416***	0.0406***	0.0343***					
	(0.0047)	(0.0048)	(0.0045)					
30-Day Window					0.0474***	0.0473***	0.0439***	
					(0.0042)	(0.0043)	(0.0043)	
Returns	-0.0055	-0.0065	-0.0094	-0.0154	-0.0036	-0.0043	-0.0065	-0.0154
	(0.0056)	(0.0055)	(0.0057)	(0.0103)	(0.0055)	(0.0054)	(0.0057)	(0.0103)
Market Cap	-0.0040***	-0.0052***	-0.0031***	-0.0018	-0.0034***	-0.0047***	-0.0028***	-0.0018
	(0.0009)	(0.0012)	(0.0011)	(0.0015)	(0.0009)	(0.0010)	(0.0010)	(0.0015)
Volume	0.0027**	0.0037***	0.0022**	0.0017*	0.0019*	0.0024**	0.0017**	0.0017*
	(0.0010)	(0.0010)	(0.0008)	(0.0010)	(0.0009)	(0.0009)	(0.0008)	(0.0010)
VIX	0.0009***	0.0009***	0.0009***		0.0010***	0.0009***	0.0010***	
	(0.0001)	(0.0001)	(0.0001)		(0.0001)	(0.0001)	(0.0001)	
WUI	-0.0000***	-0.0000***	-0.0000		-0.0000***	-0.0000***	-0.0000	
	(0.0000)	(0.0000)	(0.0000)		(0.0000)	(0.0000)	(0.0000)	
Observations	61787	61787	61787	61787	61787	61787	61787	61787
Adj. R-squared	0.082	0.092	0.116	0.455	0.136	0.147	0.159	0.455
Individual FE	NO	YES	YES	YES	NO	YES	YES	YES
Year FE	NO	NO	YES	NO	NO	NO	YES	NO
Time FE	NO	NO	NO	YES	NO	NO	NO	YES

Note: *This table reports difference-in-differences estimates of the effect of the Chinese cryptocurrency ban proposal (May 18, 2021) on cryptocurrency market liquidity within discrete event windows. The dependent variable is Roll Measure. The coefficient of interest, [5-Day and 30-Day] × DEX, captures the differential change in Roll Measure for DEX-linked tokens relative to CEX-linked tokens within the specified post-announcement window. Treated (DEX) is a time-invariant indicator equal to one for cryptocurrencies classified as DEX-linked and zero for CEX-linked cryptocurrencies; this indicator is absorbed by the cryptocurrency fixed effect in columns (2), (3), (4), (6), (7), and (8). The window indicator, 5-Day and 30-Day Window, is an indicator equal to one for observations falling within the specified number of trading days after the announcement date and zero otherwise; this indicator is absorbed by the daily time fixed effect in columns (4) and (8) only. Within each window, column (1) includes no fixed effects; column (2) includes cryptocurrency fixed effects; column (3) includes cryptocurrency and year fixed effects; column (4) includes cryptocurrency and daily time fixed effects. Controls include one-period lagged returns, lagged log market capitalisation, lagged log trading volume, VIX, and WUI. All specifications are estimated using a difference-in-differences framework with two-way fixed effects. Standard errors are clustered by cryptocurrency. Standard errors in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.*

Table 4.21: American Policy Shock- Turnover

	(1)	(2)	(3)	(4)
DEX × Post	-0.0204**	-0.0251***	-0.0241***	-0.0237**
	(0.0075)	(0.0089)	(0.0085)	(0.0087)
DEX	0.0025			
	(0.0071)			
Post	0.0055	0.0119*	0.0084	
	(0.0050)	(0.0064)	(0.0064)	
Returns	0.0867***	0.0867***	0.0835***	0.1241**
	(0.0267)	(0.0261)	(0.0264)	(0.0476)
Market Cap	-0.0512***	-0.0548***	-0.0512***	-0.0513***
	(0.0075)	(0.0091)	(0.0085)	(0.0096)
Volume	0.0475***	0.0463***	0.0442***	0.0447***
	(0.0069)	(0.0069)	(0.0066)	(0.0073)
VIX	0.0005***	0.0003*	0.0003*	
	(0.0002)	(0.0002)	(0.0002)	
WUI	-0.0000	-0.0000*	-0.0000	
	(0.0000)	(0.0000)	(0.0000)	
Observations	61814	61814	61814	61814
Adj. R-squared	0.360	0.397	0.402	0.453
Individual FE	NO	YES	YES	YES
Year FE	NO	NO	YES	NO
Time FE	NO	NO	NO	YES

Note: *This table reports difference-in-differences estimates of the effect of the GENIUS Act proposal announcement (February 4, 2025) on cryptocurrency market liquidity. The dependent variable is Turnover. The coefficient of interest, DiD (DEX × Post), captures the differential change in Turnover for DEX-linked tokens relative to CEX-linked tokens following the proposal announcement. Treated (DEX) is a time-invariant indicator equal to one for cryptocurrencies classified as DEX-linked and zero for CEX-linked cryptocurrencies; this indicator is absorbed by the cryptocurrency fixed effect in columns (2)–(4). Post-GENIUS is an indicator equal to one for observations after February 4, 2025 and zero otherwise; this indicator is absorbed by the daily time fixed effect in column (4) only. Column (1) includes no fixed effects; column (2) includes cryptocurrency fixed effects; column (3) includes cryptocurrency and year fixed effects; column (4) includes cryptocurrency and daily time fixed effects. Controls include one-period lagged returns, lagged log market capitalisation, lagged log trading volume, VIX, and WUI. All specifications are estimated using a difference-in-differences framework with two-way fixed effects. Standard errors are clustered by cryptocurrency. Standard errors in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.*

Table 4.22: American Policy Shock- Amihud Illiquidity

	(1)	(2)	(3)	(4)
DEX × Post	0.0006	-0.0008	-0.0009	-0.0006
	(0.0008)	(0.0008)	(0.0008)	(0.0009)
DEX	-0.0004			
	(0.0012)			
Post	-0.0017	-0.0004	-0.0012	
	(0.0014)	(0.0012)	(0.0007)	
Returns	0.0016	0.0010	0.0005	0.0114***
	(0.0013)	(0.0013)	(0.0010)	(0.0037)
Market Cap	0.0016***	-0.0000	0.0005	0.0017**
	(0.0006)	(0.0004)	(0.0005)	(0.0008)
Volume	-0.0032***	-0.0027***	-0.0033***	-0.0048***
	(0.0008)	(0.0008)	(0.0009)	(0.0012)
VIX	0.0001***	0.0001**	0.0000*	
	(0.0000)	(0.0000)	(0.0000)	
WUI	0.0000	0.0000	0.0000	
	(0.0000)	(0.0000)	(0.0000)	
Observations	61815	61815	61815	61815
Adj. R-squared	0.314	0.390	0.432	0.481
Individual FE	NO	YES	YES	YES
Year FE	NO	NO	YES	NO
Time FE	NO	NO	NO	YES

Note: *This table reports difference-in-differences estimates of the effect of the GENIUS Act proposal announcement (February 4, 2025) on cryptocurrency market liquidity. The dependent variable is Amihud Illiquidity. The coefficient of interest, DiD (DEX × Post), captures the differential change in Amihud Illiquidity for DEX-linked tokens relative to CEX-linked tokens following the proposal announcement. Treated (DEX) is a time-invariant indicator equal to one for cryptocurrencies classified as DEX-linked and zero for CEX-linked cryptocurrencies; this indicator is absorbed by the cryptocurrency fixed effect in columns (2)–(4). Post-GENIUS is an indicator equal to one for observations after February 4, 2025 and zero otherwise; this indicator is absorbed by the daily time fixed effect in column (4) only. Column (1) includes no fixed effects; column (2) includes cryptocurrency fixed effects; column (3) includes cryptocurrency and year fixed effects; column (4) includes cryptocurrency and daily time fixed effects. Controls include one-period lagged returns, lagged log market capitalisation, lagged log trading volume, VIX, and WUI. All specifications are estimated using a difference-in-differences framework with two-way fixed effects. Standard errors are clustered by cryptocurrency. Standard errors in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.*

Table 4.23: American Policy Shock- Roll Measure

	(1)	(2)	(3)	(4)
DEX × Post	-0.0024	-0.0036	-0.0030	-0.0028
	(0.0028)	(0.0030)	(0.0029)	(0.0030)
DEX	-0.0007			
	(0.0020)			
Post	0.0103***	0.0112***	0.0180***	
	(0.0032)	(0.0036)	(0.0032)	
Returns	-0.0085	-0.0096*	-0.0126**	-0.0155
	(0.0055)	(0.0054)	(0.0057)	(0.0103)
Markt Cap	-0.0042***	-0.0056***	-0.0032***	-0.0020
	(0.0009)	(0.0012)	(0.0011)	(0.0015)
Volume	0.0029***	0.0040***	0.0024***	0.0017*
	(0.0010)	(0.0010)	(0.0008)	(0.0010)
VIX	0.0009***	0.0009***	0.0009***	
	(0.0001)	(0.0001)	(0.0001)	
WUI	-0.0000***	-0.0000***	-0.0000**	
	(0.0000)	(0.0000)	(0.0000)	
Observations	61787	61787	61787	61787
Adj. R-squared	0.076	0.088	0.115	0.455
Individual FE	NO	YES	YES	YES
Year FE	NO	NO	YES	NO
Time FE	NO	NO	NO	YES

Note: *This table reports difference-in-differences estimates of the effect of the GENIUS Act proposal announcement (February 4, 2025) on cryptocurrency market liquidity. The dependent variable is Amihud Illiquidity. The coefficient of interest, DiD (DEX × Post), captures the differential change in Roll Measure for DEX-linked tokens relative to CEX-linked tokens following the proposal announcement. Treated (DEX) is a time-invariant indicator equal to one for cryptocurrencies classified as DEX-linked and zero for CEX-linked cryptocurrencies; this indicator is absorbed by the cryptocurrency fixed effect in columns (2)–(4). Post-GENIUS is an indicator equal to one for observations after February 4, 2025 and zero otherwise; this indicator is absorbed by the daily time fixed effect in column (4) only. Column (1) includes no fixed effects; column (2) includes cryptocurrency fixed effects; column (3) includes cryptocurrency and year fixed effects; column (4) includes cryptocurrency and daily time fixed effects. Controls include one-period lagged returns, lagged log market capitalisation, lagged log trading volume, VIX, and WUI. All specifications are estimated using a difference-in-differences framework with two-way fixed effects. Standard errors are clustered by cryptocurrency. Standard errors in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.*

Table 4.24: American Policy Shock - Event Windows – Part 1: Turnover

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1-Day Window × DEX	0.0125	0.0092	0.0094	0.0104				
	(0.0084)	(0.0089)	(0.0091)	(0.0093)				
3-Day Window × DEX					-0.0013	-0.0045	-0.0041	-0.0033
					(0.0046)	(0.0054)	(0.0054)	(0.0055)
DEX	0.0001				0.0001			
	(0.0067)				(0.0067)			
1-Day Window	-0.0083*	-0.0046	-0.0046					
	(0.0048)	(0.0044)	(0.0059)					
3-Day Window					0.0044**	0.0073***	0.0063*	
					(0.0021)	(0.0023)	(0.0034)	
Returns	0.0865***	0.0868***	0.0833***	0.1249**	0.0868***	0.0871***	0.0835***	0.1249**
	(0.0267)	(0.0261)	(0.0264)	(0.0475)	(0.0267)	(0.0261)	(0.0265)	(0.0475)
Market Cap	-0.0508***	-0.0534***	-0.0496***	-0.0494***	-0.0508***	-0.0534***	-0.0496***	-0.0494***
	(0.0075)	(0.0089)	(0.0083)	(0.0094)	(0.0075)	(0.0089)	(0.0083)	(0.0094)
Volume	0.0473***	0.0458***	0.0437***	0.0440***	0.0472***	0.0458***	0.0437***	0.0440***
	(0.0069)	(0.0069)	(0.0066)	(0.0072)	(0.0069)	(0.0069)	(0.0065)	(0.0072)
VIX	0.0005***	0.0004*	0.0003*		0.0005***	0.0004*	0.0003*	
	(0.0002)	(0.0002)	(0.0002)		(0.0002)	(0.0002)	(0.0002)	
WUI	-0.0000***	-0.0000***	-0.0000*		-0.0000***	-0.0000***	-0.0000*	
	(0.0000)	(0.0000)	(0.0000)		(0.0000)	(0.0000)	(0.0000)	
Observations	61814	61814	61814	61814	61814	61814	61814	61814
Adj. R-squared	0.358	0.395	0.400	0.451	0.358	0.395	0.400	0.451
Individual FE	NO	YES	YES	YES	NO	YES	YES	YES
Year FE	NO	NO	YES	NO	NO	NO	YES	NO
Time FE	NO	NO	NO	YES	NO	NO	NO	YES

Note: *This table reports difference-in-differences estimates of the effect of the GENIUS Act proposal announcement (February 4, 2025) on cryptocurrency market liquidity within discrete event windows. The dependent variable is Turnover. The coefficient of interest, [1-Day and 3-Day] × DEX, captures the differential change in Turnover for DEX-linked tokens relative to CEX-linked tokens within the specified post-announcement window. Treated (DEX) is a time-invariant indicator equal to one for cryptocurrencies classified as DEX-linked and zero for CEX-linked cryptocurrencies; this indicator is absorbed by the cryptocurrency fixed effect in columns (2), (3), (4), (6), (7), and (8). The window indicator, 1-Day and 3-Day Window, is an indicator equal to one for observations falling within the specified number of trading days after the announcement date and zero otherwise; this indicator is absorbed by the daily time fixed effect in columns (4) and (8) only. Within each window, column (1) includes no fixed effects; column (2) includes cryptocurrency fixed effects; column (3) includes cryptocurrency and year fixed effects; column (4) includes cryptocurrency and daily time fixed effects. Controls include one-period lagged returns, lagged log market capitalisation, lagged log trading volume, VIX, and WUI. All specifications are estimated using a difference-in-differences framework with two-way fixed effects. Standard errors are clustered by cryptocurrency. Standard errors in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.*

Table 4.25: American Policy Shock - Event Windows – Part 2: Turnover

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
5-Day Window × DEX	-0.0095*	-0.0125**	-0.0120**	-0.0113**				
	(0.0047)	(0.0055)	(0.0053)	(0.0053)				
30-Day Window × DEX					-0.0162***	-0.0193***	-0.0189***	-0.0183***
					(0.0059)	(0.0065)	(0.0062)	(0.0062)
DEX	0.0001				0.0005			
	(0.0067)				(0.0068)			
5-Day Window	0.0036*	0.0061**	0.0045					
	(0.0020)	(0.0026)	(0.0028)					
30-Day Window					0.0043	0.0070**	0.0024	
					(0.0025)	(0.0033)	(0.0043)	
Returns	0.0865***	0.0868***	0.0832***	0.1248**	0.0862***	0.0865***	0.0828***	0.1245**
	(0.0267)	(0.0261)	(0.0265)	(0.0475)	(0.0267)	(0.0261)	(0.0265)	(0.0476)
Market Cap	-0.0508***	-0.0535***	-0.0497***	-0.0495***	-0.0509***	-0.0536***	-0.0498***	-0.0497***
	(0.0075)	(0.0089)	(0.0083)	(0.0094)	(0.0075)	(0.0089)	(0.0083)	(0.0094)
Volume	0.0473***	0.0458***	0.0438***	0.0440***	0.0473***	0.0458***	0.0438***	0.0441***
	(0.0069)	(0.0069)	(0.0065)	(0.0072)	(0.0069)	(0.0069)	(0.0065)	(0.0072)
VIX	0.0005***	0.0004*	0.0003*		0.0005***	0.0004*	0.0003*	
	(0.0002)	(0.0002)	(0.0002)		(0.0002)	(0.0002)	(0.0002)	
WUI	-0.0000***	-0.0000***	-0.0000*		-0.0000***	-0.0000***	-0.0000*	
	(0.0000)	(0.0000)	(0.0000)		(0.0000)	(0.0000)	(0.0000)	
Observations	61814	61814	61814	61814	61814	61814	61814	61814
Adj. R-squared	0.358	0.395	0.400	0.451	0.358	0.395	0.401	0.451
Individual FE	NO	YES	YES	YES	NO	YES	YES	YES
Year FE	NO	NO	YES	NO	NO	NO	YES	NO
Time FE	NO	NO	NO	YES	NO	NO	NO	YES

Note: *This table reports difference-in-differences estimates of the effect of the GENIUS Act proposal announcement (February 4, 2025) on cryptocurrency market liquidity within discrete event windows. The dependent variable is Turnover. The coefficient of interest, [5-Day and 30-Day] × DEX, captures the differential change in Turnover for DEX-linked tokens relative to CEX-linked tokens within the specified post-announcement window. Treated (DEX) is a time-invariant indicator equal to one for cryptocurrencies classified as DEX-linked and zero for CEX-linked cryptocurrencies; this indicator is absorbed by the cryptocurrency fixed effect in columns (2), (3), (4), (6), (7), and (8). The window indicator, 5-Day and 30-Day Window, is an indicator equal to one for observations falling within the specified number of trading days after the announcement date and zero otherwise; this indicator is absorbed by the daily time fixed effect in columns (4) and (8) only. Within each window, column (1) includes no fixed effects; column (2) includes cryptocurrency fixed effects; column (3) includes cryptocurrency and year fixed effects; column (4) includes cryptocurrency and daily time fixed effects. Controls include one-period lagged returns, lagged log market capitalisation, lagged log trading volume, VIX, and WUI. All specifications are estimated using a difference-in-differences framework with two-way fixed effects. Standard errors are clustered by cryptocurrency. Standard errors in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.*

Table 4.26: American Policy Shock - Event Windows – Part 1: Amihud Illiquidity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1-Day Window × DEX	-0.0011*	-0.0021***	-0.0023***	-0.0022***				
	(0.0006)	(0.0007)	(0.0007)	(0.0007)				
3-Day Window × DEX					0.0016	0.0006	0.0005	0.0006
					(0.0012)	(0.0012)	(0.0012)	(0.0012)
DEX	-0.0004				-0.0004			
	(0.0012)				(0.0012)			
1-Day Window	0.0028***	0.0031***	0.0042***					
	(0.0006)	(0.0009)	(0.0011)					
Returns	0.0017	0.0011	0.0005	0.0114***	0.0017	0.0011	0.0006	0.0114***
	(0.0014)	(0.0013)	(0.0010)	(0.0037)	(0.0014)	(0.0013)	(0.0010)	(0.0037)
Market Cap	0.0016***	0.0000	0.0006	0.0018**	0.0016***	0.0000	0.0006	0.0018**
	(0.0006)	(0.0004)	(0.0005)	(0.0007)	(0.0006)	(0.0004)	(0.0005)	(0.0007)
Volume	-0.0032***	-0.0027***	-0.0034***	-0.0048***	-0.0032***	-0.0027***	-0.0034***	-0.0048***
	(0.0008)	(0.0008)	(0.0009)	(0.0012)	(0.0008)	(0.0008)	(0.0009)	(0.0012)
VIX	0.0001***	0.0001**	0.0000*		0.0001***	0.0001**	0.0000*	
	(0.0001)	(0.0000)	(0.0000)		(0.0001)	(0.0000)	(0.0000)	
WUI	-0.0000	-0.0000	0.0000		-0.0000	-0.0000	0.0000	
	(0.0000)	(0.0000)	(0.0000)		(0.0000)	(0.0000)	(0.0000)	
3-Day Window					0.0013***	0.0018***	0.0026***	
					(0.0003)	(0.0005)	(0.0008)	
Observations	61815	61815	61815	61815	61815	61815	61815	61815
Adj. R-squared	0.313	0.390	0.431	0.481	0.313	0.390	0.432	0.480
Individual FE	NO	YES	YES	YES	NO	YES	YES	YES
Year FE	NO	NO	YES	NO	NO	NO	YES	NO
Time FE	NO	NO	NO	YES	NO	NO	NO	YES

Note: *This table reports difference-in-differences estimates of the effect of the GENIUS Act proposal announcement (February 4, 2025) on cryptocurrency market liquidity within discrete event windows. The dependent variable is Amihud Illiquidity. The coefficient of interest, [1-Day and 3-Day] × DEX, captures the differential change in Amihud Illiquidity for DEX-linked tokens relative to CEX-linked tokens within the specified post-announcement window. Treated (DEX) is a time-invariant indicator equal to one for cryptocurrencies classified as DEX-linked and zero for CEX-linked cryptocurrencies; this indicator is absorbed by the cryptocurrency fixed effect in columns (2), (3), (4), (6), (7), and (8). The window indicator, 1-Day and 3-Day Window, is an indicator equal to one for observations falling within the specified number of trading days after the announcement date and zero otherwise; this indicator is absorbed by the daily time fixed effect in columns (4) and (8) only. Within each window, column (1) includes no fixed effects; column (2) includes cryptocurrency fixed effects; column (3) includes cryptocurrency and year fixed effects; column (4) includes cryptocurrency and daily time fixed effects. Controls include one-period lagged returns, lagged log market capitalisation, lagged log trading volume, VIX, and WUI. All specifications are estimated using a difference-in-differences framework with two-way fixed effects. Standard errors are clustered by cryptocurrency. Standard errors in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.*

Table 4.27: American Policy Shock - Event Windows – Part 2: Amihud Illiquidity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
5-Day Window × DEX	0.0009	-0.0001	-0.0002	-0.0001				
	(0.0009)	(0.0009)	(0.0009)	(0.0009)				
30-Day Window × DEX					0.0003	-0.0007	-0.0008	-0.0007
					(0.0008)	(0.0008)	(0.0008)	(0.0008)
DEX	-0.0004				-0.0004			
	(0.0012)				(0.0012)			
5-Day Window	0.0007**	0.0012***	0.0019***					
	(0.0003)	(0.0004)	(0.0006)					
Returns	0.0017	0.0011	0.0005	0.0114***	0.0017	0.0011	0.0006	0.0114***
	(0.0014)	(0.0013)	(0.0010)	(0.0037)	(0.0013)	(0.0013)	(0.0010)	(0.0037)
Market Cap	0.0015***	0.0000	0.0006	0.0018**	0.0015***	0.0000	0.0006	0.0018**
	(0.0006)	(0.0004)	(0.0005)	(0.0007)	(0.0006)	(0.0004)	(0.0005)	(0.0007)
Volume	-0.0032***	-0.0027***	-0.0034***	-0.0048***	-0.0032***	-0.0027***	-0.0034***	-0.0048***
	(0.0008)	(0.0008)	(0.0009)	(0.0012)	(0.0008)	(0.0008)	(0.0009)	(0.0012)
VIX	0.0001***	0.0001**	0.0000*		0.0001***	0.0001**	0.0000*	
	(0.0001)	(0.0000)	(0.0000)		(0.0001)	(0.0000)	(0.0000)	
WUI	-0.0000	-0.0000	0.0000		-0.0000	-0.0000	0.0000	
	(0.0000)	(0.0000)	(0.0000)		(0.0000)	(0.0000)	(0.0000)	
30-Day Window					0.0002	0.0009**	0.0023***	
					(0.0004)	(0.0004)	(0.0008)	
Observations	61815	61815	61815	61815	61815	61815	61815	61815
Adj. R-squared	0.313	0.390	0.431	0.480	0.313	0.390	0.432	0.481
Individual FE	NO	YES	YES	YES	NO	YES	YES	YES
Year FE	NO	NO	YES	NO	NO	NO	YES	NO
Time FE	NO	NO	NO	YES	NO	NO	NO	YES

Note: *This table reports difference-in-differences estimates of the effect of the GENIUS Act proposal announcement (February 4, 2025) on cryptocurrency market liquidity within discrete event windows. The dependent variable is Amihud Illiquidity. The coefficient of interest, [5-Day and 30-Day] × DEX, captures the differential change in Amihud Illiquidity for DEX-linked tokens relative to CEX-linked tokens within the specified post-announcement window. Treated (DEX) is a time-invariant indicator equal to one for cryptocurrencies classified as DEX-linked and zero for CEX-linked cryptocurrencies; this indicator is absorbed by the cryptocurrency fixed effect in columns (2), (3), (4), (6), (7), and (8). The window indicator, 5-Day and 30-Day Window, is an indicator equal to one for observations falling within the specified number of trading days after the announcement date and zero otherwise; this indicator is absorbed by the daily time fixed effect in columns (4) and (8) only. Within each window, column (1) includes no fixed effects; column (2) includes cryptocurrency fixed effects; column (3) includes cryptocurrency and year fixed effects; column (4) includes cryptocurrency and daily time fixed effects. Controls include one-period lagged returns, lagged log market capitalisation, lagged log trading volume, VIX, and WUI. All specifications are estimated using a difference-in-differences framework with two-way fixed effects. Standard errors are clustered by cryptocurrency. Standard errors in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.*

Table 4.28: American Policy Shock - Event Windows – Part 1: Roll's Measure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1-Day Window × *DEX*	0.0021	0.0016	0.0014	0.0015				
	(0.0065)	(0.0065)	(0.0063)	(0.0064)				
3-Day Window × *DEX*					0.0021	0.0015	0.0015	0.0016
					(0.0057)	(0.0057)	(0.0055)	(0.0056)
DEX	-0.0008				-0.0008			
	(0.0019)				(0.0019)			
1-Day Window	-0.0142***	-0.0148***	-0.0121***					
	(0.0031)	(0.0032)	(0.0037)					
3-Day Window					-0.0131***	-0.0132***	-0.0117***	
					(0.0024)	(0.0025)	(0.0032)	
Returns	-0.0091	-0.0102*	-0.0124**	-0.0154	-0.0093	-0.0104*	-0.0126**	-0.0154
	(0.0055)	(0.0054)	(0.0057)	(0.0103)	(0.0055)	(0.0054)	(0.0057)	(0.0103)
Market Cap	-0.0042***	-0.0054***	-0.0033***	-0.0018	-0.0042***	-0.0054***	-0.0032***	-0.0018
	(0.0009)	(0.0012)	(0.0011)	(0.0015)	(0.0009)	(0.0012)	(0.0011)	(0.0015)
Volume	0.0030***	0.0040***	0.0024***	0.0017*	0.0030***	0.0040***	0.0024***	0.0017*
	(0.0010)	(0.0010)	(0.0008)	(0.0010)	(0.0010)	(0.0010)	(0.0008)	(0.0010)
VIX	0.0009***	0.0009***	0.0009***		0.0009***	0.0009***	0.0009***	
	(0.0001)	(0.0001)	(0.0001)		(0.0001)	(0.0001)	(0.0001)	
WUI	-0.0000***	-0.0000***	-0.0000		-0.0000***	-0.0000***	-0.0000	
	(0.0000)	(0.0000)	(0.0000)		(0.0000)	(0.0000)	(0.0000)	
Observations	61787	61787	61787	61787	61787	61787	61787	61787
Adj. R-squared	0.074	0.085	0.112	0.455	0.074	0.086	0.112	0.455
Individual FE	NO	YES	YES	YES	NO	YES	YES	YES
Year FE	NO	NO	YES	NO	NO	NO	YES	NO
Time FE	NO	NO	NO	YES	NO	NO	NO	YES

Note: *This table reports difference-in-differences estimates of the effect of the GENIUS Act proposal announcement (February 4, 2025) on cryptocurrency market liquidity within discrete event windows. The dependent variable is Roll Measure. The coefficient of interest, [1-Day and 3-Day] × DEX, captures the differential change in Roll Measure for DEX-linked tokens relative to CEX-linked tokens within the specified post-announcement window. Treated (DEX) is a time-invariant indicator equal to one for cryptocurrencies classified as DEX-linked and zero for CEX-linked cryptocurrencies; this indicator is absorbed by the cryptocurrency fixed effect in columns (2), (3), (4), (6), (7), and (8). The window indicator, 1-Day and 3-Day Window, is an indicator equal to one for observations falling within the specified number of trading days after the announcement date and zero otherwise; this indicator is absorbed by the daily time fixed effect in columns (4) and (8) only. Within each window, column (1) includes no fixed effects; column (2) includes cryptocurrency fixed effects; column (3) includes cryptocurrency and year fixed effects; column (4) includes cryptocurrency and daily time fixed effects. Controls include one-period lagged returns, lagged log market capitalisation, lagged log trading volume, VIX, and WUI. All specifications are estimated using a difference-in-differences framework with two-way fixed effects. Standard errors are clustered by cryptocurrency. Standard errors in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.*

Table 4.29: American Policy Shock - Event Windows – Part 2: Roll's Measure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
5-Day Window × DEX	0.0022	0.0016	0.0017	0.0019				
	(0.0056)	(0.0056)	(0.0054)	(0.0054)				
30-Day Window × DEX					-0.0016	-0.0021	-0.0022	-0.0021
					(0.0038)	(0.0038)	(0.0036)	(0.0036)
DEX	-0.0008				-0.0007			
	(0.0019)				(0.0020)			
5-Day Window	-0.0124***	-0.0122***	-0.0113***					
	(0.0023)	(0.0023)	(0.0031)					
30-Day Window					-0.0073***	-0.0070***	-0.0106***	
					(0.0016)	(0.0016)	(0.0033)	
Returns	-0.0091	-0.0102*	-0.0124**	-0.0154	-0.0095*	-0.0105*	-0.0128**	-0.0154
	(0.0055)	(0.0054)	(0.0057)	(0.0103)	(0.0055)	(0.0054)	(0.0058)	(0.0103)
Market Cap	-0.0042***	-0.0053***	-0.0032***	-0.0018	-0.0042***	-0.0053***	-0.0031***	-0.0018
	(0.0009)	(0.0012)	(0.0011)	(0.0015)	(0.0009)	(0.0012)	(0.0011)	(0.0015)
Volume	0.0030***	0.0040***	0.0024***	0.0017*	0.0030***	0.0040***	0.0024***	0.0017*
	(0.0010)	(0.0010)	(0.0008)	(0.0010)	(0.0010)	(0.0010)	(0.0008)	(0.0010)
VIX	0.0009***	0.0009***	0.0009***	0.0000	0.0009***	0.0009***	0.0009***	
	(0.0001)	(0.0001)	(0.0001)	(.)	(0.0001)	(0.0001)	(0.0001)	
WUI	-0.0000***	-0.0000***	-0.0000	0.0000	-0.0000***	-0.0000***	-0.0000**	
	(0.0000)	(0.0000)	(0.0000)	(.)	(0.0000)	(0.0000)	(0.0000)	
Observations	61787	61787	61787	61787	61787	61787	61787	61787
Adj. R-squared	0.075	0.086	0.112	0.455	0.076	0.087	0.114	0.455
Individual FE	NO	YES	YES	YES	NO	YES	YES	YES
Year FE	NO	NO	YES	NO	NO	NO	YES	NO
Time FE	NO	NO	NO	YES	NO	NO	NO	YES

Note: *This table reports difference-in-differences estimates of the effect of the GENIUS Act proposal announcement (February 4, 2025) on cryptocurrency market liquidity within discrete event windows. The dependent variable is Roll Measure. The coefficient of interest, [5-Day and 30-Day] × DEX, captures the differential change in Roll Measure for DEX-linked tokens relative to CEX-linked tokens within the specified post-announcement window. Treated (DEX) is a time-invariant indicator equal to one for cryptocurrencies classified as DEX-linked and zero for CEX-linked cryptocurrencies; this indicator is absorbed by the cryptocurrency fixed effect in columns (2), (3), (4), (6), (7), and (8). The window indicator, 5-Day and 30-Day Window, is an indicator equal to one for observations falling within the specified number of trading days after the announcement date and zero otherwise; this indicator is absorbed by the daily time fixed effect in columns (4) and (8) only. Within each window, column (1) includes no fixed effects; column (2) includes cryptocurrency fixed effects; column (3) includes cryptocurrency and year fixed effects; column (4) includes cryptocurrency and daily time fixed effects. Controls include one-period lagged returns, lagged log market capitalisation, lagged log trading volume, VIX, and WUI. All specifications are estimated using a difference-in-differences framework with two-way fixed effects. Standard errors are clustered by cryptocurrency. Standard errors in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.*

Table 4.30: Summary of Key Interaction Coefficients across Regulatory Events.

Event	Measure	Baseline	1 day	3 day	5 day	30 day
European	Turnover	−0.0894** [4/4]	0.1105* [4/4]	0.1047* [4/4]	0.1048** [4/4]	0.1212** [4/4]
	Amihud	−0.0124** [4/4]	0.0033* [1/4]	0.0026 [0/4]	0.0025 [0/4]	0.0012 [0/4]
	Roll	−0.0175 [0/4]	0.0137 [0/4]	0.0179 [0/4]	0.0195 [0/4]	0.0239 [0/4]
Chinese	Turnover	−0.0763** [4/4]	0.0658* [4/4]	0.0408 [0/4]	0.0439 [0/4]	0.0164 [0/4]
	Amihud	−0.0042** [2/4]	−0.0006 [0/4]	−0.0004 [0/4]	0.0000 [0/4]	−0.0003 [0/4]
	Roll	−0.0109** [2/4]	−0.0071 [0/4]	−0.0078 [0/4]	−0.0101 [0/4]	−0.0030 [0/4]
American	Turnover	−0.0237** [4/4]	0.0104 [0/4]	−0.0033 [0/4]	−0.0113** [4/4]	−0.0183*** [4/4]
	Amihud	−0.0006 [0/4]	−0.0022*** [4/4]	0.0006 [0/4]	−0.0001 [0/4]	−0.0007 [0/4]
	Roll	−0.0028 [0/4]	0.0015 [0/4]	0.0016 [0/4]	0.0019 [0/4]	−0.0021 [0/4]

Note: This table summarises the coefficients of interest reported in Tables 4.3 to 4.29. The Baseline column reports DEX × Post over the full post-announcement period. The 1 day, 3 day, 5 day and 30 day columns report the corresponding Window × DEX interaction. Each cell reports the coefficient from the specification with cryptocurrency and daily time fixed effects (column 4 of the relevant table). The figure in brackets gives the number of the four specifications in which the coefficient is statistically significant at the 10% level or better. The European, Chinese and American events refer to the MiCA proposal announcement, the Chinese cryptocurrency ban and the GENIUS Act, respectively. *Higher Amihud and Roll values indicate lower liquidity. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.*

Appendix

Table 4.A1: European Regulatory Shock -Price Impact Illiquidity across Event Windows: DEX-Linked Subsample

	(1) Baseline	(2) ±1 Day	(3) ±3 Days	(4) ±5 Days	(5) ±30 Days
Intercept	0.09685***	0.08343***	0.08344***	0.08343***	0.08347***
	(0.01812)	(0.01846)	(0.01846)	(0.01846)	(0.01831)
Post	-0.01159***				
	(0.00265)				
Window ±1d		-0.00268**			
		(0.00103)			
Window ±3d			-0.00343**		
			(0.00124)		
Window ±5d				-0.00409**	
				(0.00138)	
Window ±30d					-0.00669***
					(0.00188)
Returns	0.00087	0.00124	0.00121	0.00116	0.00074
	(0.00103)	(0.00110)	(0.00109)	(0.00108)	(0.00102)
Market Cap	-0.00092	-0.00056	-0.00056	-0.00057	-0.00064
	(0.00063)	(0.00071)	(0.00071)	(0.00071)	(0.00068)
Volume	-0.00376***	-0.00409***	-0.00409***	-0.00408***	-0.00398***
	(0.00064)	(0.00070)	(0.00070)	(0.00070)	(0.00067)
VIX	0.00006*	0.00010**	0.00010**	0.00010**	0.00011**
	(0.00003)	(0.00005)	(0.00005)	(0.00005)	(0.00004)
WUI	0.00000	0.00000	0.00000	0.00000	0.00000
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
GEPU	-0.00000	-0.00001	-0.00001	-0.00001	-0.00001
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Window	Post (full)	±1 day	±3 days	±5 days	±30 days
Observations	25928	25928	25928	25928	25928
Within R-sq	0.37619	0.34711	0.34739	0.34782	0.35556

Note: This table reports panel regression estimates for the DEX-linked subsample. The dependent variable is Amihud Illiquidity. Column (1) reports the baseline post-announcement coefficient using the full post-period. Columns (2) through (5) replace the post indicator with window-specific indicators equal to one for observations falling within ±1, ±3, ±5, and ±30 trading days of the announcement date respectively. All specifications include cryptocurrency and year fixed effects, estimated using reghdfe. Standard errors are clustered by cryptocurrency. *Standard errors in parentheses.* *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

Table 4.A2: European Regulatory Shock - Transaction Costs across Event Windows: DEX-Linked Subsample

	(1)	(2)	(3)	(4)	(5)
	Baseline	±1 Day	±3 Days	±5 Days	±30 Days
Intercept	0.08768***	0.05293	0.05284	0.05298	0.05278
	(0.02322)	(0.03515)	(0.03531)	(0.03530)	(0.03692)
Post	-0.02971*				
	(0.01548)				
Window ±1d		0.02397			
		(0.02806)			
Window ±3d			0.02546		
			(0.02729)		
Window ±5d				0.02847	
				(0.02812)	
Window ±30d					0.02986
					(0.02461)
Returns	-0.01665	-0.01568	-0.01541	-0.01516	-0.01351
	(0.01132)	(0.01131)	(0.01105)	(0.01088)	(0.00946)
Market Cap	-0.00531***	-0.00433**	-0.00429**	-0.00426**	-0.00396**
	(0.00132)	(0.00158)	(0.00160)	(0.00161)	(0.00169)
Volume	0.00341*	0.00250*	0.00246*	0.00242*	0.00201*
	(0.00160)	(0.00131)	(0.00129)	(0.00126)	(0.00104)
VIX	0.00068	0.00079	0.00078	0.00078	0.00075
	(0.00041)	(0.00045)	(0.00045)	(0.00046)	(0.00048)
WUI	-0.00000*	-0.00000	-0.00000	-0.00000	-0.00000
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
GEPU	0.00003	0.00002	0.00002	0.00002	0.00003
	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00003)
Window	Post (full)	±1 day	±3 days	±5 days	±30 days
Observations	25916	25916	25916	25916	25916
Within R-sq	0.03645	0.02545	0.02621	0.02730	0.03518

Note: This table reports panel regression estimates for the DEX-linked subsample. The dependent variable is Roll's Measure. Column (1) reports the baseline post-announcement coefficient using the full post-period. Columns (2) through (5) replace the post indicator with window-specific indicators equal to one for observations falling within ±1, ±3, ±5, and ±30 trading days of the announcement date respectively. All specifications include cryptocurrency and year fixed effects, estimated using reghdfe. Standard errors are clustered by cryptocurrency. *Standard errors in parentheses.* *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

Table 4.A3: European Regulatory Shock - Trading Activity across Event Windows: DEX-Linked Subsample

	(1) Baseline	(2) ±1 Day	(3) ±3 Days	(4) ±5 Days	(5) ±30 Days
Intercept	0.48042**	0.46374**	0.46376**	0.46379**	0.46361**
	(0.20317)	(0.19070)	(0.19067)	(0.19065)	(0.18970)
Post	-0.01431				
	(0.03363)				
Window ±1d		0.01444			
		(0.04807)			
Window ±3d			0.00672		
			(0.04198)		
Window ±5d				0.00529	
				(0.03717)	
Window ±30d					0.02475
					(0.02546)
Returns	0.07659**	0.07698**	0.07708**	0.07712**	0.07884**
	(0.03167)	(0.03127)	(0.03127)	(0.03134)	(0.02975)
Market Cap	-0.06567***	-0.06520***	-0.06520***	-0.06520***	-0.06489***
	(0.01680)	(0.01636)	(0.01637)	(0.01636)	(0.01620)
Volume	0.05446***	0.05402***	0.05402***	0.05402***	0.05361***
	(0.01149)	(0.01105)	(0.01107)	(0.01108)	(0.01084)
VIX	0.00025	0.00030	0.00030	0.00030	0.00027
	(0.00031)	(0.00031)	(0.00031)	(0.00031)	(0.00029)
WUI	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
GEPU	0.00001	0.00001	0.00001	0.00001	0.00002
	(0.00003)	(0.00003)	(0.00003)	(0.00003)	(0.00003)
Window	Post (full)	±1 day	±3 days	±5 days	±30 days
Observations	25927	25927	25927	25927	25927
Within R-sq	0.23390	0.23361	0.23360	0.23359	0.23442

Note: This table reports panel regression estimates for the DEX-linked subsample. The dependent variable is Turnover. Column (1) reports the baseline post-announcement coefficient using the full post-period. Columns (2) through (5) replace the post indicator with window-specific indicators equal to one for observations falling within ±1, ±3, ±5, and ±30 trading days of the announcement date respectively. All specifications include cryptocurrency and year fixed effects, estimated using reghdfe. Standard errors are clustered by cryptocurrency. *Standard errors in parentheses.* *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$*

Table 4.A4: Chinese Regulatory Shock - Price Impact Illiquidity across Event Windows: DEX-Linked Subsample

	(1) Baseline	(2) ±1 Day	(3) ±3 Days	(4) ±5 Days	(5) ±30 Days
Intercept	0.08484***	0.08351***	0.08359***	0.08368***	0.08338***
	(0.01868)	(0.01845)	(0.01842)	(0.01839)	(0.01811)
Post	-0.00201**				
	(0.00078)				
Window ±1d		0.00433***			
		(0.00130)			
Window ±3d			0.00474***		
			(0.00120)		
Window ±5d				0.00515***	
				(0.00142)	
Window ±30d					0.00297***
					(0.00084)
Returns	0.00094	0.00122	0.00138	0.00159	0.00155
	(0.00103)	(0.00109)	(0.00111)	(0.00114)	(0.00108)
Market Cap	-0.00048	-0.00055	-0.00055	-0.00054	-0.00053
	(0.00070)	(0.00071)	(0.00071)	(0.00070)	(0.00069)
Volume	-0.00417***	-0.00410***	-0.00412***	-0.00413***	-0.00414***
	(0.00071)	(0.00071)	(0.00071)	(0.00071)	(0.00071)
VIX	0.00009*	0.00010**	0.00010**	0.00010*	0.00010**
	(0.00005)	(0.00005)	(0.00005)	(0.00005)	(0.00005)
WUI	0.00000	0.00000	0.00000	0.00000	0.00000
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
GEPU	-0.00001	-0.00001	-0.00001	-0.00000	-0.00000
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Window	Post (full)	±1 day	±3 days	±5 days	±30 days
Observations	25928	25928	25928	25928	25928
Within R-sq	0.34942	0.34741	0.34810	0.34899	0.35021

Note: This table reports panel regression estimates for the DEX-linked subsample. The dependent variable is Amihud Illiquidity. Column (1) reports the baseline post-announcement coefficient using the full post-period. Columns (2) through (5) replace the post indicator with window-specific indicators equal to one for observations falling within ±1, ±3, ±5, and ±30 trading days of the announcement date respectively. All specifications include cryptocurrency and year fixed effects, estimated using reghdfe. Standard errors are clustered by cryptocurrency. *Standard errors in parentheses.* *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$*

Table 4.A5: Chinese Regulatory Shock - Transaction Costs across Event Windows: DEX-Linked Subsample

	(1) Baseline	(2) ±1 Day	(3) ±3 Days	(4) ±5 Days	(5) ±30 Days
Intercept	0.05367	0.05337	0.05409	0.05433	0.05278
	(0.03456)	(0.03485)	(0.03461)	(0.03453)	(0.03233)
Post	-0.00084				
	(0.00425)				
Window ±1d		0.01397			
		(0.00941)			
Window ±3d			0.02665***		
			(0.00863)		
Window ±5d				0.02438***	
				(0.00789)	
Window ±30d					0.04153***
					(0.00671)
Returns	-0.01571	-0.01562	-0.01471	-0.01385	-0.01101
	(0.01120)	(0.01127)	(0.01129)	(0.01135)	(0.01130)
Market Cap	-0.00433**	-0.00436**	-0.00433**	-0.00429**	-0.00406**
	(0.00158)	(0.00156)	(0.00155)	(0.00155)	(0.00139)
Volume	0.00250*	0.00251*	0.00243*	0.00236	0.00191
	(0.00132)	(0.00134)	(0.00134)	(0.00135)	(0.00137)
VIX	0.00078	0.00079	0.00078	0.00077	0.00081*
	(0.00045)	(0.00045)	(0.00045)	(0.00045)	(0.00045)
WUI	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
GEPU	0.00002	0.00002	0.00002	0.00003	0.00004
	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)
Window	Post (full)	±1 day	±3 days	±5 days	±30 days
Observations	25916	25916	25916	25916	25916
Within R-sq	0.02499	0.02521	0.02703	0.02763	0.06255

Note: This table reports panel regression estimates for the DEX-linked subsample. The dependent variable is Roll's Measure. Column (1) reports the baseline post-announcement coefficient using the full post-period. Columns (2) through (5) replace the post indicator with window-specific indicators equal to one for observations falling within ±1, ±3, ±5, and ±30 trading days of the announcement date respectively. All specifications include cryptocurrency and year fixed effects, estimated using reghdfe. Standard errors are clustered by cryptocurrency. *Standard errors in parentheses.* *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$*

Table 4.A6: Chinese Regulatory Shock - Trading Activity across Event Windows: DEX-Linked Subsample

	(1) Baseline	(2) ±1 Day	(3) ±3 Days	(4) ±5 Days	(5) ±30 Days
Intercept	0.49182**	0.46624**	0.46613**	0.46678**	0.46375**
	(0.19521)	(0.19144)	(0.19156)	(0.19198)	(0.19106)
Post	-0.03935***				
	(0.01085)				
Window ±1d		0.11071***			
		(0.02976)			
Window ±3d			0.05979***		
			(0.01646)		
Window ±5d				0.05711***	
				(0.01701)	
Window ±30d					0.00717
					(0.00706)
Returns	0.07135**	0.07677**	0.07898**	0.08108**	0.07781**
	(0.03051)	(0.03142)	(0.03134)	(0.03126)	(0.03111)
Market Cap	-0.06372***	-0.06524***	-0.06516***	-0.06506***	-0.06517***
	(0.01597)	(0.01637)	(0.01635)	(0.01634)	(0.01634)
Volume	0.05270***	0.05390***	0.05380***	0.05364***	0.05393***
	(0.01070)	(0.01098)	(0.01095)	(0.01090)	(0.01098)
VIX	0.00003	0.00028	0.00028	0.00025	0.00031
	(0.00030)	(0.00031)	(0.00031)	(0.00030)	(0.00031)
WUI	0.00000	-0.00000	-0.00000	-0.00000	-0.00000
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
GEPU	0.00002	0.00001	0.00001	0.00002	0.00001
	(0.00003)	(0.00003)	(0.00003)	(0.00003)	(0.00003)
Window	Post (full)	±1 day	±3 days	±5 days	±30 days
Observations	25927	25927	25927	25927	25927
Within R-sq	0.24012	0.23542	0.23481	0.23531	0.23372

Note: This table reports panel regression estimates for the DEX-linked subsample. The dependent variable is Turnover. Column (1) reports the baseline post-announcement coefficient using the full post-period. Columns (2) through (5) replace the post indicator with window-specific indicators equal to one for observations falling within ±1, ±3, ±5, and ±30 trading days of the announcement date respectively. All specifications include cryptocurrency and year fixed effects, estimated using reghdfe. Standard errors are clustered by cryptocurrency. *Standard errors in parentheses.* *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$*

Table 4.A7: American Regulatory Shock - Price Impact Illiquidity across Event Windows: DEX-Linked Subsample

	(1) Baseline	(2) ±1 Day	(3) ±3 Days	(4) ±5 Days	(5) ±30 Days
Intercept	0.08380***	0.08331***	0.08315***	0.08315***	0.08232***
	(0.01842)	(0.01846)	(0.01843)	(0.01844)	(0.01831)
Post	-0.00265***				
	(0.00045)				
Window ±1d		0.00321***			
		(0.00071)			
Window ±3d			0.00420***		
			(0.00096)		
Window ±5d				0.00271***	
				(0.00062)	
Window ±30d					0.00347***
					(0.00088)
Returns	0.00125	0.00130	0.00139	0.00128	0.00130
	(0.00109)	(0.00110)	(0.00109)	(0.00109)	(0.00110)
Market Cap	-0.00061	-0.00055	-0.00055	-0.00055	-0.00062
	(0.00071)	(0.00071)	(0.00071)	(0.00071)	(0.00070)
Volume	-0.00408***	-0.00410***	-0.00410***	-0.00410***	-0.00407***
	(0.00070)	(0.00071)	(0.00071)	(0.00071)	(0.00070)
VIX	0.00010**	0.00010**	0.00010**	0.00010**	0.00010**
	(0.00005)	(0.00005)	(0.00005)	(0.00005)	(0.00004)
WUI	0.00000	0.00000	0.00000	0.00000	0.00000
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
GEPU	-0.00000	-0.00001	-0.00001	-0.00001	-0.00000
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Window	Post (full)	±1 day	±3 days	±5 days	±30 days
Observations	25928	25928	25928	25928	25928
Within R-sq	0.34830	0.34726	0.34796	0.34761	0.34963

Note: This table reports panel regression estimates for the DEX-linked subsample. The dependent variable is Amihud Illiquidity. Column (1) reports the baseline post-announcement coefficient using the full post-period. Columns (2) through (5) replace the post indicator with window-specific indicators equal to one for observations falling within ±1, ±3, ±5, and ±30 trading days of the announcement date respectively. All specifications include cryptocurrency and year fixed effects, estimated using reghdfe. Standard errors are clustered by cryptocurrency. *Standard errors in parentheses.* *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$*

Table 4.A8: American Regulatory Shock - Transaction Costs across Event Windows: DEX-Linked Subsample

	(1) Baseline	(2) ±1 Day	(3) ±3 Days	(4) ±5 Days	(5) ±30 Days
Intercept	0.05073	0.05336	0.05360	0.05382	0.05705
	(0.03505)	(0.03495)	(0.03495)	(0.03494)	(0.03535)
Post	0.01572***				
	(0.00371)				
Window ±1d		-0.00916			
		(0.00550)			
Window ±3d			-0.00859*		
			(0.00476)		
Window ±5d				-0.00780	
				(0.00449)	
Window ±30d					-0.01271**
					(0.00571)
Returns	-0.01570	-0.01580	-0.01592	-0.01574	-0.01583
	(0.01122)	(0.01128)	(0.01131)	(0.01126)	(0.01130)
Market Cap	-0.00402**	-0.00437**	-0.00437**	-0.00436**	-0.00413**
	(0.00157)	(0.00157)	(0.00157)	(0.00157)	(0.00153)
Volume	0.00241*	0.00255*	0.00254*	0.00253*	0.00243*
	(0.00135)	(0.00135)	(0.00134)	(0.00134)	(0.00133)
VIX	0.00080	0.00079	0.00079	0.00079	0.00079
	(0.00045)	(0.00045)	(0.00045)	(0.00045)	(0.00045)
WUI	-0.00000*	-0.00000	-0.00000	-0.00000	-0.00000*
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
GEPU	0.00001	0.00002	0.00002	0.00002	0.00001
	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)
Window	Post (full)	±1 day	±3 days	±5 days	±30 days
Observations	25916	25916	25916	25916	25916
Within R-sq	0.02768	0.02509	0.02520	0.02526	0.02707

Note: This table reports panel regression estimates for the DEX-linked subsample. The dependent variable is Roll's Measure. Column (1) reports the baseline post-announcement coefficient using the full post-period. Columns (2) through (5) replace the post indicator with window-specific indicators equal to one for observations falling within ±1, ±3, ±5, and ±30 trading days of the announcement date respectively. All specifications include cryptocurrency and year fixed effects, estimated using reghdfe. Standard errors are clustered by cryptocurrency. *Standard errors in parentheses.* ** p < 0.10, ** p < 0.05, *** p < 0.01*

Table 4.A9: American Regulatory Shock - Trading Activity across Event Windows: DEX-Linked Subsample

	(1) Baseline	(2) ±1 Day	(3) ±3 Days	(4) ±5 Days	(5) ±30 Days
Intercept	0.46653**	0.46341**	0.46280**	0.46300**	0.46090**
	(0.19199)	(0.19076)	(0.19064)	(0.19063)	(0.18979)
Post	-0.01828**				
	(0.00799)				
Window ±1d		0.01323*			
		(0.00713)			
Window ±3d			0.01642***		
			(0.00506)		
Window ±5d				0.00851**	
				(0.00388)	
Window ±30d					0.00932
					(0.00644)
Returns	0.07717**	0.07734**	0.07766**	0.07720**	0.07722**
	(0.03126)	(0.03114)	(0.03117)	(0.03121)	(0.03122)
Market Cap	-0.06562***	-0.06520***	-0.06521***	-0.06522***	-0.06538***
	(0.01650)	(0.01634)	(0.01634)	(0.01634)	(0.01642)
Volume	0.05418***	0.05402***	0.05402***	0.05404***	0.05411***
	(0.01106)	(0.01102)	(0.01102)	(0.01102)	(0.01105)
VIX	0.00029	0.00030	0.00030	0.00030	0.00030
	(0.00031)	(0.00031)	(0.00031)	(0.00031)	(0.00031)
WUI	0.00000	-0.00000	0.00000	0.00000	0.00000
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
GEPU	0.00002	0.00001	0.00001	0.00001	0.00002
	(0.00003)	(0.00003)	(0.00003)	(0.00003)	(0.00003)
Window	Post (full)	±1 day	±3 days	±5 days	±30 days
Observations	25927	25927	25927	25927	25927
Within R-sq	0.23402	0.23361	0.23369	0.23363	0.23372

Note: This table reports panel regression estimates for the DEX-linked subsample. The dependent variable is Turnover. Column (1) reports the baseline post-announcement coefficient using the full post-period. Columns (2) through (5) replace the post indicator with window-specific indicators equal to one for observations falling within ±1, ±3, ±5, and ±30 trading days of the announcement date respectively. All specifications include cryptocurrency and year fixed effects, estimated using reghdfe. Standard errors are clustered by cryptocurrency. *Standard errors in parentheses.* *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$*

Table 4.A10: European Regulatory Shock - Price Impact Illiquidity across Event Windows: CEX-Linked Subsample

	(1) Baseline	(2) ±1 Day	(3) ±3 Days	(4) ±5 Days	(5) ±30 Days
Intercept	0.04404***	0.04305***	0.04305***	0.04304***	0.04298***
	(0.01064)	(0.01022)	(0.01022)	(0.01022)	(0.01022)
Post	-0.00177				
	(0.00133)				
Window ±1d		-0.00043			
		(0.00073)			
Window ±3d			-0.00059		
			(0.00083)		
Window ±5d				-0.00091	
				(0.00073)	
Window ±30d					-0.00081
					(0.00074)
Returns	0.00089	0.00098	0.00097	0.00097	0.00093
	(0.00114)	(0.00118)	(0.00118)	(0.00118)	(0.00119)
Market Cap	0.00016	0.00013	0.00013	0.00013	0.00014
	(0.00122)	(0.00121)	(0.00121)	(0.00121)	(0.00121)
Volume	-0.00235	-0.00236	-0.00236	-0.00236	-0.00236
	(0.00181)	(0.00182)	(0.00182)	(0.00182)	(0.00182)
VIX	0.00001	0.00002	0.00002	0.00002	0.00002
	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)
WUI	0.00000	0.00000*	0.00000*	0.00000*	0.00000*
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
GEPU	0.00000	-0.00000	-0.00000	-0.00000	-0.00000
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Window	Post (full)	±1 day	±3 days	±5 days	±30 days
Observations	35887	35887	35887	35887	35887
Within R-sq	0.17450	0.17186	0.17188	0.17196	0.17227

Note: This table reports panel regression estimates for the CEX-linked subsample. The dependent variable is Amihud Illiquidity. Column (1) reports the baseline post-announcement coefficient using the full post-period. Columns (2) through (5) replace the post indicator with window-specific indicators equal to one for observations falling within ±1, ±3, ±5, and ±30 trading days of the announcement date respectively. All specifications include cryptocurrency and year fixed effects, estimated using reghdfe. Standard errors are clustered by cryptocurrency. *Standard errors in parentheses.* *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

Table 4.A11: European Regulatory Shock - Transaction Costs across Event Windows: CEX-Linked Subsample

	(1) Baseline	(2) ±1 Day	(3) ±3 Days	(4) ±5 Days	(5) ±30 Days
Intercept	0.04620	0.03658	0.03660	0.03670	0.03701
	(0.02723)	(0.02583)	(0.02585)	(0.02585)	(0.02586)
Post	-0.01725***				
	(0.00416)				
Window ±1d		0.01574*			
		(0.00774)			
Window ±3d			0.01265		
			(0.00745)		
Window ±5d				0.01381*	
				(0.00766)	
Window ±30d					0.00572
					(0.00661)
Returns	-0.00988**	-0.00900**	-0.00879**	-0.00872**	-0.00858**
	(0.00378)	(0.00375)	(0.00373)	(0.00373)	(0.00362)
Market Cap	-0.00301*	-0.00329**	-0.00329**	-0.00331**	-0.00333**
	(0.00149)	(0.00147)	(0.00148)	(0.00148)	(0.00151)
Volume	0.00238**	0.00233*	0.00233*	0.00234*	0.00232*
	(0.00105)	(0.00112)	(0.00112)	(0.00113)	(0.00113)
VIX	0.00085***	0.00095***	0.00095***	0.00095***	0.00096***
	(0.00008)	(0.00008)	(0.00008)	(0.00008)	(0.00008)
WUI	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
GEPU	0.00000	-0.00001	-0.00001	-0.00001	-0.00001
	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)
Window	Post (full)	±1 day	±3 days	±5 days	±30 days
Observations	35871	35871	35871	35871	35871
Within R-sq	0.06292	0.05166	0.05188	0.05244	0.05220

Note: This table reports panel regression estimates for the CEX-linked subsample. The dependent variable is Roll's Measure. Column (1) reports the baseline post-announcement coefficient using the full post-period. Columns (2) through (5) replace the post indicator with window-specific indicators equal to one for observations falling within ±1, ±3, ±5, and ±30 trading days of the announcement date respectively. All specifications include cryptocurrency and year fixed effects, estimated using reghdfe. Standard errors are clustered by cryptocurrency. *Standard errors in parentheses.* *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$*

Table 4.A12: European Regulatory Shock -Trading Activity across Event Windows: CEX-Linked Subsample

	(1) Baseline	(2) ±1 Day	(3) ±3 Days	(4) ±5 Days	(5) ±30 Days
Intercept	0.42704***	0.42518***	0.42516***	0.42511***	0.42454***
	(0.14259)	(0.13987)	(0.13986)	(0.13983)	(0.13970)
Post	-0.00333				
	(0.00610)				
Window ±1d		-0.00274			
		(0.00849)			
Window ±3d			-0.00439		
			(0.00625)		
Window ±5d				-0.00631	
				(0.00592)	
Window ±30d					-0.00720
					(0.00502)
Returns	0.09170*	0.09189*	0.09183*	0.09179*	0.09145*
	(0.04552)	(0.04548)	(0.04547)	(0.04548)	(0.04549)
Market Cap	-0.04797***	-0.04802***	-0.04802***	-0.04801***	-0.04796***
	(0.01080)	(0.01085)	(0.01085)	(0.01084)	(0.01082)
Volume	0.03712***	0.03710***	0.03710***	0.03710***	0.03711***
	(0.00645)	(0.00645)	(0.00645)	(0.00644)	(0.00644)
VIX	0.00041**	0.00043**	0.00043**	0.00043**	0.00042**
	(0.00018)	(0.00019)	(0.00019)	(0.00019)	(0.00019)
WUI	-0.00000*	-0.00000	-0.00000	-0.00000	-0.00000*
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
GEPU	-0.00002**	-0.00002*	-0.00002*	-0.00002*	-0.00002*
	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)
Window	Post (full)	±1 day	±3 days	±5 days	±30 days
Observations	35887	35887	35887	35887	35887
Within R-sq	0.25871	0.25861	0.25862	0.25866	0.25898

Note: This table reports panel regression estimates for the CEX-linked subsample. The dependent variable is Turnover. Column (1) reports the baseline post-announcement coefficient using the full post-period. Columns (2) through (5) replace the post indicator with window-specific indicators equal to one for observations falling within ±1, ±3, ±5, and ±30 trading days of the announcement date respectively. All specifications include cryptocurrency and year fixed effects, estimated using reghdfe. Standard errors are clustered by cryptocurrency. *Standard errors in parentheses.* *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$*

Table 4.A13: Chinese Regulatory Shock -Price Impact Illiquidity across Event Windows: CEX-Linked Subsample

	(1) Baseline	(2) ±1 Day	(3) ±3 Days	(4) ±5 Days	(5) ±30 Days
Intercept	0.04273***	0.04307***	0.04306***	0.04305***	0.04295***
	(0.01003)	(0.01022)	(0.01020)	(0.01018)	(0.01006)
Post	-0.00067				
	(0.00114)				
Window ±1d		0.00256			
		(0.00152)			
Window ±3d			0.00279		
			(0.00176)		
Window ±5d				0.00297	
				(0.00200)	
Window ±30d					0.00174
					(0.00107)
Returns	0.00083	0.00099	0.00110	0.00127	0.00119
	(0.00096)	(0.00118)	(0.00124)	(0.00134)	(0.00128)
Market Cap	0.00019	0.00013	0.00014	0.00015	0.00016
	(0.00131)	(0.00121)	(0.00122)	(0.00122)	(0.00122)
Volume	-0.00239	-0.00236	-0.00237	-0.00238	-0.00239
	(0.00186)	(0.00182)	(0.00183)	(0.00183)	(0.00183)
VIX	0.00001	0.00002	0.00002	0.00002	0.00002
	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)
WUI	0.00000*	0.00000*	0.00000*	0.00000*	0.00000*
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
GEPU	-0.00000	-0.00000	-0.00000	-0.00000	0.00000
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Window	Post (full)	±1 day	±3 days	±5 days	±30 days
Observations	35887	35887	35887	35887	35887
Within R-sq	0.17236	0.17213	0.17260	0.17316	0.17399

Note: This table reports panel regression estimates for the CEX-linked subsample. The dependent variable is Amihud Illiquidity. Column (1) reports the baseline post-announcement coefficient using the full post-period. Columns (2) through (5) replace the post indicator with window-specific indicators equal to one for observations falling within ±1, ±3, ±5, and ±30 trading days of the announcement date respectively. All specifications include cryptocurrency and year fixed effects, estimated using reghdfe. Standard errors are clustered by cryptocurrency. *Standard errors in parentheses.* *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

Table 4.A14: Chinese Regulatory Shock - Transaction Costs across Event Windows: CEX-Linked Subsample

	(1) Baseline	(2) ±1 Day	(3) ±3 Days	(4) ±5 Days	(5) ±30 Days
Intercept	0.04010	0.03668	0.03665	0.03647	0.03373
	(0.02428)	(0.02573)	(0.02549)	(0.02534)	(0.02292)
Post	0.00761**				
	(0.00305)				
Window ±1d		0.02161***			
		(0.00454)			
Window ±3d			0.03547***		
			(0.00443)		
Window ±5d				0.03575***	
				(0.00426)	
Window ±30d					0.04589***
					(0.00445)
Returns	-0.00720*	-0.00883**	-0.00738*	-0.00544	-0.00348
	(0.00375)	(0.00375)	(0.00378)	(0.00382)	(0.00374)
Market Cap	-0.00397**	-0.00326**	-0.00316**	-0.00307**	-0.00267*
	(0.00138)	(0.00146)	(0.00145)	(0.00144)	(0.00131)
Volume	0.00267**	0.00229*	0.00215*	0.00204*	0.00147
	(0.00115)	(0.00112)	(0.00110)	(0.00109)	(0.00092)
VIX	0.00097***	0.00095***	0.00095***	0.00094***	0.00096***
	(0.00007)	(0.00008)	(0.00008)	(0.00008)	(0.00008)
WUI	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
GEPU	-0.00001	-0.00001	-0.00000	-0.00000	0.00001
	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)
Window	Post (full)	±1 day	±3 days	±5 days	±30 days
Observations	35871	35871	35871	35871	35871
Within R-sq	0.05425	0.05215	0.05689	0.06010	0.12046

Note: This table reports panel regression estimates for the CEX-linked subsample. The dependent variable is Roll's Measure. Column (1) reports the baseline post-announcement coefficient using the full post-period. Columns (2) through (5) replace the post indicator with window-specific indicators equal to one for observations falling within ±1, ±3, ±5, and ±30 trading days of the announcement date respectively. All specifications include cryptocurrency and year fixed effects, estimated using reghdfe. Standard errors are clustered by cryptocurrency. *Standard errors in parentheses.* *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$*

Table 4.A15: Chinese Regulatory Shock -Trading Activity across Event Windows: CEX-Linked Subsample

	(1) Baseline	(2) ±1 Day	(3) ±3 Days	(4) ±5 Days	(5) ±30 Days
Intercept	0.41687**	0.42570***	0.42536***	0.42516***	0.42468***
	(0.14743)	(0.13952)	(0.13952)	(0.13949)	(0.13960)
Post	-0.01769*				
	(0.00970)				
Window ±1d		0.06328***			
		(0.00910)			
Window ±3d			0.04197***		
			(0.00684)		
Window ±5d				0.03701***	
				(0.00676)	
Window ±30d					0.00843
					(0.00553)
Returns	0.08785*	0.09220*	0.09372*	0.09548*	0.09287*
	(0.04415)	(0.04556)	(0.04541)	(0.04541)	(0.04573)
Market Cap	-0.04641***	-0.04798***	-0.04788***	-0.04781***	-0.04791***
	(0.01155)	(0.01083)	(0.01084)	(0.01084)	(0.01085)
Volume	0.03631***	0.03701***	0.03690***	0.03681***	0.03695***
	(0.00658)	(0.00644)	(0.00644)	(0.00644)	(0.00645)
VIX	0.00038*	0.00042**	0.00042**	0.00042**	0.00043**
	(0.00019)	(0.00019)	(0.00019)	(0.00019)	(0.00019)
WUI	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
GEPU	-0.00002*	-0.00002*	-0.00002*	-0.00002*	-0.00002*
	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)
Window	Post (full)	±1 day	±3 days	±5 days	±30 days
Observations	35887	35887	35887	35887	35887
Within R-sq	0.26254	0.26050	0.26052	0.26090	0.25917

Note: This table reports panel regression estimates for the CEX-linked subsample. The dependent variable is Turnover. Column (1) reports the baseline post-announcement coefficient using the full post-period. Columns (2) through (5) replace the post indicator with window-specific indicators equal to one for observations falling within ±1, ±3, ±5, and ±30 trading days of the announcement date respectively. All specifications include cryptocurrency and year fixed effects, estimated using reghdfe. Standard errors are clustered by cryptocurrency. *Standard errors in parentheses.* *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

Table 4.A16: American Regulatory Shock - Price Impact Illiquidity across Event Windows: CEX-Linked Subsample

	(1) Baseline	(2) ±1 Day	(3) ±3 Days	(4) ±5 Days	(5) ±30 Days
Intercept	0.04304***	0.04295***	0.04294***	0.04294***	0.04240***
	(0.01019)	(0.01017)	(0.01017)	(0.01017)	(0.00996)
Post	-0.00128**				
	(0.00055)				
Window ±1d		0.00272			
		(0.00204)			
Window ±3d			0.00165		
			(0.00109)		
Window ±5d				0.00112	
				(0.00067)	
Window ±30d					0.00162*
					(0.00079)
Returns	0.00097	0.00105	0.00106	0.00101	0.00101
	(0.00117)	(0.00123)	(0.00122)	(0.00119)	(0.00119)
Market Cap	0.00012	0.00014	0.00014	0.00013	0.00013
	(0.00121)	(0.00122)	(0.00121)	(0.00121)	(0.00121)
Volume	-0.00236	-0.00237	-0.00236	-0.00236	-0.00237
	(0.00182)	(0.00183)	(0.00183)	(0.00182)	(0.00182)
VIX	0.00001	0.00002	0.00002	0.00002	0.00001
	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)
WUI	0.00000**	0.00000*	0.00000*	0.00000*	0.00000**
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
GEPU	0.00000	-0.00000	-0.00000	-0.00000	0.00000
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Window	Post (full)	±1 day	±3 days	±5 days	±30 days
Observations	35887	35887	35887	35887	35887
Within R-sq	0.17241	0.17217	0.17212	0.17204	0.17295

Note: This table reports panel regression estimates for the CEX-linked subsample. The dependent variable is Amihud Illiquidity /. Column (1) reports the baseline post-announcement coefficient using the full post-period. Columns (2) through (5) replace the post indicator with window-specific indicators equal to one for observations falling within ±1, ±3, ±5, and ±30 trading days of the announcement date respectively. All specifications include cryptocurrency and year fixed effects, estimated using reghdfe. Standard errors are clustered by cryptocurrency. *Standard errors in parentheses.* *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$*

Table 4.A17: American Regulatory Shock -Transaction Costs across Event Windows: CEX-Linked Subsample

	(1) Baseline	(2) ±1 Day	(3) ±3 Days	(4) ±5 Days	(5) ±30 Days
Intercept	0.03669	0.03697	0.03732	0.03763	0.04129
	(0.02651)	(0.02585)	(0.02589)	(0.02593)	(0.02665)
Post	0.01830***				
	(0.00356)				
Window ±1d		-0.01241***			
		(0.00364)			
Window ±3d			-0.01215***		
			(0.00301)		
Window ±5d				-0.01192***	
				(0.00289)	
Window ±30d					-0.01187***
					(0.00372)
Returns	-0.00877**	-0.00927**	-0.00950**	-0.00923**	-0.00915**
	(0.00373)	(0.00375)	(0.00378)	(0.00376)	(0.00381)
Market Cap	-0.00317*	-0.00332**	-0.00332**	-0.00331**	-0.00328**
	(0.00151)	(0.00148)	(0.00148)	(0.00148)	(0.00149)
Volume	0.00235*	0.00236*	0.00236*	0.00236*	0.00240*
	(0.00114)	(0.00113)	(0.00113)	(0.00113)	(0.00115)
VIX	0.00098***	0.00095***	0.00095***	0.00095***	0.00098***
	(0.00008)	(0.00008)	(0.00008)	(0.00008)	(0.00008)
WUI	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
GEPU	-0.00002*	-0.00001	-0.00001	-0.00001	-0.00002*
	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)
Window	Post (full)	±1 day	±3 days	±5 days	±30 days
Observations	35871	35871	35871	35871	35871
Within R-sq	0.05654	0.05154	0.05190	0.05221	0.05397

Note: This table reports panel regression estimates for the CEX-linked subsample. The dependent variable is Roll's Measure. Column (1) reports the baseline post-announcement coefficient using the full post-period. Columns (2) through (5) replace the post indicator with window-specific indicators equal to one for observations falling within ±1, ±3, ±5, and ±30 trading days of the announcement date respectively. All specifications include cryptocurrency and year fixed effects, estimated using reghdfe. Standard errors are clustered by cryptocurrency. *Standard errors in parentheses.* *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

Table 4.A18: American Regulatory Shock -Trading Activity across Event Windows: CEX-Linked Subsample

	(1) Baseline	(2) ±1 Day	(3) ±3 Days	(4) ±5 Days	(5) ±30 Days
Intercept	0.42514***	0.42535***	0.42500***	0.42524***	0.42589***
	(0.13974)	(0.14005)	(0.14004)	(0.13997)	(0.13982)
Post	-0.00376				
	(0.00234)				
Window ±1d		-0.00443			
		(0.00596)			
Window ±3d			0.00266		
			(0.00306)		
Window ±5d				-0.00059	
				(0.00158)	
Window ±30d					-0.00176
					(0.00207)
Returns	0.09184*	0.09175*	0.09199*	0.09185*	0.09184*
	(0.04548)	(0.04552)	(0.04556)	(0.04549)	(0.04547)
Market Cap	-0.04804***	-0.04804***	-0.04801***	-0.04802***	-0.04802***
	(0.01085)	(0.01087)	(0.01086)	(0.01085)	(0.01085)
Volume	0.03710***	0.03712***	0.03710***	0.03711***	0.03712***
	(0.00644)	(0.00646)	(0.00645)	(0.00645)	(0.00645)
VIX	0.00042**	0.00043**	0.00043**	0.00043**	0.00043**
	(0.00019)	(0.00019)	(0.00019)	(0.00019)	(0.00019)
WUI	-0.00000	-0.00000	-0.00000	-0.00000	-0.00000
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
GEPU	-0.00002*	-0.00002*	-0.00002*	-0.00002*	-0.00002**
	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)
Window	Post (full)	±1 day	±3 days	±5 days	±30 days
Observations	35887	35887	35887	35887	35887
Within R-sq	0.25866	0.25861	0.25861	0.25860	0.25862

Note: This table reports panel regression estimates for the CEX-linked subsample. The dependent variable is Turnover. Column (1) reports the baseline post-announcement coefficient using the full post-period. Columns (2) through (5) replace the post indicator with window-specific indicators equal to one for observations falling within ±1, ±3, ±5, and ±30 trading days of the announcement date respectively. All specifications include cryptocurrency and year fixed effects, estimated using reghdfe. Standard errors are clustered by cryptocurrency. *Standard errors in parentheses.* *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$*

CHAPTER 5

5. Conclusion

5.1 Summary of Findings

This chapter summarises the findings of the three empirical chapters, draws out their collective implications, and identifies directions for future research. The evidence across all three chapters consistently shows that external announcements do not produce uniform effects across the cryptocurrency market. Instead, responses vary by asset class, by coin, by platform, by liquidity dimension, and by time horizon.

Chapter 2 provides the first empirical separation of cryptocurrencies by issuer identifiability status, a classification that maps directly to how MiCA determines regulatory scope. The finding that issuer identifiability becomes a priced characteristic, with a 2.1 percentage point divergence between identifiable and unidentifiable issuer cryptocurrencies, demonstrates that markets price regulatory accountability structures at the announcement stage, before any enforcement begins. This has direct relevance for how new crypto-assets may be designed and launched. The finding that DeFi protocols experience a decline in returns despite exemption challenges the assumption that lighter regulatory treatment translates into market advantage. DeFi's dependence on regulated infrastructure, including stablecoins, fiat on-ramps, and custodial services, creates spillover channels that exemption cannot insulate

Chapter 3 establishes that Ethereum has overtaken Bitcoin as the dominant net volatility transmitter across the cryptocurrency market. This finding, consistent across three of four volatility measures, challenges the longstanding assumption that Bitcoin anchors the market's risk structure. For portfolio construction and risk management, this means that Ethereum's

behaviour, particularly its role in the decentralised finance ecosystem, now warrants closer attention than Bitcoin's historical dominance might suggest. The finding that MiCA's announcement produced larger structural effects than the Russia-Ukraine War indicates that the cryptocurrency market's sensitivity hierarchy has shifted. Crypto-specific regulation now dominates traditional macroeconomic and geopolitical factors in reshaping market interconnections. This suggests the market has matured beyond sentiment-driven dynamics toward one that responds most strongly to formal policy frameworks.

Chapter 4 demonstrates that regulatory pressure on centralised exchange infrastructure does not produce sustained migration toward decentralised alternatives. Across three regulatory announcements differing in jurisdiction and design, DEX-linked trading activity declined relative to CEX-linked activity in the sustained post-announcement period. This contradicts the expectation that decentralised venues benefit when centralised infrastructure faces oversight. The finding that trading activity and price-impact liquidity move in opposite directions confirms that liquidity is multidimensional and that studies treating these dimensions as interchangeable may reach incomplete conclusions. For policymakers, this suggests that concerns about regulatory pressure creating a backdoor to unregulated markets may be overstated.

This thesis contributes to several literatures. It extends the regulatory finance literature by documenting how comprehensive regulatory frameworks produce differential responses across diverse crypto-asset classes, moving beyond the Bitcoin-centric focus of prior studies. It advances the volatility spillover literature by providing the first systematic comparison of price-based and idiosyncratic volatility measures in cryptocurrency connectedness analysis. It contributes to the CEX-DEX dynamics literature by showing that regulatory announcements, not only listing events, are associated with measurable differences across venue-linked assets.

It responds to calls for examining cryptocurrencies from a heterogeneous perspective rather than treating them as a homogeneous market.

5.2 Integrated Implications

Taken together, the three chapters advance a common argument: cryptocurrency markets are internally segmented, and external announcements do not eliminate that segmentation but reveal and amplify it. Each chapter approaches this from a different angle, asset classification, volatility transmission, and venue-level liquidity, and each arrives at evidence that the market's internal structure determines how pressure is absorbed and redistributed.

Three implications emerge across all chapters. The first concerns the practical reach of regulation beyond its formal boundaries. Chapter 2 shows that exemption from a regulatory framework does not guarantee market advantage when exempt assets depend on regulated infrastructure, with DeFi protocols declining despite formal exclusion from MiCA's scope. Chapter 4 reinforces this from the venue side: DeFi protocols that were not the direct target of any of the three regulatory interventions examined nonetheless experienced declining relative trading activity in the sustained post-period across all three events. Together these findings suggest that regulatory frameworks with explicit exemptions for decentralised systems should account for the indirect transmission channels that the data reveals even when they are absent from the regulatory text. The evidence here suggests those boundaries are more permeable than their formal design implies.

The contribution of issuer identifiability as a priced characteristic carries a forward-looking dimension that extends beyond MiCA's announcement. Under MiCA, CASPs operating a trading platform are required to determine whether an identifiable issuer exists for any asset they admit to trading, and where one does, a crypto-asset white paper disclosing the issuer, the technology, and the associated risks must be published. Where no identifiable issuer exists, MiCA places that disclosure burden on the exchange itself. The GENIUS Act moves in

a parallel direction from the American side: foreign payment stablecoin issuers wishing to reach US customers must register with the Office of the Comptroller of the Currency and hold reserves in a US financial institution, making the identity and physical presence of the issuer a condition of market access. Issuer identifiability, which this thesis demonstrates became a priced characteristic at MiCA's announcement in 2020, is therefore not a feature specific to one regulation. It is emerging as a shared regulatory criterion across major jurisdictions. The finding that markets priced this dimension at the proposal stage, before any compliance obligation became binding, suggests that investors recognised early what regulators are now formalising: that knowing who stands behind an asset is the foundation on which all other regulatory accountability rests.

The second concerns the market's shifting sensitivity hierarchy. Chapter 3's finding that MiCA produced larger structural breaks than the Russia-Ukraine War indicates that crypto-specific regulation now dominates traditional geopolitical and macroeconomic shocks in reshaping market interconnections. Chapter 2 reinforces this by showing that markets priced regulatory accountability structures at the announcement stage before any compliance obligation became binding, consistent with evidence that institutional policy signals drive significant market responses and amplify investor attention (Auer and Claessens, 2018; Huang et al., 2022). Taken together, these findings suggest that institutional recognition has become a meaningful dimension of cryptocurrency asset valuation, with direct consequences for how regulators communicate and how investors position around policy events.

The third concerns the multidimensionality of liquidity and the risks of single-measure analysis. Chapter 4 demonstrates that Turnover, Amihud Illiquidity, and Roll's Measure do not move together under regulatory pressure, and that conclusions about market quality change depending on which dimension is examined and over what horizon. This implies that prior studies examining regulatory effects on cryptocurrency market quality through a single

liquidity proxy may have captured one dimension of the response while missing others. The apparent contradictions in that literature may reflect measurement choices rather than genuine disagreement about market behaviour.

These implications are directly relevant to the United Kingdom, which is introducing its own comprehensive regime. Under the Financial Services and Markets Act 2000 (Cryptoassets) Regulations 2026, cryptoasset trading platforms, intermediaries, custodians and stablecoin issuers will require authorisation from the Financial Conduct Authority from October 2027 (FCA, 2026). As under MiCA, the regime is built around identifiable persons: decentralised arrangements fall within scope only where a controlling person can be identified, while genuinely decentralised arrangements remain outside it. The findings of this thesis suggest that this boundary will not be neutral in its market effects. Chapter 2 shows that issuer identifiability is priced at the announcement stage, and Chapter 4 shows that regulatory pressure on centralised infrastructure is associated with improved price impact liquidity for decentralised venues without a sustained shift in trading activity towards them. UK regulators could therefore expect the regime to differentiate across asset classes and trading venues well before it takes effect, and would benefit from monitoring both centralised and decentralised markets from announcement through to implementation, rather than treating decentralised venues as outside the regime's economic reach.

5.3 MiCA Across Three Chapters

One pattern runs through all three empirical chapters. The European Union's Markets in Crypto-Assets regulatory proposal is the primary event in Chapter 2, one of four events in Chapter 3, and one of three events in Chapter 4. It is the same regulatory announcement, examined through three different outcomes: returns, volatility transmission, and liquidity. Each time, it produces a different result. That is not an inconsistency. It is the thesis's central finding.

In Chapter 2, MiCA's announcement produces heterogeneous returns across asset classes. Even within exempt categories, responses diverged: uCrypto gained while DeFi declined despite both being exempt. The market processed MiCA's classification logic, not just its coverage, and priced it at the proposal stage. This is consistent with evidence that markets respond to institutional signals early (Auer and Claessens, 2018; Huang et al., 2022), and extends the MiCA literature, where to our knowledge only Conlon et al. (2024a) have examined MiCA's impact empirically, by providing causal identification across six asset classes simultaneously.

In Chapter 3, the staggered difference-in-differences analysis places MiCA alongside COVID-19, the Russia-Ukraine War, and the Gaza War and tests which produces the largest change in how volatility transmits across cryptocurrencies. MiCA's announcement produces the largest and most persistent effect among all four events, with Wald statistics substantially exceeding those of the other shocks. The Gaza War produces statistically insignificant effects. Prior studies have examined these events separately (Umar et al., 2021; Aharon et al., 2023; Khalfaoui et al., 2023; Będowska-Sójka et al., 2024; Conlon et al., 2024a) but no prior study has placed them in direct comparison within a unified framework. The result that crypto-specific regulation produces a stronger shift in inter-cryptocurrency volatility dynamics than a major armed conflict suggesting that cryptocurrency markets now process regulatory information with greater precision than geopolitical shocks.

In Chapter 4, MiCA is associated with a short to medium-term increase in DEX trading activity relative to CEX around the announcement, but in the sustained post-announcement period DEX-linked trading activity declines relative to CEX. At the same time, price-impact liquidity improves for DEX-linked assets. These two outcomes move in different directions from the same event, confirming that liquidity dimensions do not respond uniformly to regulatory pressure. Regulatory pressure on centralised infrastructure does not discourage

participants from the centralised ecosystem. Markets are not isolated, and exemption is not relief from impact, as DeFi's decline in Chapter 2 and the sustained DEX activity decline in Chapter 4 both confirm.

Taken together, these three results speak to something broader about how this market receives information. MiCA is the first comprehensive regulatory framework to enter this ecosystem, and what is remarkable is not just that the market reacted, but how it reacted. At the announcement stage alone, before any implementation, the market was able to differentiate at multiple levels what this regulation meant and for whom. Chapter 2 shows this at the asset-class level in two ways: different classes responded differently, and more revealingly, they organised their responses around regulatory status, with regulated classes behaving more mildly and unregulated classes showing the most significant reactions. This raises a natural question about the rest of the ecosystem. Chapter 4 addresses it directly, and the results confirm that these markets are not isolated. Participants do not migrate toward exempt venues. The two ecosystems move together, and regulatory decisions directed at one part of the market transmit measurable effects to the other regardless of where the formal boundary is drawn. Chapter 3 confirms the scale of what MiCA's announcement represents: placed alongside three major global events, it emerges as the most significant structural change in volatility transmission observed in the sample. This is all observed at the earliest stage of the regulatory process. As oversight develops further, understanding how the entire ecosystem responds is something all participants and policymakers will need to consider. The market is in a new regime, and this thesis observes it at the beginning of that transition.

5.4 Limitations and Future Research

The thesis has limitations. The analysis focuses on announcement-level responses and does not capture full implementation effects. Data availability remains a persistent and growing

challenge in cryptocurrency research, with exchange-level data particularly scarce and API access increasingly restricted. The sample periods and asset coverage vary across chapters due to these constraints. The classification of tokens as CEX-linked or DEX-linked is based on ecosystem character and requires judgement that may not capture all relevant variation.

The mechanisms documented in this thesis are unlikely to be confined to MiCA. Because market responses operate through regulatory classification and trading infrastructure rather than through features unique to the European Union, comparable frameworks elsewhere that define scope by issuer identifiability and place obligations on centralised intermediaries could be expected to produce a similar differentiation across asset classes and venues. Chapter 4 lends support to this view, as three events differing in jurisdiction and regulatory design were associated with the same sustained direction in relative trading activity. The strength of such responses, however, may not be repeated. MiCA was the first comprehensive framework of its kind, and part of the market reaction may reflect that novelty; frameworks that follow a similar design may be partly anticipated and therefore priced in advance. As crypto markets continue to mature, the response to any future framework will also depend on the market conditions at the time it is introduced.

Future research should examine how governance requirements and compliance costs shape longer-run behavioural responses as regulatory frameworks move from announcement to enforcement. MiCA's implementation phases present opportunities to test whether announcement-level patterns persist, reverse, or evolve as compliance requirements become binding. The extension of venue-level analysis as data availability improves would allow more direct examination of exchange-level trading dynamics. The divergence between trading activity and price-impact liquidity documented in this thesis warrants further investigation to understand the mechanisms through which these dimensions respond differently to regulatory shocks.

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