Essays on the oil price volatility implications on macroeconomics and corporate finance

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Abstract

This thesis examines the impact of crude oil market volatility on both macroeconomic conditions and corporate financial activities. Crude oil price fluctuations act as the central theme, explored across three empirical studies. These studies first consider crude oil volatility as a driver of key economic variables such as trade balances, inflation, and monetary policy, particularly in oil-dependent nations. The thesis also addresses how oil volatility creates financial uncertainty for firms and evaluates the role of Environmental, Social, and Governance (ESG) practices in mitigating these risks. By connecting the macroeconomic effects of oil price volatility with the role of ESG in corporate resilience, the research offers a comprehensive analysis of how oil price uncertainty influences both national economies and firm-level financial outcomes.

The second chapter, the first empirical study, investigates the differing responses of crude oil-exporting and importing countries to oil returns and volatility shocks. It examines how these countries react to price fluctuations, with the assumption that exporters may increase production, appreciating their exchange rates, while importers may reduce oil imports, leading to exchange rate depreciation. The chapter also explores central banks' responses to these shocks, investigating how volatility affects inflation, policy rates, and economic output. To conduct the analysis, we employ two VAR models: one that includes both crude oil returns and crude oil volatility, and another that focuses solely on volatility. The findings suggest that the expected asymmetric reactions between exporters and importers are not highly pronounced, as both sets of countries show similar responses in terms of trade balances and exchange rates. However, the United States is an exception, where the exchange rate tends to appreciate after volatility shocks. Overall, return shocks generally have a larger and quicker impact on the variables, while volatility shocks have a more gradual effect.

The third chapter shifts the focus to corporate finance, investigating whether companies with high Environmental, Social, and Governance (ESG) scores are less vulnerable to the adverse effects of crude oil price volatility. The study examines data from firms listed on the S&P 500 Index, focusing on the interaction between ESG scores and oil volatility. Our main analysis

reveals that ESG activities play a dynamic role, initially showing a negative relationship with returns but acting as a hedge during periods of high oil volatility. A threshold of volatility is identified, below which ESG activities negatively affect returns, while above this point, ESG efforts provide a significant protective effect. This finding suggests that ESG serves as an insurance-like mechanism during heightened market uncertainty. Sectoral and quartile analyses further highlight that firms in oil-sensitive industries tend to benefit more from ESG initiatives during high volatility, with firms in the middle quartiles of ESG performance experiencing the strongest protection. Ultimately, ESG leaders emerge as better shielded from oil price shocks, demonstrating that ESG activities can enhance a firm's resilience in the face of crude oil market uncertainty.

The fourth chapter uses the same set of firms to further examine how ESG factors influence corporate finance indicators, centring the attention on the cost of debt. The analysis investigates whether companies with higher ESG scores benefit from lower borrowing costs during periods of heightened oil price fluctuations. Our findings support a negative relationship between ESG scores and the cost of debt, suggesting that firms with stronger ESG performance experience reduced borrowing costs by signalling lower risk to lenders. Additionally, increased oil price volatility is shown to raise borrowing costs, as volatility constraints imposed on financial intermediaries are passed on to firms. The study also confirms that ESG activities act as a hedging mechanism during volatile periods, with ESG leaders enjoying a significant reduction in debt costs.

The final chapter brings together the insights from these empirical studies, drawing out key themes and wider implications for both academic research and practical applications. It emphasises the critical need to understand crude oil price volatility and its broad effects on financial markets and corporate strategies. These findings are especially relevant to economists, financial analysts, policymakers, and corporate leaders, providing valuable insights that can help shape more effective economic policies and sustainable business strategies.

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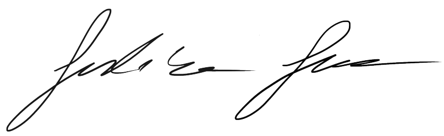
Author's Declaration

I hereby declare that this thesis is an original work conducted by me, Ludovico Luce, under the supervision of Alexandros Kontonikas, Ali Gencay Özbekler, and Athanasios Triantafyllou at the University of Essex, Essex Business School. This research was undertaken as a 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 indicated in the thesis.

Any errors or omissions in this work are my own.



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CHAPTER 1

Introduction

Crude oil price volatility has always been a significant focus in economics and finance research due to its profound implications for global markets. Recent macroeconomic developments underscore its importance, with substantial price fluctuations observed during the pandemic — highlighted by the unprecedented negative price on 20 April 2020 — followed by considerable instability during post-pandemic recovery, and further exacerbation by the war in Ukraine and escalating geopolitical tensions in the Middle East (Chiţu et al. 2024). These fluctuations have profound consequences for global financial markets and economic stability, making this study on oil price volatility both timely and crucial.

This thesis centres on the analysis of crude oil price volatility, which serves as the unifying element that ties together the examination of macroeconomic dynamics and corporate financial strategies. Crude oil volatility underpins two key components of the research. First, it is explored as the source of macroeconomic shocks, affecting key variables on a country level such as trade balances, inflation, and monetary policy. Second, it is analysed as a source of financial market uncertainty, where firms' Environmental, Social, and Governance (ESG) practices are positioned to mitigate its negative impacts. These two components — commodity volatility and its macroeconomic implications, and the role of ESG as a mediator between commodity shocks and financial outcomes — are tightly interconnected, offering a comprehensive framework for understanding how crude oil volatility affects both national economies and corporate financial performance.

Focusing on the first component of this research, crude oil volatility significantly impacts both exporting and importing countries, affecting their economic stability and growth. The assumption is that an increase in oil price volatility generates different economic responses for exporters and importers. While both sets of countries can potentially benefit from the volatility, exporters might capitalise on sharp price increases, whereas importers may gain from price declines when purchasing oil at lower costs. Conversely, oil-importing countries face heightened uncertainty regarding their oil costs, which can influence inflation rates, trade balances, and overall economic performance (Blanchard and Galí 2008). An increase in oil price volatility might prompt these countries to exercise greater caution, potentially reducing their oil imports, relying more on existing reserves, and adjusting their economic strategies accordingly. Meanwhile, exporters may increase production to take advantage of favourable prices, leading to currency appreciation. The volatility in oil prices can thus have cascading effects on investment decisions, exchange rates, and monetary policies, making it a critical factor for economic policymakers in both exporting and importing economies. Understanding and managing this volatility is essential for fostering economic resilience and stability in a globally interconnected market.

The second component of this thesis examines how crude oil price volatility influences corporate financial markets. Fluctuations in oil prices can directly impact firms' performance, returns, and borrowing costs. ESG scores, which measure a company's ability to manage risks stemming from environmental, social, and governance factors, have gained prominence in corporate finance literature in the recent years. However, the relationship between ESG scores and crude oil price volatility remains unexplored. Research indicates that firms with robust environmental practices are better positioned to manage risks associated with volatile oil prices, thereby safeguarding their financial performance and reducing borrowing costs (Eccles et al. 2014; Garcia et al. 2017).

Fluctuations in crude oil prices can lead to notable repercussions in equity returns. Sadorsky (1999) is a pioneering study indicating a relationship between oil volatility shocks and stock returns, followed by contributions from Papapetrou (2001) and more recent evidence (e.g., Bani-Khalaf and Taspinar (2022), Coskun and Taspinar (2022), Cevik et al. (2023), and Mao et al. (2024)). The literature suggests that high volatility in the crude oil market induces considerable economic and financial instability (Hamilton 2009; Kilian and Park 2009). This effect permeates various equity markets globally, as demonstrated by sectoral and national-level analyses (Miller and Ratti 2009).

The relationship between corporate governance and the cost of debt has been widely studied, particularly with the growing importance of ESG factors in financial evaluations. In the recent years, ESG considerations have become more central in how financial institutions assess companies for lending, although the literature remains divided on the nature of the relationship between ESG scores and debt costs. Some studies, such as Dhaliwal et al. (2011), suggest that higher ESG scores lead to increased borrowing costs, while others, like Gao et al. (2016), argue that strong ESG performance lowers these costs.

Given these considerations, the exploration of crude oil price volatility within this thesis is both timely and essential. Beyond its relevance, this research as a whole makes significant contributions to both macroeconomic and corporate finance literature, offering new insights into how crude oil volatility impacts economies and firms. In addition to focusing on the macroeconomic effect of oil price volatility over crude oil exporter and importer countries, this research also contributes to the literature on corporate finance. As said previously, this study addresses previously unexplored areas. Specifically, this thesis sheds light on the relationship between crude oil price volatility and firms' cost of debt, a topic that, to the best of our knowledge, has not yet been explored. Furthermore, it breaks new ground by examining the role of ESG as a buffer against the financial impacts of crude oil price volatility. There is no other research that addresses this specific problem in a direct way.

1.1 Structure

This thesis comprises three empirical chapters, each addressing distinct aspects of crude oil price volatility and its implications for macroeconomic and financial variables. Together, these chapters provide a comprehensive examination of how crude oil market dynamics affect both national economies and corporate financial strategies.

Chapter 2: Asymmetric Reactions of Exporter and Importer Countries to Crude Oil Returns and Volatility Shocks

The second chapter bridges the fields of finance and economics by investigating the divergent reactions of crude oil exporter and importer countries to oil returns and volatility shocks. This study explores the asymmetric effects, hypothesising that high volatility in oil prices forecasts future price increases. For oil-exporting countries, it is posited that they may ramp up production to capitalise on anticipated price hikes, leading to an enhanced crude oil trade and appreciation of the real exchange rate. Conversely, oil-importing countries are expected to hedge against future price increases by reducing oil imports, negatively impacting the trade balance and causing depreciation of the exchange rate.

Additionally, the chapter examines central banks' responses to oil returns and uncertainty shocks. It hypothesises that exporter countries' central banks will raise short-term policy rates to prevent economic overheating, whereas importer countries' central banks will lower rates to mitigate exchange rate depreciation. The study further analyses the impact of these shocks on inflation and output levels in both types of countries.

The results reveal that crude oil return shocks tend to increase trade balances and real exchange rates in both exporter and importer countries, although volatility shocks generally reduce these variables. Notably, the United States stands out with a unique response, where the USD appreciates following volatility shocks. Policy rate responses are varied, with initial rate decreases followed by increases as central banks respond to inflationary pressures.

These findings challenge the conventional view that crude oil exporters and importers exhibit fundamentally different responses to oil price shocks. While theoretical expectations suggest opposing effects, the evidence indicates that both groups adopt similar stabilisation measures, reinforcing the systemic nature of crude oil volatility. This study extends prior research on the macroeconomic effects of oil price shocks (Baumeister and Peersman 2013; Hamilton 2009) by providing empirical evidence that crude oil price fluctuations influence exporters and importers in more comparable ways than previously assumed.

Additionally, this chapter highlights the role of monetary policy in shaping these responses, demonstrating that central banks react differently to return-driven and uncertainty-driven fluctuations. By building on literature examining the transmission of oil shocks into exchange rates and policy adjustments (Hamilton 2009; Kilian and Park 2009), this study provides a more comprehensive understanding of how macroeconomic policies evolve in response to crude oil market instability. The findings contribute to both economic theory and policy design, suggesting that stabilisation policies should account for the broader, systemic risks posed by crude oil price volatility rather than treating them as isolated shocks to specific economies.

Chapter 3: ESG Activities and Firm Returns during High Crude Oil Price Volatility

The third chapter delves into corporate finance, specifically examining whether firms with high Environmental, Social, and Governance (ESG) scores exhibit greater resilience to the adverse effects of crude oil price volatility on firm returns. The study utilises a sample of firms listed on the S&P 500 Index, collecting data on firm returns and ESG scores from February 2003 to December 2022. The analysis employs a proxy for market volatility based on an empirically derived measure of crude oil price fluctuations.

This research focuses on the interaction effect between ESG scores and oil volatility to determine if ESG activities provide a hedging effect against oil price volatility. The analysis dissects the marginal effects of ESG scores and crude oil volatility on firm returns by breaking down the regression equations into partial derivatives. This approach clarifies the individual and joint impacts of ESG and oil volatility on firm performance. To enhance interpretability, the study also employs graphical representations of the marginal effects.

The analysis shows that while firms with higher ESG scores may experience slightly lower direct returns, these scores act as a significant hedge when oil volatility surpasses a certain threshold. In high-volatility conditions, ESG practices provide a protective effect, mitigating the negative impact of oil price fluctuations on firm returns. This hedging effect becomes stronger as volatility rises, underscoring the strategic value of ESG activities in enhancing firm resilience during periods of market instability.

This study contributes to the growing body of research on ESG and financial performance (Broadstock et al. 2021; Friede et al. 2015) by demonstrating that ESG's role in firm stability is conditional on market conditions rather than universally beneficial. Unlike prior studies that focus on ESG's long-term effects, this research highlights its function as a volatility-dependent hedge, particularly in commodity-sensitive sectors. By identifying a threshold at which ESG engagement transitions from a potential drag on returns to a risk-mitigation tool, this study advances the understanding of ESG as a dynamic strategy for managing financial uncertainty in energy-driven markets.

Chapter 4: ESG Scores as a Hedge against Cost of Debt under Crude Oil Market Volatility

The fourth chapter continues the exploration of ESG factors, focusing on their role in mitigating the cost of debt during periods of crude oil market volatility. Using firms listed on the S&P 500 Index as a representative sample, this chapter examines data from the first quarter of 2000 to the fourth quarter of 2023. It incorporates firm-level information on the cost of debt and ESG scores, with crude oil price volatility serving as a uniform time series indicator of external volatility.

This chapter investigates whether high ESG scores serve as an effective hedge against the increased cost of debt associated with high crude oil price volatility. By analysing the interaction between firm-level ESG scores and external market volatility, the research aims to determine the extent to which sustainable practices can shield firms from financial distress related to fluctuating oil prices.

The results demonstrate that firms with high ESG scores experience lower borrowing costs during periods of high crude oil price volatility. This is especially evident once firms surpass a critical ESG score threshold, where the cost of debt begins to decrease as crude oil volatility rises. The findings highlight that strong ESG practices not only signal reduced risk to lenders but also provide a measurable financial buffer during times of commodity market instability, helping firms maintain more favourable financing conditions.

A key contribution of this analysis is the identification of ESG's role as a conditional hedge in corporate borrowing during crude oil market volatility. While ESG performance is associated with lower borrowing costs (El Ghoul et al. 2011; Giese et al. 2019), this study demonstrates that its effectiveness is amplified under high volatility.

The findings reveal that firms with strong ESG commitments not only secure lower borrowing costs in stable conditions but also experience enhanced financial protection beyond a critical ESG threshold. By establishing this non-linear relationship, the study provides new insights into how sustainability-driven financial strategies can enhance firms' resilience to external shocks, contributing to the broader discourse on ESG as a risk-mitigation tool.

Chapter 5: Conclusion

The final chapter of this thesis synthesises the insights from the preceding empirical analyses, highlighting the key themes, broader implications, and limitations of the research. It summarises the main findings, discusses their significance for the literature and practice, and outlines potential avenues for future research. By integrating macroeconomic and corporate finance perspectives, this thesis contributes to the understanding of crude oil price volatility as a significant driver shaping both macroeconomic conditions and firm-level financial decisions. This conclusion underscores the importance of understanding crude oil price volatility and its effects on both national economies and corporate financial strategies, contributing to the ongoing discourse on resilience and sustainability in global markets.

CHAPTER 2

Empirical Chapter 1

Analysis of the potential asymmetric reaction of crude oil exporter and importer countries to shocks in crude oil return and uncertainty

2.1 Introduction

Crude oil is crucial to the worldwide economy, playing a key role in impacting the manufacturing of products and services and acting as the main energy source globally. Hamilton (1983) foundational research extensively examines its effects on macroeconomic indicators like exchange rates, trade balances, inflation, and GDP. Amano and Van Norden (1998a,b) emphasise that crude oil prices impact exchange rates primarily through terms of trade, as indicated in the literature. These researches indicate that changes in oil prices usually have positive effects on exporting nations, as they boost their trade balances and strengthen their currencies, whereas importers tend to face negative consequences. Additional research, like the studies conducted by Chen and Rogoff (2003) and Cashin et al. (2004), examines the correlation between commodity prices and exchange rates, showing that, despite temporary fluctuations, this connection typically moves towards a stable state in the long term. In addition, research conducted by Coudert et al. (2015) and Singh et al. (2018) indicates that fluctuations in crude oil prices can exacerbate and occasionally even change the relationship between oil prices and exchange rates, especially in times of market turbulence, highlighting the intricate connection between these factors in a interconnected global market.

The purpose of this study is to investigate the asymmetric reaction of exporter and importer countries to shocks in crude oil returns of crude oil price uncertainty. The general assumption is that periods of high volatility in oil prices lead to higher prices in the future. From this assumption, we explore the asymmetrical reactions that exporter and importer countries might have to crude oil returns and uncertainty shock. From the point of view of an exporter, a country might want to take advantage of the future oil price increase by boosting production, which leads, in turn, to an increase in the country's crude oil trade. For an exporter country, this dynamic is assumed to induce an appreciation of the real exchange rate. A crude oil importer instead might want to hedge the risk of an increase in the oil price by reducing the imports of oil which reduces the trade balance leading to a depreciation of the exchange rate. We also want to investigate the reaction of central banks to oil returns and uncertainty shocks and the consequent changes in the exchange rate. The assumptions are that for an exporter country, a central bank will increase the short-term policy rate to avoid the economy overheating while in the case of an importer country, the central bank will decrease the short-term interest rates to compensate for the exchange rate depreciation. In this analysis, we also consider the effect of those two shocks on the countries' inflation and the level of output.

Our contributions primarily concern the asymmetric reaction of oil-exporter and oil-importer countries to crude oil returns and uncertainty shocks. Our analysis reveals a consistent pattern in the responses of trade balances and real exchange rates across the countries examined, suggesting that both exporters and importers exhibit similar adjustments following crude oil return and volatility shocks. This finding challenges the expectation that these two groups of countries would experience fundamentally different exchange rate dynamics in response to oil market fluctuations.

An important implication of this result is that the observed exchange rate depreciation following volatility shocks suggests that both exporters and importers implement precautionary measures to shield their economies from heightened crude oil market uncertainty. This indicates a shared economic strategy, where both groups of countries adopt similar protective mechanisms to mitigate the risks associated with increased volatility.

Additionally, this study contributes to the literature through a comparative analysis of the impact of return and volatility shocks. Our findings suggest that return shocks induce a more immediate and pronounced effect on all variables under consideration, whereas volatility shocks lead to more gradual and subdued adjustments. This distinction provides valuable insights into the transmission mechanisms of crude oil market disturbances, highlighting the differences in speed and intensity between these two types of shocks.

The remainder of this study is presented as follows: the next section describes the review of the literature in which seminal papers and the most important contribution are analysed and discussed. Chapter 3 presents the methodology used in this research. This section is followed by a description of the dataset collected in this analysis. The section that follows includes the presentation of the findings of the research. In the last section, the conclusions of the study are examined and discussed, alongside proposals for future research. Appendix A details the stationarity tests conducted on the variables, with particular focus on the stationarity of inflation, while Appendix B offers robustness tests and additional results to support the analysis.

2.2 Review of the Literature

This research aims to analyse the asymmetric effects of uncertainty in the crude oil market on crude oil exporters and importers, with a particular focus on the reactions of real exchange rates and subsequent central bank responses following a crude oil uncertainty shock. This study seeks to address a gap in the literature, as no existing research has specifically examined this issue for crude oil or commodities in general.

Commodity prices and commodity currencies

The literature extensively examines commodity prices as drivers of commodity currencies. It is generally assumed that the exchange rates of countries heavily engaged in exporting or importing a particular commodity are closely linked to the behaviour of that commodity's prices, particularly in terms of trade and exchange rates.

Numerous studies investigate the fundamental factors influencing the real exchange rates of countries where commodities constitute a significant portion of exports. Most agree that commodity prices are the primary drivers of exchange rates for these commodity currencies. For instance, the study by Chen and Rogoff (2003) analyses the exchange rate movements of Canada, Australia, and New Zealand in response to commodity price changes. Their findings indicate a strong connection between commodity prices and local currencies for New Zealand and Australia, while for Canada, this relationship is more evident in the long run, likely due to the Canadian dollar's strong linkage to the US dollar. This work is further supported and extended by Cashin et al. (2004), who incorporate structural breaks (Gregory and Hansen 1996a,b) to explain the relationship between real exchange rates and commodity prices.

Oil prices and oil exporter countries

The literature on oil prices highlights the presence of causality between oil prices and exchange rates in oil-exporting countries. Several studies, including those by Bénassy-Quéré et al. (2007), Bouoiyour et al. (2015), and Ferraro et al. (2015), emphasise the impact of oil prices on exchange rates, illustrating the oil-to-exchange rate direction. Conversely, studies by Sadorsky (2008), Chen and Rogoff (2003), and Beckmann and Czudaj (2013) address the reverse causality, exploring if and how exchange rates can influence oil prices. These studies generally agree that oil prices, traded in US dollars, are affected by exchange rates, as noted in the Canadian case by Chen and Rogoff (2003).

An intriguing study by Clements and Fry (2008) questions whether a country's significant commodity production can influence the commodity's price via the exchange rate, introducing the concept of "currency commodity". Building on this perspective, studies by Fratzscher et al. (2014), Kisswani (2015), and Gómez-González et al. (2017)

identify a bidirectional link between oil prices and exchange rates. However, a smaller body of literature, including works by Habib and Kalamova (2007), Bjørnland and H. Hungnes (2008), and Mohammadi and Jahan-Parvar (2012), suggests no causality between oil prices and exchange rates, often focusing on specific countries like Mexico, Norway, Saudi Arabia, and Bolivia.

Terms of trade and real exchange rates

Another relevant strand of literature explores the relationship between terms of trade and real exchange rates. According to Coudert et al. (2015), in the long run, an increase in terms of trade can lead to currency appreciation by enhancing national wealth and income. The focus on this relationship gains prominence after the onset of the phenomenon known as "Dutch disease", named by The Economist in 1977. This term describes the economic paradox experienced by the Netherlands in the 1960s, where the discovery of a major natural gas deposit led to a significant appreciation of the real exchange rate, adversely affecting other export sectors and causing economic difficulties[1].

Fewer papers explore the volatility spillover between types of markets. As suggested by Bagheri and Ebrahimi (2020), this might be due to the complex nature of the financial markets and the curse of dimensionality that arises when analysing different markets. The paper of Antonakakis and Kizys (2015) shows the linkage between returns and volatility between the commodity market and the currency market. They consider commodities (gold, silver, platinum, palladium, crude oil) and currencies (EUR/USD, JPY/USD, GBP/USD, and CHF/USD) exploring the spillover effect that one market has on the other. Their work shows that gold primarily, followed by silver and platinum are the commodities that affect the rest of the other assets considered in the paper. Among the currencies instead, CHF/USD has proven to be the leading currency to transmit the volatility to the other assets.

Nevertheless, the literature contains a very limited number of papers that examine the effect of uncertainty in the commodity market on commodity currencies. Few

[1]The "Dutch Disease" is a term that refers to paradoxes that might happen when good news brings unexpected and negative consequences to the economy of a country (i.e. 1970s in the UK (Corden 1984), 2014 in Canada (Papyrakis and Raveh 2014).

studies address the impact of commodity market volatility on the behaviour of commodity currencies and the determination of real exchange rates. Analysing the long-run equilibrium of the exchange rates, Coudert et al. (2015) state that the real exchange rates of commodity currencies are not only related to commodity prices but that this relationship proves to be more pronounced in times of high volatility in commodity and financial markets. Times of high volatility affect the exchange rate also in the short run. Volatility spillovers are much more pronounced in the commodity market as well as in the equity market and, since commodities are often used as safe havens, rising uncertainty in the equity market affects consequently the behaviour of the commodity prices. The resulting effect is that the exchange rate of a commodity shows a non-linear response to shocks as stated in the paper. The work of Yin et al. (2022) on the other side considers the volatility risk premium of oil as proxy to forecast the returns of commodity currency. The volatility risk premium (VRP) is evaluated as the difference between the implied volatility and the realised volatility of oil and its predictive power is tested in different economic conditions including the peculiar COVID-19 pandemic. The authors prove that four of the five commodity currencies (Australian dollar, Canadian dollar, Norwegian krone and South African rand) can be successfully predicted using the VRP as a proxy for one-month ahead forecasting.

This work is in line with the strand of the literature that focuses on the effect that oil price uncertainty generates on the economy following the work of Kilian (2009), Kilian and Murphy (2012), Baumeister and Peersman (2013), and Jo (2014). The paper of Baumeister and Peersman (2013) analyses how the crude oil price volatility affects the global crude oil production proving that even when the oil price fluctuates significantly, the volatility of the oil production does not increase. They analyse the historical evolution of the two volatilities, the volatility of the oil price and volatility of the oil production, finding out that the increase in the oil price volatility from the middle of the 1980s is accompanied by a significant decrease in the volatility of the oil production. Another paper that is close to our research is the work of Jo (2014). Her work is inspired by Baumeister and Peersman but it differs from the latter since the author investigates the effect of oil uncertainty on the global economic activity. The methodology of the paper is similar to the previous one since in both of the papers the authors deploy a Structural VAR with time-varying parameters where the volatility is modelled with a stochastic model. This methodological approach allows to investigate the effect that uncertainty shocks have on the other variable of the model and modelling the volatility with a stochastic model is proven to be suitable since it allows to the first and the second moment to evolve independently.

However, despite these important contributions, previous studies have not fully addressed the asymmetric macroeconomic effects of oil price uncertainty on oil-exporting and oil-importing economies. This research fills this gap by explicitly distinguishing between these two types of economies, examining how real exchange rates and central bank responses vary following crude oil return and uncertainty shocks. While prior studies have analysed oil volatility's impact on macroeconomic indicators, this study provides a deeper understanding of how exchange rate adjustments and monetary policy decisions respond to oil price shocks, highlighting key asymmetries between economies with varying degrees of oil reliance.

Furthermore, recent studies have reinforced the importance of understanding oil price uncertainty in macroeconomic settings. For example, Kilian et al. (2024) investigate the role of geopolitical oil price risk and economic fluctuations, while Blomkvist et al. (2023) explore the effects of oil price uncertainty on investment and IPO activity in oil-dependent industries. Additionally, Li et al. (2023) confirm that demand-driven oil price shocks exert stronger financial market effects than supply shocks, particularly in periods of economic downturn. This study contributes to this growing body of literature by demonstrating that the response asymmetry between exporters and importers is more pronounced in terms of exchange rate dynamics and central bank policy adjustments than previously documented.

2.3 Methodology

Researchers often seek to identify the impact of exogenous shocks on variables of interest. This is frequently achieved through identifying restrictions in a VAR model (Sims 1980). Finding and imposing appropriate restrictions can be difficult. In our case, we are able to treat the returns and volatility of the crude oil price as exogenous to the country variables we analyse. In this analysis, we employ two vector autoregressive models, both including exogenous variable(s) as sources of shocks. In the first one, the system is perturbed by shocks of oil returns and crude oil volatility, which are the exogenous variables. In the second model instead, crude oil price volatility is considered as the only exogenous variable.

The set of endogenous variables used for each country includes crude oil trade balance tb, real exchange rate er, short-term policy rate pr, Consumer Price Index as a proxy for inflation in, and Industrial Production Index as a proxy for the output ou. This set of variables is specific to each country and they are included in both models as endogenous variables.

The approach used in this research takes inspiration from Kilian (2008), where the oil supply shocks are treated as "strictly exogenous" so that current or lagged values of the endogenous variables do not have any effect on the exogenous once. Regarding the ordering of the two exogenous variables, we drew inspiration from Carrière-Swallow and Céspedes (2013). The underpinning idea is allowing the first exogenous variable, oil returns, to have an effect on the crude oil uncertainty while preserving the exogeneity of this dynamic from the rest of the endogenous variables. The ordering of the two exogenous variables is proven not to affect the outcome of the model significantly, but we keep the returns first, assuming that a shock in the returns generates a reaction in the volatility of the oil price (Van Robays 2016).

We also generate a series of oil returns so that the values at time $t + 1$ of the original series occur at time t in the new series ($R_{(t+1)}$). We do the same for the crude oil volatility ($U_{(t+1)}$). This analysis departs from others in the literature since the exogeneity of oil returns and oil uncertainty is ensured by setting restrictions on the coefficients matrix. To incorporate the two variables in the VAR as endogenous we then restrict the coefficient as follows.

Restrictions of the coefficients

The model which includes both of the exogenous variables can be written as:

$$\begin{bmatrix} R_{(t+1)} \\ U_{(t+1)} \\ tb_t \\ er_t \\ pr_t \\ in_t \\ ou_t \end{bmatrix} = B_0 + B_1 \begin{bmatrix} R_{(t+1)-1} \\ U_{(t+1)-1} \\ tb_{t-1} \\ er_{t-1} \\ pr_{t-1} \\ in_{t-1} \\ ou_{t-1} \end{bmatrix} + B_2 \begin{bmatrix} R_{(t+1)-2} \\ U_{(t+1)-2} \\ tb_{t-2} \\ er_{t-2} \\ pr_{t-2} \\ in_{t-2} \\ ou_{t-2} \end{bmatrix} + \ldots + B_p \begin{bmatrix} R_{(t+1)-p} \\ U_{(t+1)-p} \\ tb_{t-p} \\ er_{t-p} \\ pr_{t-p} \\ in_{t-p} \\ ou_{t-p} \end{bmatrix} + \begin{bmatrix} \varepsilon_{R_{t+1,t}} \\ \varepsilon_{U_{t+1,t}} \\ \varepsilon_{tb,t} \\ \varepsilon_{er,t} \\ \varepsilon_{pr,t} \\ \varepsilon_{in,t} \\ \varepsilon_{ou,t} \end{bmatrix}. \tag{2.1}$$

In the model above, on the left side there is a 7×1 vector of the dependent variables that contains monthly data for the two exogenous variables, the sources of shocks, and the endogenous variables for each country. On the right-hand side, B_0 is the 7×1 vector that contains the intercepts, $B_1 \ldots B_p$ are the 7×7 matrices of the lagged coefficients, which are related to the 7×1 vectors of the lagged values of the dependent variable, and the ε_t is the 7×1 vector of the error terms. We set restrictions on the coefficients matrix so that, given an unrestricted lag n with $n = 2, \ldots, N$:

$$B_n = \begin{bmatrix} B_{R_{(t+1)-n},R_{(t+1)}} & B_{U_{(t+1)-n},R_{(t+1)}} & B_{tb_{t-n},R_{(t+1)}} & B_{er_{t-n},R_{(t+1)}} & B_{pr_{t-n},R_{(t+1)}} & B_{in_{t-n},R_{(t+1)}} & B_{ou_{t-n},R_{(t+1)}} \\ B_{R_{(t+1)-n},U_{(t+1)}} & B_{U_{(t+1)-n},U_{(t+1)}} & B_{tb_{t-n},U_{(t+1)}} & B_{er_{t-n},U_{(t+1)}} & B_{pr_{t-n},U_{(t+1)}} & B_{in_{t-n},U_{(t+1)}} & B_{ou_{t-n},U_{(t+1)}} \\ B_{R_{t+1-n},tb_t} & B_{U_{t+1-n},tb_t} & B_{tb_{t-n},tb_t} & B_{er_{t-n},tb_t} & B_{pr_{t-n},tb_t} & B_{in_{t-n},tb_t} & B_{ou_{t-n},tb_t} \\ B_{R_{t+1-n},er_t} & B_{U_{t+1-n},er_t} & B_{tb_{t-n},er_t} & B_{er_{t-n},er_t} & B_{pr_{t-n},er_t} & B_{in_{t-n},er_t} & B_{ou_{t-n},er_t} \\ B_{R_{t+1-n},pr_t} & B_{U_{t+1-n},pr_t} & B_{tb_{t-n},pr_t} & B_{er_{t-n},pr_t} & B_{pr_{t-n},pr_t} & B_{in_{t-n},pr_t} & B_{ou_{t-n},pr_t} \\ B_{R_{t+1-n},in_t} & B_{U_{t+1-n},in_t} & B_{tb_{t-n},in_t} & B_{er_{t-n},in_t} & B_{pr_{t-n},in_t} & B_{in_{t-n},in_t} & B_{ou_{t-n},in_t} \\ B_{R_{t+1-n},ou_t} & B_{U_{t+1-n},ou_t} & B_{tb_{t-n},ou_t} & B_{er_{t-n},ou_t} & B_{pr_{t-n},ou_t} & B_{in_{t-n},ou_t} & B_{ou_{t-n},ou_t} \end{bmatrix}, \tag{2.2}$$

we impose restrictions on the coefficients such that the lagged values of oil returns ($R_{(t+1)-n}$) and oil uncertainty ($U_{(t+1)-n}$) do not affect their own current value, the current value of the other exogenous variable, or any other variables in the model. So the restricted matrix of the coefficient for a given lag n is:

$$B_n = \begin{bmatrix} 0 & 0 & B_{tb_{t-n},R_{(t+1)}} & B_{er_{t-n},R_{(t+1)}} & B_{pr_{t-n},R_{(t+1)}} & B_{in_{t-n},R_{(t+1)}} & B_{ou_{t-n},R_{(t+1)}} \\ 0 & 0 & B_{tb_{t-n},U_{(t+1)}} & B_{er_{t-n},U_{(t+1)}} & B_{pr_{t-n},U_{(t+1)}} & B_{in_{t-n},U_{(t+1)}} & B_{ou_{t-n},U_{(t+1)}} \\ 0 & 0 & B_{tb_{t-n},tb_t} & B_{er_{t-n},tb_t} & B_{pr_{t-n},tb_t} & B_{in_{t-n},tb_t} & B_{ou_{t-n},tb_t} \\ 0 & 0 & B_{tb_{t-n},er_t} & B_{er_{t-n},er_t} & B_{pr_{t-n},er_t} & B_{in_{t-n},er_t} & B_{ou_{t-n},er_t} \\ 0 & 0 & B_{tb_{t-n},pr_t} & B_{er_{t-n},pr_t} & B_{pr_{t-n},pr_t} & B_{in_{t-n},pr_t} & B_{ou_{t-n},pr_t} \\ 0 & 0 & B_{tb_{t-n},in_t} & B_{er_{t-n},in_t} & B_{pr_{t-n},in_t} & B_{in_{t-n},in_t} & B_{ou_{t-n},in_t} \\ 0 & 0 & B_{tb_{t-n},ou_t} & B_{er_{t-n},ou_t} & B_{pr_{t-n},ou_t} & B_{in_{t-n},ou_t} & B_{ou_{t-n},ou_t} \end{bmatrix}. \tag{2.3}$$

We set all the lags as per the above with the exception of the first lag. In the first lag, we allow the lagged value of the crude oil returns $R_{(t+1)-1}$ and uncertainty $U_{(t+1)-1}$ to affect their current value $R_{(t+1)}$ and $U_{(t+1)}$ respectively, but we include these effects only if the coefficients are significant. If they are not significant, we set the coefficients to zero. As such, since we find significance only in the first lag of oil returns $R_{(t+1)-1}$ and oil uncertainty $U_{(t+1)-1}$ affecting the current value of oil uncertainty $U_{(t+1)}$, we restrict the first lag of the exogenous variables to zero in their effect on the current value of oil returns $R_{(t+1)}$, as it is not significant, while we allow their lagged values to affect the current value of uncertainty $U_{(t+1)}$.

Therefore, the coefficients matrix for the first lag can be shown as follows:

$$B_1 = \begin{bmatrix} 0 & 0 & B_{tb_{t-1},R_{(t+1)}} & B_{er_{t-1},R_{(t+1)}} & B_{pr_{t-1},R_{(t+1)}} & B_{in_{t-1},R_{(t+1)}} & B_{ou_{t-1},R_{(t+1)}} \\ B_{R_{(t+1)-1},U_{(t+1)}} & B_{U_{(t+1)-1},U_{(t+1)}} & B_{tb_{t-1},U_{(t+1)}} & B_{er_{t-1},U_{(t+1)}} & B_{pr_{t-1},U_{(t+1)}} & B_{in_{t-1},U_{(t+1)}} & B_{ou_{t-1},U_{(t+1)}} \\ 0 & 0 & B_{tb_{t-1},tb_t} & B_{er_{t-1},tb_t} & B_{pr_{t-1},tb_t} & B_{in_{t-1},tb_t} & B_{ou_{t-1},tb_t} \\ 0 & 0 & B_{tb_{t-1},er_t} & B_{er_{t-1},er_t} & B_{pr_{t-1},er_t} & B_{in_{t-1},er_t} & B_{ou_{t-1},er_t} \\ 0 & 0 & B_{tb_{t-1},pr_t} & B_{er_{t-1},pr_t} & B_{pr_{t-1},pr_t} & B_{in_{t-1},pr_t} & B_{ou_{t-1},pr_t} \\ 0 & 0 & B_{tb_{t-1},in_t} & B_{er_{t-1},in_t} & B_{pr_{t-1},in_t} & B_{in_{t-1},in_t} & B_{ou_{t-1},in_t} \\ 0 & 0 & B_{tb_{t-1},ou_t} & B_{er_{t-1},ou_t} & B_{pr_{t-1},ou_t} & B_{in_{t-1},ou_t} & B_{ou_{t-1},ou_t} \end{bmatrix}. \tag{2.4}$$

The model in which only the crude oil volatility is treated as exogenous variable can be shown as:

$$
\begin{aligned}
\begin{bmatrix} U_{(t+1)} \\ tb_t \\ er_t \\ pr_t \\ in_t \\ ou_t \end{bmatrix} &= B_0 + B_1 \begin{bmatrix} U_{(t+1)-1} \\ tb_{t-1} \\ er_{t-1} \\ pr_{t-1} \\ in_{t-1} \\ ou_{t-1} \end{bmatrix} + B_2 \begin{bmatrix} U_{(t+1)-2} \\ tb_{t-2} \\ er_{t-2} \\ pr_{t-2} \\ in_{t-2} \\ ou_{t-2} \end{bmatrix} + \dots \\
&+ B_p \begin{bmatrix} U_{(t+1)-p} \\ tb_{t-p} \\ er_{t-p} \\ pr_{t-p} \\ in_{t-p} \\ ou_{t-p} \end{bmatrix} + \begin{bmatrix} \varepsilon_{U_{(t+1),t}} \\ \varepsilon_{tb,t} \\ \varepsilon_{er,t} \\ \varepsilon_{pr,t} \\ \varepsilon_{in,t} \\ \varepsilon_{ou,t} \end{bmatrix},
\end{aligned} \tag{2.5}
$$

and the restriction in the 6×6 coefficient matrix for a lag n can be expressed as:

$$
B_n = \begin{bmatrix}
0 & B_{tb_{t-n},U_{(t+1)}} & B_{er_{t-n},U_{(t+1)}} & B_{pr_{t-n},U_{(t+1)}} & B_{in_{t-n},U_{(t+1)}} & B_{ou_{t-n},U_{(t+1)}} \\
0 & B_{tb_{t-n},tb_t} & B_{er_{t-n},tb_t} & B_{pr_{t-n},tb_t} & B_{in_{t-n},tb_t} & B_{ou_{t-n},tb_t} \\
0 & B_{tb_{t-n},er_t} & B_{er_{t-n},er_t} & B_{pr_{t-n},er_t} & B_{in_{t-n},er_t} & B_{ou_{t-n},er_t} \\
0 & B_{tb_{t-n},pr_t} & B_{er_{t-n},pr_t} & B_{pr_{t-n},pr_t} & B_{in_{t-n},pr_t} & B_{ou_{t-n},pr_t} \\
0 & B_{tb_{t-n},in_t} & B_{er_{t-n},in_t} & B_{pr_{t-n},in_t} & B_{in_{t-n},in_t} & B_{ou_{t-n},in_t} \\
0 & B_{tb_{t-n},ou_t} & B_{er_{t-n},ou_t} & B_{pr_{t-n},ou_t} & B_{in_{t-n},ou_t} & B_{ou_{t-n},ou_t}
\end{bmatrix}. \tag{2.6}
$$

In this case, the first column ensures that the crude oil volatility is treated as exogenous variable in the model. On the first lag B_1, we allow for the first lag of the oil volatility $U_{(t+1)-1}$ to have an effect on the current value $U_{(t+1)}$ since we find that it is statistically significant. The first lag of the coefficient matrix can therefore be shown as:

$$
B_1 = \begin{bmatrix}
B_{U_{(t+1)-1},U_{(t+1)}} & B_{tb_{(t+1)},U_{(t+1)}} & B_{er_{t-1},U_{(t+1)}} & B_{pr_{t-1},U_{(t+1)}} & B_{in_{t-1},U_{(t+1)}} & B_{ou_{t-1},U_{(t+1)}} \\
0 & B_{tb_{t-1},tb_t} & B_{er_{t-1},tb_t} & B_{pr_{t-1},tb_t} & B_{in_{t-1},tb_t} & B_{ou_{t-1},tb_t} \\
0 & B_{tb_{t-1},er_t} & B_{er_{t-1},er_t} & B_{pr_{t-1},er_t} & B_{in_{t-1},er_t} & B_{ou_{t-1},er_t} \\
0 & B_{tb_{t-1},pr_t} & B_{er_{t-1},pr_t} & B_{pr_{t-1},pr_t} & B_{in_{t-1},pr_t} & B_{ou_{t-1},pr_t} \\
0 & B_{tb_{t-1},in_t} & B_{er_{t-1},in_t} & B_{pr_{t-1},in_t} & B_{in_{t-1},in_t} & B_{ou_{t-1},in_t} \\
0 & B_{tb_{t-1},ou_t} & B_{er_{t-1},ou_t} & B_{pr_{t-1},ou_t} & B_{in_{t-1},ou_t} & B_{ou_{t-1},ou_t}
\end{bmatrix}. \tag{2.7}
$$

Identifying assumptions

Exogenous shocks. The main assumption underpinning the order of the exogenous variables in the model with oil returns and crude oil volatility should be sought in the causes of the roots that generate changes in crude oil volatility. Even if the debate about which are the roots that lead the volatility to change is still an active discussion among authors, literature agrees in stating that volatility changes over time. Van Robays (2016) suggests two main reasons for the changes in volatility. On one side, it is observed in real life and highlighted in the literature that large oil supply and demand changes have the effect of rising oil price volatility[2]. On the other side, when studying crude oil volatility, the elasticity of oil price to shocks in the demand and supply is proven to be critical. One of the major findings of Baumeister and Peersman (2013) is indeed to prove that systematic high volatility starting from the mid-1980s is due to a sensible reduction of the oil price elasticity to oil supply and demand. In light of the above, we order them such that the oil returns have an impact on the crude oil volatility. It should be noted that we observe that the order of the exogenous variables does not have a sensible impact on the outcome. As stated above, we allow the two exogenous variables to have an impact on the first lag of themselves assuming that a shock in the oil returns triggers a shock in the volatility.

Endogenous Shocks. The transmission mechanism of the exogenous shocks to the endogenous variables can be explained as follows. The literature does not offer an analysis on the effect that both oil returns and oil volatility generate on the crude oil trade balance since the crude oil trade balance is newly created in this analysis as the difference between the level of crude oil export and import of a country. On the other side, after the collapse of the Bretton Wood agreement in 1971, oil shocks are proven to have significant influences on the terms of trade of the major industrialised countries starting from the early 1970s. This is proven by the work of Dohner (1981) and Backus and Crucini (2000) which clearly state that oil price and its volatility are able to explain most of the fluctuation of the terms of trade. Rafiq et al. (2009), in their survey, prove that the oil price-macroeconomy nexus has effects not only on the terms of trade, but it has relevant implications also for countries' inflation, interest rate, and exchange rate.

[2]See Hamilton (2009) and Kilian (2010) for the case of high volatility in the 1970s.

Impulse responses

In this section, we define the Impulse Response Functions (IRF) which are used to present the results of the VAR models. Considering the reduced-form VAR model:

$$y_t = B_1 y_{t-1} + \ldots + B_p y_{t-p} + u_t, \tag{2.8}$$

where y_t is the vector of dependent variables and p represents the number of lags. We set $p = 12$ for the main VAR model while we also examine models with $p = 6$ and $p = IC$, representing VAR(6) and the VAR specification suggested by the information criterion (IC). The results for these models are presented in Appendix B. The appendix also includes detailed explanations of the robustness checks, the methodology for determining the optimal lag length for the IC-based specification, and the corresponding impulse response functions.

We then define the impulse response matrix as follows:

$$\phi_j = \frac{\partial y_{t+j}}{\partial u_t}, \tag{2.9}$$

where $j = 1, \ldots, 12$ represents the period (in months) through which the IRF are displayed and u_t the source of shock. In our case, we analyse the effect of a one-standard-deviation shock over the following 12 months in each IRF for each VAR specification.

Then, differentiating Equation (2.8) using the impulse response matrix, we obtain:

$$\frac{\partial y_{t+j}}{\partial u_t} = B_1 \frac{\partial y_{t+j-1}}{\partial u_t} + \ldots + B_p \frac{\partial y_{t+j-p}}{\partial u_t}, \tag{2.10}$$

so that ϕ_j satisfies the recursive relationship:

$$\phi_j = \sum_{i=1}^{p} B_i \phi_{j-i}. \tag{2.11}$$

This recursive structure, as it stands, leads to non-orthogonalised impulse responses. According to the literature, such as the foundational work by Sims (1980), the order of the variables is critical in understanding how the dynamics of shock propagation unfold across the variables in a VAR model. One method to achieve this is by factorising the covariance matrix of the errors in the VAR model using the Cholesky (2005) decomposition. This method involves decomposing a positive definite matrix into the product of a lower triangular matrix and its transpose. Defining $\sum$ as the covariance matrix of the VAR, the definition of the Cholesky factorisation allows to rewrite the covariance matrix $\sum$ as $\sum = LL'$ where L is the lower triangular matrix that, multiplied by its transpose L', gives the covariance matrix. The orthogonalised impulse response function can now be defined as:

$$\Theta_j = \phi_j L. \tag{2.12}$$

The recursive structure in our analysis does not require a reordering of the variables. Indeed, recalling Equation (2.8):

$$y_t = B_1 y_{t-1} + \ldots + B_p y_{t-p} + u_t, \tag{2.8}$$

$y_t = \left[R_{t+1}\ U_{t+1}\ pr_t\ in_t\ er_t\ ou_t\ tb_t\right]'$ is the ordering for the VAR with two exogenous variables and $y_t = \left[U_{t+1}\ pr_t\ in_t\ er_t\ ou_t\ tb_t\right]'$ is the ones for the VAR with one exogenous.

The application of the Cholesky decomposition in identifying orthogonalised IRFs is crucial in econometric analyses, as noted by Hamilton (1994) and further detailed by Lütkepohl (2005). This method ensures that the shocks are uncorrelated, which simplifies the interpretation of the IRFs. Moreover, as demonstrated by Cao and Sun (2011), the use of orthogonalised IRFs can provide valuable insights into the transmission of shocks within VAR models.

2.4 Data Description

This research is led by using two exogenous variables which are the source of the perturbation of the system and a set of endogenous variables for which the effect of these shocks is analysed.

Exogenous variables

The two exogenous variables that generate shocks in the system are proxies for crude oil returns and crude oil uncertainty. The crude oil returns are derived by evaluating the logarithmic change in crude oil prices. To develop a proxy for crude oil uncertainty, this study employs an empirically derived measure of the volatility of daily West Texas Intermediate (WTI) prices. These daily data points are subsequently aggregated into monthly data to align with the frequency of the rest of the dataset.

Crude oil returns calculation

Crude oil returns (R_{t+1}) is calculated as follows:

$$R_{t+1} = \ln(P_{t+1}) - \ln(P_t), \tag{2.13}$$

where P_{t+1} represents the WTI price at time $t+1$ and P_t denotes the crude oil price at the previous time period.

Empirical Volatility Estimate calculation

The Empirical Volatility Estimate is computed using the following equation:

$$\begin{aligned} EV_t &= \frac{1}{d}\sum_{i=1}^{d} r_i^2, \\ EVol_t &= \sqrt{EV_t} \times 100. \end{aligned} \tag{2.14}$$

In the above equations, r_i denotes the daily log-return on WTI for the $i-th$ day of month t. The variable d represents the number of trading days in month t. The empirical variance (EV_t) is computed as the average of the squared daily log-returns within the month. The monthly empirical volatility ($EVol_t$) is then obtained by taking the square root of the empirical volatility and scaling it by 100.

Table 2.1 presents the descriptive statistics for the exogenous variables: crude oil returns and crude oil volatility. The mean monthly return for WTI crude oil prices is 0.0035, with a standard deviation of 0.1026, highlighting significant variability in oil price movements during the analysed period. The minimum return of -0.3610 reflects sharp declines in oil prices, while the maximum of 0.3210 corresponds to periods of rapid price increases.

Crude oil volatility, measured as the empirical volatility of daily returns, exhibits a mean of 8.97×10^{-3} with a standard deviation of 1.62×10^{-2}, indicating relatively low average volatility but occasional spikes. The minimum volatility of 1.66×10^{-6} represents periods of market calm, while the maximum value of 1.56×10^{-1} corresponds

Table 2.1: Descriptive Statistics for Crude Oil Returns and Volatility

Variable	Mean	Std. dev.	Min	Max	Obs
Oil Returns	0.003536	0.102553	-3.61E-01	0.321001	274
Oil Volatility	0.008970	0.016192	1.66E-06	0.155899	274

Table 2.1 reports crude oil returns and volatility statistics for the sample period.

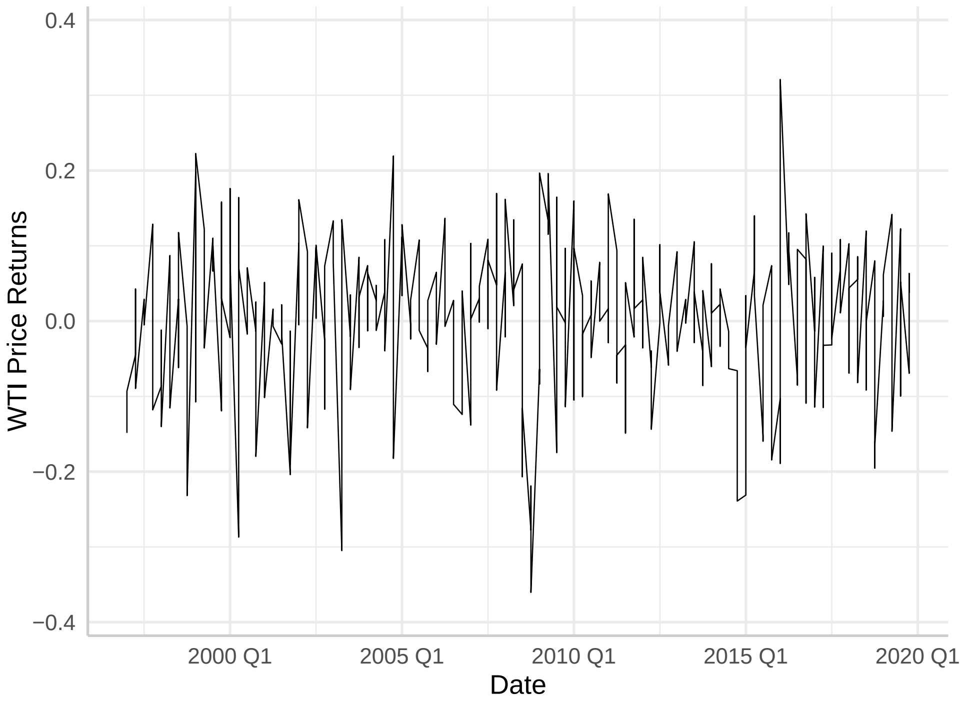
to heightened market uncertainty during periods of significant economic or geopolitical events.

Figures 2.1, 2.2, and 2.3 illustrate key aspects of the West Texas Intermediate (WTI) crude oil market: the evolution of WTI prices, the corresponding returns, and the empirical volatility of crude oil prices.

Figure 2.1: WTI Prices

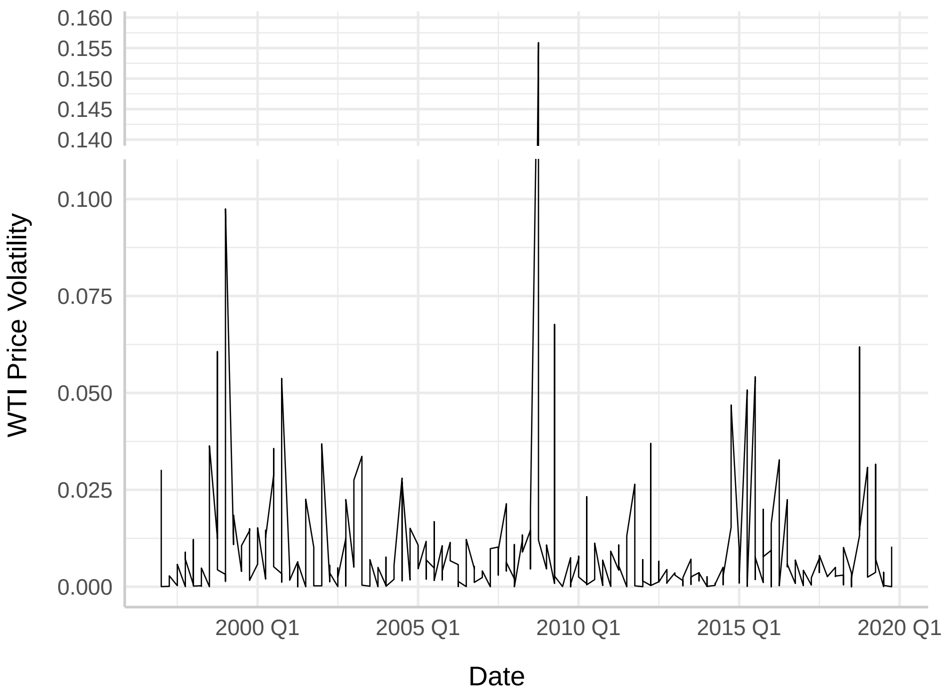
Evolution of West Texas Intermediate (WTI) prices.

Figure 2.2: WTI Prices: Returns



Evolution of the WTI returns.

Figure 2.3: WTI Prices: Empirical Volatility



Evolution of the crude oil empirical volatility.

Endogenous variables

The set of endogenous variables collected for each country consists of monthly data of crude oil trade balance, real exchange rate, short-term policy rate, Consumer Price Index (CPI), and Industrial Production Index (IPI) covering from 1997M2-2019M12. All variables are in first difference of log and constitute the monthly growth rate except inflation which is considered as annual changes to remove the seasonal component form the series. The crude oil trade balance is a key variable in the dataset. It is not only relevant for the analysis, but it also defines whether a country is defined as exporter or importer. The crude oil trade balance is constructed as the difference between the level of crude oil export and import for the time span of the dataset and therefore a country is defined as an exporter if the trade balance is positive while if the trade balance is negative, the country is considered as an importer. In this analysis, it is preferred to define exporter and importer countries by the sign of their crude oil trade balance instead of using the OECD database. In this way, the definition of exporter and importer results to be more accurate and tailored for the time span considered in the research. The real exchange rates of each country are collected directly from the Bruegel Dataset website. The reason why the short-term interest rate of each country is included in the dataset is to analyse the reaction of central banks to a crude oil uncertainty shock and the subsequent fluctuation of the real exchange rate.

Table 2.2 provides descriptive statistics for the endogenous variables across nine countries, including crude oil trade balance, real exchange rate (REER), short-term policy rate, Consumer Price Index (CPI), and Industrial Production Index (IPI). The statistics summarise the mean, standard deviation, minimum, and maximum values, along with the number of observations for each variable.

The crude oil trade balance reveals notable differences between oil-exporting countries, such as Norway and Canada, which show higher mean values, and oil-importing countries, such as Italy and Spain, where the mean trade balance is closer to or below zero. The variability, reflected in the standard deviation, is generally higher for exporters, emphasising the influence of global oil price fluctuations. The REER statistics show relative stability across countries, with limited variability, indicating moderate currency adjustments during the sample period. However, Norway and Mexico exhibit slightly higher variability, potentially due to their dependence on oil exports, which can create volatility in currency markets. The short-term policy rates vary significantly between countries, with higher values observed in emerging markets like Mexico, while more developed economies, such as the United States and Germany, show lower and less volatile rates.

Inflation, measured by the CPI, reflects stable growth patterns across all countries, with slightly higher averages in developing economies, such as Mexico and Spain, compared to industrialised nations like Germany and the United States. The IPI exhibits modest fluctuations in all countries, with Norway and Canada showing higher variability, possibly reflecting the sensitivity of their industrial output to changes in crude oil prices. These cross-country patterns highlight the diverse economic structures and policy responses represented in the dataset, providing a robust basis for analysing the impact of crude oil volatility on macroeconomic indicators.

Graphs of the endogenous variables for each country are shown by Figures 2.4 - 2.12.

Table 2.2: Descriptive Statistics for Endogenous Variables Across Countries

	Norway				
Variable	Mean	Std. dev.	Min	Max	Obs
Trade Balance	0.013640	0.146889	-3.71E-01	0.443798	275
REER	-3.71E-04	0.014287	-5.68E-02	0.045236	275
Policy Rate	-2.37E-04	0.065375	-3.50E-01	0.434862	275
CPI	0.021347	0.010498	-1.83E-02	0.054118	275
IPI	-1.75E-04	0.029226	-9.34E-02	0.119460	275

	Canada				
Variable	Mean	Std. dev.	Min	Max	Obs
Trade Balance	0.064872	0.393955	-6.87E-01	2.981973	275
REER	0.000233	0.016005	-9.16E-02	0.055668	275
Policy Rate	0.000919	0.072578	-3.22E-01	0.355298	275
CPI	0.018663	0.008515	-9.50E-03	0.046843	275
IPI	0.001092	0.010211	-3.83E-02	0.035170	275

	Mexico				
Variable	Mean	Std. dev.	Min	Max	Obs
Trade Balance	0.011143	0.133791	-4.19E-01	0.444102	275
REER	0.000145	0.023737	-1.28E-01	0.092263	275
Policy Rate	-2.55E-03	0.061817	-2.25E-01	0.483456	275
CPI	0.062398	0.046729	0.021308	0.256355	275
IPI	0.001028	0.009272	-4.37E-02	0.031571	275

	UK				
Variable	Mean	Std. dev.	Min	Max	Obs
Trade Balance	0.061599	0.371190	-5.73E-01	2.531250	275
REER	-2.57E-04	0.016226	-6.71E-02	0.043642	275
Policy Rate	-5.51E-03	0.063138	-2.88E-01	0.368421	275
CPI	0.019761	0.010545	-1.25E-03	0.052116	275
IPI	0.000775	0.013671	-5.47E-02	0.052574	275

	US				
Variable	Mean	Std. dev.	Min	Max	Obs
Trade Balance	0.003470	0.090649	-3.88E-01	0.294857	275
REER	0.000713	0.012631	-3.76E-02	0.063694	275
Policy Rate	0.000443	0.091317	-4.38E-01	0.471438	275
CPI	0.021499	0.011699	-1.96E-02	0.054975	275
IPI	0.001003	0.006488	-4.37E-02	0.020594	275

	Germany				
Variable	Mean	Std. dev.	Min	Max	Obs
Trade Balance	0.015541	0.160741	-3.68E-01	0.726398	275
REER	-3.70E-04	0.008579	-2.54E-02	0.031461	275
Policy Rate	-2.20E-03	0.121211	-8.27E-01	0.634957	275
CPI	0.014176	0.006972	-5.39E-03	0.034247	275
IPI	0.001178	0.014404	-6.98E-02	0.043810	275

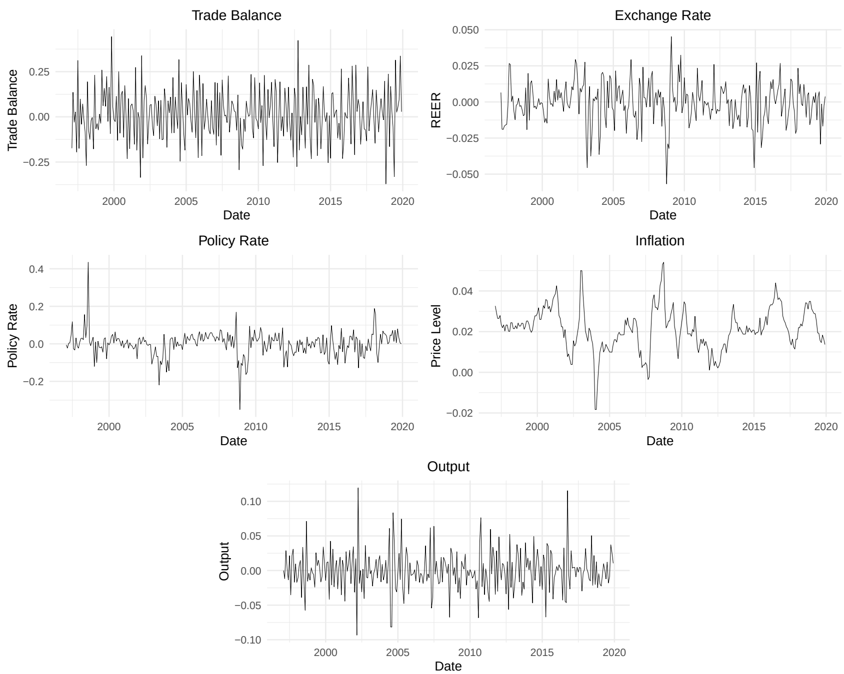
	Italy				
Variable	Mean	Std. dev.	Min	Max	Obs
Trade Balance	0.012409	0.137163	-3.20E-01	0.409346	275
REER	-6.70E-05	0.007846	-2.49E-02	0.027122	275
Policy Rate	-2.20E-03	0.121211	-8.27E-01	0.634957	275
CPI	0.017982	0.010322	-5.08E-03	0.042529	275
IPI	-3.63E-04	0.014944	-4.21E-02	0.038941	275

	Spain				
Variable	Mean	Std. dev.	Min	Max	Obs
Trade Balance	0.007052	0.080135	-2.70E-01	0.221011	275
REER	0.000296	0.006555	-1.87E-02	0.020144	275
Policy Rate	-2.20E-03	0.121211	-8.27E-01	0.634957	275
CPI	0.020888	0.014735	-1.38E-02	0.052842	275
IPI	3.77E-05	0.011884	-5.96E-02	0.040201	275

	Sweden				
Variable	Mean	Std. dev.	Min	Max	Obs
Trade Balance	0.047026	0.310442	-6.01E-01	1.347921	275
REER	-1.07E-03	0.013995	-4.50E-02	0.059820	275
Policy Rate	0.016382	0.321985	-1.18E+00	4.500000	275
CPI	0.011787	0.011424	-1.55E-02	0.043722	275
IPI	0.010464	0.113478	-3.38E-01	0.298300	275

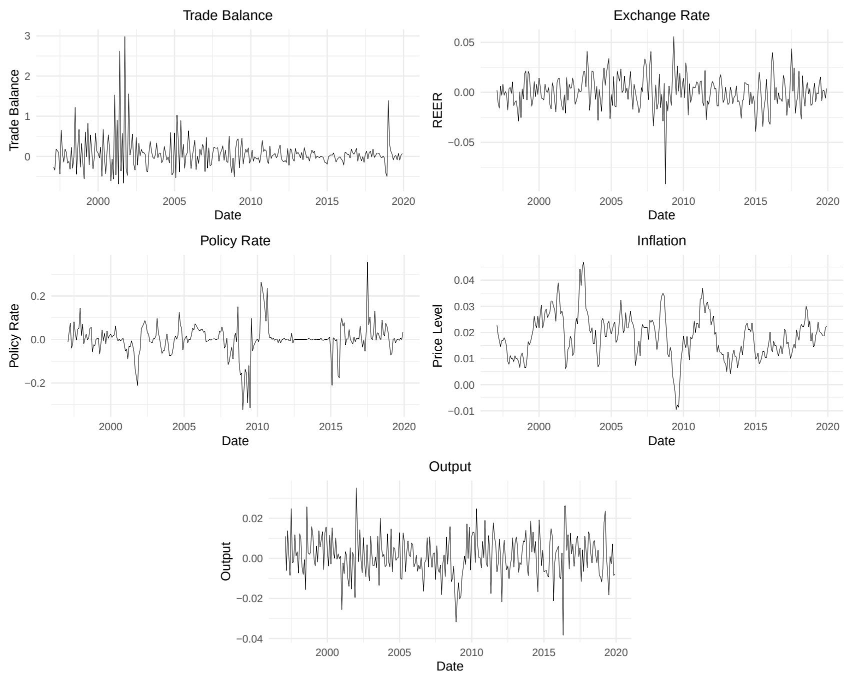
Table 2.2 summarises the mean, standard deviation, minimum, maximum, and observations for the endogenous variables across nine countries. These variables include crude oil trade balance, real exchange rate (REER), short-term policy rate, Consumer Price Index (CPI), and Industrial Production Index (IPI).

Figure 2.4: Macroeconomic Indicators for Norway



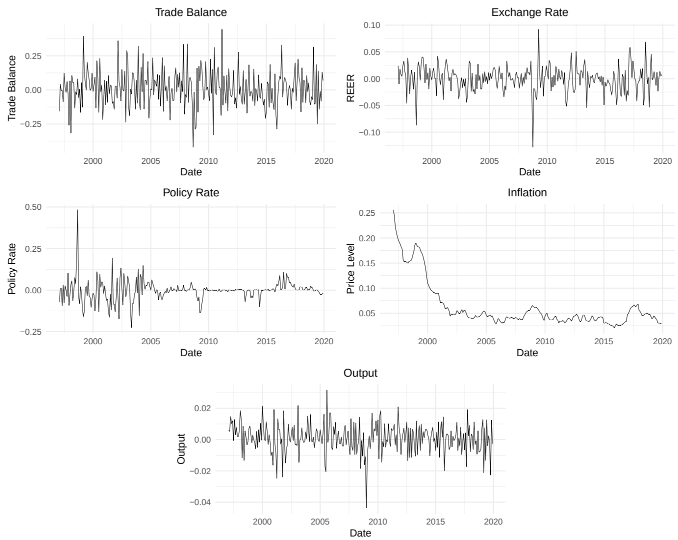
The figure shows key macroeconomic indicators for Norway.

Figure 2.5: Macroeconomic Indicators for Canada



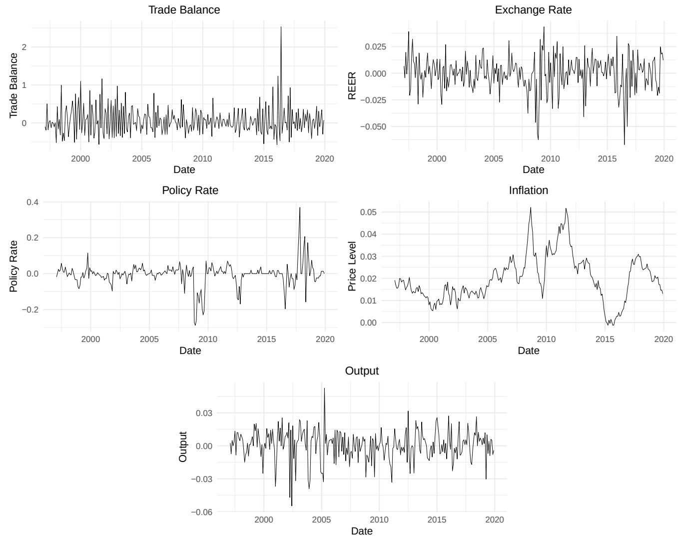
The figure shows key macroeconomic indicators for Canada.

Figure 2.6: Macroeconomic Indicators for Mexico



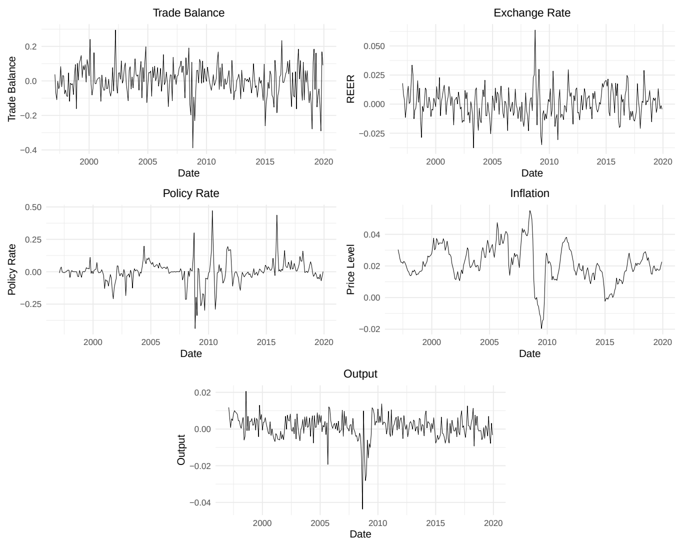
The figure shows key macroeconomic indicators for Mexico.

Figure 2.7: Macroeconomic Indicators for the United Kingdom



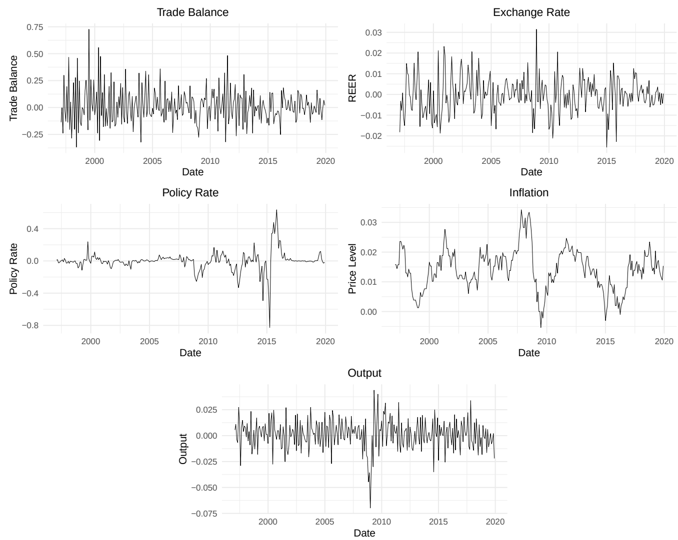
The figure shows key macroeconomic indicators for the United Kingdom.

Figure 2.8: Macroeconomic Indicators for the United States



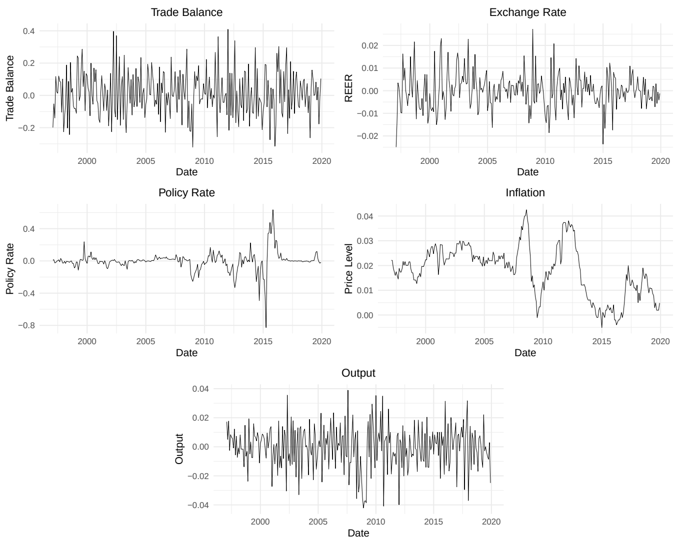
The figure shows key macroeconomic indicators for the United States.

Figure 2.9: Macroeconomic Indicators for Germany



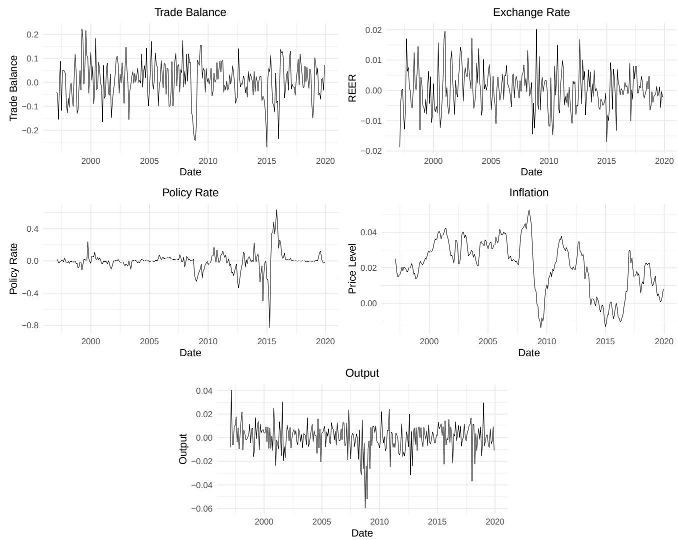
The figure shows key macroeconomic indicators for Germany.

Figure 2.10: Macroeconomic Indicators for Italy



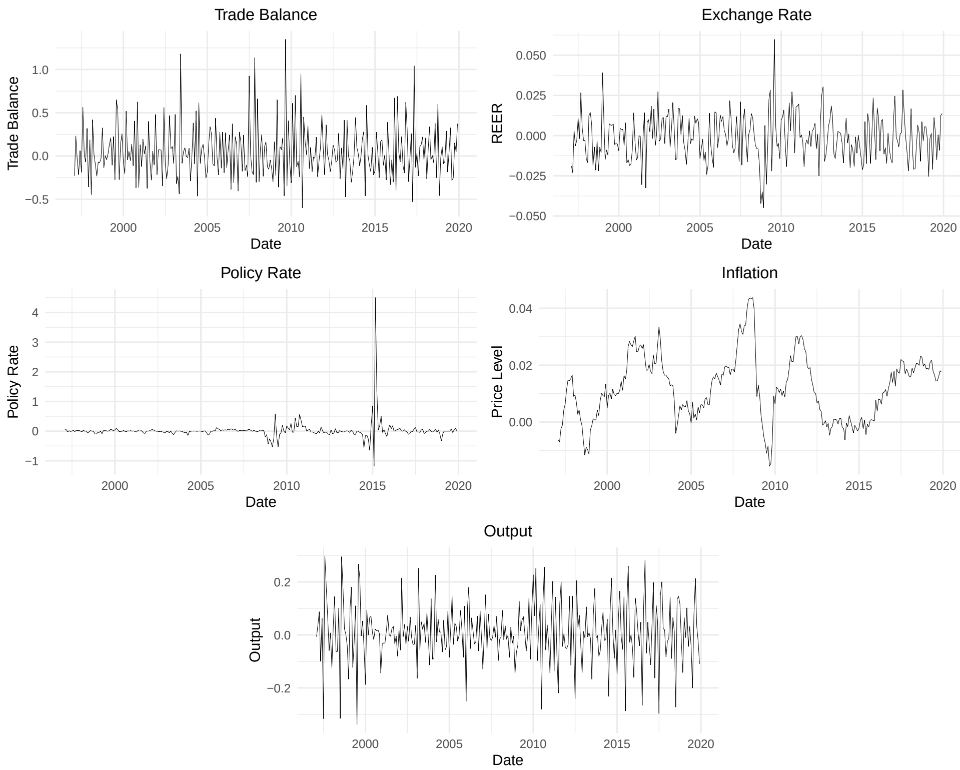
The figure shows key macroeconomic indicators for Italy.

Figure 2.11: Macroeconomic Indicators for Spain



The figure shows key macroeconomic indicators for Spain.

Figure 2.12: Macroeconomic Indicators for Sweden



The figure shows key macroeconomic indicators for Sweden.

2.5 Empirical Evidence

This section examines the persistence of oil returns and oil volatility shocks on the exogenous variables of the countries analysed in this study. The main results presented here are based on the VAR model with one year of lags (VAR(12)), as recommended by Hamilton (1996) and Edelstein and Kilian (2007). This VAR specification provides the primary findings of this research.

In Appendix B of this chapter, we conduct a similar analysis using a VAR model with 6 months of lags (VAR(6)) and other VAR models with lag specifications determined by the Information Criteria for each country (VAR(p)), which serve as robustness tests.

In both this section and Appendix B, we examine two VAR specifications across all lag lengths: a VAR with two exogenous variables, oil returns and oil volatility, and another VAR in which only the crude oil volatility is included as the exogenous variable. In doing so, we highlight the different reactions of the endogenous variables of each country given by the two models. To present the results, we illustrate impulse response functions which capture the reactions of the endogenous variables over the following 12 months.

Figures 2.13 to 2.21 show the impulse response functions generated by the VAR(12) model with two exogenous variables while in Figures 2.22 to 2.30 are displayed the reactions of the endogenous variables to the VAR(12) model with only the crude oil volatility as exogenous variable.

VAR(12) analysis

Trade Balance — The crude oil trade balance is the most sensitive variable to shocks in crude oil returns. This sensitivity can be attributed to several factors. Firstly, crude oil is a major component of production costs, and changes in its price directly influence the trade balance by affecting both the value and volume of trade (Baek et al. 2019). Countries that are net exporters of crude oil, such as Canada, exhibit pronounced positive reactions to return shocks, as seen with a surge of 11% in the second month post-shock (Figure 2.14). Similar positive initial reactions are observed in other countries, including a 9.8% spike in the United Kingdom in the third month after the shock, and an 8.3% spike in Sweden. Mexico also shows a significant positive response, with a 4.8% increase in the first month that rises to 7.7% in the subsequent month. This is consistent with the findings of Hamilton (1983), who suggests that oil price increases often precede economic downturns due to the higher production costs associated with rising oil prices. Similarly, Kilian (2009) illustrates that higher oil prices can increase export revenues for oil-producing countries, thereby leading to an improved trade balance.

REER — The reactions of the real exchange rate exhibit an effect that is consistent across all the countries with most of the results being statistically significant. A one-standard-deviation shock on the crude oil returns generates a positive reaction followed by a positive spike in the second month and the effect gradually fades away to its steady state by the end of the following year. This behaviour can be explained by the fact that oil-importing countries experience higher inflation due to increased oil costs, leading to temporary real exchange rate appreciation. For instance, an increase in oil prices raises import costs, which can cause inflationary pressures and result in a stronger currency as more of it is needed to purchase oil. This aligns with findings by Chen and Chen (2007) and further supported by literature showing how oil price volatility creates economic uncertainty, causing initial negative responses that stabilise over time (Akram 2009; Basher et al. 2016). The reaction of the countries' exchange rate to a crude oil volatility shock is also consistent across the countries showing an initial negative response which tends to show a positive spike in the second half of the year, as can be clearly seen for instance in Figures 2.15 and 2.24 for the case of Mexico. The only country that differed from this pattern is the United States. Figure 2.17 indicates indeed that the first reaction of the US real exchange rate to an oil return shock is negative which is followed by an even deeper negative spike in the following month that reduces the real exchange rate by 37 basis points. Figure 2.26 denotes instead a positive reaction of 27 basis points after a shock coming from crude oil volatility.

Policy Rate — The policy rate of the countries analysed in this study shows heterogeneous results with two main reactions to crude oil returns and oil volatility shocks. On one side, for most of the countries, an oil return shock generates an immediate negative reaction which becomes positive after 3-5 months to die off within the following 12 months. This is consistent with the findings of Kilian and Lewis (2011), who suggest that, even if oil price shocks do not directly influence monetary policy decisions, they can influence the economic outlook and therefore indirectly affect monetary policy via expected inflation and economic activity. A surprise in the volatility instead exhibits an initial positive change in the short-term policy rate with a sharp downturn starting from the second month. This suggests that central banks attempt to manage the economic impact of increased uncertainty due to oil price volatility. Studies show that oil price uncertainty can heighten macroeconomic volatility (Choi et al. 2018; Elder and Serletis 2010; Peter Ferderer 1996), prompting central banks to use counter-cyclical measures. Initially, they raise rates to control inflation but then quickly lower them to stabilise the economy as uncertainty impacts economic activity. The Eurozone on the other hand shows a different reaction which, although the IRFs are not significant for most of the period, a clear positive spike is recorded in the last quarter of the following year. This observation aligns with the analysis of Lippi and Nobili (2012), which highlights the heterogeneity of monetary policy responses to oil price shocks across different economic regions, driven by varying degrees of oil dependence, economic structure, and monetary policy objectives.

CPI — To remove the seasonality in the countries' inflation, in this research the CPI is considered as yearly percentage change. This generates some non-stationary series in some cases such as UK and Italy, as it is summarised in the Appendix A of this chapter. Overall, the impulse response functions show a consistent pattern in the reactions of the countries' inflation after the two sources of shocks with a broad negative reaction after a crude oil volatility shock and a widespread positive reactions that follow an oil return shock. This aligns with findings in the literature, which suggest that oil price shocks can have significant effects on both inflation and broader economic activity, as shown by changes in consumer spending (Blanchard and Gali 2007) and economic downturns (Hamilton 2003). In some of the IRFs, the zero is consistently within the confidence level bound suggesting no statistical significance in the responses recorded. This suggests that while oil shocks can impact inflation, the extent and significance of these impacts can vary across different contexts, as also noted by Kilian and Lewis (2011) and Baumeister and Peersman (2013).

Output — The effect of volatility and return shocks on the output of countries varies significantly. Generally, a volatility shock tends to generate a widespread negative impact on output across most countries, which is consistent with the notion that increased uncertainty reduces investment and consumption, as discussed by Bloom (2009). However, Sweden presents an exception, where an oil volatility shock initially results in a positive output response of 1% (Figure 2.21). Regarding oil return shocks, most are find to be statistically insignificant, indicating that returns pass-through to output is limited, which may reflect well-anchored inflation expectations and effective monetary policy responses, as noted by Clarida et al. (2000). Notably, the United States and Sweden record initial increases in output levels of 0.18% and 1.5%, respectively, a response that Hamilton (1996) attributes to short-term boosts in investment driven by expectations of higher future prices.

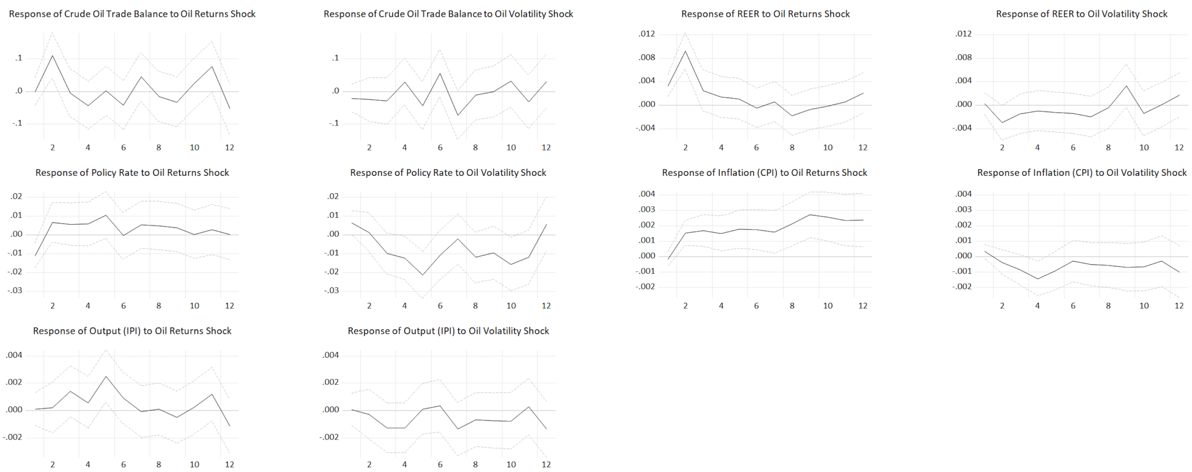
VAR(12) — Impulse responses

In this section, we present the impulse response functions from the VAR(12) models.

Figure 2.13: VAR(12) with 2 Exogenous Variables — Norway

The figure displays the impulse response functions for Norway using a VAR(12) model with two exogenous variables. The responses of various economic indicators to shocks in oil returns and uncertainty are shown, with confidence intervals.

Figure 2.14: VAR(12) with 2 Exogenous Variables — Canada



The figure displays the impulse response functions for Canada using a VAR(12) model with two exogenous variables. The responses of various economic indicators to shocks in oil returns and uncertainty are shown, with confidence intervals.

Figure 2.15: VAR(12) with 2 Exogenous Variables — Mexico

The figure displays the impulse response functions for Mexico using a VAR(12) model with two exogenous variables. The responses of various economic indicators to shocks in oil returns and uncertainty are shown, with confidence intervals.

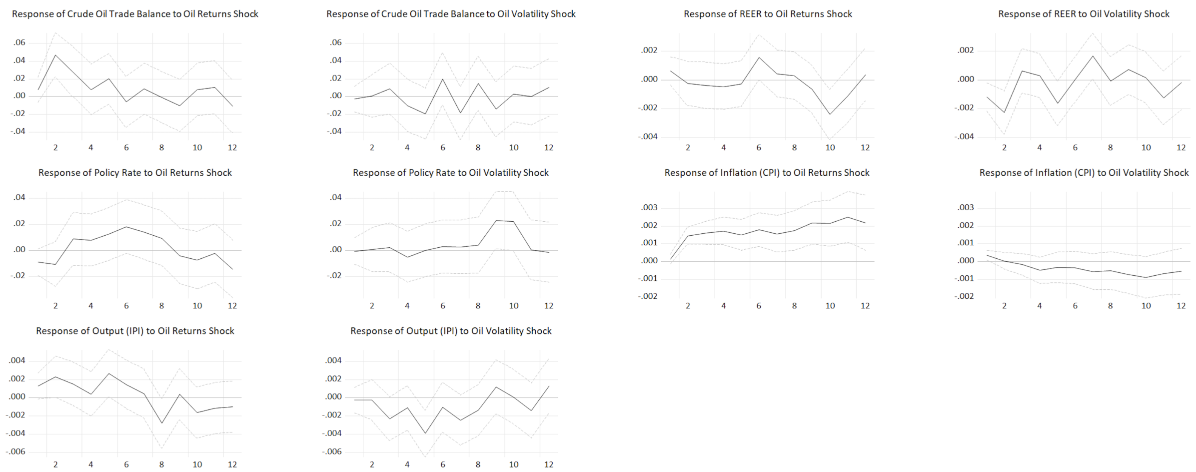
Figure 2.16: VAR(12) with 2 Exogenous Variables — UK

The figure displays the impulse response functions for the UK using a VAR(12) model with two exogenous variables. The responses of various economic indicators to shocks in oil returns and uncertainty are shown, with confidence intervals.

Figure 2.17: VAR(12) with 2 Exogenous Variables — US

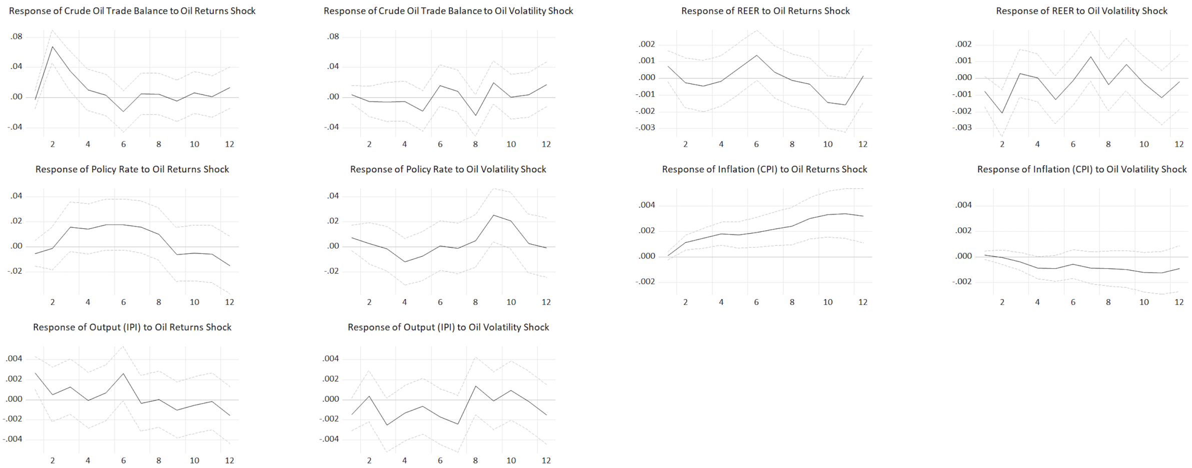
The figure displays the impulse response functions for the US using a VAR(12) model with two exogenous variables. The responses of various economic indicators to shocks in oil returns and uncertainty are shown, with confidence intervals.

Figure 2.18: VAR(12) with 2 Exogenous Variables — Germany



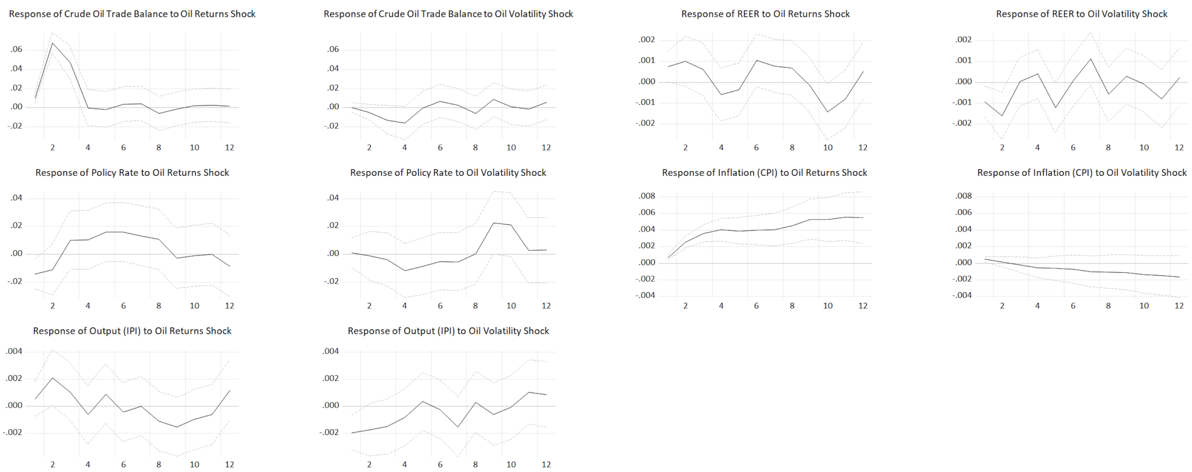
The figure displays the impulse response functions for Germany using a VAR(12) model with two exogenous variables. The responses of various economic indicators to shocks in oil returns and uncertainty are shown, with confidence intervals.

Figure 2.19: VAR(12) with 2 Exogenous Variables — Italy



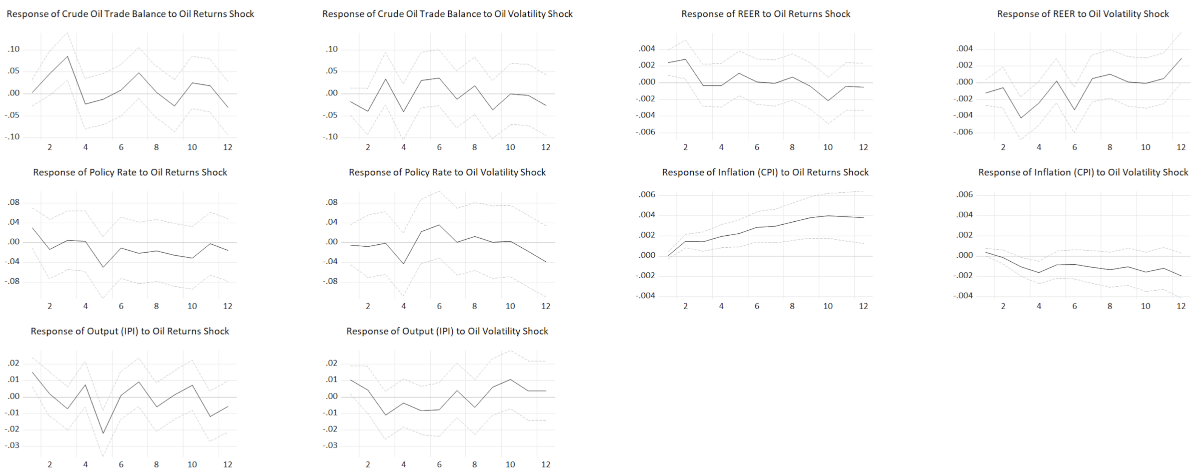
The figure displays the impulse response functions for Italy using a VAR(12) model with two exogenous variables. The responses of various economic indicators to shocks in oil returns and uncertainty are shown, with confidence intervals.

Figure 2.20: VAR(12) with 2 Exogenous Variables — Spain



The figure displays the impulse response functions for Spain using a VAR(12) model with two exogenous variables. The responses of various economic indicators to shocks in oil returns and uncertainty are shown, with confidence intervals.

Figure 2.21: VAR(12) with 2 Exogenous Variables — Sweden



The figure displays the impulse response functions for Sweden using a VAR(12) model with two exogenous variables. The responses of various economic indicators to shocks in oil returns and uncertainty are shown, with confidence intervals.

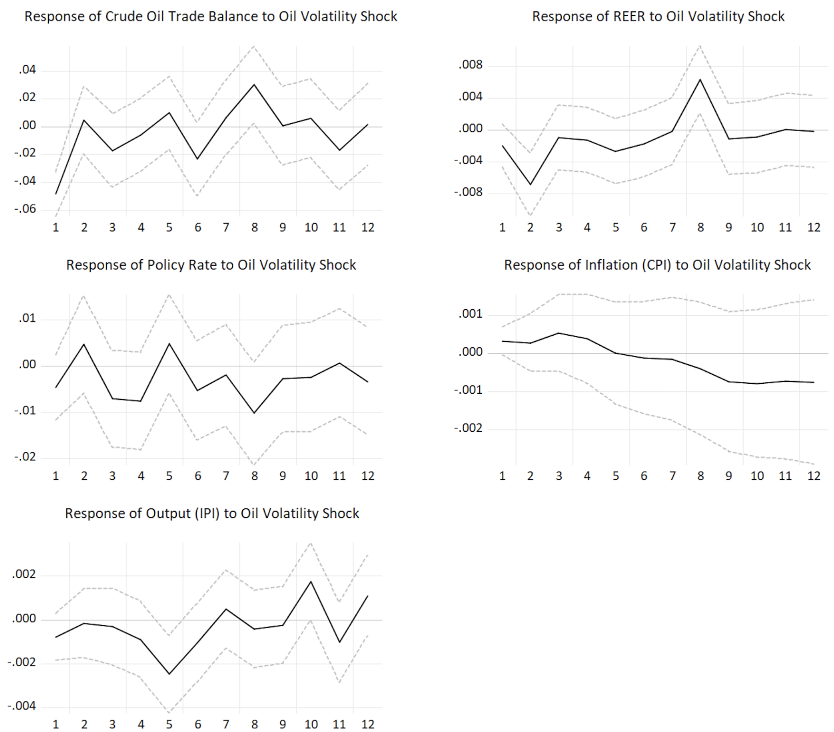
Figure 2.22: VAR(12) with 1 Exogenous Variable — Norway

The figure displays the impulse response functions for Norway using a VAR(12) model with one exogenous variable. The responses of various economic indicators to shocks in the selected variable are shown, with confidence intervals.

Figure 2.23: VAR(12) with 1 Exogenous Variable — Canada

The figure displays the impulse response functions for Canada using a VAR(12) model with one exogenous variable. The responses of various economic indicators to shocks in the selected variable are shown, with confidence intervals.

Figure 2.24: VAR(12) with 1 Exogenous Variable — Mexico



The figure displays the impulse response functions for Mexico using a VAR(12) model with one exogenous variable. The responses of various economic indicators to shocks in the selected variable are shown, with confidence intervals.

Figure 2.25: VAR(12) with 1 Exogenous Variable — UK

The figure displays the impulse response functions for UK using a VAR(12) model with one exogenous variable. The responses of various economic indicators to shocks in the selected variable are shown, with confidence intervals.

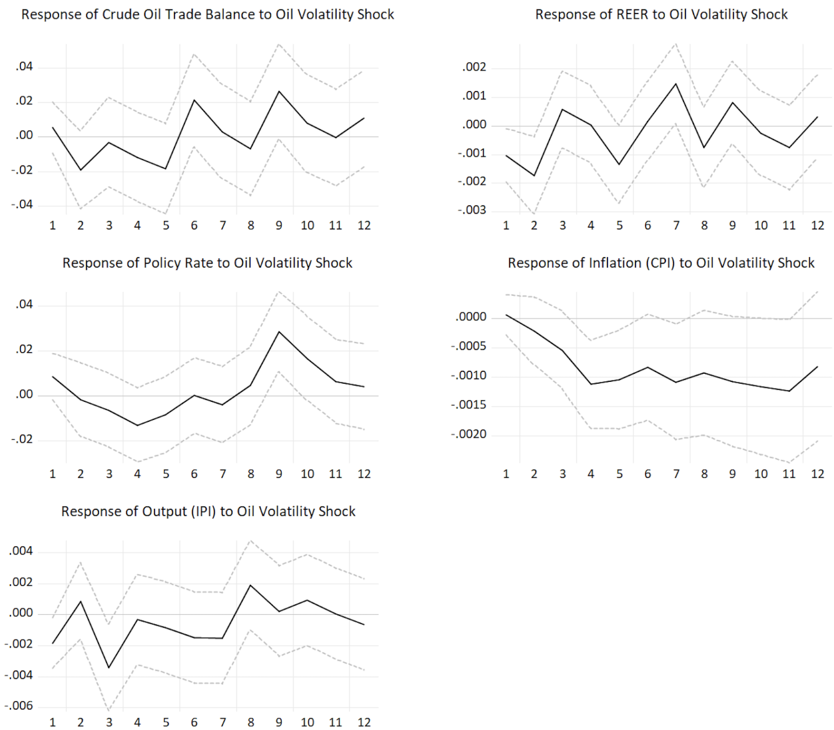
Figure 2.26: VAR(12) with 1 Exogenous Variable — US

The figure displays the impulse response functions for US using a VAR(12) model with one exogenous variable. The responses of various economic indicators to shocks in the selected variable are shown, with confidence intervals.

Figure 2.27: VAR(12) with 1 Exogenous Variable — Germany

The figure displays the impulse response functions for Germany using a VAR(12) model with one exogenous variable. The responses of various economic indicators to shocks in the selected variable are shown, with confidence intervals.

Figure 2.28: VAR(12) with 1 Exogenous Variable — Italy

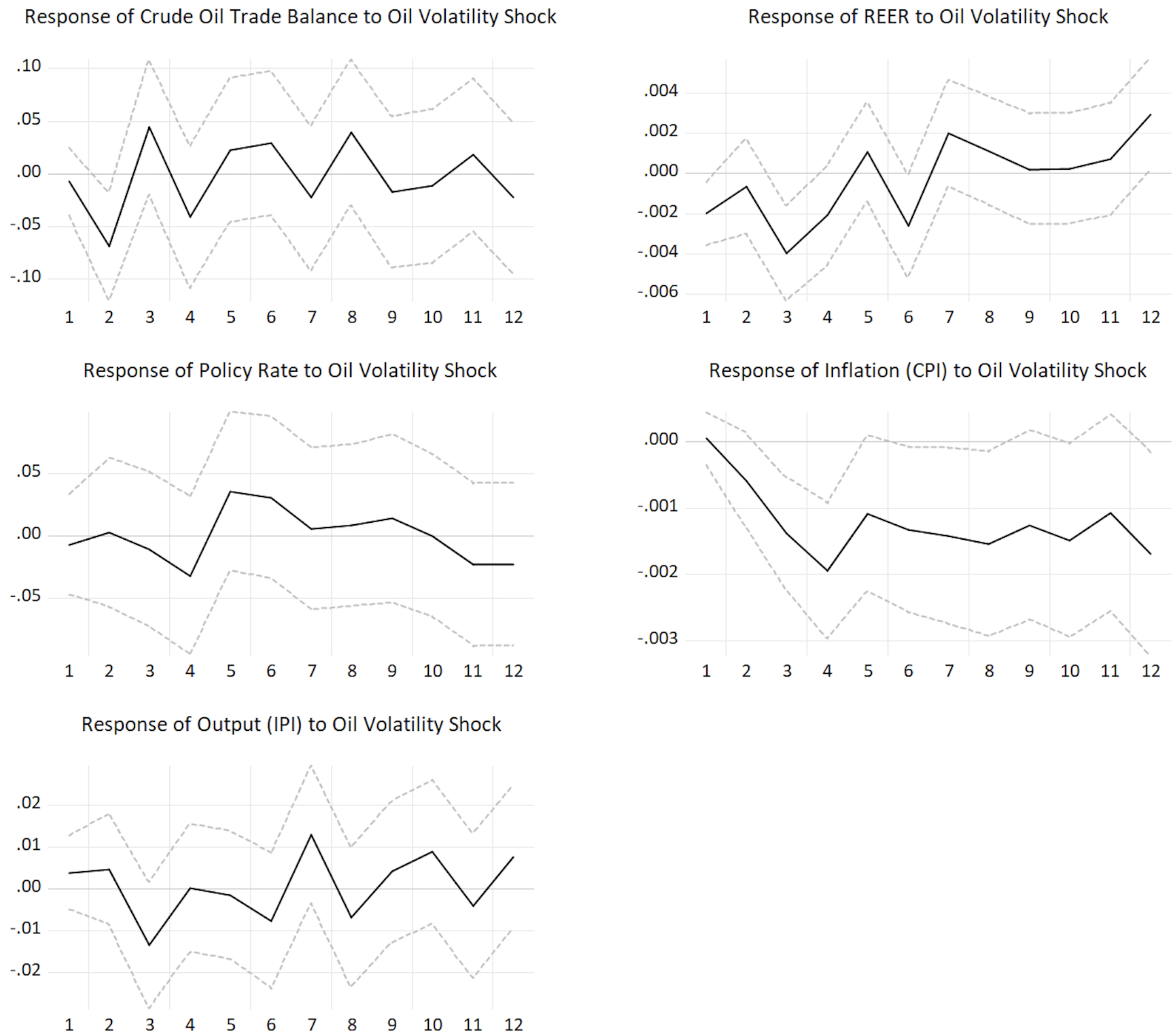


The figure displays the impulse response functions for Italy using a VAR(12) model with one exogenous variable. The responses of various economic indicators to shocks in the selected variable are shown, with confidence intervals.

Figure 2.29: VAR(12) with 1 Exogenous Variable — Spain

The figure displays the impulse response functions for Spain using a VAR(12) model with one exogenous variable. The responses of various economic indicators to shocks in the selected variable are shown, with confidence intervals.

Figure 2.30: VAR(12) with 1 Exogenous Variable — Sweden



The figure displays the impulse response functions for Sweden using a VAR(12) model with one exogenous variable. The responses of various economic indicators to shocks in the selected variable are shown, with confidence intervals.

2.6 Conclusion

This research contributes to the literature by examining the asymmetric reaction of crude oil exporter and importer countries to crude oil returns and uncertainty shocks. While existing studies have explored the relationship between crude oil prices and macroeconomic variables, this study uniquely investigates whether exporters and importers respond differently to return and volatility shocks, thereby extending the discourse on exchange rate and trade balance adjustments in commodity-dependent economies. The general assumption for volatility shocks is that periods of rising volatility are generally followed by higher crude oil prices. This is assumed to trigger different reactions between crude oil exporter and importer countries. An exporter country would seize the opportunity of higher prices by boosting the oil exports which will increase the crude oil trade balance of the country and, in turn, this dynamic will trigger an appreciation in the real exchange rate of the country. An importer country, on the other hand, would be keen to hedge against the risk of high volatility in the crude oil market and future higher prices. To do so, an importer country might want to decrease the purchase of oil reducing the crude oil import and consequently decreasing the crude oil trade balance. The real exchange rate is assumed to depreciate after the drop in the crude oil import and the reduction in the trade balance. This study also investigates the response of central banks to the fluctuation of the exchange rate. The assumptions are that the central bank of an exporter country might want to avoid the market overheating so the central bank is assumed to increase the short-term policy rate while a central bank of an importer country might want to stimulate the market decreasing the short-term interest rate after the depreciation on the real exchange rate.

The dataset represents 9 countries, 3 exporters and 6 importers, and for each country the data collected consists of monthly data of crude oil trade balance, real exchange rate, short-term policy rate, country inflation, and country output for a period that covers from 1997:M02 to 2019:M12. We employ two VARs models, one with two exogenous variables that generate the shocks, hence crude oil returns and volatility, and another VAR with only volatility as exogenous variable. The VAR specification for the main analysis takes into account 12 lags allowing us to investigate the effect of one-standard-deviation shocks over a year. The robustness test is conducted using the same methodology framework, but utilising VARs with 6 lags and VARs with the specification suggested by the information criteria to back up the findings of the VAR(12). The results from these robustness tests confirm the main findings, with VAR(12) being the most detailed in capturing long-term effects. The VAR(6) models accurately capture effects for up to 6–8 months but fail to show long-term impacts, while the models based on information criteria capture the shocks for only 3–6 months. This indicates that models with fewer lags are less accurate for longer-term analysis.

The consistency of the results across the countries analysed in this analysis suggests that the expected asymmetry between exporters and importers is less pronounced than initially assumed. This finding indicates that, despite differing oil trade positions, both groups of countries tend to implement similar economic strategies in response to crude oil market volatility, potentially reflecting coordinated policy measures or common structural constraints. The sources of shocks utilised in this research trigger indeed the same responses between oil exporters and importers with a general surge in crude oil trade balance and an appreciation of the real exchange rate after a return shock and a dwindling of the two variables after volatility shocks.

A key finding of this research is that the real exchange rates consistently depreciate following volatility shocks. This suggests that rather than responding differently based on oil trade positions, both exporter and importer countries tend to apply defensive and cautionary measures in order to protect themselves from uncertainty in the crude oil market. The only exception is the case of the United States. The VAR analysis that focuses only on volatility shock (Figure 2.26), as well as the robustness exercises (Figures 2.44 and 2.62), suggest indeed that USD tends to appreciate after a crude oil volatility shock.

An important addition of this research to the literature lies in the comparative analysis of return and volatility shocks, demonstrating that both crude oil trade balances and real exchange rates react similarly to these shocks. While previous studies have primarily focused on return shocks, this study provides new evidence that volatility shocks, although milder, can trigger similar macroeconomic adjustments. This insight enhances our understanding of the distinct transmission mechanisms through which crude oil price fluctuations impact economic variables. Generally, return shocks generate an increase in the crude oil trade balances and in the real exchange rates while uncertainty shocks, although with some non-statistically significant values for a few countries, generate a negative initial impact on trade balances and exchange rates. The United States is the only case in which a return shock generates a positive spike in the trade balance and a reaction of the opposite sign in the real exchange rate. As can be seen from the VAR analysis of the United States case which also includes shocks of the crude oil returns (Figure 2.17) and the robustness tests (Figures 2.35 and 2.53), return shocks generate a sharp and highly statistically significant increase in the exports of crude oil since the trade balance shows a positive value after two months from the shock of 3.2% which raises up to 5.6% in the following month while, on the other side, the real exchange rate exhibits a negative spike of 37 basis points after two months.

Overall, this analysis suggests another contribution which comes from the comparison between the effect of returns and volatility shocks over the variables used for the countries. This research suggests that return shocks tend to have a larger and faster impact on all the variables considered while volatility shocks have a milder and slower effect.

One of the main advancements of this study is its contribution to understanding the interaction between crude oil volatility and macroeconomic variables. While this research provides valuable insights, certain limitations should be acknowledged. Given that this study finds consistent exchange rate and trade balance responses across exporters and importers, future research could explore how these dynamics evolve under different macroeconomic conditions. For instance, investigating how crude oil price uncertainty interacts with broader financial variables — such as stock market fluctuations or capital flows —could provide deeper insights into the global transmission of commodity price shocks. Similarly, examining structural breaks, geopolitical risks, or alternative econometric approaches could refine our understanding of how crude oil market uncertainty affects economic stability. Beyond crude oil, similar analyses could be conducted for other key commodities such as gold, wheat, cotton, or corn, which also play significant roles in global economic stability. A comparative study across multiple commodities could help assess whether the observed patterns in crude oil markets hold across different asset classes and economic conditions.

Additionally, this study is based on a specific dataset and time period, which may influence the generalisability of the findings. Expanding the time horizon or incorporating alternative data sources could provide further validation of the results. Additionally, while the econometric framework employed is well-founded, exploring different modelling approaches — such as machine learning or regime-switching models — could offer alternative perspectives on the relationship between uncertainty and crude oil prices. Another aspect not explicitly considered in this study is the role of exogenous shocks, such as policy changes, supply chain disruptions, or extreme market events, which could have significant implications for crude oil price behaviour. Future research addressing these aspects could enhance the understanding of commodity market dynamics and improve forecasting accuracy.

2.7 Appendix A

Stationarity tests

This section examines the stationarity of the endogenous variables using three well-established econometric tests: the Augmented Dickey-Fuller (ADF) test (Dickey and Fuller 1979), the Phillips-Perron (PP) test (Phillips and Perron 1988), and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test (Kwiatkowski et al. 1992). Each test is conducted under two scenarios: one assuming a constant mean over time (Intercept) and the other assuming a constant mean with a linear trend over time (Trend and Intercept). It is crucial to note that the ADF and PP tests are designed to test the null hypothesis of non-stationarity, while the KPSS test tests the null hypothesis of stationarity. This difference reflects fundamentally different statistical perspectives on the time series being studied, a distinction that goes beyond semantics.

The results of the ADF test are presented in Tables 2.3 through 2.7, while the outcomes of the PP test are shown in Tables 2.8 through 2.12. The KPSS test results are summarised in Tables 2.13 through 2.17.

All variables are analysed in their first differences. Except for inflation, all variables demonstrate stationarity. Inflation, being the only variable that has been de-seasonalised, presents unique challenges for stationarity testing.

The ADF test indicates that inflation is non-stationary for Mexico under the Trend and Intercept condition, and for the UK and Italy under both the Intercept and Trend and Intercept conditions. For Sweden, inflation is non-stationary under the Intercept condition. Similarly, the PP test reveals non-stationarity for inflation in the UK and Italy under both conditions. The KPSS test identifies non-stationarity for Mexico under both conditions and for Italy and Spain under the Intercept condition.

Research on inflation provides mixed evidence regarding its stationarity. Byrne et al. (2010) find that aggregate inflation data often appear non-stationary, but this may mask stationary behaviours at the disaggregate level. Their analysis suggests that inflation's persistence can vary significantly across different sectors, indicating that aggregation can introduce biases. For instance, the persistence observed in the aggregate inflation series may result from a few highly persistent components, while the majority of the sectors exhibit stationarity. This aggregation bias is crucial for econometric analysis and has implications for monetary policy, especially in contexts like the UK, where inflation targeting is central to economic stability.

Moreover, significant shifts in the UK's monetary policy regimes, including the entry into and exit from the Exchange Rate Mechanism (ERM) and the subsequent adoption of inflation targeting, continue to have substantial impacts on the dynamics of inflation in the UK, marking ongoing structural shifts in the monetary policy framework, influencing the behaviour and expectations around inflation. Such shifts can lead to structural breaks in the time-series properties of inflation, which should be considered when testing for stationarity, as indicated by research into the UK's inflation targeting practices (Srinivasan et al. 2006; Turner 2022).

In a broader context, Byrne et al. (2013) examine the New Keynesian Phillips Curve using both aggregate and disaggregate data across multiple countries. Their findings provide international evidence that supports the presence of a unit root in inflation, suggesting that aggregation can obscure important sector-specific behaviours and reinforcing the importance of considering both aggregate and sector-specific dynamics. This international perspective highlights that inflation persistence and stationarity issues are not unique to the UK but are also prevalent in other economies, thereby affecting global economic policy frameworks.

Clark (2006) provides further evidence from the US, showing that inflation persistence is generally lower for disaggregated data compared to aggregate measures, supporting the notion of aggregation bias. Additionally, Stock and Watson (2007) argue that changing dynamics in inflation forecasting, potentially due to non-stationarity, pose challenges for economic predictions and policy formulation.

Table 2.3: ADF Test for Crude Oil Trade Balance

	Norway		Canada		Mexico		UK		US	
	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept
t-Statistic	-16.1897	-16.1592	-23.3789	-23.7113	-20.6833	-20.6834	-16.3129	-16.3071	-15.5416	-15.6835
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
Crit value	-3.4542	-3.9920	-3.4541	-3.9919	-3.4541	-3.9919	-3.4542	-3.9920	-3.4541	-3.9919
	1% level	1% level	1% level	1% level	1% level	1% level	1% level	1% level	1% level	1% level

	Germany		Italy		Spain		Sweden	
	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept
t-Statistic	-25.8922	-26.0176	-20.04761	-20.0303	-11.3150	-11.3088	-27.9578	-27.9068
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
Crit value	-3.4541	-3.9919	-3.4541	-3.9919	-3.4541	-3.9919	-3.4541	-3.9919
	1% level	1% level	1% level	1% level	1% level	1% level	1% level	1% level

This table shows the results of the Augmented Dickey-Fuller (ADF) test for Crude Oil Trade Balance for various countries.
*** Significant at 1%, ** Significant at 5%, * Significant at 10%. The parenthesis represents the standard errors.

Table 2.4: ADF Test for REER

	Norway		Canada		Mexico		UK		US	
	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept
t-Statistic	-12.7187	-12.7122	-13.2867	-13.2821	-13.4110	-13.4323	-15.6008	-15.5831	-11.0119	-10.9979
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
Crit value	-3.4541	-3.9919	-3.4541	-3.9919	-3.4541	-3.9919	-3.4541	-3.9919	-3.4542	-3.9920
	1% level	1% level	1% level	1% level	1% level	1% level	1% level	1% level	1% level	1% level

	Germany		Italy		Spain		Sweden	
	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept
t-Statistic	-13.0426	-13.0176	-13.5937	-13.5939	-12.9653	-13.0235	-13.3762	-13.3543
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
Crit value	-3.4541	-3.9919	-3.4541	-3.9919	-3.4541	-3.9919	-3.4541	-3.9919
	1% level	1% level	1% level	1% level	1% level	1% level	1% level	1% level

This table presents the results of the Augmented Dickey-Fuller (ADF) test for Real Effective Exchange Rate (REER) for various countries.
*** Significant at 1%, ** Significant at 5%, * Significant at 10%. The parenthesis represents the standard errors.

Table 2.5: ADF Test for Policy Rate

		Norway		Canada		Mexico		UK		US
	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept
t-Statistic	-7.9462	-7.9356	-6.4386	-6.4378	-12.79	-12.829	-5.8419	-5.8466	-8.8143	-8.8754
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
Crit value	-3.4542	-3.9920	-3.4542	-3.9920	-3.4541	-3.9919	-3.4543	-3.9922	-3.4541	-3.9919
	1% level	1% level	1% level	1% level	1% level	1% level	1% level	1% level	1% level	1% level

		Germany		Italy		Spain		Sweden
	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept
t-Statistic	-6.8794	-6.8801	-6.8794	-6.8801	-6.8794	-6.8801	-15.5804	-15.6031
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
Crit value	-3.4541	-3.9919	-3.4541	-3.9919	-3.4541	-3.9919	-3.4541	-3.9919
	1% level	1% level	1% level	1% level	1% level	1% level	1% level	1% level

This table shows the results of the Augmented Dickey-Fuller (ADF) test for Policy Rate for various countries.
*** Significant at 1%, ** Significant at 5%, * Significant at 10%. The parenthesis represents the standard errors.

Table 2.6: ADF Test for Inflation

		Norway		Canada		Mexico		UK		US
	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept
t-Statistic	-3.7242	-3.7186	-3.2998	-3.4409	-3.374	-2.6497	-2.4289	-2.408	-2.947	-3.2791
	(0.0043)**	(0.0228)**	(0.0159)**	(0.0483)**	(0.0128)**	-0.2588	-0.1347	-0.3745	(0.0415)**	(0.0720)*
Crit value	-3.4553	-3.4271	-2.8724	-3.4271	-2.8724	-3.1369	-2.5724	-3.1364	-2.8725	-3.1369
	1% level	5% level	5% level	5% level	5% level	10% level	10% level	10% level	5% level	10% level

		Germany		Italy		Spain		Sweden
	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept
t-Statistic	-3.5765	-3.5755	-2.146	-2.6658	-3.0424	-3.6733	-2.6524	-2.6469
	(0.0069)***	(0.0339)**	-0.227	-0.2518	(0.0323)**	(0.0258)**	(0.0839)*	-0.26
Crit value	-3.4552	-3.4271	-2.5724	-3.1364	-2.8719	-3.4264	-2.5726	-3.1368
	1% level	5% level	10% level	10% level	5% level	5% level	10% level	10% level

This table shows the results of the Augmented Dickey-Fuller (ADF) test for Inflation for various countries.
*** Significant at 1%, ** Significant at 5%, * Significant at 10%. The parenthesis represents the standard errors.

Table 2.7: ADF Test for Output

	Norway		Canada		Mexico		UK		US	
	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept
t-Statistic	-12.2054	-12.1778	-15.4268	-15.4139	-19.5411	-19.7281	-9.3778	-9.372	-4.27557	-4.32445
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
Crit value	-3.4544	-3.9923	-3.4541	-3.9919	-3.4541	-3.9919	-3.4542	-3.992	-3.4544	-3.9923
	1% level	1% level	1% level	1% level	1% level	1% level	1% level	1% level	1% level	1% level

	Germany		Italy		Spain		Sweden	
	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept
t-Statistic	-6.8465	-6.8879	-20.2647	-20.249	-7.6599	-10.5293	-4.44999	-4.44153
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
Crit value	-3.4543	-3.9922	-3.4541	-3.9919	-3.4543	-3.992	-3.4554	-3.9937
	1% level	1% level	1% level	1% level	1% level	1% level	1% level	1% level

This table shows the results of the Augmented Dickey-Fuller (ADF) test for Output for various countries.
*** Significant at 1%, ** Significant at 5%, * Significant at 10%. The parenthesis represents the standard errors.

Table 2.8: Philip Perron Test for Crude Oil Trade Balance

	Norway		Canada		Mexico		UK		US	
	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept
t-Statistic	-26.0325	-25.9850	-22.3531	-23.0122	-20.4733	-20.4691	-28.1594	-28.1428	-15.6378	-15.6897
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
Crit value	-3.4541	-3.9919	-3.4541	-3.9919	-3.4541	-3.9919	-3.4541	-3.9919	-3.4541	-3.9919
	1% level	1% level	1% level	1% level	1% level	1% level	1% level	1% level	1% level	1% level
	Germany		Italy		Spain		Sweden			
	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept		
t-Statistic	-25.5597	-26.1862	-21.1227	-21.1938	-11.1946	-11.1801	-31.2619	-31.2057		
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***		
Crit value	-3.4541	-3.9919	-3.4541	-3.9919	-3.4541	-3.9919	-3.4541	-3.9919		
	1% level	1% level	1% level	1% level	1% level	1% level	1% level	1% level		

This table shows the results of the Philip Perron test for Crude Oil Trade Balance for various countries.
*** Significant at 1%, ** Significant at 5%, * Significant at 10%. The parenthesis represents the standard errors.

Table 2.9: Philip Perron Test for REER

	Norway		Canada		Mexico		UK		US	
	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept
t-Statistic	-12.2969	-12.2764	-13.2902	-13.2846	-13.1551	-13.1618	-15.6379	-15.6190	-11.0061	-10.9879
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
Crit value	-3.4541	-3.9919	-3.4541	-3.9919	-3.4541	-3.9919	-3.4541	-3.9919	-3.4541	-3.9919
	1% level	1% level	1% level	1% level	1% level	1% level	1% level	1% level	1% level	1% level
	Germany		Italy		Spain		Sweden			
	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept		
t-Statistic	-12.8657	-12.8386	-13.4857	-13.4904	-12.8100	-12.8566	-13.2793	-13.2555		
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***		
Crit value	-3.4541	-3.9919	-3.4541	-3.9919	-3.4541	-3.9919	-3.4541	-3.9919		
	1% level	1% level	1% level	1% level	1% level	1% level	1% level	1% level		

This table presents the results of the Philip Perron test for Real Effective Exchange Rate (REER) for various countries.
*** Significant at 1%, ** Significant at 5%, * Significant at 10%. The parenthesis represents the standard errors.

Table 2.10: Philip Perron Test for Policy Rate

	Norway		Canada		Mexico		UK		US	
	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept
t-Statistic	-12.4462	-12.4298	-9.1300	-9.1222	-13.0013	-13.0205	-8.6982	-8.6882	-8.8817	-8.8754
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
Crit value	-3.4541	-3.9919	-3.4541	-3.9919	-3.4541	-3.9919	-3.4541	-3.9919	-3.4541	-3.9919
	1% level	1% level	1% level	1% level	1% level	1% level	1% level	1% level	1% level	1% level

	Germany		Italy		Spain		Sweden	
	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept
t-Statistic	-6.9845	-6.8202	-6.9845	-6.8202	-6.9845	-6.8202	-15.7560	-15.7716
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
Crit value	-3.4541	-3.9919	-3.4541	-3.9919	-3.4541	-3.9919	-3.4541	-3.9919
	1% level	1% level	1% level	1% level	1% level	1% level	1% level	1% level

This table shows the results of the Philip Perron test for Policy Rate for various countries.
*** Significant at 1%, ** Significant at 5%, * Significant at 10%. The parenthesis represents the standard errors.

Table 2.11: Philip Perron Test for Inflation

	Norway		Canada		Mexico		UK		US	
	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept
t-Statistic	-4.1779	-4.1700	-4.4973	-4.5125	-4.9083	-4.2157	-2.5215	-2.5291	-3.6081	-3.6776
	(0.0009)***	(0.0056)***	(0.0003)***	(0.0017)***	(0.0000)***	(0.0048)***	(0.1115)	(0.3139)	(0.0062)***	(0.0255)**
Crit value	-3.4541	-3.9919	-3.4541	-3.9919	-3.4541	-3.9919	-2.5724	-3.1364	-3.4541	-3.4263
	1% level	1% level	1% level	1% level	1% level	1% level	10% level	10% level	1% level	5% level

	Germany		Italy		Spain		Sweden	
	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept
t-Statistic	-3.6721	-3.6665	-2.5035	-3.0708	-2.6796	-3.2109	-3.4041	-3.3871
	(0.0050)***	(0.0263)**	(0.1157)	(0.1155)	(0.0789)**	(0.0844)**	(0.0116)**	(0.0552)*
Crit value	-3.4541	-3.4263	-2.5724	-3.1364	-2.5724	-3.1364	-2.8719	-3.1364
	1% level	5% level	10% level	10% level	10% level	10% level	5% level	10% level

This table shows the results of the Philip Perron test for Inflation for various countries.
*** Significant at 1%, ** Significant at 5%, * Significant at 10%. The parenthesis represents the standard errors.

Table 2.12: Philip Perron Test for Output

	Norway		Canada		Mexico		UK		US	
	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept
t-Statistic	-43.2495	-43.1319	-15.6563	-15.6433	-19.2730	-19.4374	-15.4607	-15.4481	-15.0558	-15.1467
	(0.0001)***	(0.0001)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
Crit value	-3.4541	-3.9919	-3.4541	-3.9919	-3.4541	-3.9919	-3.4541	-3.9919	-3.4541	-3.9919
	1% level	1% level	1% level	1% level	1% level	1% level	1% level	1% level	1% level	1% level
	Germany		Italy		Spain		Sweden			
	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept		
t-Statistic	-18.9846	-19.0070	-19.9583	-19.9460	-18.5883	-18.6111	-35.1718	-35.0612		
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***	(0.0001)***	(0.0000)***		
Crit value	-3.4541	-3.9919	-3.4541	-3.9919	-3.4541	-3.9919	-3.4541	-3.9919		
	1% level	1% level	1% level	1% level	1% level	1% level	1% level	1% level		

This table shows the results of the Philip Perron test for Output for various countries.

*** Significant at 1%, ** Significant at 5%, * Significant at 10%. The parenthesis represents the standard errors.

Table 2.13: KPSS Test for Crude Oil Trade Balance

	Norway		Canada		Mexico		UK		US	
	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept
LM-Stat	0.0451	0.0469	0.5454	0.0726	0.1084	0.0556	0.1042	0.0768	0.3763	0.0779
Crit value	0.7390	0.1190	0.7390	0.1190	0.3470	0.1190	0.3470	0.1190	0.4630	0.1190
	10% level	10% level	1% level	10% level	10% level	10% level	10% level	10% level	5% level	10% level

	Germany		Italy		Spain		Sweden	
	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept
LM-Stat	0.2531	0.0343	0.0722	0.0400	0.1073	0.0626	0.0754	0.0768
Crit value	0.3470	0.1190	0.3470	0.1190	0.3470	0.1190	0.3470	0.1190
	10% level	10% level	10% level	10% level	10% level	10% level	10% level	10% level

This table shows the results of the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test for Crude Oil Trade Balance for various countries.
*** Significant at 1%, ** Significant at 5%, * Significant at 10%. The parenthesis represents the standard errors.

Table 2.14: KPSS Test for REER

	Norway		Canada		Mexico		UK		US	
	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept
LM-Stat	0.1069	0.0458	0.1529	0.0916	0.1761	0.0601	0.0910	0.0758	0.1328	0.1246
Crit value	0.3470	0.1190	0.3470	0.1190	0.3470	0.1190	0.3470	0.1190	0.3470	0.1460
	10% level	10% level	10% level	10% level	10% level	10% level	10% level	10% level	10% level	5% level

	Germany		Italy		Spain		Sweden	
	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept
LM-Stat	0.3470	0.1190	0.3470	0.1190	0.3470	0.1190	0.3470	0.1190
Crit value	0.7390	0.2160	0.7390	0.2160	0.7390	0.2160	0.7390	0.2160
	10% level	10% level	10% level	10% level	10% level	10% level	10% level	10% level

This table presents the results of the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test for Real Effective Exchange Rate (REER) for various countries.
*** Significant at 1%, ** Significant at 5%, * Significant at 10%. The parenthesis represents the standard errors.

Table 2.15: KPSS Test for Policy Rate

	Norway		Canada		Mexico		UK		US	
	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept
LM-Stat	0.0829	0.0781	0.0653	0.0530	0.1739	0.0474	0.0862	0.0771	0.2110	0.0880
Crit value	0.3470	0.1190	0.3470	0.1190	0.3470	0.1190	0.3470	0.1190	0.3470	0.1190
	10% level	10% level	10% level	10% level	10% level	10% level	10% level	10% level	10% level	10% level
	Germany		Italy		Spain		Sweden			
	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept		
LM-Stat	0.0660	0.0481	0.0660	0.0481	0.0660	0.0481	0.1186	0.0354		
Crit value	0.3470	0.1190	0.3470	0.1190	0.3470	0.1190	0.3470	0.1190		
	10% level	10% level	10% level	10% level	10% level	10% level	10% level	10% level		

This table shows the results of the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test for Policy Rate for various countries.
*** Significant at 1%, ** Significant at 5%, * Significant at 10%. The parenthesis represents the standard errors.

Table 2.16: KPSS Test for Inflation

	Norway		Canada		Mexico		UK		US	
	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept
LM-Stat	0.1048	0.1049	0.1979	0.0814	1.0374	0.3445	0.3147	0.2041	0.3581	0.0854
Crit value	0.3470	0.1190	0.3470	0.1190	0.7390	0.2160	0.3470	0.2160	0.4630	0.1190
	10% level	10% level	10% level	10% level	1% level	1% level	10% level	1% level	5% level	10% level
	Germany		Italy		Spain		Sweden			
	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept		
LM-Stat	0.3470	0.1190	0.7435	0.1606	0.8575	0.1469	0.3470	0.1190		
Crit value	0.7390	0.2160	0.7390	0.2160	0.7390	0.2160	0.7390	0.2160		
	10% level	10% level	1% level	1% level	1% level	1% level	10% level	10% level		

This table shows the results of the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test for Inflation for various countries.
*** Significant at 1%, ** Significant at 5%, * Significant at 10%. The parenthesis represents the standard errors.

Table 2.17: KPSS Test for Output

	Norway		Canada		Mexico		UK		US	
	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept
LM-Stat	0.3470	0.1190	0.3470	0.1109	0.2644	0.0604	0.1427	0.1329	0.3470	0.1190
Crit value	0.7390	0.2160	0.7390	0.1460	0.7390	0.2160	0.7390	0.1460	0.7390	0.2160
	10% level	10% level	10% level	5% level	10% level	10% level	10% level	5% level	10% level	10% level

	Germany		Italy		Spain		Sweden	
	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept
LM-Stat	0.3470	0.1190	0.3470	0.1190	0.3470	0.1669	0.3470	0.1190
Crit value	0.7390	0.2160	0.7390	0.2160	0.7390	0.2160	0.7390	0.2160
	10% level	10% level	10% level	10% level	10% level	1% level	10% level	10% level

This table shows the results of the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test for Output for various countries.
*** Significant at 1%, ** Significant at 5%, * Significant at 10%. The parenthesis represents the standard errors.

2.8 Appendix B

Robustness Tests and Additional Results

In this section, we analyse the generalised impulse response functions generated by VAR models with 6 lags (Figures 2.31 - 2.48) and VAR models with the number of lags suggested by the information criteria (Figures 2.49 - 2.66), both in response to one-standard-deviation shocks. This section is considered a robustness test since we are mainly focused on potential discrepancies that different lag specifications might show to the main findings presented in the previous section. From an overall analysis, the two other sets of models confirme the main finding. Among all the VAR specifications, VAR(12) is the one that was able to incorporate more details in the propagation of the shocks over a longer period of time. VAR(6) manages to accurately capture most of the effect until 6-8 months after the shock tending to neglect the long-term effect of the shocks. This is more pronounced in the IRF generated by the VAR specification recommended by the IC. In this case, the effect of the shock dies away generally after three to six months. In other words, the fewer lags considered in the VAR, the less accurate the model shows over the longer period.

VAR(6) — Impulse responses

In this section, we employ a VAR(6) model, which incorporates six months of lags to analyse the dynamics of the data. Consistent with the main analysis, we use two different VAR(6) models: one model includes two exogenous variables, and the other model includes a single exogenous variable. Figures 2.31 through 2.39 display the IRFs over the next 12 months for the model with two exogenous variables. Similarly, Figures 2.40 through 2.48 present the IRFs for the model with one exogenous variable.

Figure 2.31: VAR(6) with 2 Exogenous Variables — Norway

The figure displays the impulse response functions for Norway using a VAR(6) model with two exogenous variables. The responses of various economic indicators to shocks in the selected variables are shown, with confidence intervals.

Figure 2.32: VAR(6) with 2 Exogenous Variables — Canada

The figure displays the impulse response functions for Canada using a VAR(6) model with two exogenous variables. The responses of various economic indicators to shocks in the selected variables are shown, with confidence intervals.

Figure 2.33: VAR(6) with 2 Exogenous Variables — Mexico

The figure displays the impulse response functions for Mexico using a VAR(6) model with two exogenous variables. The responses of various economic indicators to shocks in the selected variables are shown, with confidence intervals.

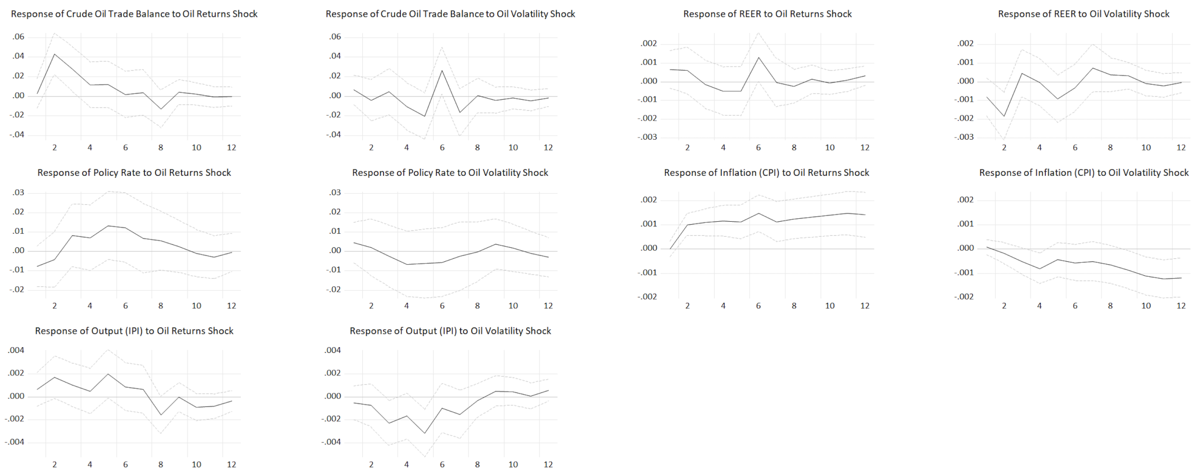
Figure 2.34: VAR(6) with 2 Exogenous Variables — UK

The figure displays the impulse response functions for the UK using a VAR(6) model with two exogenous variables. The responses of various economic indicators to shocks in the selected variables are shown, with confidence intervals.

Figure 2.35: VAR(6) with 2 Exogenous Variables — US

The figure displays the impulse response functions for the US using a VAR(6) model with two exogenous variables. The responses of various economic indicators to shocks in the selected variables are shown, with confidence intervals.

Figure 2.36: VAR(6) with 2 Exogenous Variables — Germany



The figure displays the impulse response functions for Germany using a VAR(6) model with two exogenous variables. The responses of various economic indicators to shocks in the selected variables are shown, with confidence intervals.

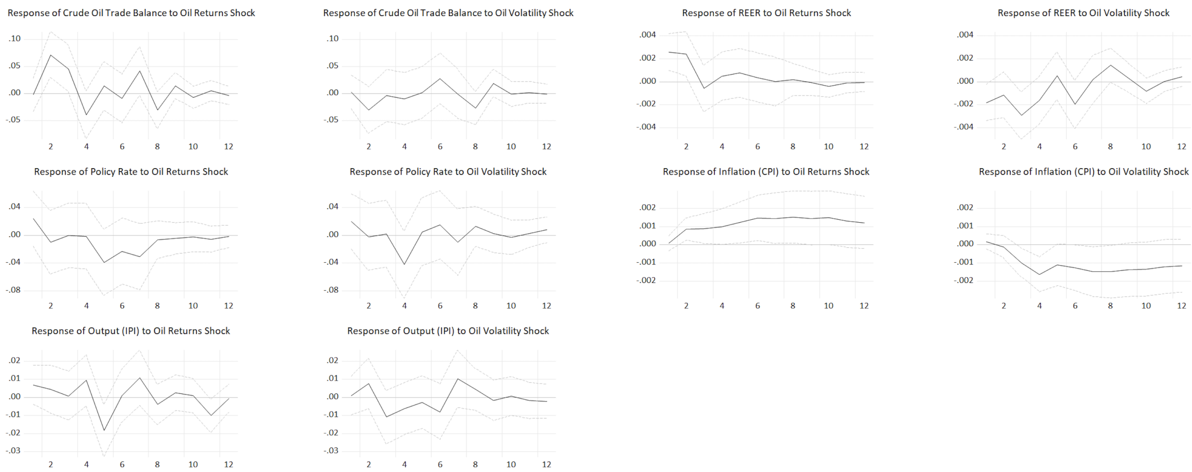
Figure 2.37: VAR(6) with 2 Exogenous Variables — Italy

The figure displays the impulse response functions for Italy using a VAR(6) model with two exogenous variables. The responses of various economic indicators to shocks in the selected variables are shown, with confidence intervals.

Figure 2.38: VAR(6) with 2 Exogenous Variables — Spain

The figure displays the impulse response functions for Spain using a VAR(6) model with two exogenous variables. The responses of various economic indicators to shocks in the selected variables are shown, with confidence intervals.

Figure 2.39: VAR(6) with 2 Exogenous Variables — Sweden

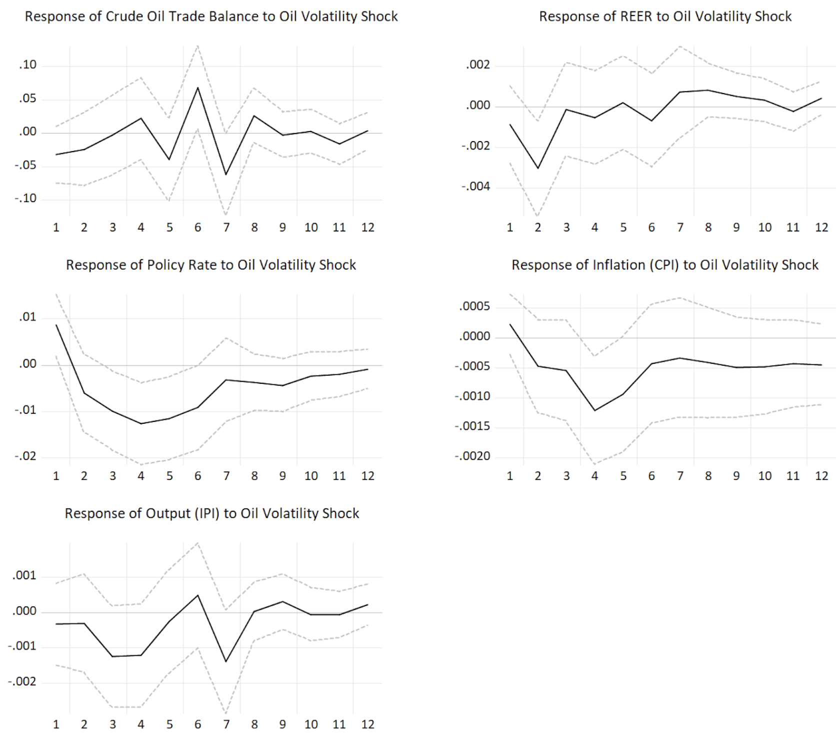


The figure displays the impulse response functions for Sweden using a VAR(6) model with two exogenous variables. The responses of various economic indicators to shocks in the selected variables are shown, with confidence intervals.

Figure 2.40: VAR(6) with 1 Exogenous Variable — Norway

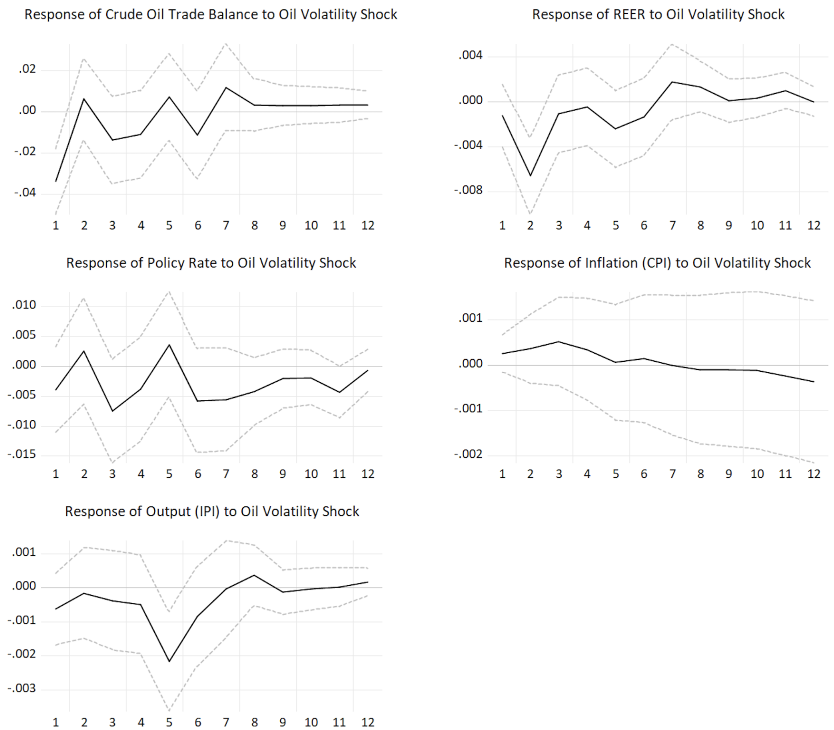
The figure displays the impulse response functions for Norway using a VAR(6) model with one exogenous variable. The responses of various economic indicators to shocks in the selected variable are shown, with confidence intervals.

Figure 2.41: VAR(6) with 1 Exogenous Variable — Canada



The figure displays the impulse response functions for Canada using a VAR(6) model with one exogenous variable. The responses of various economic indicators to shocks in the selected variable are shown, with confidence intervals.

Figure 2.42: VAR(6) with 1 Exogenous Variable — Mexico

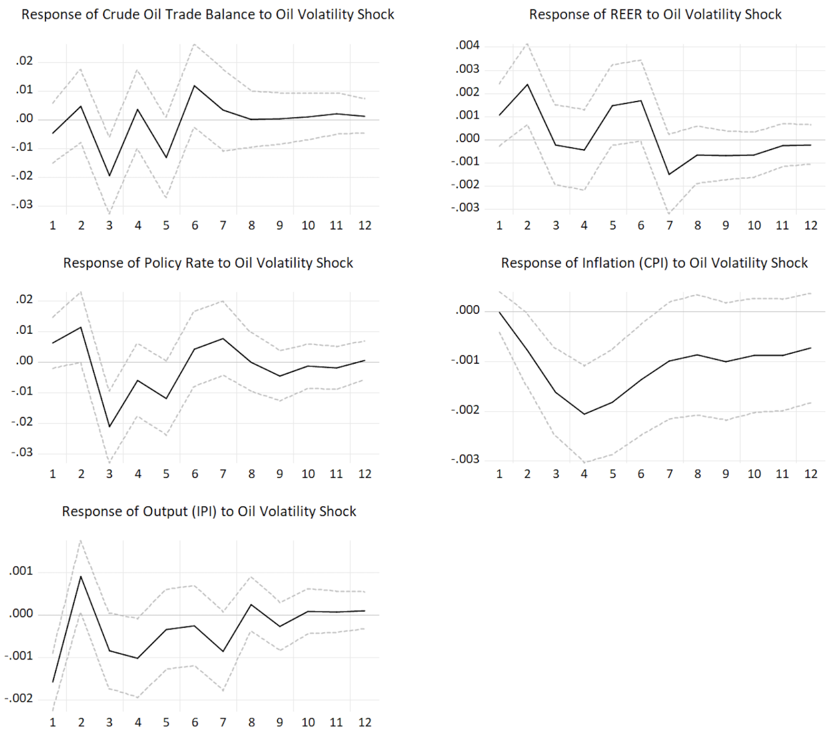


The figure displays the impulse response functions for Mexico using a VAR(6) model with one exogenous variable. The responses of various economic indicators to shocks in the selected variable are shown, with confidence intervals.

Figure 2.43: VAR(6) with 1 Exogenous Variable — UK

The figure displays the impulse response functions for the UK using a VAR(6) model with one exogenous variable. The responses of various economic indicators to shocks in the selected variable are shown, with confidence intervals.

Figure 2.44: VAR(6) with 1 Exogenous Variable — US

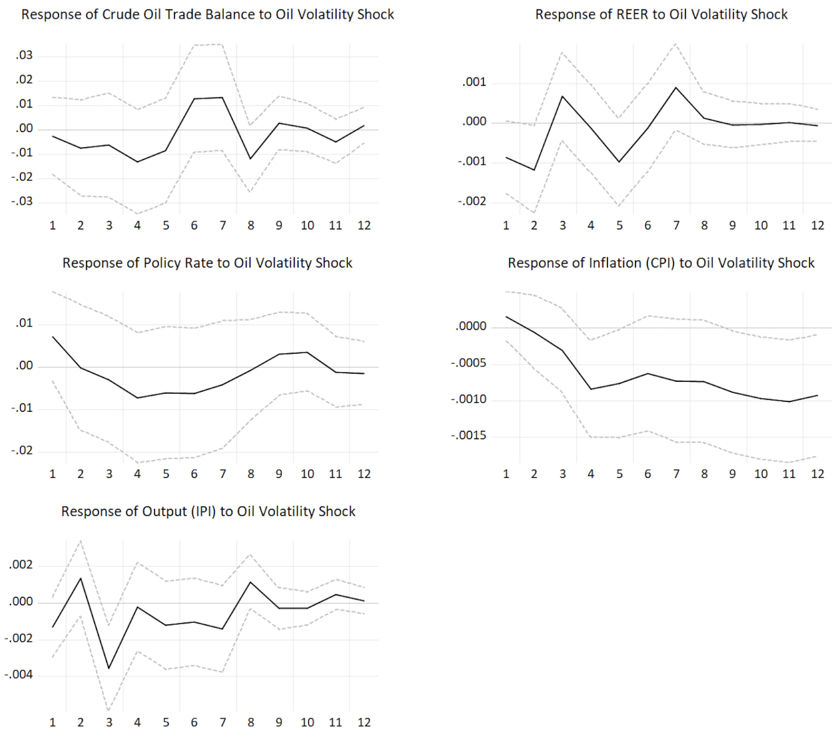


The figure displays the impulse response functions for the US using a VAR(6) model with one exogenous variable. The responses of various economic indicators to shocks in the selected variable are shown, with confidence intervals.

Figure 2.45: VAR(6) with 1 Exogenous Variable — Germany

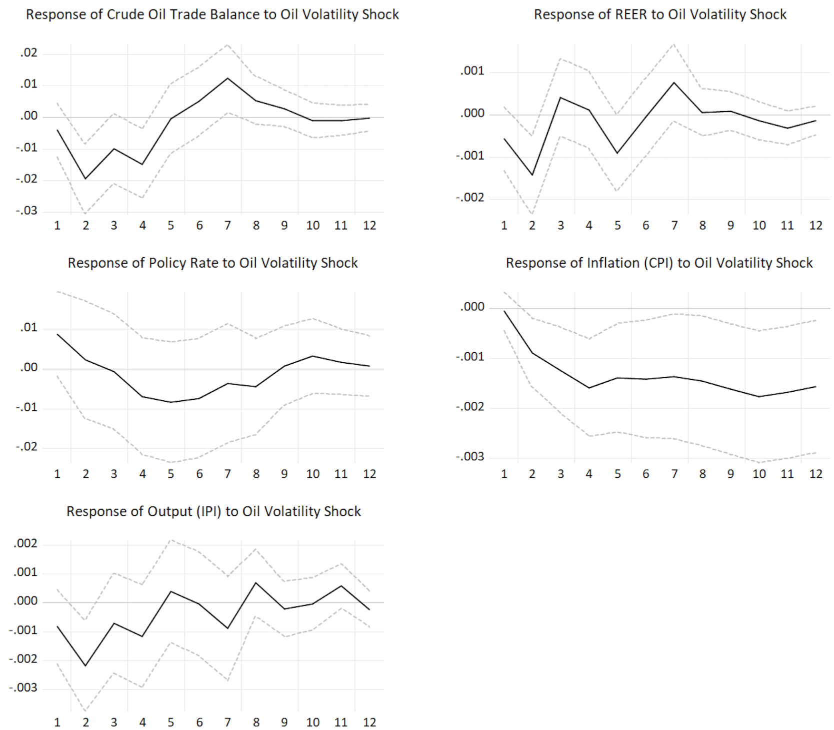
The figure displays the impulse response functions for Germany using a VAR(6) model with one exogenous variable. The responses of various economic indicators to shocks in the selected variable are shown, with confidence intervals.

Figure 2.46: VAR(6) with 1 Exogenous Variable — Italy



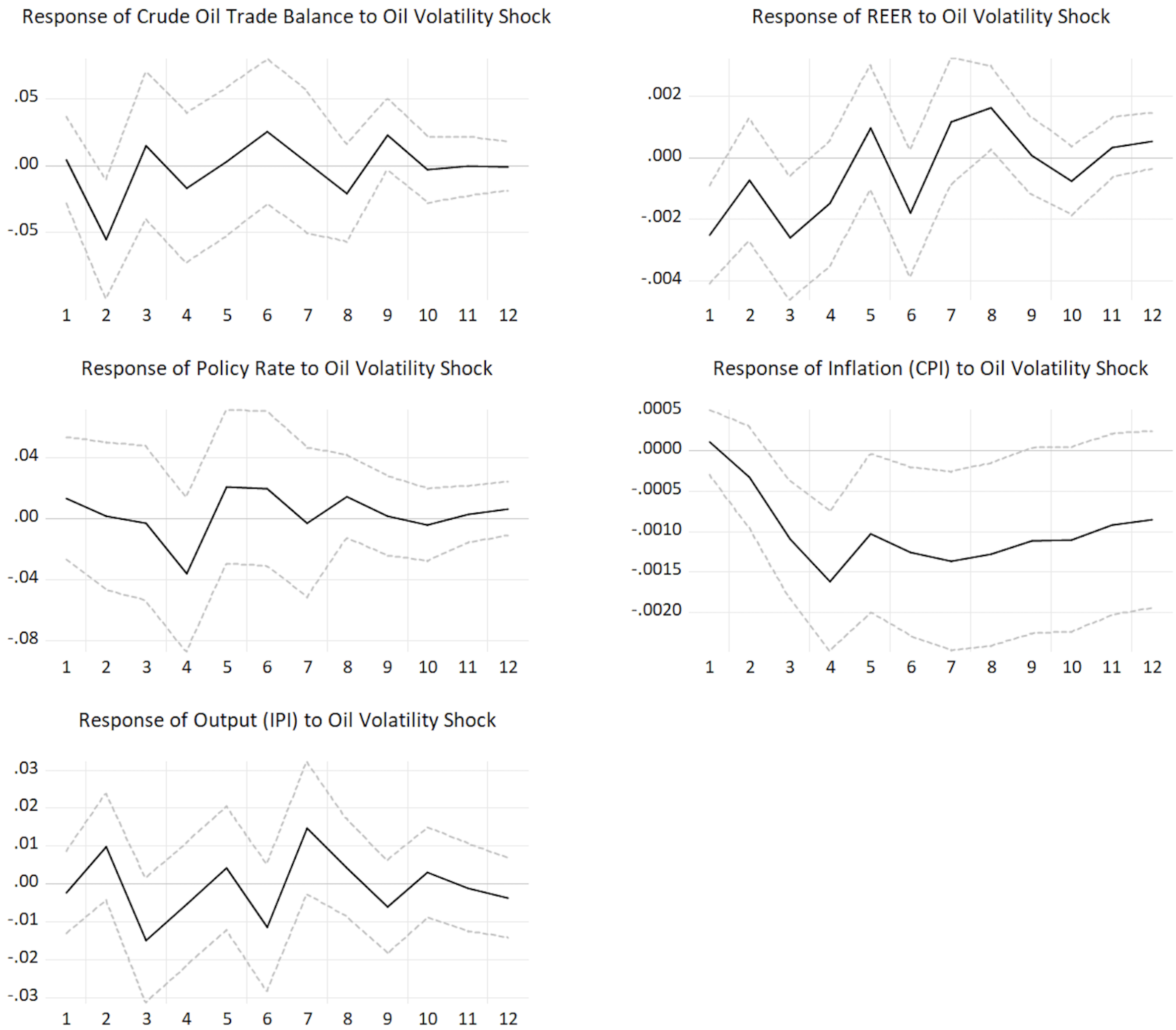
The figure displays the impulse response functions for Italy using a VAR(6) model with one exogenous variable. The responses of various economic indicators to shocks in the selected variable are shown, with confidence intervals.

Figure 2.47: VAR(6) with 1 Exogenous Variable — Spain



The figure displays the impulse response functions for Spain using a VAR(6) model with one exogenous variable. The responses of various economic indicators to shocks in the selected variable are shown, with confidence intervals.

Figure 2.48: VAR(6) with 1 Exogenous Variable — Sweden



The figure displays the impulse response functions for Sweden using a VAR(6) model with one exogenous variable. The responses of various economic indicators to shocks in the selected variable are shown, with confidence intervals.

VAR(p) — Impulse responses

To determine the optimal lag length for the two VAR(p) models utilised in this analysis — one including two exogenous variables and the other with a single exogenous variable — we employ three established information criteria: the Akaike (1974) Information Criterion (AIC), the Schwarz (1978) Information Criterion (SIC), and the Hannan and Quinn (1979) Criterion (HQ). These criteria assess the trade-off between model fit and complexity, aiming to identify the model that offers the best predictive performance while avoiding overfitting. The impulse response functions (IRFs) for the VAR model with two exogenous variables are shown in Figures 2.49 through 2.57, while Figures 2.58 through 2.66 present the IRFs for the model with one exogenous variable.

The AIC seeks to minimise information loss by selecting a model that achieves an optimal balance between fit and the number of parameters used. The SIC, also referred to as the Bayesian Information Criterion (BIC), imposes a stronger penalty for the inclusion of additional parameters, thus favouring more parsimonious models. This makes the SIC more conservative in terms of model complexity compared to the AIC. Lastly, the HQ criterion offers a middle ground between the AIC and SIC by applying a penalty that increases at a rate slower than that of the SIC but faster than the AIC.

The results of the information criteria for the VAR(p) model with two exogenous variables are presented in Table 2.18, while Table 2.19 displays the information criteria for the VAR(p) model with one exogenous variable. After applying these criteria, we used the Schwarz Information Criterion (SIC) to determine the optimal lag length. The choice of SIC is justified by its known robustness in selecting parsimonious models, which is particularly valuable in macroeconomic and financial applications where overfitting can lead to misleading inferences. Studies such as those by Ng and Perron (2001) and Neely et al. (2014) demonstrate that SIC performs well in selecting the correct lag length in various time series contexts, especially when sample sizes are relatively large, as is the case in our analysis.

The results of our analysis, using the SIC, indicate that a VAR(p) model with one lag provides the best fit for both models across each country. This choice ensures that our models are both parsimonious and capable of capturing the essential dynamics of the underlying data, thereby enhancing the reliability of our results.

Table 2.18: Information Criteria for VAR(p) with 2 Exogenous Variables

	Norway			Canada			Mexico		
Lag	AIC	SIC	HQ	AIC	SC	HQ	AIC	SC	HQ
0	-27.15339	-27.05909	-27.11551	-27.12388	-27.02958	-27.086	-26.08285	-25.98854	-26.04496
1	-29.40684	-28.65242*	-29.10376*	-29.42766*	-28.67324*	-29.12458*	-31.36006	-30.60564*	-31.05698*
2	-29.59256*	-28.17803	-29.02429	-29.36378	-27.94924	-28.7955	-31.58240*	-30.16786	-31.01413
3	-29.53516	-27.4605	-28.70169	-29.28057	-27.20592	-28.4471	-31.49296	-29.4183	-30.65949
4	-29.42869	-26.69392	-28.33003	-29.23503	-26.50026	-28.13637	-31.44819	-28.71342	-30.34953
5	-29.27768	-25.88279	-27.91382	-29.06489	-25.66999	-27.70103	-31.38308	-27.98819	-30.01922
6	-29.17689	-25.12189	-27.54784	-29.02439	-24.96938	-27.39533	-31.29048	-27.23547	-29.66143
7	-29.03024	-24.31512	-27.13599	-28.91393	-24.19881	-27.01968	-31.18875	-26.47362	-29.2945
8	-28.90877	-23.53353	-26.74933	-28.90616	-23.53091	-26.74671	-31.05216	-25.67692	-28.89272

	UK			US			Germany		
	AIC	SIC	HQ	AIC	SC	HQ	AIC	SC	HQ
0	-26.3787	-26.2844	-26.34082	-30.58477	-30.49047	-30.54689	-28.85492	-28.76061	-28.81703
1	-29.80141	-29.04699*	-29.49833*	-33.58217	-32.82775*	-33.27909	-31.67478	-30.92036*	-31.37170*
2	-29.89773	-28.48319	-29.32946	-34.12158	-32.70704	-33.55330*	-31.87603	-30.46149	-31.30775
3	-29.92409*	-27.84944	-29.09062	-34.16073*	-32.08607	-33.32726	-31.89532*	-29.82066	-31.06185
4	-29.91351	-27.17874	-28.81485	-34.11457	-31.3798	-33.01591	-31.84539	-29.11062	-30.74673
5	-29.75673	-26.36184	-28.39287	-34.00383	-30.60894	-32.63997	-31.7785	-28.38361	-30.41464
6	-29.71847	-25.66346	-28.08941	-34.05263	-29.99762	-32.42357	-31.67504	-27.62003	-30.04598
7	-29.70405	-24.98892	-27.8098	-34.15698	-29.44185	-32.26273	-31.49847	-26.78334	-29.60422
8	-29.63251	-24.25726	-27.47306	-34.05646	-28.68122	-31.89702	-31.61518	-26.23994	-29.45574

	Italy			Spain			Sweden		
	AIC	SIC	HQ	AIC	SC	HQ	AIC	SC	HQ
0	-28.43558	-28.34128	-28.3977	-29.77816	-29.68385	-29.74027	-19.46777	-19.37347	-19.42989
1	-32.04591	-31.29149*	-31.74283*	-34.32093	-33.56651*	-34.01785	-22.2443	-21.48988*	-21.94122*
2	-32.23634	-30.8218	-31.66806	-34.82812*	-33.41358	-34.25984*	-22.38729*	-20.97275	-21.81902
3	-32.26050*	-30.18584	-31.42703	-34.64688	-32.57222	-33.81341	-22.28592	-20.21126	-21.45245
4	-32.158	-29.42322	-31.05933	-34.51575	-31.78098	-33.41708	-22.33059	-19.59581	-21.23192
5	-31.99809	-28.6032	-30.63423	-34.40366	-31.00877	-33.0398	-22.24493	-18.85004	-20.88107
6	-31.96129	-27.90628	-30.33223	-34.41101	-30.35601	-32.78196	-22.19035	-18.13534	-20.56129
7	-31.86408	-27.14895	-29.96983	-34.31721	-29.60208	-32.42296	-22.14238	-17.42725	-20.24813
8	-31.95567	-26.58042	-29.79622	-34.34673	-28.97149	-32.18729	-22.00603	-16.63079	-19.84659

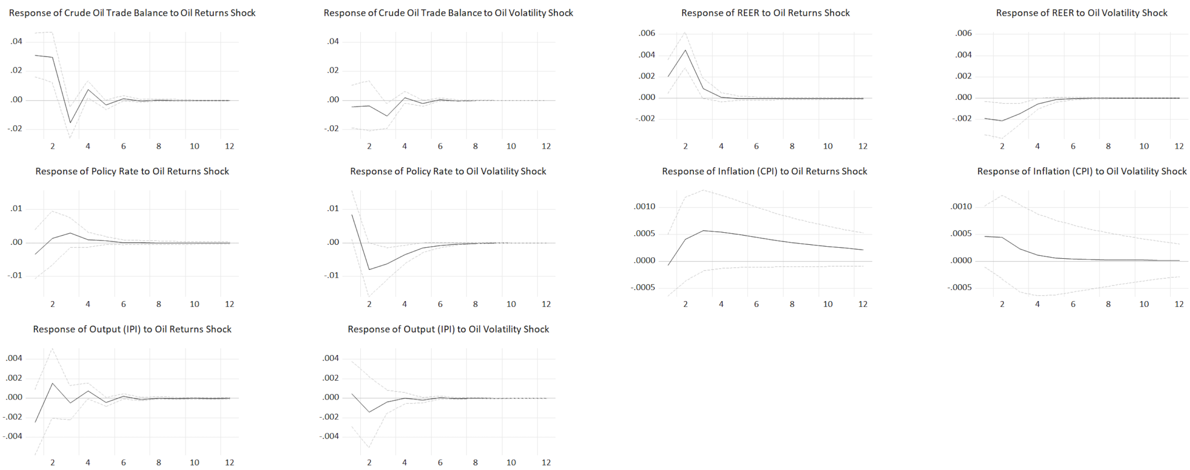
This table presents the information criteria values for determining the optimal lag length in a VAR(p) model with two exogenous variables. The table evaluates up to 8 lags using the three most commonly applied information criteria: Akaike Information Criterion (AIC), Schwarz Information Criterion (SIC), and Hannan-Quinn Criterion (HQ). The values marked with an asterisk ($*$) indicate the lowest values for each criterion, suggesting the optimal lag length according to each respective information criterion.

Table 2.19: Information Criteria for VAR(p) with 1 Exogenous Variable

	Norway			Canada			Mexico		
Lag	AIC	SC	HQ	AIC	SC	HQ	AIC	SIC	HQ
0	-25.34727	-25.26644	-25.3148	-25.34678	-25.26595	-25.31431	-24.30735	-24.22652	-24.27487
1	-27.41458	-26.84876*	-27.18727*	-27.45165*	-26.88584*	-27.22434*	-29.18055	-28.61473*	-28.95324*
2	-27.52522*	-26.47442	-27.10307	-27.40781	-26.35701	-26.98566	-29.33034*	-28.27954	-28.90819
3	-27.46887	-25.93309	-26.85189	-27.38358	-25.8478	-26.7666	-29.21171	-27.67593	-28.59473
4	-27.40118	-25.38041	-26.58936	-27.34396	-25.32319	-26.53213	-29.18321	-27.16244	-28.37139
5	-27.31695	-24.8112	-26.3103	-27.22546	-24.71971	-26.2188	-29.10855	-26.60279	-28.10189
6	-27.23695	-24.24621	-26.03545	-27.19788	-24.20715	-25.99639	-29.05777	-26.06703	-27.85627
7	-27.09323	-23.61751	-25.6969	-27.11009	-23.63436	-25.71375	-28.99268	-25.51696	-27.59635
8	-26.95054	-22.98983	-25.35937	-27.03826	-23.07755	-25.44709	-28.87907	-24.91836	-27.2879
	UK			US			Germany		
	AIC	SIC	HQ	AIC	SC	HQ	AIC	SC	HQ
0	-24.62767	-24.54684	-24.5952	-28.80379	-28.72296	-28.77132	-27.09676	-27.01592	-27.06428
1	-28.05825	-27.49243*	-27.83094*	-31.60392	-31.03811*	-31.37661	-29.76934	-29.20352*	-29.54202*
2	-28.15428	-27.10348	-27.73213	-31.94742	-30.89662	-31.52527*	-29.90004	-28.84924	-29.47789
3	-28.19129*	-26.6555	-27.5743	-31.95666	-30.42088	-31.33968	-29.96014*	-28.42435	-29.34315
4	-28.18942	-26.16866	-27.3776	-31.96635*	-29.94558	-31.15453	-29.93988	-27.91911	-29.12806
5	-28.02334	-25.51758	-27.01668	-31.81249	-29.30673	-30.80583	-29.85051	-27.34475	-28.84385
6	-28.01875	-25.02802	-26.81726	-31.85694	-28.8662	-30.65545	-29.75483	-26.76409	-28.55333
7	-27.98441	-24.50868	-26.58807	-31.93724	-28.46152	-30.54091	-29.62848	-26.15276	-28.23215
8	-27.89272	-23.93201	-26.30155	-31.87246	-27.91176	-30.28129	-29.6568	-25.69609	-28.06563
	Italy			Spain			Sweden		
	AIC	SIC	HQ	AIC	SC	HQ	AIC	SC	HQ
0	-26.67847	-26.59764	-26.64599	-27.98951	-27.90868	-27.95703	-17.67648	-17.59565	-17.64401
1	-30.08449	-29.51868*	-29.85718*	-31.97354	-31.40773*	-31.74623*	-20.38578	-19.81996*	-20.15847*
2	-30.15558*	-29.10478	-29.73343	-32.03699*	-30.9862	-31.61485	-20.54237	-19.49157	-20.12023
3	-30.11228	-28.57649	-29.49529	-31.91823	-30.38245	-31.30125	-20.46729	-18.9315	-19.8503
4	-30.05316	-28.03239	-29.24133	-31.84248	-29.82171	-31.03066	-20.56263*	-18.54187	-19.75081
5	-29.89615	-27.39039	-28.88949	-31.76202	-29.25626	-30.75536	-20.53323	-18.02747	-19.52657
6	-29.87008	-26.87934	-28.66858	-31.75013	-28.75939	-30.54864	-20.48779	-17.49706	-19.2863
7	-29.84538	-26.36965	-28.44904	-31.74082	-28.2651	-30.34448	-20.40695	-16.93123	-19.01062
8	-29.8852	-25.92449	-28.29403	-31.76129	-27.80058	-30.17012	-20.27134	-16.31063	-18.68017

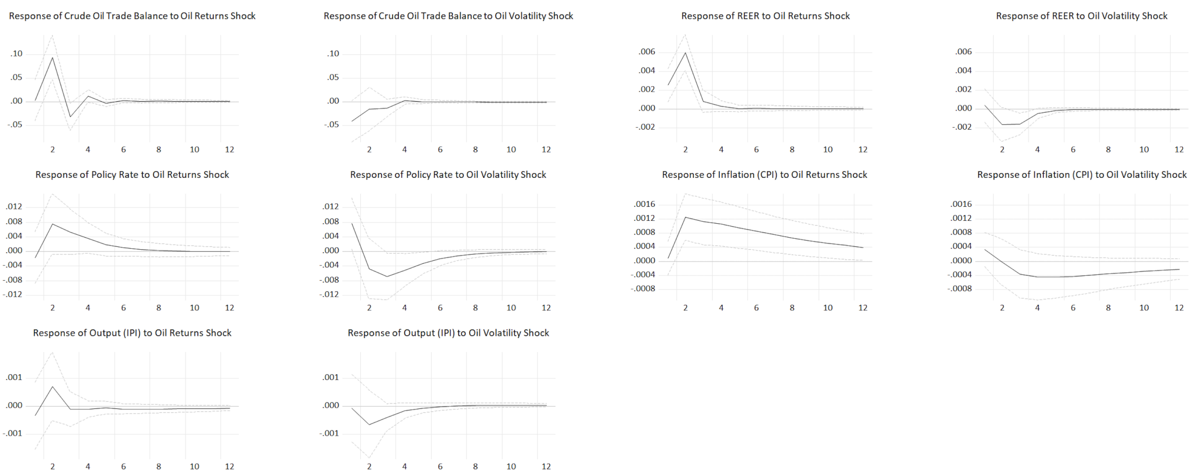
This table presents the information criteria values for determining the optimal lag length in a VAR(p) model with two exogenous variables. The table evaluates up to 8 lags using the three most commonly applied information criteria: Akaike Information Criterion (AIC), Schwarz Information Criterion (SIC), and Hannan-Quinn Criterion (HQ). The values marked with an asterisk (*) indicate the lowest values for each criterion, suggesting the optimal lag length according to each respective information criterion.

Figure 2.49: VAR(p) with 2 Exogenous Variables — Norway



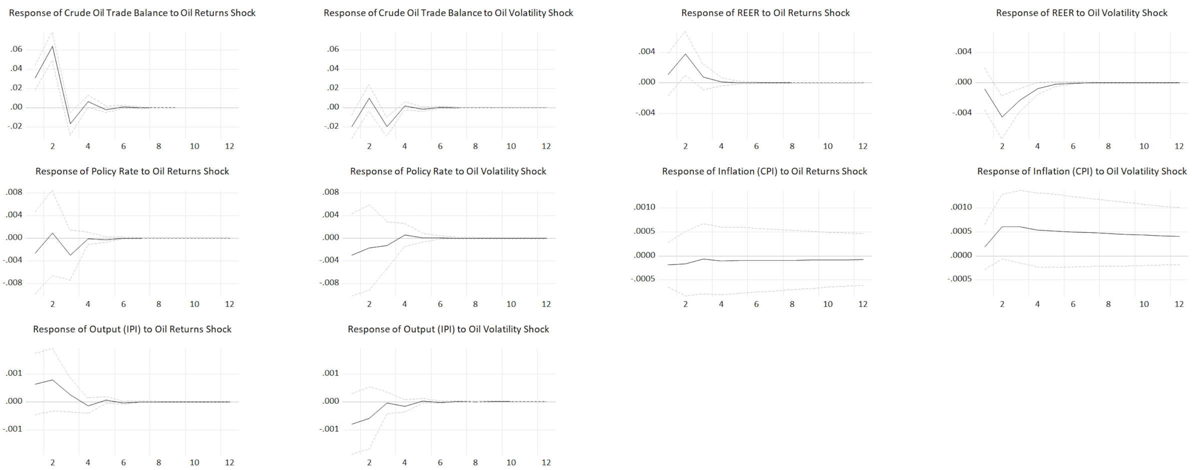
The figure displays the impulse response functions for Norway using a VAR(1) model with two exogenous variables. The lag length of 1 was selected based on the Information Criteria (IC). The responses of various economic indicators to shocks in the selected variables are shown, with confidence intervals.

Figure 2.50: VAR(p) with 2 Exogenous Variables — Canada



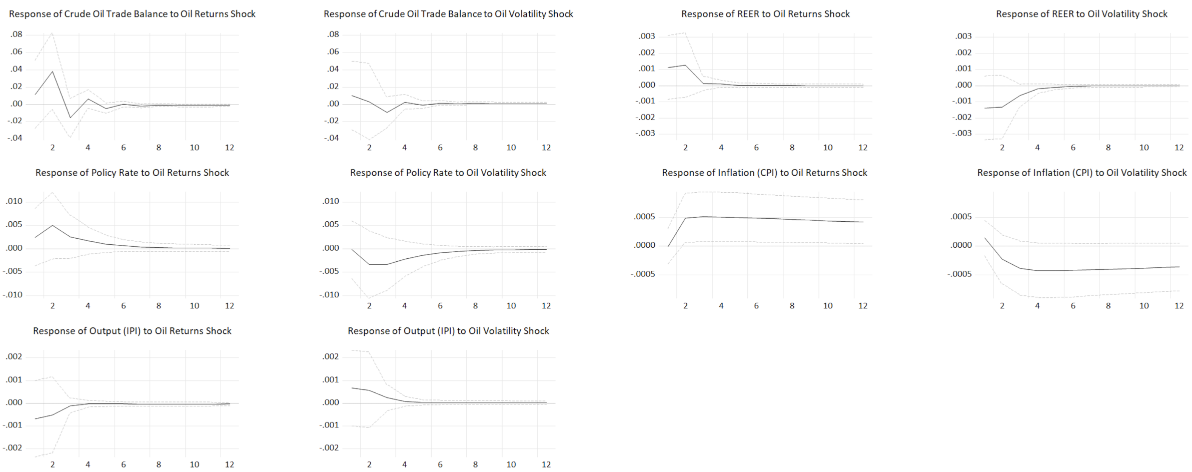
The figure displays the impulse response functions for Canada using a VAR(1) model with two exogenous variables. The lag length of 1 was selected based on the Information Criteria (IC). The responses of various economic indicators to shocks in the selected variables are shown, with confidence intervals.

Figure 2.51: VAR(p) with 2 Exogenous Variables — Mexico



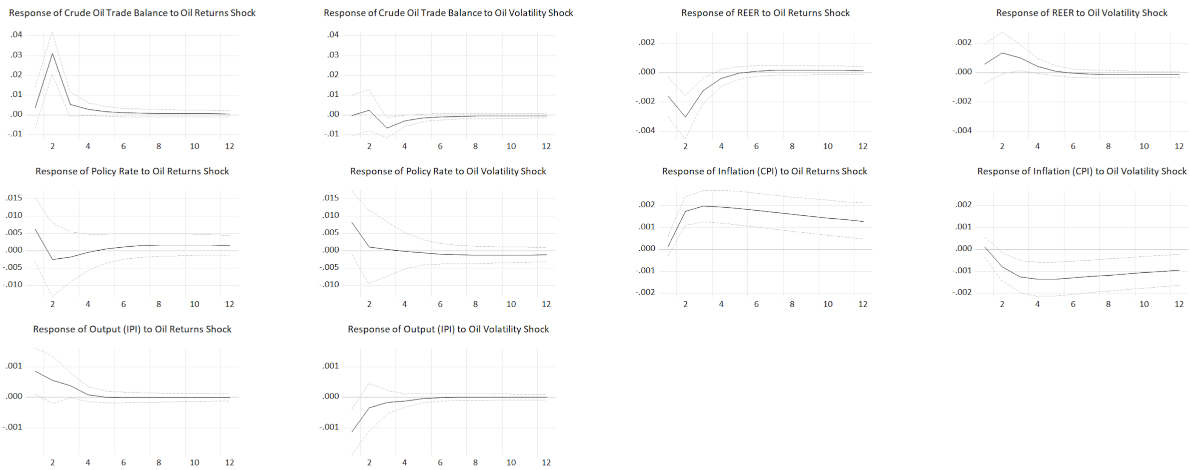
The figure displays the impulse response functions for Mexico using a VAR(1) model with two exogenous variables. The lag length of 1 was selected based on the Information Criteria (IC). The responses of various economic indicators to shocks in the selected variables are shown, with confidence intervals.

Figure 2.52: VAR(p) with 2 Exogenous Variables — UK



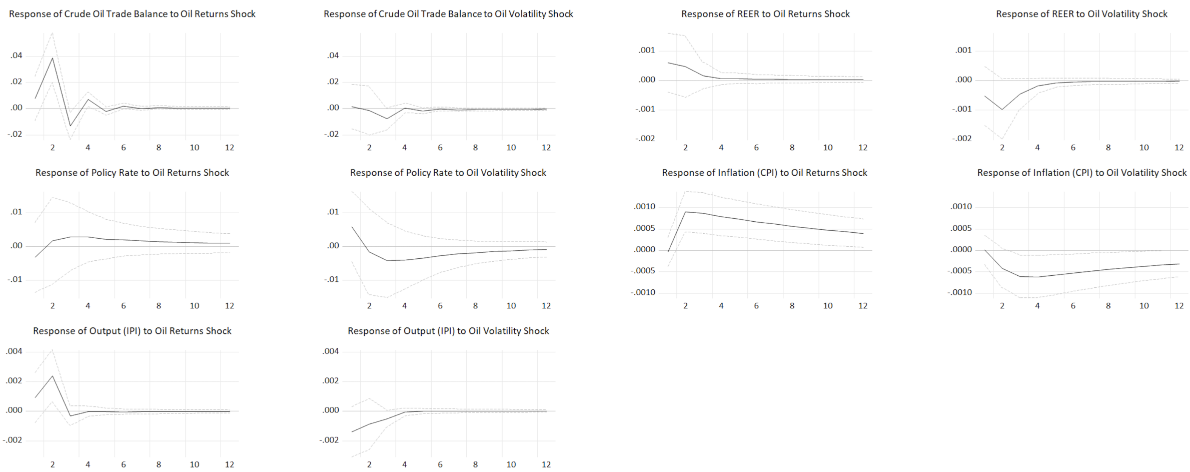
The figure displays the impulse response functions for the UK using a VAR(1) model with two exogenous variables. The lag length of 1 was selected based on the Information Criteria (IC). The responses of various economic indicators to shocks in the selected variables are shown, with confidence intervals.

Figure 2.53: VAR(p) with 2 Exogenous Variables — US



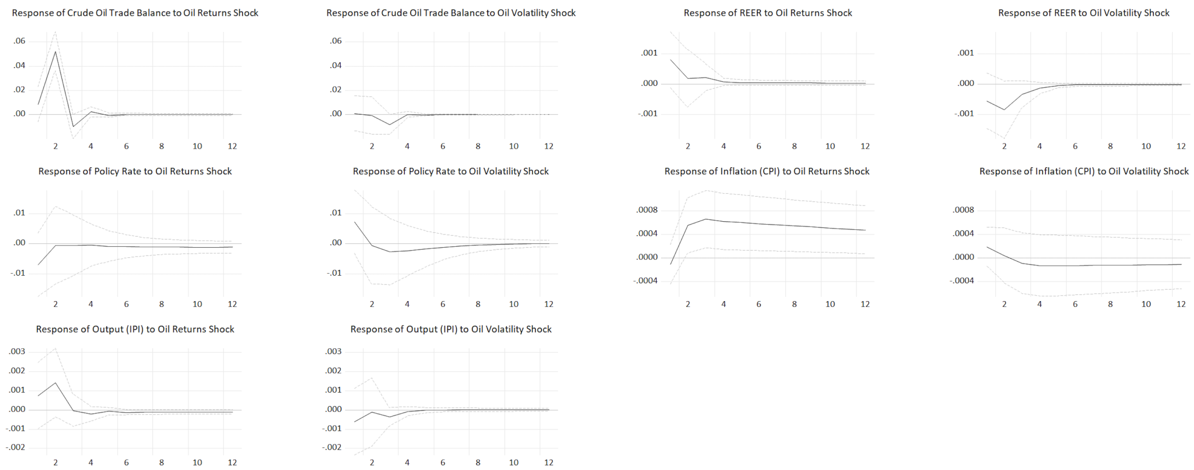
The figure displays the impulse response functions for the US using a VAR(1) model with two exogenous variables. The lag length of 1 was selected based on the Information Criteria (IC). The responses of various economic indicators to shocks in the selected variables are shown, with confidence intervals.

Figure 2.54: VAR(p) with 2 Exogenous Variables — Germany



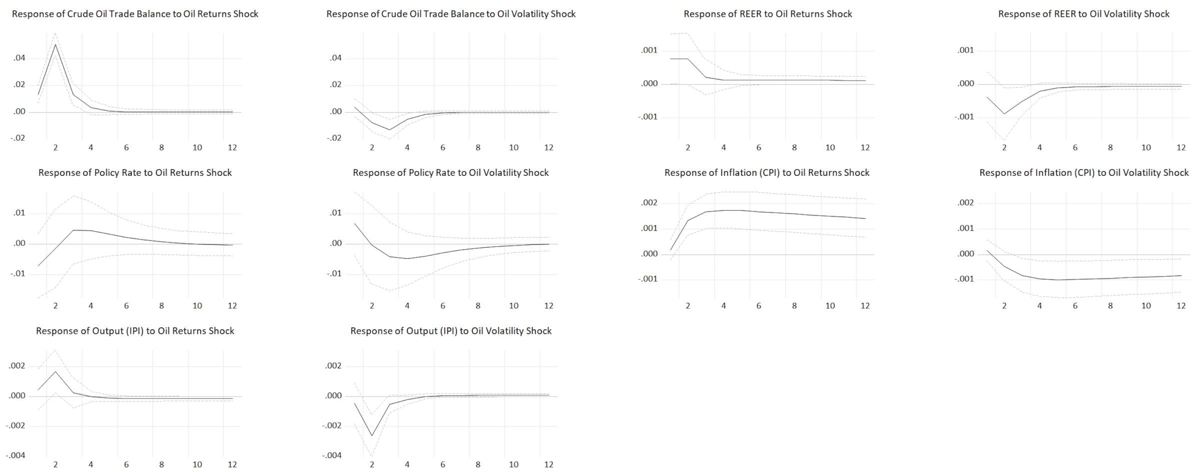
The figure displays the impulse response functions for Germany using a VAR(1) model with two exogenous variables. The lag length of 1 was selected based on the Information Criteria (IC). The responses of various economic indicators to shocks in the selected variables are shown, with confidence intervals.

Figure 2.55: VAR(p) with 2 Exogenous Variables — Italy



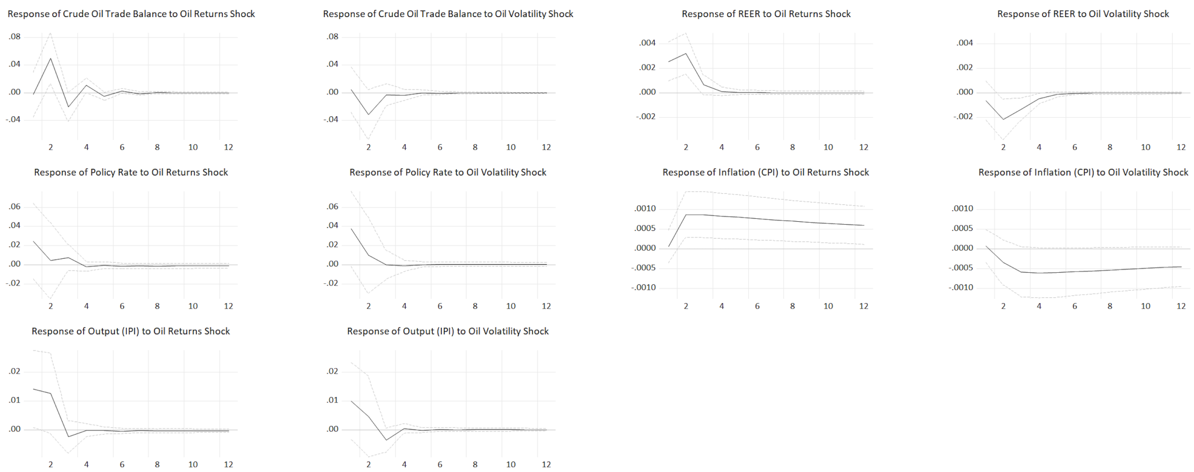
The figure displays the impulse response functions for Italy using a VAR(1) model with two exogenous variables. The lag length of 1 was selected based on the Information Criteria (IC). The responses of various economic indicators to shocks in the selected variables are shown, with confidence intervals.

Figure 2.56: VAR(p) with 2 Exogenous Variables — Spain



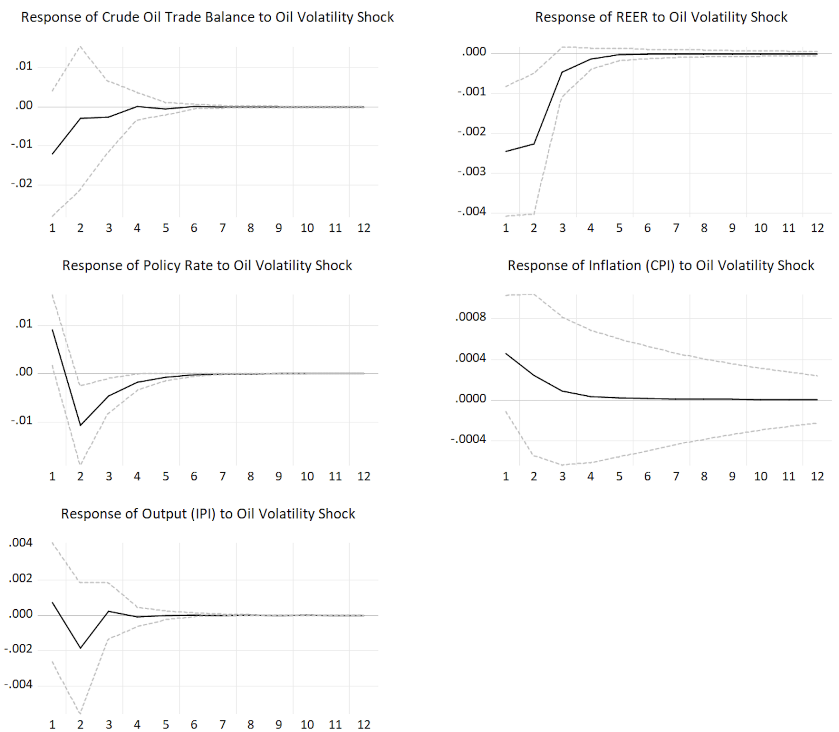
The figure displays the impulse response functions for Spain using a VAR(1) model with two exogenous variables. The lag length of 1 was selected based on the Information Criteria (IC). The responses of various economic indicators to shocks in the selected variables are shown, with confidence intervals.

Figure 2.57: VAR(p) with 2 Exogenous Variables — Sweden



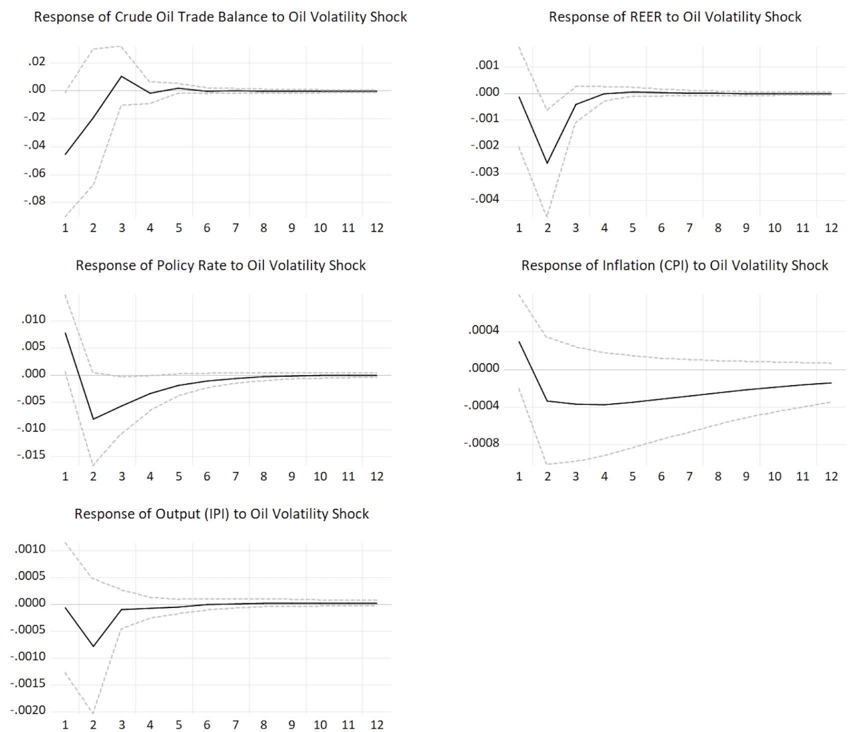
The figure displays the impulse response functions for Sweden using a VAR(1) model with two exogenous variables. The lag length of 1 was selected based on the Information Criteria (IC). The responses of various economic indicators to shocks in the selected variables are shown, with confidence intervals.

Figure 2.58: VAR(p) with 1 Exogenous Variable — Norway



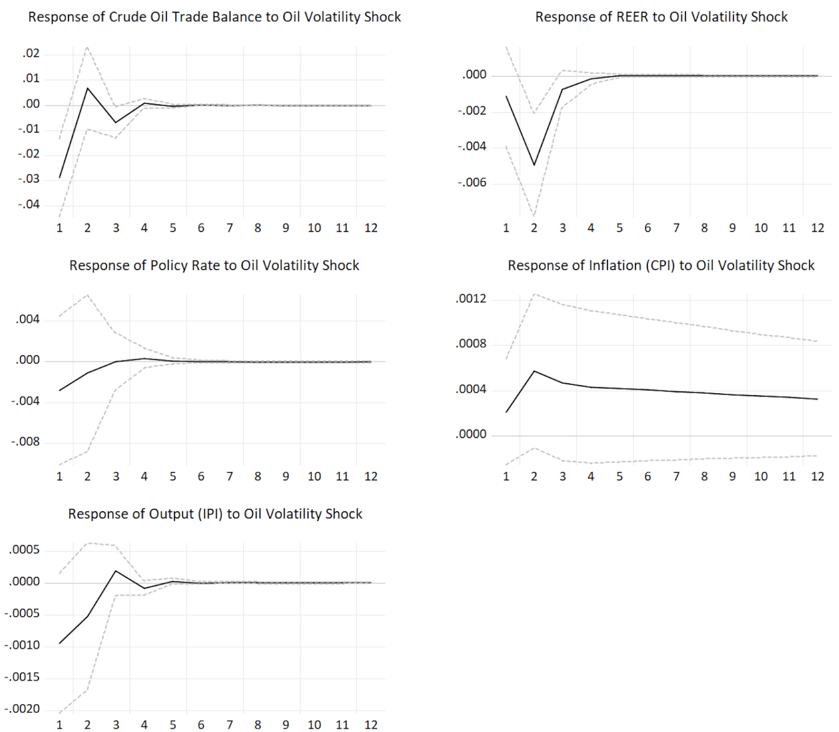
The figure displays the impulse response functions for Norway using a VAR(1) model with one exogenous variable. The lag length of 1 was selected based on the Information Criteria (IC). The responses of various economic indicators to shocks in the selected variable are shown, with confidence intervals.

Figure 2.59: VAR(p) with 1 Exogenous Variable — Canada



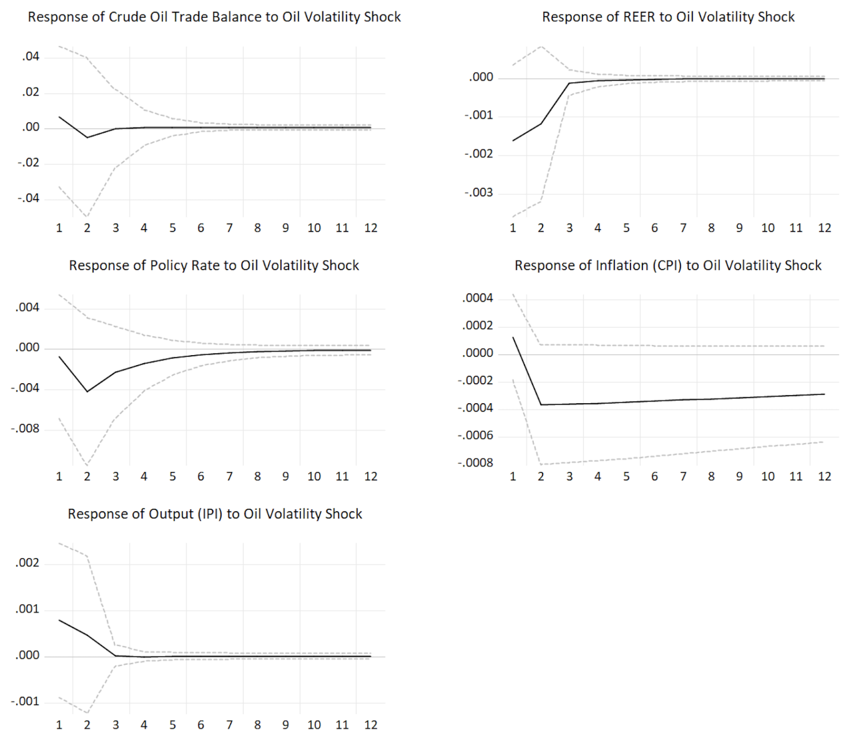
The figure displays the impulse response functions for Canada using a VAR(1) model with one exogenous variable. The lag length of 1 was selected based on the Information Criteria (IC). The responses of various economic indicators to shocks in the selected variable are shown, with confidence intervals.

Figure 2.60: VAR(p) with 1 Exogenous Variable — Mexico



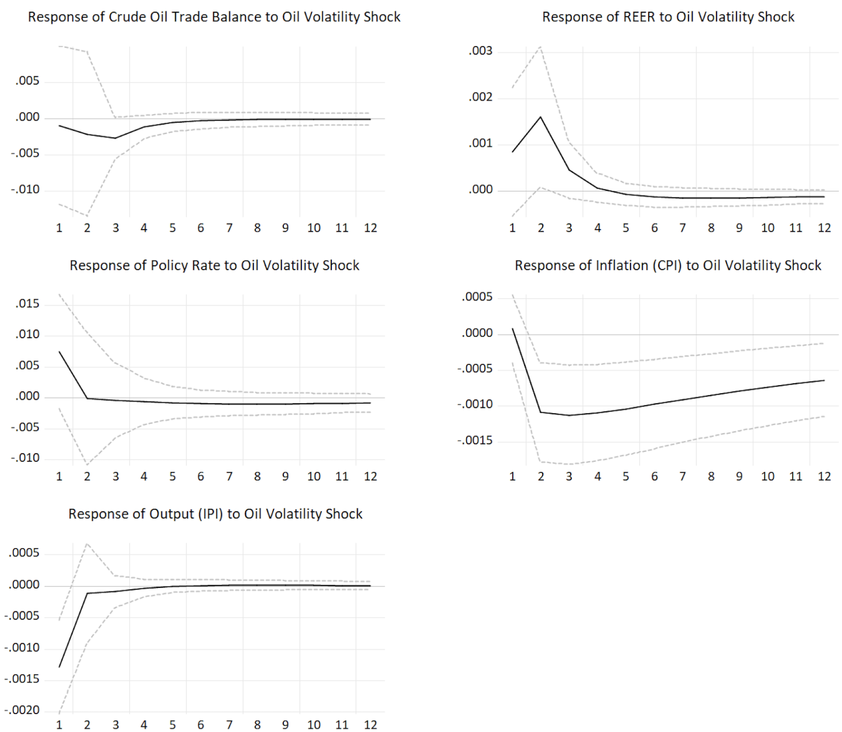
The figure displays the impulse response functions for Mexico using a VAR(1) model with one exogenous variable. The lag length of 1 was selected based on the Information Criteria (IC). The responses of various economic indicators to shocks in the selected variable are shown, with confidence intervals.

Figure 2.61: VAR(p) with 1 Exogenous Variable — UK



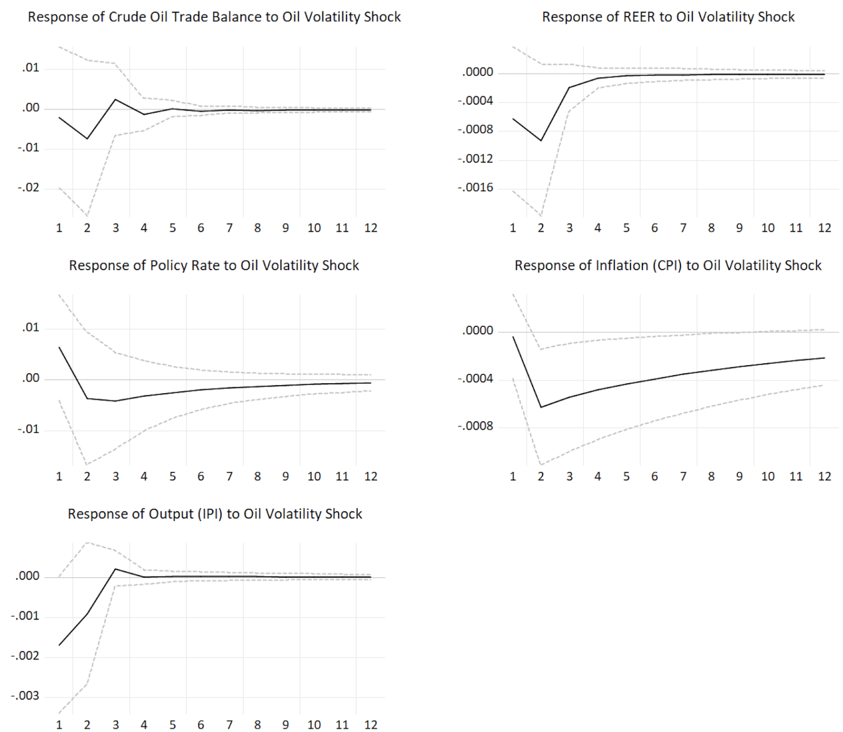
The figure displays the impulse response functions for the UK using a VAR(1) model with one exogenous variable. The lag length of 1 was selected based on the Information Criteria (IC). The responses of various economic indicators to shocks in the selected variable are shown, with confidence intervals.

Figure 2.62: VAR(p) with 1 Exogenous Variable — US



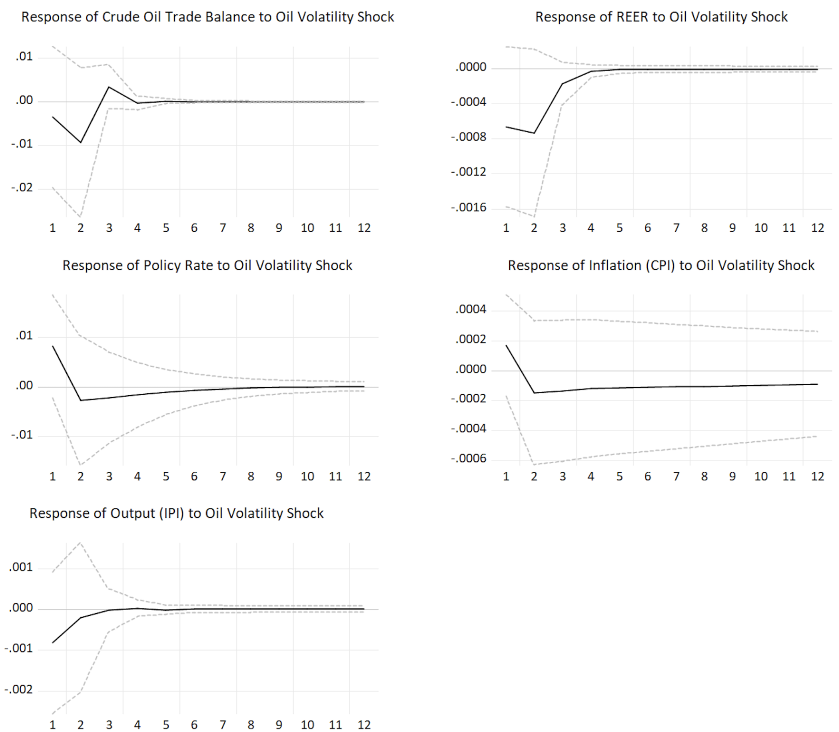
The figure displays the impulse response functions for the US using a VAR(2) model with one exogenous variable. The lag length of 1 was selected based on the Information Criteria (IC). The responses of various economic indicators to shocks in the selected variable are shown, with confidence intervals.

Figure 2.63: VAR(p) with 1 Exogenous Variable — Germany



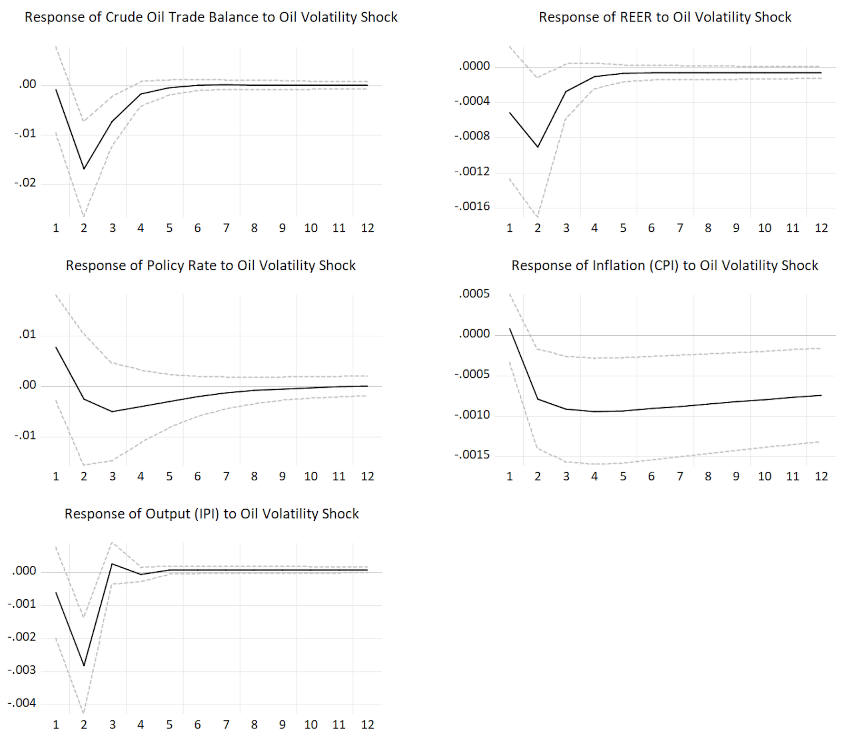
The figure displays the impulse response functions for Germany using a VAR(1) model with one exogenous variable. The lag length of 1 was selected based on the Information Criteria (IC). The responses of various economic indicators to shocks in the selected variable are shown, with confidence intervals.

Figure 2.64: VAR(p) with 1 Exogenous Variable — Italy



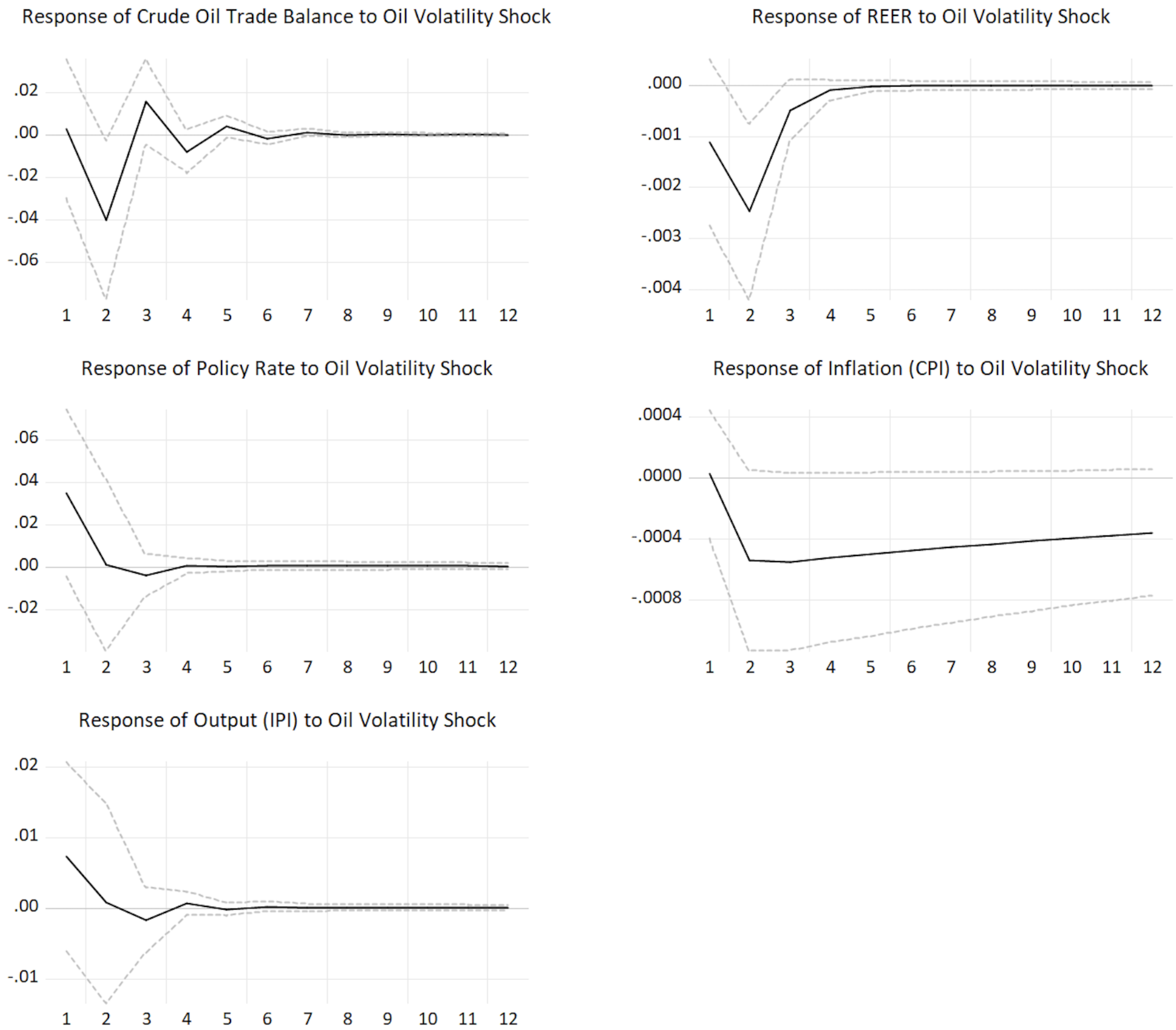
The figure displays the impulse response functions for Italy using a VAR(1) model with one exogenous variable. The lag length of 1 was selected based on the Information Criteria (IC). The responses of various economic indicators to shocks in the selected variable are shown, with confidence intervals.

Figure 2.65: VAR(p) with 1 Exogenous Variable — Spain



The figure displays the impulse response functions for Spain using a VAR(1) model with one exogenous variable. The lag length of 1 was selected based on the Information Criteria (IC). The responses of various economic indicators to shocks in the selected variable are shown, with confidence intervals.

Figure 2.66: VAR(p) with 1 Exogenous Variable — Sweden



The figure displays the impulse response functions for Sweden using a VAR(1) model with one exogenous variable. The lag length of 1 was selected based on the Information Criteria (IC). The responses of various economic indicators to shocks in the selected variable are shown, with confidence intervals.

CHAPTER 3

Empirical Chapter 2

Navigating Market Turbulence: Unveiling ESG's Potential as a "Safe Haven" Amid High Crude Oil Volatility

3.1 Introduction

"In essence, adhering to an ESG framework means you are future-proofing your business ..." (Soler 2020).

In recent years, Environmental, Social, and Governance (ESG) frameworks have gained substantial traction in corporate practices. Companies are not just adopting ESG activities for positive publicity; they recognise that ESG scores, as forward-looking indicators of ESG risk, provide a shield against external uncertainties. As emphasised by Henry Fernandez, MSCI's CEO and Chairman, on several occasions (Bloomberg Originals 2021; CNBC International TV 2022; CNBC Television 2020), ESG scores assess how changes in the external environment affect a company, rather than the other way around. ESG leaders are, in essence, hedged against future risks arising from Environmental, Social, and Governance factors. The crude oil market has long demonstrated a negative correlation with financial returns, with periods of high volatility typically leading to lower returns. This research addresses a critical challenge: addressing whether ESG scores effectively hedge company returns during times of heightened volatility in the crude oil market. The key lies in unravelling the intricate relationship between ESG activities and crude oil volatility. Building on prior research on interaction effects, our aim is to provide a comprehensive examination of how ESG scores and crude oil volatility mutually influence financial returns.

The main purpose of this study is to investigate whether firms with high ESG scores are less affected by the negative externality stemming from periods of high volatility in the crude oil market. To have a homogenous sample of the universe of firms, we select the companies listed in the S&P 500 Index. We collect the returns and ESG scores for each asset and employ a measure reflecting the empirical volatility of crude oil prices as a proxy for crude oil market volatility over the period from February 2003 to December 2022. This study focuses on the interaction effect between ESG scores and oil volatility to investigate whether the interplay between the two variables indicates that ESG activities have a substantial hedging effect over the returns during times of different crude oil volatility levels. It is crucial in our analysis to disentangle the role of the interplay between ESG and oil volatility from the single variables, while at the same time, it is necessary to jointly analyse the single and interaction effects of the two variables over the returns. We employ empirical analysis that focuses on the margin effect of each of the two variables by breaking down the regression equation into two partial derivatives with respect to the firms' ESG and the crude oil volatility which gives us respectively the effect of ESG and the crude oil volatility over the returns *ceteris paribus*. To enhance the clearness of the interpretation of the results, we also utilise a plot to graph the marginal effects.

Our core findings reveal an intriguing hedging effect of the ESG activities over returns when we account for uncertainty stemming from the crude oil market. While we do observe a direct, negative link between ESG scores and returns, our comprehensive exploration uncovers a more intricate and more truthful picture. We find that this negative relationship is counterbalanced by the interplay of ESG scores and crude oil volatility as the crude oil uncertainty increases. We identify a turning point in the volatility levels which lies at a relatively low level of crude oil volatility. Below this threshold, ESG activities tend to have a negative impact on returns, as mentioned earlier.

Beyond this threshold, ESG activities become a protective mechanism, especially during periods of elevated crude oil uncertainty. This suggests that ESG leaders experience greater protection compared to ESG laggards from a relatively low level of volatility, indicating an overall positive connection between the protective effect of ESG activities and firms' ESG scores.

Additionally, we conduct sector based and quartile analyses to discover more on ESG dynamics. In the sector analysis, firms are categorised into eight sectors based on the 2-digit codes of the US Standard Industrial Classification (SIC) divisions. In the quartile analysis, they are divided into four quartiles based on their average ESG scores. Through sector analysis, we identify two distinct dynamics. In some sectors, akin to our main analysis, we discover a threshold in the volatility level indicating that ESG activities initially have a negative influence on returns, shifting to a positive effect above this threshold. Importantly, sectors more sensible to crude oil uncertainty have lower threshold values. In other sectors, we observe a consistent and sustained hedging effect of ESG scores, evident across all levels of volatility. Notably, the effectiveness of this hedging increases with rising levels of oil market volatility. This underscores that ESG's protective impact intensifies as oil volatility escalates. Our quartile analysis further reveals a positive association between returns and ESG scores across all quartiles, with the most pronounced effect observed in the second-highest and third-best quartiles. These diverse patterns emphasise the multifaceted nature of ESG's impact on firm returns when focusing on hedging returns from the volatility risk stemming from the crude oil market.

A body of literature has examined the relationship between stock returns and average ESG ratings (Friede et al. (2015) among others therein). While prior research has explored the connection between ESG performance and financial returns, this study is the first to investigate the interplay between ESG scores and the volatility risk stemming from crude oil markets. Our primary contribution lies in shedding light on the mitigating effect that ESG scores have in relation to ESG risk. Our findings reinforce the consensus in the literature that firms with high ESG scores generally generate superior returns, aligning with established research (Cornett et al. 2016; Derwall et al. 2005; Statman and Glushkov 2009; Zhang et al. 2022). They also affirm the well-documented negative correlation between returns and oil price volatility, in line with existing research (Chiou and Lee 2009; Doko Tchatoka et al. 2019; Jones and Kaul 1996; Zhang and Hamori 2021). However, the central focus of our study lies in unravelling the intricate relationship between firms' ESG scores and the extent to which crude oil volatility impacts stock returns. In essence, our research fits into the debate about the role and influence of ESG on financial returns. What differentiates this study from previous work is its specific examination of ESG's stabilising role within the context of crude oil market uncertainty. Moreover, we provide insights into how these dynamics operate within industry sectors and across ESG quartiles. In this context, our study addresses the fundamental question: "To what extent does a high ESG score mitigate the adverse effects of crude oil market uncertainty on stock returns?".

The remainder of this document is structured as follows: the next chapter is a comprehensive narrative review of the academic literature, focused on examining the association between firms' ESG performance and diverse aspects of firms. The investigation delves into the interplay of ESG performance with key firms' metrics, such as cost of capital, profitability, and returns, while also exploring the influence of the oil market on the financial markets. Chapter 3 outlines the research methodology employed in this study. The subsequent section provides an overview of the dataset utilised in the investigation. The following section sets out the research findings. The study's conclusions are then presented, accompanied by proposals for potential avenues of future research. We conclude this chapter with two appendices. The first appendix provides a detailed explanation of the control variables, while the second examines how the results change when the spike in volatility during the COVID-19 pandemic is included in the time series. The analysis is especially important since incorporating the spike introduces bias into the results.

3.2 Review of the Literature

Investigating whether a high ESG score can be a sign for a company to perform well has often been of interest to academic researchers interested in disentangling the ESG score-firms' performance relationship. It has also attracted practitioners interested in exploiting a high ESG score to improve the performances of the company. Assuming financial markets are described by the Modigliani and Miller (1958) framework, hedging is irrelevant for investors since shareholders can reduce the risk of their investments on their own. However, in the presence of financial frictions, such as market uncertainty or the cost of bankruptcy, a company that has a hedge over these risks can increase its value (Smith and Stulz 1985). In this context, ESG performance plays a crucial role since it defines how well a company is hedged against environmental sustainability, social responsibility, and corporate governance risks that might rise reducing both the *probability* and the *cost* of those unfavourable events (El Ghoul et al. 2018). The first example of examining whether corporate policies, such as the ones required for a company to obtain and maintain a high ESG score, can affect firms' returns can be found in the work of Aldag and Kathryn (1978). The proper formulation of the ESG score-corporate performances nexus as it is known today can be found instead in the work of Arlow and Gannon (1982) which gave rise to the increasing interest in the topic that has become a significant trend since the early 1990s (Capon et al. 1990; Griffin and Mahon 1997; Pava and Krausz 1996; Wood and Jones 1995) with its higher peak from 2010s after the launch of the United Nations Principles for Responsible Investment (PRI)[1] in 2006. As Friede et al. (2015) state, more than 2200 works on the relationship between ESG scores and firms' performances were conducted up to 2015.

Although there are numerous studies conducted in the field, there is no unique view on how to assess the ESG score of a company. Several agencies have provided ESG ratings for firms in recent years and the most prominent and widely used are Morgan Stanley Capital International (MSCI), Sustainalytics, and RobecoSAM. The MSCI ESG database, MSCI Intangible Value Assessment (IVA) database, is used by many authors in the literature (Nagy et al. (2013) and Jo et al. (2015) among others) establishing itself also as the most used by practitioners. As Simpson et al. (2021) state "UBS Group [...] found MSCI earns almost 40¢ out of every dollar the investment industry spends on such data, far more than any rival".

Many authors in the literature tackle this puzzling problem. A strand of the literature faces it by investigating the determinants underpinning the ESG measure examining whether some firm's characteristics have an impact on the firm's ESG score. In this regard, some authors set the ESG score as the dependent variable and some firms' characteristics as independent variables. Among those, many studies identify firm's location

[1]See https://www.unpri.org/pri.

as the main firm's characteristic that has a relevant impact on the ESG measures. The work of Cai et al. (2016) and Liang and Renneboog (2017) show indeed that the scores given by the MSCI's IVA database, used as dependent variable, is tightly connected with the location or legal origin of the companies examined. Both of the analyses find that geographical location is a key factor, and the work of Cai et al. (2016) suggested that the legal system, the level of economic development, and the country's culture are the key factors that drive the implementation of ESG measures and, consequently, the ESG score. Similar findings can be observed in the research conducted by Daugaard and Ding (2022), which examines the Sustainalytics ESG score. The relevance of firms' location and ESG regulations is a pressing topic at this point in time, with an increasing demands for ESG providers to clarify their evaluation methodologies. Recent literature highlights this issue, indicating a pivotal moment in the evolution of ESG assessments. As highlighted by Damodaran (2023), the changing landscape influences the selective application of ESG regulations based on firms' locations, highlighting disparities in regulatory stringency across different countries. European lawmakers are poised to deliberate a proposal later this year, compelling ESG agencies to disclose more comprehensive details regarding their assessment methodologies. India has already made significant strides in ESG regulation (Kenza 2023).

Other studies account for the sector in which a firm operates as the driver for the implementation of ESG measures. The industry effect is proven to be of great impact as a determinant for the firms' involvement in ESG practices. Borghesi et al. (2014) apply a similar methodology setup using the KLD Research & Analytics[2] database to prove that the sector in which a firm operates is relevant for the level of ESG measure deployed. The authors suggest that firms that operate in sectors such as high-tech or consumer goods tend to have a higher ESG score than companies that work on commodities (petroleum, natural gas) or the aeroplane industry. The "industry effect" is so pronounced that in research, the ESG score is generally not used in level but it is used "demeaned" by the industry sector.

[2]KDL Research & Analytics was acquired by MSCI in 2010 which is now one of the most relevant ESG rating firms.

Impact of ESG on firms

To better define the relationship between ESG performances and firms' returns, we analyse different aspects of the transmission channels that tie ESG scores and the company's performances.

ESG and cost of capital

We start analysing the relationship between ESG performance and cost of capital. Despite the extensive body of research, there remains a lack of consensus regarding the perception of a high ESG score by lenders and investors.

ESG and cost of equity

Focusing on the cost of equity, most of the research suggests that high ESG performances are perceived as good signs for investors suggesting a negative relationship between ESG performance and cost of equity. Sharfman and Fernando (2008) analyse the linkage between ESG score and cost of capital for 267 U.S. firms pointing out that companies' measures designed to prevent environmental risk are effective to reduce the cost of capital by reducing the cost of equity. Jiao (2010) and El Ghoul et al. (2018) drawing upon their previous research (El Ghoul et al. 2011), suggest some rationales that explain this negative relationship. Shareholders are by nature risk-averse, as per the Modern Portfolio Theory of Markowitz (1967). Firms with high ESG performances are better prepared for ESG risks which are perceived as reassuring by shareholders. This, in turn, eases the relationship between the company and shareholders so a high ESG-scored firm is less likely to face tensions with shareholders that might lead for instance to strikes or scandals due to bad governance practices. A high ESG score can also be a strategy to attract shareholders, as suggested by Deng et al. (2013), but the pressure for a high ESG score might lead to a long-term returns pitfall. Fatemi and Fooladi (2013) suggest that aiming for the maximisation of the shareholder's wealth might not be the best "compass" to use for the creation of sustainable wealth. In the short term, the changes imposed by the drive to increase ESG performances might lead companies to implement measures that will damage the company in the long run. The authors suggest indeed that on one side the benefits of neglecting or externalising actions or procedures aimed at improving the firm's ESG performance in the short run might offer immediate advantages. However, this would ultimately result in relatively diminished benefits compared to the costs that the firm would later incur to align with necessary changes in the future. In this context, costs are not only related to potential lower financial returns but also the likelihood of encountering adverse consequences or risks that could significantly impact the firm's stability. On the other side, high ESG performances encourage "green investors" and therefore firms will have more moral investors who are willing to compromise a little extra profit for the acknowledgement that they are investing in green companies having also in mind that high ESG scores reduce ESG risks.

Studies by El Ghoul et al. (2018, 2011) and Avramov et al. (2022) delve into this discourse, highlighting that high ESG performance can increase a company's cost of equity. Avramov's work underscores the impact of ESG rating uncertainty, suggesting that during periods of heightened uncertainty, investors tend to decrease investments in "green" companies, potentially leading to a higher cost of equity as investors are less keen to invest in sustainable organisations. Consequently, this phenomenon can adversely affect companies that leverage their ESG scores as a competitive advantage, underscoring the growing need for stricter regulations in ESG assessments, as advocated by Kenza (2023)[3].

ESG and profitability

Most of the research finds a positive relationship between companies' ESG performance and firm profitability and firm value (Murphy 2002). The extensive analysis carried out by Friede et al. (2015) strongly reinforces the notion that "green" investments tend to be financially rewarding. This latter study, which examines approximately 2,200 research papers, finds that roughly 90% of them establish a positive connection between ESG performance and a company's financial performance. A possible transmission channel is proposed by Konar and Cohen (2001) finding that companies with a low number of environmental lawsuits and release of toxic material have a higher Tobin's Q. Decomposing the firm's value into tangible V_T and intangible assets V_I and defining

[3]The relationship between the ESG and the firms' cost of debt is thoroughly covered in the next chapter of this thesis.

Tobin's q as $1 + V_I/V_T$, the authors suggest that if a company has high ESG score, it impacts the Intangible assets. The transmission channel centres on the impact of actions such as lawsuits or other adverse events which may arise due to a low level of hedge against ESG risks, represented by low ESG score. These events have the potential to diminish Tobin's q by reducing the value of the intangible assets. Guenster et al. (2011) employ a similar interpretation of Tobin's Q, measuring market value relative to the book value of assets, to highlight a positive relationship between the aforementioned performance measure and the companies' "Eco-Efficiency". "Eco-Efficiency" is defined as "the ability to create more value while using fewer environmental resources, such as water, air, oil, coal and other limited natural endowments.". Similar results can be found in the work of Kim and Li (2021) which suggests that a high ESG performance affects the profitability of larger firms. The study explores also the different effects that the three ESG pillars have on firms' performance indicating that measures that aim to increase corporate governance have the highest effect on a firm's profitability.

Although not very extensive, a strand of the literature finds a negative relationship between ESG performances and firm's profitability. Examining this literature across different locations, the findings of Brammer et al. (2006) show that between July 2002 and June 2003 UK firms with high ESG scores underperform the sector benchmark. Similar results are presented for the Italian financial landscape by the work of Landi and Sciarelli (2018) which reports a negative ESG scores-firms performances correlation for the period between 2007 and 2015 for 54 companies. This inverse correlation observed in Italy is also documented in the research conducted by Gavrilakis and Floros (2023). Folger-Laronde et al. (2022) present the case of Canada during the COVID-19 period highlighting that high ESG scores do not help firms to hedge the risk coming from an unexpected downturn in the financial markets.

ESG and returns

As demonstrated previously in relation to the cost of equity and profitability, it would be overly ambitious to assume that a high ESG score would inevitably result in high returns. Many studies indicate indeed that high ESG-rated firms do not outperform "sin" firms. From a portfolio-oriented perspective, a possible interpretation of the "green" firms' underperformances can be found in the work of Barnett and Salomon (2006).

Finding a negative relationship between the returns of "green" portfolios compared to the "non-green" counterparties, the authors attribute this gap to the lower level of diversification that ESG investment needs to accept to allow sustainability. It must be pointed out that the research analyses the UK stock market before 2000. The already mentioned work of Brammer et al. (2006) about UK firms extends the research to state that "non-sin" firms realise lower returns compared to high ESG-scored firms. The study conducted by Renneboog et al. (2008) on a global sample of firms yields similar findings. They focus their research on US, UK, and some countries within Europe and Asia-Pacific area to find that, with the exception of few countries, ESG funds drastically underperform their benchmarks. Similar results can be found in the work of Utz and Wimmer (2014) focussing on US mutual funds taken from the CRSP database.

A particularly critical perspective comes from Damodaran (2023), which highlights several factors contributing to ESG activities potentially causing firms to underperform. One significant concern, as previously mentioned, is the lack of clear regulation, which leads to the broad field they measure, ultimately resulting in the criticism that "ESG scores measure everything – consequently, they measure nothing". Another crucial point raised by Damodaran concerns the perspective of investors. Investors may be inclined to incorporate ESG into their portfolios, driven by the belief that ESG firms are less risky and offer higher returns. However, this belief creates a paradox: investors cannot simultaneously "have their cake" (by bearing lower risk) and "eat it too" (by earning higher returns). According to his view, if ESG is neither "good for value" (i.e., returns) nor "good for investors", it may be left with the somewhat weaker purpose of being "good for society".

A large part of the research suggests that there is no difference in terms of returns between green and brown firms. Fama and MacBeth (1973) are among the first to analyse the embryonic version of this relationship. The analysis is carried out by regressing firms' returns over some firms' performances (beta, size, book-to-market and momentum risk factors) and also to some characteristics that will then be associated with the ESG measure (community relations, corporate governance, diversity, employee relations, environment, human rights and product safety). Their analysis suggests that only community relations affect sensibly firms' returns while the work of Halbritter and Dorfleitner (2015) finds that there is no substantial difference in terms of returns and variance between green and brown firms indexes. Mănescu (2011) states that ESG performance is not a key factor to influence firms' returns. Analysing different ESG databases, Halbritter and Dorfleitner (2015) are not able to find significant differences between ESG leader and ESG laggard firms. Focusing on the behaviour of retail investors, Moss et al. (2023) find that retail investment decisions are not notably influenced by ESG scores. Instead, similar to professional investors, non-ESG-related announcements notably impact their investment choices, particularly in response to earnings announcements.

An alternative body of research identifies a positive association between ESG performance and investment returns, aligning with the "doing good while doing well" proposition. This theory posits that socially responsible companies tend to exhibit higher expected stock returns compared to their conventional counterparts. One notable study conducted by Derwall et al. (2005) employ the concept of "Eco-Efficiency" introduced by Guenster et al. (2011). Examining a sample of sustainable US firms from 1995 to 2003, their analysis demonstrates that these companies outperform their counterparts with lower sustainability ratings.

Similar results can be found in the study of Statman and Glushkov (2009) which analyses the Domini 400 Social Index (DS 400)[4] over a similar period (1992–2007). Their research indicates that companies included in the DS 400, composed of firms deemed socially responsible, deliver higher returns. Focusing on the "100 Best Companies to Work For in America", Edmans (2011) finds that companies with high employee satisfaction outscored the industry's benchmarks. Eccles et al. (2014) utilise a combined approach, incorporating various data sources, to identify high and low sustainability firms within a sample of 180 US companies. They discover annual abnormal returns of up to 4.8% for higher ESG-rated firms. Additional studies by Dimson et al. (2015), Krüger (2015) and Flammer (2015) further support the positive relationship between ESG factors and investment returns. Cornett et al. (2016) focus on US commercial banks and finds similar results. Meanwhile Lins et al. (2017) state that a good relationship with stakeholders and investors helps mitigate the financial crises. They identify higher employee satisfaction as a key driver for firms to deliver higher returns in times of

[4]Introduced in May 1990 under the name Domini 400 Social Index, the MSCI KLD 400 Social Index emerged as one of the pioneering socially responsible investing (SRI) indexes during a time when such indexes were scarce. Its launch in May 1990 marks a significant milestone in the development of SRI indexes. See MSCI KLD 400 Social Index for more details.

financial turmoil. This stands in stark contrast with the already mentioned case of Canada analysed by Folger-Laronde et al. (2022). The research conducted by Alsayegh et al. (2020) explores the Asian context and reveals a positive correlation between environmental and social performance among Asian companies from 2005 to 2017. More recently, Broadstock et al. (2021) examine Chinese firms during the Covid-19 pandemic and find that portfolios with a higher number of ESG assets outperform portfolios with fewer ESG assets. To conclude, Zhang et al. (2022) conduct an empirical investigation in China, building upon the theoretical framework proposed by Pedersen et al. (2021).

The analysis focuses on the portfolio-level relationship between ESG performances and portfolio excess returns. Notably, a non-linear association is observed, whereby both high- and low-level ESG portfolios generate higher abnormal returns. Furthermore, the study delves into the stock-level analysis, exploring how ESG factors influence future stock returns across various pillars and sectors. The findings reveals that the impact of ESG varies depending on the specific pillar and sector under examination. Specifically, the governance and social pillars exhibit contrasting effects on return prediction. Moreover, within the secondary (tertiary) sector, higher ESG scores is linked to lower (higher) returns. Shifting the focus, the study of Cao et al. (2023) emphasises the influence that the increasing number of Socially Responsible (SR) investors has on the shape of firms' return patterns. SR institutions place more emphasis on ESG performances over quantitative value signals and therefore SR investing focused institutions react less to quantitative mispricing signals. Consequently, the effectiveness of mispricing signals has diminished in recent times as SR investors have increased. Their research finds that stocks primarily held by SR investors tend to yield higher abnormal returns due to quantitative mispricing. The dynamic of the ESG investing by SR investors likely contributes to the higher returns of ESG scores on one side, as a higher ESG score is considered an attractive characteristic for SR investors and secondly this potentially further widens the gap between ESG leaders and laggards, favouring the former.

In summary, the literature on the relationship between ESG performance and investment returns remains inconclusive. While some studies indicate that high ESG scores are associated with lower costs of capital and higher valuations, others highlight the challenges and potential drawbacks of ESG investing. Despite these mixed results, there is substantial evidence suggesting that firms with strong ESG credentials can outperform their counterparts with weaker ESG commitments. This positive impact is often attributed to enhanced corporate reputation, reduced regulatory risks, and improved operational efficiencies. Therefore, we hypothesise the following:

Hypothesis 3.1. *ESG scores and firms' returns have a positive relationship.*

How oil shocks affect the stock markets

The modern economy relies upon several sources of energy and with crude oil being widely recognised as a predominant energy resource. The study of Bashir et al. (2022) emphasises that despite a recent slowdown in global energy demand, the crude oil market has consistently experienced price increases leading up to the pandemic. It suggests that the importance of crude oil in the energy markets is unlikely to diminish. Bashir et al. (2021a,b) indicate that the demand for crude oil from emerging countries will lead to a 30% increase in price until 2040 suggesting that the fluctuations of crude oil market will play a key role in the stock market (Bashir et al. 2021c). Xia et al. (2022) ascertain that the United States exhibits the highest consumption of crude oil, followed by China and India.

Impact of crude oil and stock markets

The extensive body of literature investigating the relationship between crude oil and stock markets has prompted recent scholarly contributions adopting a scientometric approach. Noticeable studies are the work of Lin and Su (2020), Nazlioglu et al. (2020), and Chowdhury and Garg (2023) which undertake efforts to analyse and structure the vast number of publications on this subject focusing also on the temporal distribution of the papers. Through their analyses, it appears evident that the literature exhibits distinct characteristics before and after the Global Financial Crisis (GFC) of 2007-2008 identifying the bankruptcy of Lehman Brothers as a proper breakthrough. Liu et al. (2018) offer two possible explanations for this shift. On one side, the GFC heightens volatility and unpredictability in the macroeconomy and financial markets, leading to increased attention towards both topics. On the other side, the crude oil market itself becomes substantially more volatile after 2007, influenced not only by the GFC but also by external circumstances.

Examining the research by Chowdhury and Garg (2023), it is apparent that the topic initially received limited attention from scholars, with most studies providing only superficial exploration as stated also by Lin and Su (2020) (*Budding* phase (1985-2007)). Nevertheless, it is worth mentioning seminal exceptions, such as the seminal contributions made by Kilian (2009) and Kilian and Park (2009). They emphasise the importance of defining the source of a crude oil shock and expanding the consequences that each shock has on the economy and therefore on the stock market instead of analysing a crude oil shock *ceteris paribus*. In these papers the authors divide crude oil shocks into three main sources of shocks: a shock coming from the actual availability of the commodity (*supply shock*), a shock deriving from a sudden change in the demand of the commodity in line with the business cycle (*aggregate demand shock*), and a shock coming from the expectations of future change in the crude oil (*precautionary demand shock*). The *Development* phase starts after the bankruptcy of Lehman Brothers and it clearly witnesses a notable surge in the number of publications and a significant deepening of analytical investigations with the stock markets being more affected by movements in the crude oil (Ji and Fan 2010; Wang et al. 2023; Wen et al. 2012). The study of Kilian and Park (2009) reveals a strong association between stock market returns and shocks originating from the crude oil market, with the nature and origin of these shocks playing a crucial role. Specifically, the findings highlight that shocks in oil demand exert a more substantial impact on changes in U.S. stock market returns compared to oil supply shocks.

Those results for the US firms are corroborated by the subsequent work of Ahmadi et al. (2016), Clements et al. (2019), and Hwang and Kim (2021). These studies strengthen the idea that the response of U.S. stock market returns to shocks in the global oil market is contingent upon the specific sources of these shocks. Notably, it highlights the significant influence of demand-driven shocks on U.S. stock market returns and in some cases, the nexus is positive, as suggested by Kang et al. (2017) for some energy companies in the USA. On the other side, Kang et al. (2016) focus on the weaker nexus between US stocks and US and non-US oil supply shocks to find out that there is no difference in the reaction of the US stock market. The analysis of Wei et al. (2023)

adopts a similar categorisation of oil shocks as introduced by Kilian (2009) (*supply shock*, *aggregate demand shock*, and *precautionary demand shock*) to examine the impact of these shocks on the Chinese and U.S. stock markets. The findings of their research align with the literature strand that supports demand-driven shocks as the main source of perturbation of the stock markets. Additionally, their research suggests that the variance of the US stock market is more influenced by demand shocks in a regime of low business cycles, while speculative demand shocks are the key drivers of stock volatility during high business cycle periods in both markets.

Despite the different natures of the shocks, the literature generally agrees that there is a significant relationship between crude oil price volatility and firms' returns. Thus, we propose the following hypothesis:

Hypothesis 3.2. *Crude oil volatility and firms' returns have a negative relationship.*

Crude oil and sectors

To gain a deeper understanding of the effects of oil price shocks, it is valuable to extend the discussion to an sector level.

The academic literature provides numerous analyses that examine the effects of crude oil shocks on various sectors, revealing heterogeneous results in both sector-specific and location-specific outcomes, as resulting by the work of Scholtens and Yurtsever (2012), Xu (2015), and Salisu et al. (2019). Very similar findings can be found in the works of Degiannakis et al. (2013), Broadstock and Filis (2014), Bouri et al. (2016), and Badeeb and Lean (2018). With regard to the correlation between crude oil movements and US transportation companies, Mohanty and Nandha (2011) posit that the relationship exhibits inconsistency throughout the period spanning 1999 to 2008. This inconsistency implies that the impact of crude oil movements on transportation firms is not uniform and may vary over time. Similarly, Aggarwal et al. (2012) conduct a similar analysis on the S&P Transportation industry index from January 1986 to July 2008, finding a negative relationship between crude oil movements and transportation companies. Mohanty et al. (2014) investigate the relationship between crude oil movements and the travel and leisure industry in the USA. They break down their research into six sub-sectors: (1) Travel and Tourism, (2) Airlines (3) Gambling, (4) Hotels, (5) Recreational Services, and (6) Restaurant and Bar. The analysis covers the period from September 1983 to August 2011. Consistent with the existing body of literature, the findings of the study indicate that the impact of crude oil shocks on stocks varies across sectors and exhibits temporal variability. Specifically, the study reveals a significant negative correlation in several sub-sectors, including airlines, recreational services, and restaurants and bars, throughout the period from 1983 to 2011.

As previously discussed, the academic literature on the asymmetric impact of demand and supply shocks extends to sectors, and it generally indicates that similar patterns can be observed across sectors (Mohanty et al. 2012; Nandha and Brooks 2009; Swaray and Salisu 2018). Specifically, the non-monotonic nature of the effect of crude oil shocks, driven by demand shocks, tends to have a more pronounced impact on stock prices across all sectors compared to supply shocks.

Focusing on the effect of crude oil shocks over other commodities, the relationship between crude oil shocks and precious metals has garnered significant interest within the literature. Yıldırım et al. (2020) employ a causality-in-variance test to examine the return and volatility spillover effects between oil prices and precious metal prices from 1990 to 2019. The empirical findings reveal that oil returns Granger cause precious metal returns. Shafiullah et al. (2021), on the other hand, discover that the causality running from oil to metal prices is quantile-dependent and varies across different metals. Ahmed et al. (2022) conduct research on crude oil and precious metals, specifically gold, platinum, palladium, and silver. The findings suggest that tail risk for these commodities tends to be lower during the 2007 Global Financial Crisis and the 2015 oil price crisis, with the notable exception of the COVID-19 pandemic crisis, where tail risk remains elevated. Gold demonstrates the lowest tail risk, confirming its role as a “safe haven” during market downturns. Additionally, the study shows that these commodities can serve as diversified assets for hedging against financial assets’ volatility. The spillover risk of crude oil and precious metals varies over time, with a decline observed during the global financial crisis, the European sovereign debt crisis, and the COVID-19 pandemic. Notably, crude oil is found to have both positive and negative impacts as a stimulator of spillover risk for precious metals, highlighting its significant influence.

Mitigating effect of ESG from crude oil price volatility over firms' return

The main driver of the study is to investigate the potential impact and mechanisms through which ESG scores influence the returns of companies in times of turmoil in the oil market. To achieve this, we consider the volatility of the crude oil prices and examine their influence on firms listed in the S&P 500 Index, which represents a cross-section of companies characterised by different ESG scores.

This study contributes to the existing literature by providing more insights into the dynamic interplay between ESG performance and crude oil volatility. Specifically, it investigates the potential safe-haven characteristics of high ESG scores in times of rising uncertainty of oil prices. While previous research has largely focused on the relationship between ESG scores and firm performance in broader financial crises (e.g., the Global Financial Crisis of 2008-2009), less attention has been given to how ESG functions as a stabilising mechanism against financial risks triggered by fluctuations in the crude oil market. Given the fundamental role of crude oil in global economic activity, understanding how its volatility influences corporate financial outcomes is crucial.

Since the role of ESG scores in times of crises is still limited, with a primary focus on the global financial crisis of 2008-2009 (Broadstock et al. 2021), the main contribution of this study is to extend the literature by exploring the role of ESG scores in shaping firms' financial resilience amid crude oil price volatility. On one side, it is proved that times of rising volatility in the oil market generate a negative effect on the stock firms, as per Kling (1985), El Hedi Arouri et al. (2011), Christoffersen and Pan (2018), and Bashir (2022) among others. A possible economic mechanism that drives returns down in times of rising volatility can be found in the funding constraints that financial intermediaries face in times of high volatility. Intermediaries are financial entities that operate across different sectors simultaneously relying on self-generated capital and external borrowing to facilitate trading endeavors. Brunnermeier and Pedersen (2009) suggest that in times of rising volatility, the capitalisation of intermediaries shrinks primarily due to augmented margins and potential portfolio value depreciation. Based on this theory, oil price volatility tightens financial conditions by reducing the liquidity available to intermediaries, which in turn constrains firms' access to capital and increases downside risk. The dynamics of the transmission of the volatility to returns find its basis in the constrained liquidity of intermediaries, which leads to a reduction of the capacity of bearing risk.

Our conjecture is therefore that there is a negative relationship between the returns of firms listed in the S&P 500 and the volatility of the crude oil prices.

On the other hand, the impact of ESG scores on returns yields mixed results in the literature. As examined previously, the relationship between ESG scores and firms' overall performance, particularly in the post-Global Financial Crisis (GFC) era, demonstrates varying outcomes. A slight majority of studies indicate a positive relationship (Derwall et al. 2005; Friede et al. 2015; Guenster et al. 2011; Statman and Glushkov 2009; Zhang et al. 2022), while others report a negative relationship (Barnett and Salomon 2006; Brammer et al. 2006; Folger-Laronde et al. 2022; Gavrilakis and Floros 2023; Landi and Sciarelli 2018), with a small subset of studies revealing a lack of relationship (Halbritter and Dorfleitner 2015; Mănescu 2011).

However, limited attention has been given to how ESG performance interacts with shocks originating in crude oil markets and their impact on firms' financial performance. This research is in line with the idea that having a high ESG score serves as a hedge against external risks, particularly those stemming from oil market volatility. Given the negative relationship established earlier between oil price volatility and corporate returns, high volatility is perceived as a negative externality for firms. The transmission channel is that ESG scores delineate the extent of a company's preparedness to counter ESG-related risks. Consequently, our conjecture is directed towards a positive interaction effect between ESG scores and oil price volatility, wherein firms with stronger ESG commitments experience greater resilience during episodes of market turbulence. We indeed direct our attention to the interaction effect between ESG scores and oil price volatility and our conjecture is that this interaction will exhibit a positive outcome, denoting that high ESG scores provide a protective mechanism during periods of rising crude oil volatility.

Given the diverse findings regarding firms' returns in response to crude oil shocks, this study formulates the following hypothesis to explore whether a high ESG score plays a crucial role in hedging companies from oil volatility risk:

Hypothesis 3.3. *Adoption of strategies incorporating ESG scores mitigates oil price volatility risk.*

Despite the growing body of research on ESG and financial performance, limited attention has been given to its role in mitigating risks associated with commodity market volatility. While prior studies have independently examined the effects of ESG on firm performance and the impact of crude oil price fluctuations on financial markets, these two areas of research have yet to be fully integrated. This study addresses this gap by assessing whether ESG scores serve as a stabilising factor, mitigating the adverse effects of oil price volatility on stock returns.

By conceptualising ESG as a hedging mechanism, this research extends prior work on ESG's role in financial stability beyond traditional macroeconomic shocks and systemic crises. Unlike previous studies that primarily focus on ESG's influence during financial downturns such as the Global Financial Crisis (Broadstock et al. 2021), this study provides new empirical evidence on how ESG engagement helps firms navigate periods of heightened uncertainty in the crude oil market. Furthermore, this research contributes to the broader discourse on market risk mitigation by illustrating how ESG factors interact with commodity price fluctuations to shape corporate financial outcomes.

Through this contribution, the study enhances our understanding of how sustainability-driven corporate strategies impact financial resilience in volatile market conditions. The findings have direct implications for investors, policymakers, and corporate leaders, reinforcing the strategic importance of ESG integration in risk management frameworks and providing empirical support for ESG's role in stabilising firm performance amid commodity-driven financial instability.

3.3 Methodology

To investigate the potential role of ESG activities over the returns during times of rising uncertainty in the crude oil market, we build a panel data comprising the returns and the ESG scores of the firms listed in the Standards and Poor's 500 Index and a time series of the crude oil volatility which is common for the whole firms. Specifically, the way in which we align the yearly assessment of the firms' ESG scores and the monthly frequency of our dataset is by ensuring that the monthly return of each individual firm is associated with its most recent available ESG score. Consequently, we maintain a constant ESG score between two successive ESG assessments for each firm. This approach ensures that the returns are correlated with the most recently updated ESG score applicable to each respective company.

The methodology we employ in this analysis draws inspiration from the study conducted by Ozdagli (2017) in terms of capturing the interaction effect. However, there are notable differences between our study and the aforementioned work by Ozdagli. Specifically, his research focuses on the response of firms with varying degrees of financial friction to monetary policy shocks, and it adopts a more event-study-oriented approach by considering a limited number of events as shocks. In contrast, our study utilises a broader dataset and a different analytical framework to explore the interaction effects in a more comprehensive manner.

Our regression model therefore focuses on the interaction effect between the firms' ESG scores and the crude oil volatility to investigate the impact of the interplay between the two variables on the returns, as per Equation (3.1):

$$\begin{aligned} r_{it} = \alpha \ + \ \beta_1 \, OilVol_t \ + \ \beta_2 \, ESGScore_{it_U} \\ + \beta_3 \, ESGScore_{it_U} \times OilVol_t \ + \ ControlVariables + \varepsilon_{it}. \end{aligned} \tag{3.1}$$

In the regression equation, i is related to each single firm, while t denotes the month of each observation. In the formula, to indicate that the ESG scores are kept constant between the assessments, we utilise the t_U subscript on the ESG variable to underline that for each time t, we deploy the last updated ESG score.

We control for a set of firm-level variables, as well as a set of macro-level variables, as per Equation (3.2):

$$\begin{aligned} ControlVariables = \{CompanySize_{it}, \ TotalAssets_{it}, \ ROA_{it}, \\ + BoardGendDiv_{it}, \ BoardIndep_{it}, \ BoardMeetings_{it}, \ CSR_{it}, \\ + VIX_{t-1}, \ GPD_{t-1}, \ CPI_{t-1}, \ IPI_{t-1}\}. \end{aligned} \tag{3.2}$$

In the equation above, the controls with a it subscript correspond to firm-level controls, as they pertain to individual firms for each observation. Variables designated with a $t-1$ subscript denote instead macro controls, which are consistent across all firms and lagged by one period to reflect their impact on the current period. Specifically, for each firm, we collect the following variables: company size, total assets, and return on assets (ROA). Furthermore, we introduce control measures that describe the composition of the board, encompassing gender diversity, the count of independent members, the frequency of board meetings, and the presence of a CSR Committee. The macro controls encompass the VIX as a proxy for market volatility, US GDP, US CPI as an indicator of inflation, and US IPI as a gauge of industrial growth, all lagged by one period to ensure they reflect the macroeconomic conditions preceding the current firm-level observations.

We conduct both pooled OLS regression and fixed effect models accounting for firm-specific effects to capture the influence of individual firms on the results. The Hausman (1978) test is employed to determine whether a model accounting for fixed effects should be favoured over a random effect model.

To dissect and analyse the coefficients stemming from the main variables, we examine the interaction effect between ESG scores and oil volatility isolating the effect of each one *ceteris paribus*. Specifically, referencing Equation (3.1), we assess the partial derivatives of the returns with respect to ESG and crude oil volatility respectively. Equations (3.3) and (3.4) delineate these partial derivatives derived from the principal regression equation, showing the margin effects of the ESG scores and the crude oil volatility on the firms' returns.

$$\frac{\partial\, r_{it}}{\partial\, ESG_{it}} = \beta_2 + \beta_3\, OilVol_t, \tag{3.3}$$

$$\frac{\partial\, r_{it}}{\partial\, OilVol_t} = \beta_1 + \beta_3\, ESG_{it}. \tag{3.4}$$

Equation (3.3) represents therefore the partial derivatives of return with respect to the firms' ESG scores. This shows the effect of variations in ESG scores on returns while holding oil volatility at a constant value. On the other side, the partial derivative of returns over crude oil volatility is displayed in Equation (3.4) which portrays how changes in the crude oil market volatility affect the firms' returns while holding the ESG constant.

We do this exercise across various levels of oil volatility for Equation (3.3) and similarly, for several magnitudes of ESG scores for Equation (3.4). This allows us to disentangle the effect of each scenario on the returns. We then report the impact on the returns when the variable held constant in each instance attains its minimum, average, and maximum values.

To visually portray the interplay between ESG scores and oil volatility in relation to returns, we graphically present the outcomes of the marginal effects of each of the two variables. Through this approach, we generate two distinct graphs that present the changes in the marginal effect of one variable on returns, while considering different levels of the other variable held constant. Specifically, by plotting the margin effect of oil volatility over returns, we are able to gain insights into how different ESG scores influence the relationship between oil volatility and firms' returns. On the other side, plotting the margin effect of ESG over returns for different levels of volatility allows us to investigate the extent to which different ESG scores protect firms during periods characterised by diverse levels of crude oil volatility.

3.4 Data Description

The sample examined in this research comprises the firms listed in the Standards and Poor's 500 Index from February 2003 to December 2022. The dataset is compiled by gathering monthly data of firms' returns, ESG scores, and a time series for the crude oil volatility, alongside a set of firm-level and macro-level control variables.

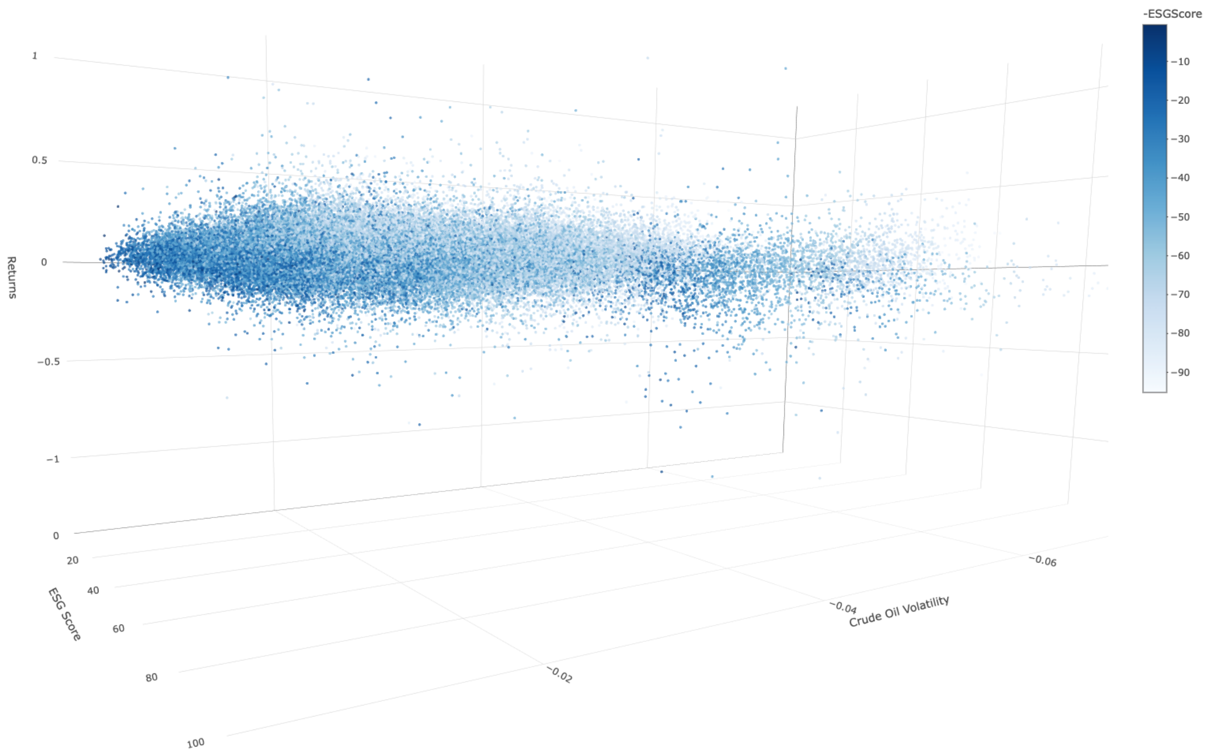
Main variables

The dependent variable in this study is the firms' monthly returns, calculated by converting monthly price data into logarithmic returns and scaling by a factor of 100. The main variables of interest in this study are the firms' ESG scores and a time series measure of crude oil volatility.

Firms' ESG scores

We use Refinitiv's database to collect the combined ESG scores for each firm (Borokova and Wu 2020; Gavrilakis and Floros 2023). Refintiv relies on the RepRisk ESG Risk Platform to scrape ESG (and each of the three pillars singularly) scores covering more than 235.000 companies being one of the largest and most reliable ESG databases. Generally, firms' ESG assessments are updated every fiscal year. We harmonise this with our monthly dataset by specifically looking at the month of the year in which the new ESG score is assigned to a company and we keep it constant until the next ESG assessment is made. This approach ensures us to relate each firm's returns to its most updated ESG score.

Figure 3.1: 3D Scatter Plot of Oil Volatility, ESG, and Returns

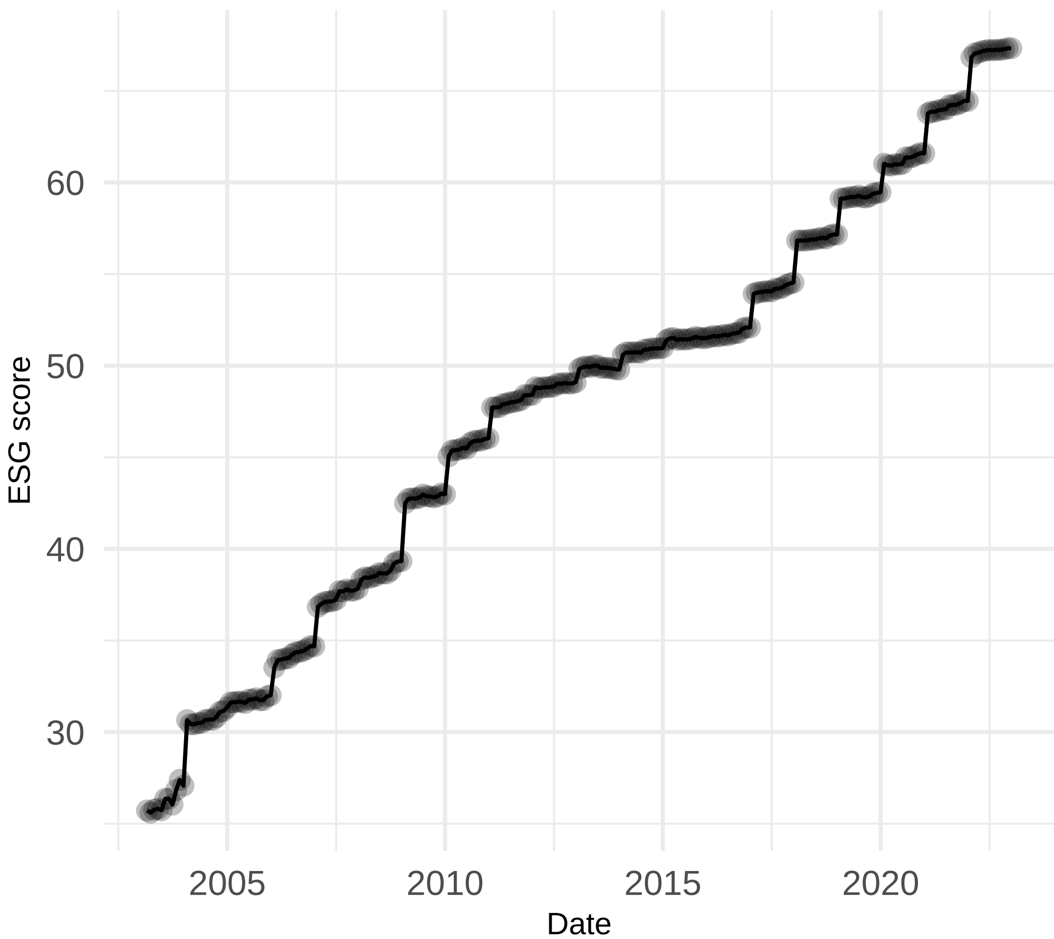


3D scatter plot showing the relationship between oil market volatility, ESG scores, and financial returns. Each point represents a data observation, with the axes capturing the respective variables. This visualisation highlights the interaction between these three dimensions.

Figure 3.1 provides a three-dimensional scatter plot that aims to disentangle the relationship between Crude Oil Volatility, ESG Scores, and Returns. The x-axis represents Crude Oil Volatility, the y-axis denotes ESG Scores, and the z-axis shows Returns. The data points are colour-coded, with darker shades indicating lower ESG scores and lighter shades representing higher scores.

As expected, most returns cluster around the mean (0.8784) on the z-axis. However, the plot reveals an important dynamic: although return volatility is noticeable even during periods of low crude oil market volatility (on the left side of the graph), there is no strong differentiation between firms with high and low ESG scores, as indicated by the consistent blue shading along the y-axis. In contrast, as crude oil volatility increases (towards the right side of the graph), a more pronounced distinction emerges between firms with differing ESG scores. Firms with lower ESG scores (represented by the darker points) experience more frequent negative returns, as shown by the points located in the lower part of the graph. This pattern underscores their vulnerability in high-volatility environments. Conversely, firms with higher ESG scores display greater resilience, with returns becoming increasingly stratified according to ESG performance.

Figure 3.2: ESG Scores: All Firms



Evolution of the ESG scores across time for the firms listed in the S&P 500 Index.

Figure 3.2 depicts the evolution of the firms' ESG scores within the S&P 500 Index across the time frame utilised in this research. The data show a consistent increase in ESG scores, suggesting a widespread improvement in ESG efforts by companies. This aligns with results from previous research, such as Eccles et al. (2014), that illustrate a similar pattern in ESG performance across various sectors.

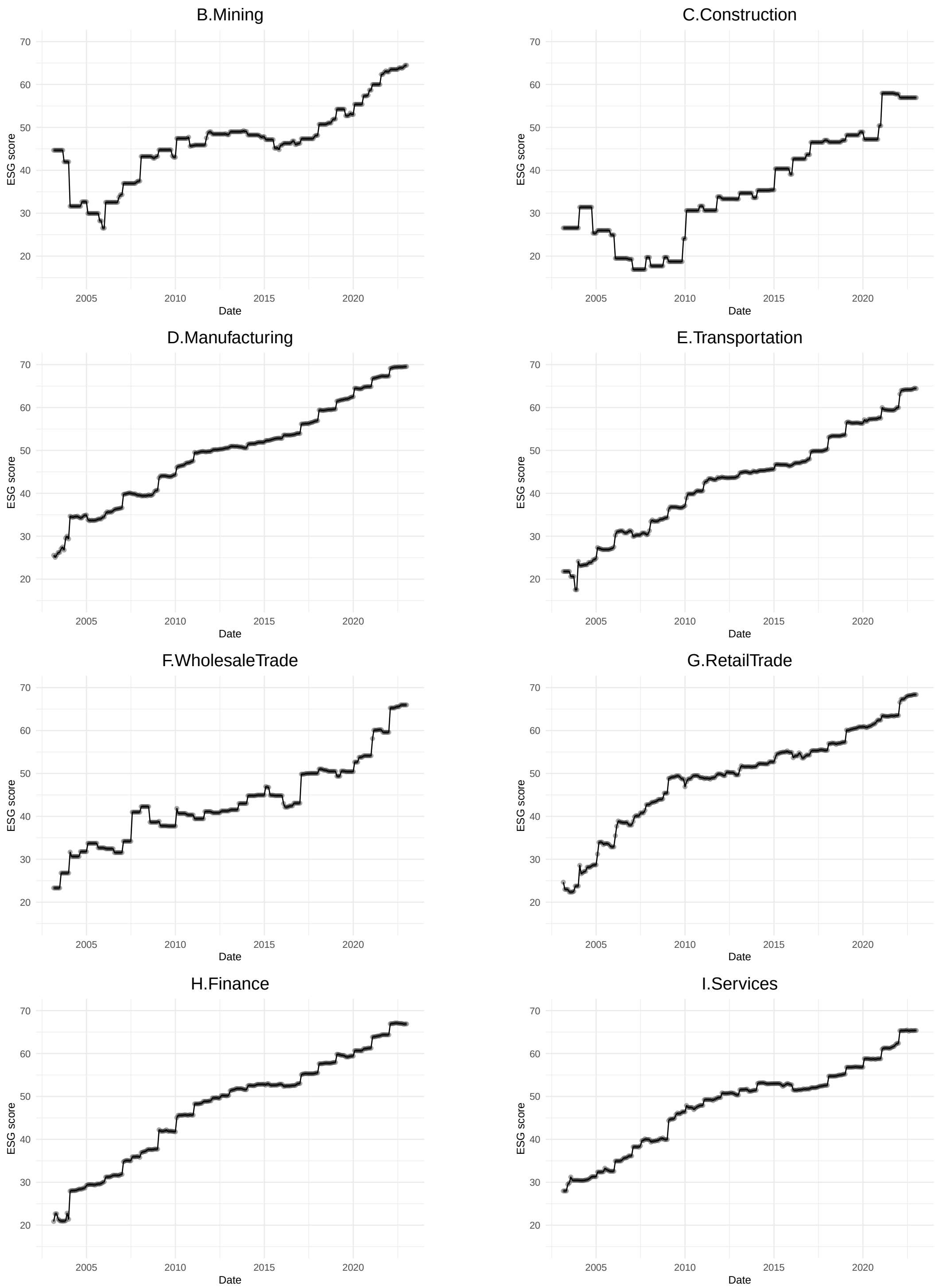
Several crucial factors, both within and outside companies, are responsible for the continuous increase in ESG ratings. Initially, the implementation of the Kyoto Protocol in 1997 signaled a major change in global environmental governance, compelling firms to incorporate environmental risks into their strategic planning. Kolk and Levy (2001) underscore that in the early 2000s, companies started to address climate risks and adhere to new global norms, leading to a gradual rise in ESG ratings.

In the mid-2000s, the introduction of the UN Principles for Responsible Investment (PRI) in 2006 greatly accelerated the adoption of ESG practices. The PRI offers a worldwide structure for institutional investors to incorporate ESG factors into their decision-making strategies. The period marked a significant rise in integrating ESG factors into equity investing, as indicated by the UN PRI's 2023 technical guide on ESG integration, showcasing a growing movement towards responsible investment. The consistent increase in ESG ratings at this moment shows these strategic changes (PRI 2023).

The period between 2010 and 2015 experienced a significant increase in ESG ratings, aligning with the global adoption of the UN Sustainable Development Goals (SDGs) and the Paris Agreement. As stated by Friede et al. (2015), these frameworks offer precise instructions for corporate sustainability, encouraging companies to enhance their ESG initiatives. According to Flammer (2015), firms are not only motivated by meeting regulations but also by the recognition of the long-term financial benefits associated with strong ESG performance. It is evident from the sharp rise in scores during this period.

The late 2010s experienced a further surge in ESG ratings, primarily driven by the growing demands from stakeholders, including investors and consumers. The increase in green bonds and sustainability-linked loans emphasises the importance of strong ESG performance in order to secure favourable financial terms. Giese et al. (2019) suggest that firms with high ESG ratings experience reduced capital expenses and improved reputation, which is reflected in the significant rise in ESG scores during this period. Moreover, Liang and Renneboog (2020) contend that the focus on sustainability in financial markets has become more pronounced, leading to further improvements in

Figure 3.3: ESG Scores: SIC Divisions



Evolution of the ESG scores for the firms listed in the S&P 500 Index divided by SIC Divisions.

ESG practices.

The final spike in ESG scores around 2020 is closely associated with the onset of the COVID-19 pandemic, which intensified the focus on corporate resilience and responsible governance. Ding et al. (2021) find that companies with strong ESG practices are better positioned to navigate the crisis, which further accelerates the adoption of ESG frameworks. Albuquerque et al. (2020) suggest that during crises, firms with robust ESG performance are perceived as less risky and more resilient, leading to a marked rise in ESG scores during this period.

The analysis of this figure indicates that the consistent upward trend in ESG scores is primarily driven by a confluence of global regulatory frameworks, stakeholder pressures, and the strategic importance of ESG in contemporary corporate governance. The upward trend in ESG activities, consistent in all sectors as shown in Figure 3.3, reinforces the idea that firms are increasingly prioritising sustainability, driven by both internal motivations and external pressures. Remarkably, even in sectors like mining and construction, where initial trajectories are negative, there is a notable reversal in recent years, aligning with the broader trend of ESG enhancement.

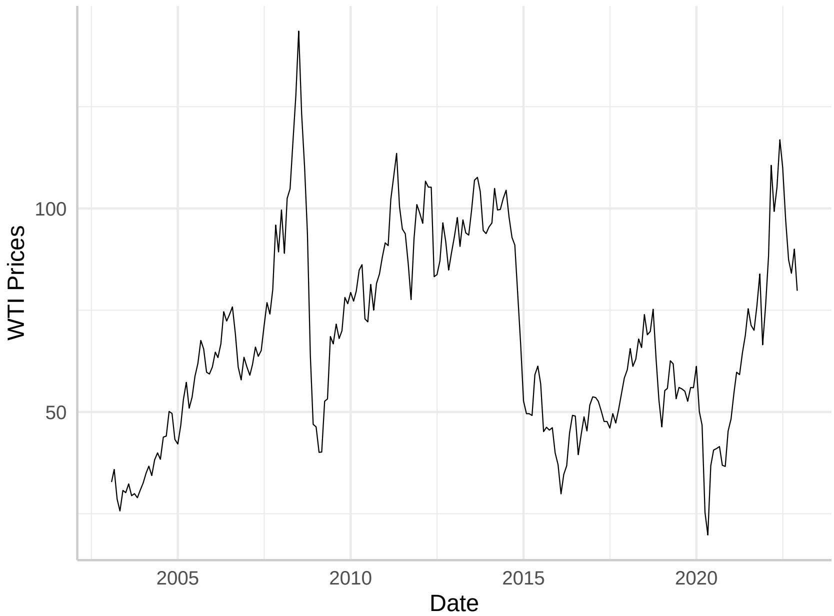
Crude oil uncertainty measure

Additionally, we collect time series data on crude oil volatility, determined in global commodity markets. As such, crude oil volatility enters our analysis as an exogenous factor, which is treated as common across firm. The crude oil volatility series is derived from an empirically constructed measure of the daily West Texas Intermediate (WTI) prices. This measure provides a reliable way to obtain a time series of the actual volatility over a given time frame. Equation (3.5) presents the methodology to evaluate this measure. This involves calculating the average of the squared daily returns of the WTI, which are then aggregated on a monthly basis and multiplied by 100. In this way, we are able to capture the volatility coming from the high-frequency daily fluctuation of the WTI within each month.

$$\begin{aligned} EV_t &= \frac{1}{d}\textstyle\sum_{i=1}^{d} r_i^2, \\ EVol_t &= \sqrt{EV_t} \times 100. \end{aligned} \tag{3.5}$$

In the equation above, $EVol_t$ indicates the crude oil volatility in month t, r_t represents the daily log-return on WTI on day i of month t, and d is the number of trading days in month t. This measure captures volatility stemming from daily WTI price fluctuations within each month.

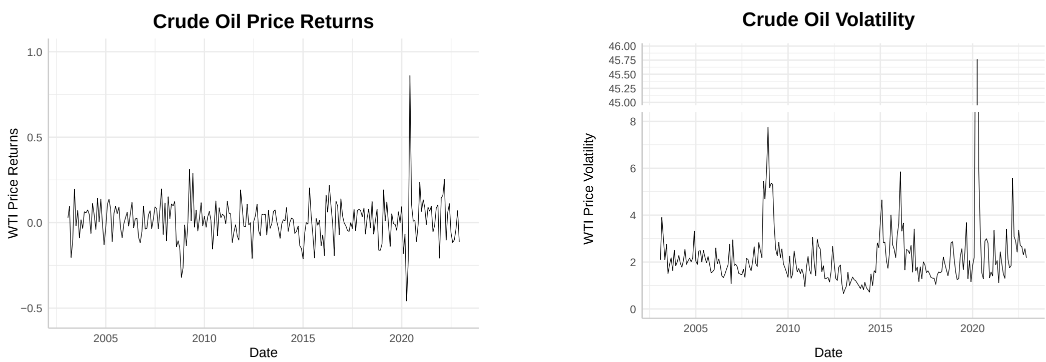
Figure 3.4: WTI Prices



Monthly WTI prices in the period February 2003 to December 2022.

Figure 3.4 shows the WTI prices while Figure 3.5 displays the monthly returns of the WTI on the left side and the level of volatility on the right side. These visual representations provide insight into the WTI prices over the period analysed in this study. Notably, the prices of crude oil are significantly influenced by economic and geopolitical events. For instance, the sample starts with a downward spike, which

Figure 3.5: WTI Price: Returns and Empirical Volatility Estimate



Monthly returns and empirical volatility of the WTI in the period February 2003 to December 2022.

coincides with the end of the geopolitical uncertainty followed by the 9/11 attack in 2001 and the subsequent US counteraction in Iraq. This reversal marks the start of an upward trend in crude oil prices, which is subsequently intensified by limited OPEC spare capacity in the first quarter of 2005. This increasing trend persists until the summer of 2006 when a series of factors lead to a shift. These factors include an oversupply of crude oil from Saudi Arabia and an overall market sentiment reflecting reduced tensions in Middle Eastern countries, thereby mitigating concerns about supply disruptions. The following positive spike is the largest of the series and represents the reaction of the crude oil prices during the peak of the Global Financial Crisis when the WTI reaches $\$143.57$ bringing the volatility to 7.76, its second-highest point. This is followed by a large negative swing due to oversupply and the measures enacted by OPEC nations to stabilise the market. OPEC countries indeed announced production cuts totalling 4.2 million barrels per day in late 2008. The following large price drop occurres at the beginning of 2015 due to OPEC's production strategy to keep its production quota unchanged to protect the market share from the rising non-OPEC countries' production. The last and largest negative spike occures during the global pandemic triggered by the rapid spread of the COVID-19 virus. It's worth noting that while this spike is visually interesting in the context of observing crude oil volatility's evolution, it is excluded from the time series in the regression analysis. This removal is undertaken to ensure a more reliable and unbiased representation of oil uncertainty[5].

Table 3.1 displays the descriptive statistics for the main variables, while the descriptive statistics of the control variables can be found in the Appendix A of this chapter. Within Table 3.1, the statistics for crude oil volatility are presented in two distinct lines: one including the spike related to the COVID-19 pandemic and one excluding it. This differentiation is necessary since, as explained in later sections, the main regression analysis considers crude oil volatility without the spike to ensure robustness and minimise bias from extreme outliers.

The mean return for all sectors is 0.8784, with a relatively high standard deviation of 9.1364. This dispersion is partly attributed to the fact that the dataset includes 500 firms listed in the S&P 500 index. This suggests substantial variation in returns, with

[5]For a detailed analysis of the COVID-19 spike's impact on the model and the rationale behind its removal, please see Appendix B.

some firms experiencing both significant gains and losses during the period. In specific sectors, returns vary considerably. For example, the Finance sector has a mean return of 0.6713, while the Services sector has a mean return of 1.1462. The minimum and maximum returns also vary significantly across sectors. For instance, the Finance sector has the lowest minimum return of -186.4615, reflecting the vulnerability of financial firms during market downturns, while the highest return of 127.9980 is observed in the Services sector, likely driven by outliers or exceptional performance in this category.

The interaction effect between oil volatility and ESG scores is notable, with a mean of 107.7505 and a relatively high standard deviation of 70.9247, indicating that the relationship between ESG scores and oil volatility is dynamic and varies significantly across the 500 firms in the dataset. Missing data points for ESG scores in certain firms result in fewer observations for this variable compared to the total dataset. This underscores the importance of sectoral patterns in understanding how ESG scores interact with oil market volatility.

The number of observations for each sector reflects the underlying composition of the dataset. For example, Manufacturing, which constitutes a substantial portion of the dataset, has 43,491 observations, while smaller sectors like Construction have only 1,434 observations. Crude oil volatility, being a time-series variable common across firms, has fewer observations (237 without the COVID-19 spike and 239 with the spike). The exclusion of two extreme observations related to the pandemic ensures a more reliable and unbiased representation of oil uncertainty. Including the spike inflates the mean of oil volatility from 2.1466 to 2.3747 and the standard deviation from 1.0258 to 3.0741, underscoring the substantial impact of this event.

These descriptive statistics highlight the diversity in the dataset, with firms in different sectors exhibiting varying returns, ESG scores, and responses to oil volatility. The sectoral and aggregate patterns presented in Table 3.1 provide a detailed foundation for the econometric analysis discussed in subsequent sections.

Control variables

We incorporate a comprehensive set of control variables at both the firms-level and macro-level. With respect to the firms-level, we collect data on the following for each

Table 3.1: Descriptive Statistics for Key Variables by Sector

Variable	Mean	Std. Dev.	Min	Max	Obs
Returns (All Sectors)	0.8784	9.1364	-186.4615	127.9980	109122
B. Mining	0.7260	12.2715	-178.5359	114.0773	3509
C. Construction	0.9295	10.2155	-67.4236	55.5051	1434
D. Manufacturing	0.9376	9.1487	-91.0560	87.0972	43491
E. Transportation	0.6184	8.3621	-154.5189	62.8898	14049
F. Wholesale Trade	0.9504	7.7292	-71.3115	45.7241	2631
G. Retail Trade	1.1457	8.1378	-62.7916	48.8945	6866
H. Finance	0.6713	8.9636	-186.4615	123.8308	21970
I. Services	1.1462	9.7018	-124.8388	127.9980	15172
Oil Volatility	2.1466	1.0258	0.6554	7.7563	237
with COVID-19 spike	2.3747	3.0741	0.6554	45.7646	239
ESG Score (All Sectors)	50.5666	20.2740	0.5986	95.1624	93614
B. Mining	48.0485	20.8163	8.8408	89.8727	2993
C. Construction	38.2904	20.3066	6.5665	84.7434	962
D. Manufacturing	52.5351	20.2894	3.2147	95.1624	38297
E. Transportation	45.9508	19.9496	1.9005	90.6594	12267
F. Wholesale Trade	46.8972	17.5259	17.1983	85.4617	1862
G. Retail Trade	51.8289	20.8669	6.6484	93.6641	5796
H. Finance	50.5491	19.9486	0.5986	92.0241	17810
I. Services	50.6490	19.9289	5.7881	93.4466	13388
Oil Volatility $\times$ ESG Score (All Sectors)	107.7505	70.9247	0.8062	715.7063	92387
B. Mining	84.2929	106.8171	0.3269	1808.7698	2991
C. Construction	65.8726	86.2240	0.3285	1441.3390	960
D. Manufacturing	91.0815	116.2004	0.3022	1872.2178	38295
E. Transportation	79.3992	104.1085	0.2767	1856.4655	12265
F. Wholesale Trade	80.0472	104.7580	0.3914	1606.9907	1860
G. Retail Trade	91.6403	113.6086	0.3847	1817.6953	5794
H. Finance	87.4873	111.8545	0.3214	1807.7639	17808
I. Services	87.8911	110.3925	0.3208	1947.6729	13386

Table 3.1 presents descriptive statistics for the primary variables under examination. For each variable, the initial row provides values for the entire sample, while subsequent rows present a sector-wise breakdown of these variables. Oil Volatility is analysed as a time series, while returns, ESG scores, and the interaction effect between ESG and oil volatility are examined as panel data. Returns and Oil Volatility are multiplied by 100.

company:

Company Size. This variable represents the market capitalisation of the firms, calculated as the aggregate market value of all relevant share types at the instrument level.

Total Assets. This variable denotes the reported total assets of the company. In cases where this data is unavailable, it is derived by summing Total Current Assets and Total Non-Current Assets.

ROA. To assess profitability relative to total assets, we use the Return on Assets (ROA) metric, calculated as the ratio of Income Before Taxes to Total Assets, multiplied by 100.

Board Size. This variable indicates the number of board members at the close of the fiscal year.

Board Gender Diversity. This variable represents the percentage of female board members, providing insights into gender representation on the board.

Board Independence. This variable captures the proportion of independent members on the board.

Board Meetings. This variable reflects the number of board meetings held during the fiscal year.

CSR Committee. This is a Boolean variable indicating whether the company has a Corporate Social Responsibility (CSR) committee (or team) or not.

Additionally, we incorporate several control variables at the macro level. All of them are expressed in changes:

VIX Index (Chicago Board Options Exchange Volatility Index). The VIX Index serves as a financial benchmark, providing real-time estimations of anticipated volatility in the S&P 500 Index. This index is calculated using the midpoint between real-time S&P 500 Index (SPX) option bid and ask quotes, drawing on the methodology of Koçak et al. (2022).

GDP (Gross Domestic Product). This variable includes the United States' Real Gross Domestic Product (GDP) figures, measured in constant prices and chained to 2009, to reflect the nation's economic performance. To integrate quarterly GDP data into the monthly dataset, we maintain a consistent log change value for each quarter. The data is sourced from the Energy Information Administration, United States.

CPI (Consumer Price Index). This index measures changes in consumer prices for a basket of goods and services, serving as a proxy for inflation in the United States. The Consumer Price Index, expressed as a percentage, is obtained from the Bureau of Labor Statistics, U.S. Department of Labor.

IPI (Industrial Production Index). The Industrial Production Index quantifies overall industrial production, presented in percentage terms. The data is sourced from the Federal Reserve of the United States.

EPU (Economic Policy Uncertainty Index). The Economic Policy Uncertainty (EPU) Index, derived from business surveys, assesses the level of economic policy uncertainty. This baseline overall index is expressed as a percentage and is sourced from Economic Policy Uncertainty, United States. The methodological framework for this variable is based on the study by Koçak et al. (2022).

3.5 Empirical Evidence

Table 3.2 presents the results of the regression model as delineated in Equation (3.1) for the panel dataset comprising companies listed in the S&P 500 Index. We utilise a fixed effect model to address firm-specific factors. The selection of this model is confirmed through the Hausman (1978) test, which consistently favours fixed effect models based on p-values consistently at zero. The model regresses the firms' return on the time series of the crude oil price volatility in which the negative spike related to the COVID-19 pandemic is removed, the firm's ESG score, and the interaction effect between the crude oil volatility and the firm's ESG score after controlling for firm-level and macro-level control variables. In the table, model (1) shows the coefficients coming from the pooled regression, while model (2) shows the outcome of the fixed effect model for firms[6].

Our research produces intriguing findings, with some results deviating from our initial expectations. As expected we find a negative correlation between returns and crude oil volatility. This is in line with the main strand of the literature as per the work of Christoffersen and Pan (2018), Bashir et al. (2021c), and Bashir (2022) among others. Unexpectedly, our analysis reveals a negative relationship between ESG scores and firms'

[6]The outcomes of the control variables of the model (3.1) are reported in Appendix A.

returns. This suggests that, on the whole, firms implementing ESG activities experience lower returns, contrasting the "doing good while doing well" concept supported in prior literature (Derwall et al. 2005; Guenster et al. 2011). However, our work makes an additional step from this since it centres its attention on the interaction effect between ESG scores and crude oil price volatility focusing on the mitigating effect of ESG activities in times of rising volatility in the crude oil market. When we account for the interaction effect to investigate the whole effect of the ESG as hedging protection from crude oil volatility, we unveil a different scenario that provides a deeper understanding beyond what is described solely by the coefficients of crude oil volatility (β_1) and the ESG scores (β_2) suggesting a picture that is more aligned with our initial expectations, especially regarding the relationship between ESG and returns. While the relationships between returns and both ESG and oil volatility are relevant aspects of our analysis, the central point of focus is the interaction effect between ESG and crude oil volatility. To gain a comprehensive understanding of the mitigating impact, it is important to consider these three interconnected coefficients jointly. This interplay shapes the overall narrative of our investigation, shedding light on the intricate dynamics between ESG, crude oil volatility, and firm returns. Moreover, we expand our analysis first by splitting the sample of the firms into sectors based on the SIC divisions. Additionally, we group the firms into four quartiles based on the average of the firms' ESG across the whole period analysed. This segmentation allows us to explore how different sectors and ESG practices influence the relationship between returns and crude oil volatility.

Interpretation of the results

As stated previously, our findings point out that there is a negative relationship between returns and ESG, a negative relationship between ESG and oil volatility, and a positive relationship between returns and the interaction effect between ESG and oil volatility. Through a comprehensive analysis of these results, the signs and the relative magnitudes of these outcomes collectively indicate that the relationship between ESG and returns becomes stronger when the crude oil volatility increases. This is in line with our initial conjectures. The scope of our research is indeed centred on exploring whether a high ESG score has a mitigating effect on returns in times of rising volatility in the oil market.

Table 3.2: Impact of Oil Volatility and ESG Scores on Returns (Main Results)

	$r_{it} = \alpha + \beta_1\, OilVol_t + \beta_2\, ESGScore_{it_U} + \beta_3\, ESGScore_{it_U} \times OilVol_t + \text{Controls} + \varepsilon_{it}$					
	(1)	(2)	(1)	(2)	(1)	(2)
Variables	Returns	Returns	Returns	Returns	Returns	Returns
Oil Volatility	-1.9733***	-1.9557***	-1.6568***	-1.6601***	-1.6258***	-1.6412***
	(0.0758)	(0.0762)	(0.0883)	(0.0888)	(0.0822)	(0.0826)
ESG Score	-0.0304***	-0.0234***	-0.0253***	-0.0255***	-0.0207***	-0.0212***
	(0.0033)	(0.0036)	(0.0037)	(0.0042)	(0.0034)	(0.0039)
Oil Volatility $\times$ ESG Score	0.0160***	0.0156***	0.0136***	0.0135***	0.0112***	0.0112***
	(0.0014)	(0.0014)	(0.0016)	(0.0016)	(0.0014)	(0.0014)
Constant	5.0092***	4.6538***	5.4113***	5.5618***	5.4764***	5.6258***
	(0.1802)	(0.1963)	(0.3190)	(0.4211)	(0.2974)	(0.3889)
Micro Controls	No	No	Yes	Yes	Yes	Yes
Macro Controls	No	No	No	No	Yes	Yes
Number of Observations	87,163	87,163	74,075	74,075	74,061	74,061
R-squared	0.0345	0.0342	0.0416	0.0399	0.0708	0.0688
Number of Firms	497	497	496	496	496	496

This table presents the regression results analysing the impact of oil volatility and ESG scores on firm returns. The sample includes companies listed on the S&P 500 Index from February 2003 to December 2022. Model (1) uses OLS regression, while model (2) accounts for firm fixed effects. Micro-level controls include firm-specific variables, and macro-level controls include broader economic factors.

*** Significant at 1%, ** Significant at 5%, * Significant at 10%. Standard errors are shown in parentheses.

Our findings reveal a significant threshold in crude oil volatility associated with low levels of volatility. Below this threshold, ESG scores exhibit the direct negative impact on returns shown by the β_2 coefficient in the regression. However, when volatility exceeds this turning point, the interaction effect between ESG scores and crude oil volatility comes into play, and ESG scores become effective in hedging returns. This hedging effect intensifies as oil volatility continues to rise. In essence, our results suggest an insurance-like effect of ESG. They are linked to negative returns during low volatility but act as a hedge as volatility increases.

To properly interpret the results, we break down the regression equation, Eq. (3.1), into its partial derivatives. The partial derivative with respect to the ESG scores describes how the effect of different ESG scores on returns changes as crude oil volatility varies while holding all else constant. Conversely, the partial derivative with respect to the crude oil volatility shows how the relationship between crude oil volatility and returns varies, depending on the firms' ESG scores, again *ceteris paribus*. Equation (3.6) represents therefore how changes in the ESG scores impact the returns for different levels of volatility while Equation (3.7) shows how changes in the crude oil market volatility affect the firms' returns of companies with different ESG scores. In both instances, we employ the coefficients stemming from the fixed-effect model encompassing both firm-level and macro-level control variables.

$$\frac{\partial\, r_{it}}{\partial\, ESG_{it}} = -0.0212 + 0.0112\, OilVol_t. \tag{3.6}$$

$$\frac{\partial\, r_{it}}{\partial\, OilVol_t} = -1.6412 + 0.0112\, ESG_{it}. \tag{3.7}$$

This setup gives an optimal framework to analyse whether increasing the ESG score by one unit generates different changes in the companies' returns at different levels of crude oil volatility (Eq. 3.6), and, on the other side, whether the magnitude of the change in the firms' returns followed by a one-unit change in the crude oil volatility differs based on the different levels of ESG activities put in action by the firms (Eq. 3.7).

In Table 3.3 we apply Equation (3.6) using three values of the crude oil uncertainty to better investigate the behaviour of the returns across all ranges of values that the

Table 3.3: Impact of ESG on Returns under Different Oil Volatility Levels

$\partial r_{it}/\partial ESG_{it}$	β_2	$\beta_3 \times OilVol_t$	$OilVol$	
-0.0138	-0.0212	0.0073	$OilVol_{min}$	0.66
0.0028	-0.0212	0.0240	$OilVol_{avg}$	2.15
0.0656	-0.0212	0.0868	$OilVol_{max}$	7.76

This table shows the partial derivatives of returns with respect to ESG scores under three levels of crude oil volatility: minimum ($OilVol_{min} = 0.66$), average ($OilVol_{avg} = 2.15$), and maximum ($OilVol_{max} = 7.76$). The coefficients β_2 and $\beta_3 \times OilVol_t$ represent the direct and interaction effects, respectively.

crude oil volatility reaches during the time span analysed in this study. These levels represent the minimum, average, and maximum values of crude oil volatility (0.66, 2.15, and 7.76). As said previously, in this analysis the spike in the volatility related to COVID-19 is removed.

Analysing the results, it can be seen that the partial derivative takes on a negative value when we consider low levels of volatility. This implies that, for low levels of crude oil volatility, a company's effort to improve its ESG scores corresponds to a reduction in the company's returns. Put differently, when comparing two companies with different ESG scores in periods of low oil volatility, the company with the lower ESG score manages to yield higher returns. As the uncertainty in the crude oil market increases, the positive effect that the interaction between ESG scores and crude oil volatility has on firms' returns outweighs the negative relationship between returns and ESG. The negative value of β_2 stemming from the regression indeed implies a negative relationship between returns and ESG without considering the interplay between ESG and oil volatility. However, the overall effect of the interaction analysis points out that the interaction effect exceeds this negative relationship after a specific volatility threshold. Once the interaction effect overcomes the negative effect of the ESG over the returns, the relationship between returns and ESG scores becomes stronger as the volatility increases. The largest change in the returns occurs in times of high volatility which suggests that an increase in the ESG in times of rising volatility generates a larger positive effect than in periods of relatively lower volatility in the oil market. In other words, the mitigating effect of high ESG scores affects the returns more profoundly in times of high volatility and this effect reduces when the volatility decreases, and even

Table 3.4: Impact of Oil Volatility on Returns under Different ESG Levels

$\partial r_{it}/\partial OilVol_t$	β_1	$\beta_3 \times ESG_{it}$	ESG	
-1.6345	-1.6412	0.0067	ESG_{min}	0.59
-1.0756	-1.6412	0.5656	ESG_{avg}	50.57
-0.5769	-1.6412	1.0643	ESG_{max}	95.16

This table shows the partial derivatives of returns with respect to oil volatility under three levels of ESG: minimum ($ESG_{min} = 0.59$), average ($ESG_{avg} = 50.57$), and maximum ($ESG_{max} = 95.16$). The coefficients β_1 and $\beta_3 \times ESG_{it}$ represent the direct and interaction effects, respectively.

becomes negative during instances of very low volatility.

With the same spirit, in Table 3.4 we apply Equation (3.7) for different levels of ESG scores. We focus on three scenarios in which companies with different ESG scores face the whole spectrum of crude oil volatility levels and we test whether the amount of the change in the returns results to be different among the firms. We choose to test those scenarios taking into account the case of the company with the lowest ESG score that has been assessed during the period analysed (0.59), the case of a company with an ESG score equal to the average (50.57), and the company with the best ESG score that has been assessed (95.16).

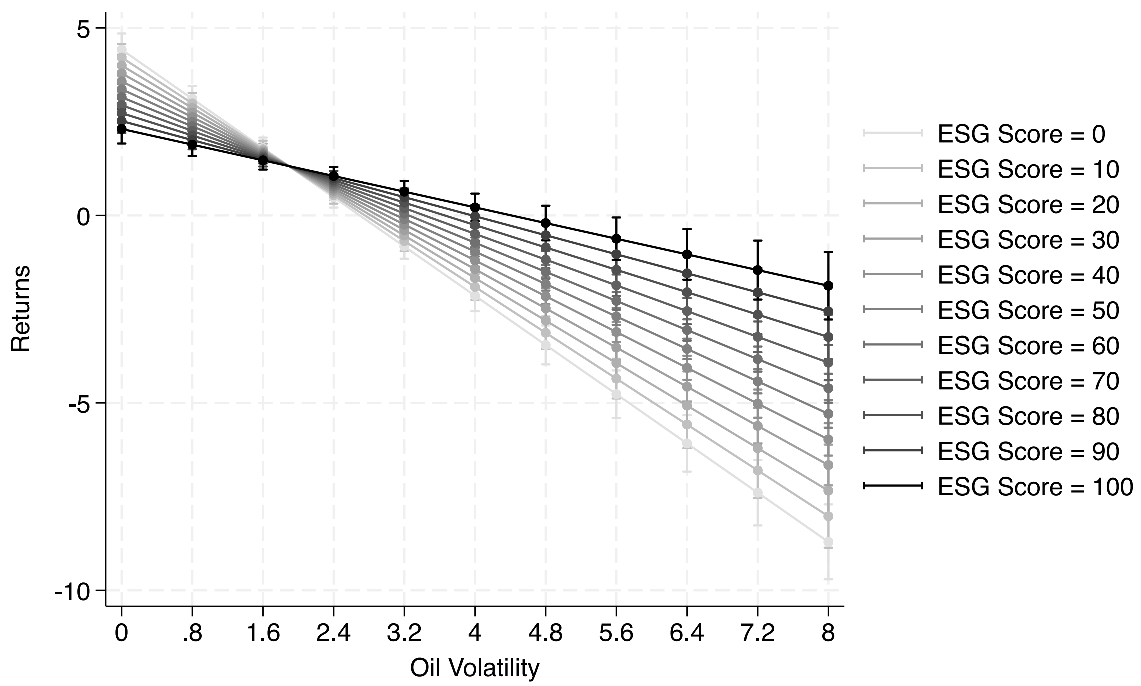
As can be noticed, a one-unit change in oil volatility generates different magnitudes of changes in the returns for different ESG scores. The negative changes are in line with the already mentioned negative relationship between returns and volatility therefore a lower change is associated with a lower loss. Said that, the ESG leader experiences the lowest change, hence the lowest loss, for a change in the crude oil volatility. Comparing this result with the other two reported in the table, it appears evident that different ESG scores give different levels of protection to changes in crude oil volatility and this hedging level reaches its maximum for companies with the highest ESG scores. As the ESG scores decrease, the effect of a one-unit increase in oil volatility over the returns becomes more pronounced meaning that the negative impact of a crude oil volatility change becomes larger. Focusing on the results of the table, the negative impact of oil volatility is minimised for the case of the ESG leader (-0.5769), it is less pronounced for firms with an ESG equal to the average (-1.0756), and lowest for the ESG laggard (-1.6345).

Returning our attention to Table 3.3, to pinpoint the turning point where the partial derivatives of return with respect to ESG scores start assuming positive values, we set Equation (3.6) equal to zero, as outlined in Equation (3.8). This calculation enables us to identify the threshold level of volatility at which the returns of firms with different ESG scores are equal.

$$\begin{aligned} \frac{\partial\, r_{it}}{\partial\, ESG_{it}} &= 0, \\ -0.0212 \;+ 0.0112\, OilVol_t &= 0, \\ \frac{0.0212}{0.0112} &= 1.8929. \end{aligned} \tag{3.8}$$

The precise value of this turning point is illustrated by the evaluation in Equation (3.8), which is equal to 1.8929.

Figure 3.6: Margin Plot: Returns Across Oil Volatility Levels at Different ESG Levels

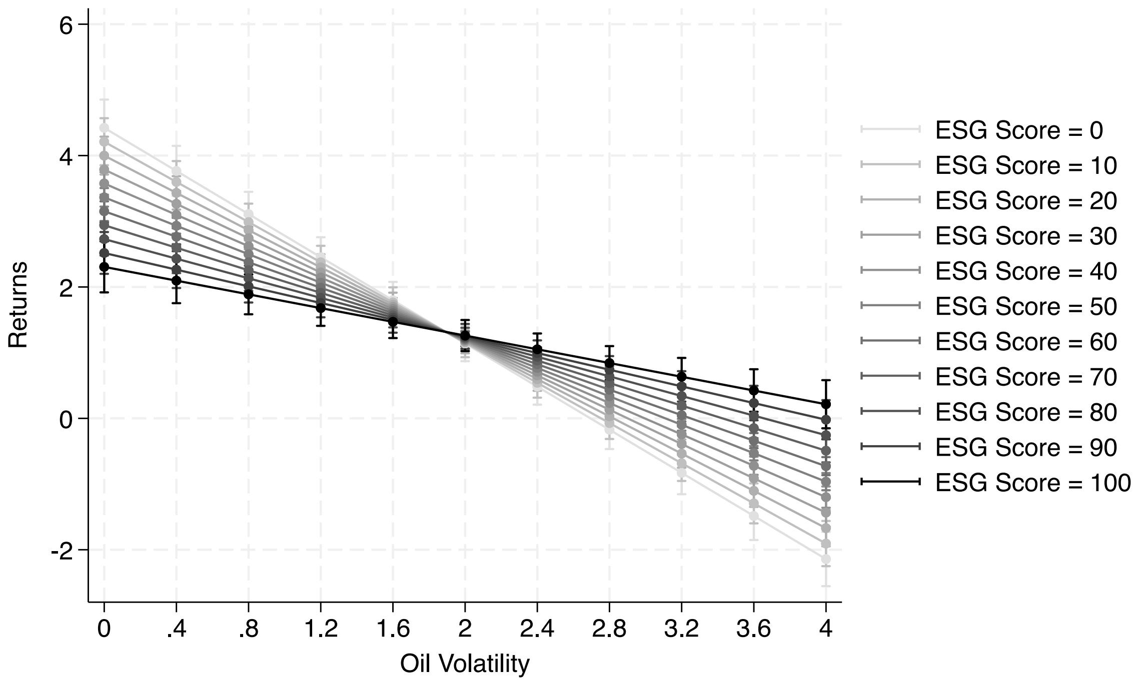


Effect of oil volatility over returns for different levels of ESG scores. The confidence levels are set to 95% and are represented by the vertical bars.

To have a visual representation of our findings, Figure 3.6 displays how the returns change after a one-unit increase in the oil volatility for firms with different ESG scores while Figure 3.8 exhibits the different relationships between returns and ESG scores for several levels of crude oil volatility. This extends and makes clearer the prior finding since it portrays the partial derivatives as the slopes of the curves allowing us to have a more comprehensive view of the interplay between ESG scores and oil volatility.

Figure 3.6 displays the effect of volatility over firms' returns for 11 different ESG scores ranging from zero to 100. The range of the volatility and the ESG scores varies from their minimum level (0 in both cases) to their maximum (7.76 for the volatility and 100 for the ESG score). From the figure, it can be noticed that the relative hedging effect of ESG activities between ESG leaders and ESG laggards is not consistent across all the levels of crude oil volatility as can be clearly noticed by the turning point with respect to the crude oil volatility. Below this volatility threshold, companies with high ESG scores yield lower returns compared to their lower-scored counterparts. Conversely, as volatility surges beyond this point, the hedging effect of the ESG scores becomes increasingly more crucial and the spread in the returns between ESG leaders and laggards increases as the volatility increases. Figure 3.7 provides an in-depth view of Figure 3.6, focusing on the close-up of the surrounding of the turning point.

Figure 3.7: Margin Plot: Focus on Volatility Range Around Turning Point at Different ESG Levels

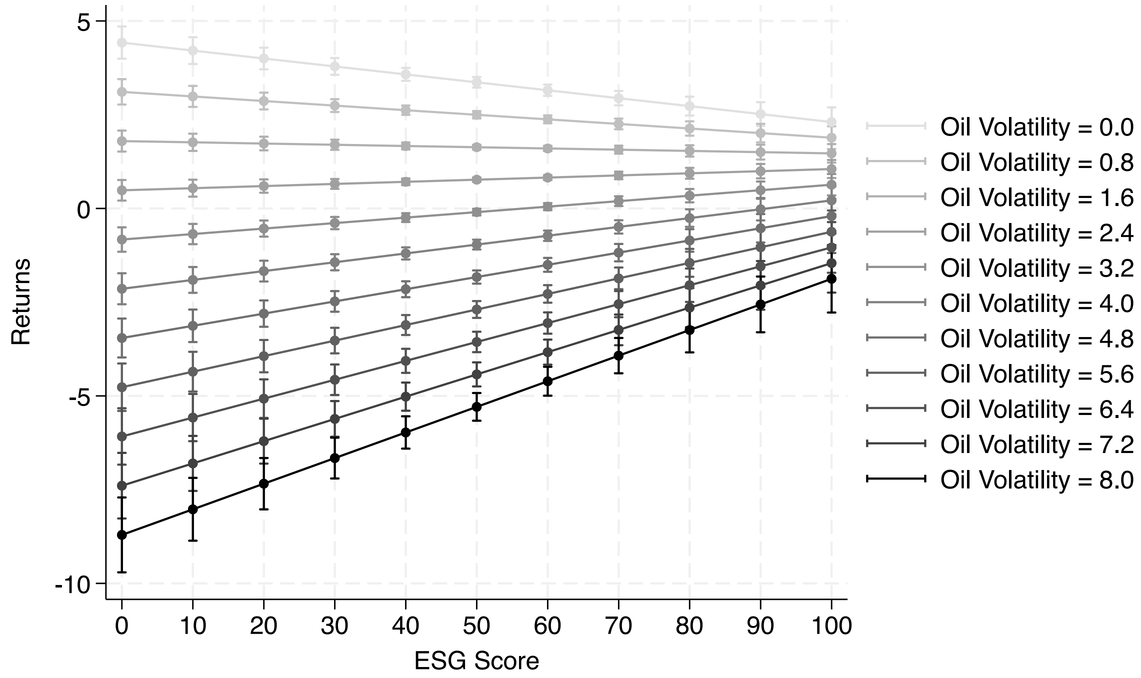


Zoomed-in view of the volatility range (0-4) around the turning point (1.8929). The confidence levels are set to 95% and are represented by the vertical bars.

As can be appreciated in Figure 3.7, the turning point represents the juncture at which all the returns of firms, irrespective of their ESG scores, are equal. In other words, this marks the point in which the hedging effect of ESG scores does not generate any difference between ESG leaders and ESG laggards. Within the context of this study, this inflexion point represents the point from which the hedging effect of the ESG scores begins to act as a protecting hedge against volatility stemming from the crude oil market. Focusing on the curves of Figure 3.6, it is worth noticing that all the slopes are negative and that the slopes of the curves related to firms with high ESG scores are flatter comparing them with the ones related to companies with low ESG scores. This leads to two notable conclusions. Firstly, the consistent negative slopes is the graphical representation of the already mentioned negative relationship between returns and crude oil uncertainty. Secondly, the fluctuation in returns between ESG leaders and laggards due to different levels of uncertainty in the crude oil market is more pronounced for the latter rather than the former. This phenomenon is directly linked to the hedging effect of ESG scores. In the graph, this can be seen by the vertical difference between the returns of ESG leaders and ESG laggards. This spread is more noticeable during periods of rising volatility in the crude oil market, as clearly depicted on the right side of the graph. As already mentioned, Equation (3.7) displays the impact of changes in crude oil market volatility on the returns of companies with different ESG scores. When ESG is equal to zero, the slope of the curve in Figure 3.6 is equal to β_2, hence the sensitivity of returns to the crude oil uncertainty without accounting for firms' ESG performances. In the graph, this is indicated by the white line. Since the sign of the interaction effect β_3 is positive, an increase in the ESG scores reduces the negative slope of the curves. This graphical depiction illustrates how ESG scores function as a hedge, mitigating the impact of high volatility originating from the crude oil market on returns.

The diverse lines depicted in Figure 3.8 correspond to varying degrees of volatility. The graph illustrates how ESG scores influence companies' returns across 11 discrete levels of oil volatility, ranging from the lowest value of 0.00 to the highest value of 7.76. The light grey lines atop the graph represent periods of low volatility while the darker lines at the bottom represent periods in which the oil volatility is close to its maximum level. Analysing the curves, we observe that during periods of low volatility (lighter

Figure 3.8: Margin Plot: Returns Across ESG Levels at Different Oil Volatility Levels



Effect of ESG over returns for different levels of crude oil volatility. The confidence levels are set to 95% and are represented by the vertical bars.

curves), firms with lower ESG scores on the left side of the graph tend to generate higher returns than those with high ESG scores on the right side. This relationship reverses as volatility increases. When the volatility curve reaches the turning point at a value of 1.8929, it becomes flat, indicating that the returns of firms are comparable regardless of their ESG scores. However, when volatility surpasses the turning point (darker curves), the relationship between ESG leaders and laggards changes. Firms with lower ESG scores now yield lower returns, as evident from the negative slopes of the darker curves. The difference in returns, as indicated by the negative slopes, increases with higher volatility. This inversion occurs due to the strengthening impact of the interaction between ESG scores and crude oil volatility, which overrides the initial negative effect of ESG scores on returns, as indicated by the β_2 coefficient in the regression. Indeed, when we examine high levels of volatility (darker lines), the slope of the line becomes steeper. This indicates a more pronounced relationship between ESG scores and returns, indicating a stronger relationship between ESG scores and returns during times of heightened volatility. In other words, there is a more substantial difference in returns between firms with low and high ESG scores in these high-volatility periods. Conversely, at low volatility levels, the slope is less pronounced, as evident from the light to medium grey lines. In these instances, when volatility is low, the difference between high and low-ESG-scored firms is sensibly less pronounced.

At this point, it is worth reiterating the importance of accounting for the interplay between ESG scores and oil volatility when investigating the hedging impact of ESG in times of crude oil uncertainty. By considering the interaction effect, the relationship between ESG and returns becomes positive after the turning point, overcoming the direct negative effect that ESG scores have on return as shown by the regression coefficient β_2.

Sector analysis

We extend our analysis to investigate how ESG activities shield returns from crude oil volatility uncertainty across various industry sectors. To classify companies into sectors, we employ the US Standard Industrial Classification (SIC) system. Specifically, we utilise the 2-digit SIC codes to categorise the companies into eight distinct groups representing mining, construction, manufacturing, transportation, wholesale trade, retail trade, finance, and services. The grouping of companies based on these divisions is outlined in Table 3.7, along with a more granular breakdown outlined by the SIC major groups. The Pearson (1896) correlation coefficient is employed to identify the extent to which each of these eight sectors is influenced by crude oil volatility.

The negative relationship between returns and crude oil uncertainty, as previously identified in the regression for the entire sample, is further supported by the consistently negative Pearson coefficients listed in Table 3.5. Specifically, Mining emerges as the most sensitive sector to crude oil volatility, demonstrating a strong correlation with fluctuations in oil prices. Following closely, the Finance and Wholesale Trade sectors display considerable sensitivity, positioning them as moderately responsive to oil price shifts. Transportation, Manufacturing, and Services exhibit moderate sensitivities, while Retail Trade shows the least sensitivity to changes in crude oil volatility among the listed sectors. It's worth mentioning that the Construction sector is excluded since it is the only sector that shows a lack of statistical significance in the interaction effect

Table 3.5: Sector Analysis - Pearson Correlation Coefficients

Sectors	Oil Volatility Correlation	ESG Sector Mean	Returns Sector Mean
B. Mining	-0.3611	48.05	0.7260
C. Construction	-0.2216	38.29	0.9295
D. Manufacturing	-0.1980	52.54	0.9376
E. Transportation	-0.2284	45.95	0.6184
F. Wholesale Trade	-0.2376	46.90	0.9504
G. Retail Trade	-0.1766	51.83	1.1457
H. Finance	-0.2733	50.55	0.6713
I. Services	-0.1977	50.65	1.1462

This table presents the Pearson correlation coefficients between returns and oil volatility, along with the mean ESG scores and returns for each sector.
Oil volatility and firms' returns are multiplied by 100.

coefficient β_3.

After identifying the sectors most impacted by crude oil uncertainty, we conduct the same analysis for each sector as we do for the entire sample. Looking at Table 3.6 alongside Figure 3.9, which display respectively the output of the regression and the margins plots for each sector, the hedging effect can be seen in the interaction effect coefficient β_3 of Table 3.6 which translate into the slopes of the curves on Figure 3.9 as outlined in the methodology section. This effect is captured by $\beta_1 + \beta_3 \times ESG_{it}$ for the left-hand graphs and $\beta_2 + \beta_3 \times OilVol_t$ for the right-hand graphs in Figure 3.9.

The sector analysis unravels a more articulated picture compared to the main analysis giving credit to the importance of dividing the companies listed on the S&P 500 Index into sectors. The interaction effect coefficient β_3 is a measure of how ESG activities become more effective in hedging returns as volatility surges by being responsible for the magnitude of the difference in the returns between ESG leaders and ESG laggards. This, together with the volatility threshold, evaluated as β_2/β_3, gives a picture of how ESG activities of firms operating in different sectors help reduce the negative impact of crude oil volatility over the returns. Specifically, lower volatility turning points imply the effectiveness of ESG activities at lower volatility levels, while β_3 coefficient is a measure of the effectiveness of the ESG activities. Graphically, the effectiveness of the ESG scores can be appreciated as the vertical spread of returns between ESG leaders and laggards. Higher β_3 magnitudes correspond to a quicker widening of this spread, accentuating the effectiveness of ESG practices.

When examining the interaction effect coefficient β_3, it is noteworthy that the sector with the highest Pearson correlation with crude oil volatility, Mining (-0.3611), also exhibits the highest magnitude of the β_3 coefficient (0.0202). This indicates a significant interaction between ESG scores and crude oil volatility in the Mining sector. Retail Trade follows, showing a notable relationship between ESG performance and oil volatility with a β_3 coefficient of 0.0136 and a Pearson correlation of -0.1766. Wholesale Trade and Services display moderate interaction effects, with β_3 coefficients of 0.0122 and 0.0100 respectively, and Pearson correlations of -0.2376 and -0.1977. In contrast, Manufacturing, Transportation, and Finance sectors exhibit comparatively lower interaction coefficients (β_3 of 0.0081, 0.0051, and 0.0039 respectively) and Pearson correlations of -0.1980, -0.2284, and -0.2733, suggesting less pronounced associations between ESG performance and crude oil volatility within these sectors.

Our research reveals that the effectiveness of ESG activities as hedges against crude oil volatility varies significantly across sectors. Each sector indeed shows a peculiar dynamic. By assessing both the *"when"*, represented by the volatility threshold from which the ESG scores begin to act as a hedge for returns, and the *"how fast"* ESG activities protect the returns, depicted analytically by the β_3 coefficient and graphically by the vertical spread of the returns, we find that sectors with higher β_3 values or lower thresholds experience stronger protection from ESG activities. Mining and Wholesale Trading sectors, having the highest β_3 and the lowest threshold respectively, demonstrate significant protection against crude oil volatility. Conversely, Finance, displaying the lowest β_3 coefficient, appears to be the sector in which the effectiveness of the ESG scores is less pronounced. These findings underscore the importance of sector analysis, aligning with existing literature examining diverse dynamics of ESG scores on returns, even without considering the crude oil market uncertainty (Brammer et al. 2006; Damodaran 2023; Gonçalves et al. 2022; Renneboog et al. 2008).

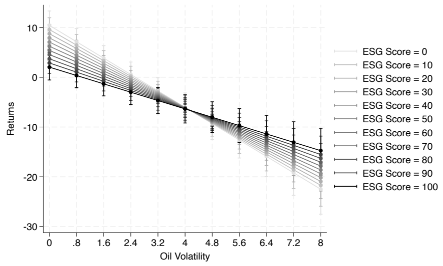
Table 3.6: Sector Analysis - Regression Results

	B. Mining	C. Construction	D. Manufacturing	E. Transportation	F. Wholesale Trade	G. Retail Trade	H. Finance	I. Services
Variables	Returns	Returns	Returns	Returns	Returns	Returns	Returns	Returns
Oil Volatility	-4.1162***	-1.7549***	-1.3078***	-1.3091***	-1.5033***	-1.6156***	-1.4019***	-1.4852***
	(0.3712)	(0.4325)	(0.0916)	(0.1342)	(0.2595)	(0.1943)	(0.1149)	(0.1448)
ESG Score	-0.0840***	-0.0345	-0.0290***	-0.0195**	0.0065	-0.0446***	-0.0153**	-0.0128
	(0.0271)	(0.0330)	(0.0047)	(0.0079)	(0.0218)	(0.0114)	(0.0067)	(0.0088)
Oil Volatility × ESG Score	0.0202***	0.0129	0.0081***	0.0051**	0.0122***	0.0136***	0.0039**	0.0100***
	(0.0061)	(0.0092)	(0.0014)	(0.0023)	(0.0046)	(0.0031)	(0.0019)	(0.0024)
Constant	14.8191***	15.0258**	6.4467***	7.6073***	12.3835***	6.8786***	6.3132***	5.6247***
	(3.2126)	(7.2276)	(0.5693)	(1.0293)	(3.1288)	(1.3688)	(0.8733)	(1.0631)
Number of Observations	2,435	875	30,253	10,153	1,431	5,027	14,880	9,960
R-squared	0.3099	0.2478	0.1977	0.1887	0.2794	0.1822	0.2316	0.2188
Number of Firms	16	5	201	63	12	30	96	73

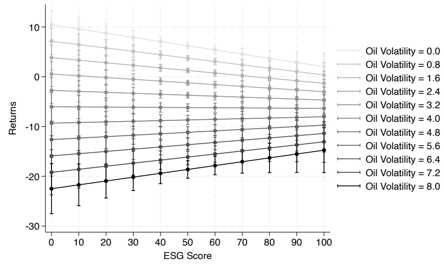
This table presents the regression results of Equation 3.1 applied to the eight SIC divisions. For conciseness, only the results of the fixed effects models with the micro and macro variables are included.

*** Significant at 1%, ** Significant at 5%, * Significant at 10%. The parenthesis represents the standard errors. Oil volatility and firms' returns are multiplied by 100.

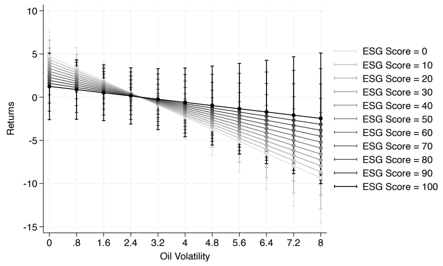
Figure 3.9: Sector Analysis - Margin Plots



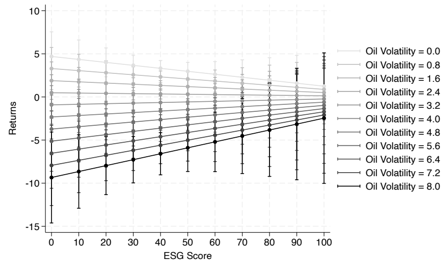
(a) B. Mining: Oil Volatility over returns for different ESG levels



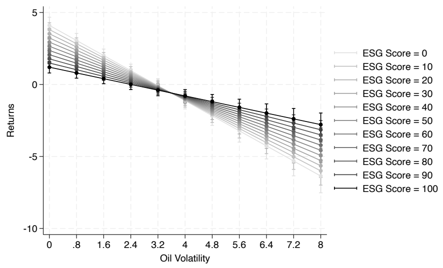
(b) B. Mining: Oil Volatility over returns for different uncertainty levels



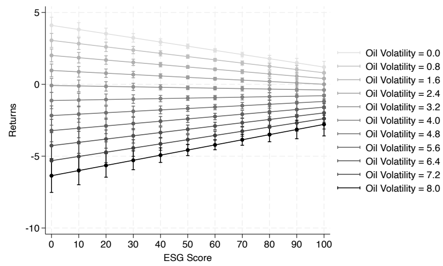
(c) C. Construction: Oil Volatility over returns for different ESG levels



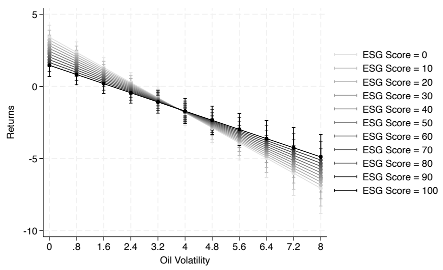
(d) C. Construction: Oil Volatility over returns for different uncertainty levels



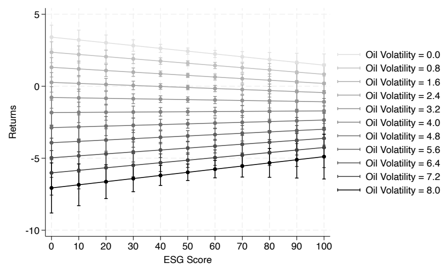
(e) D. Manufacturing: Oil Volatility over returns for different ESG levels



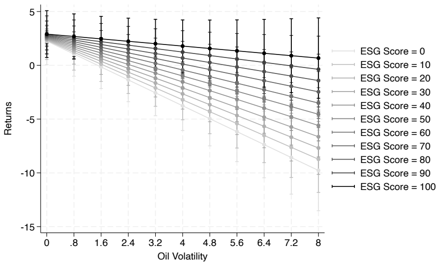
(f) D. Manufacturing: Oil Volatility over returns for different uncertainty levels



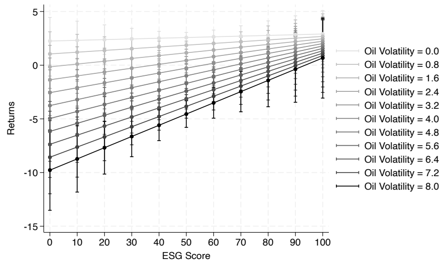
(g) E. Transportation: Oil Volatility over returns for different ESG levels



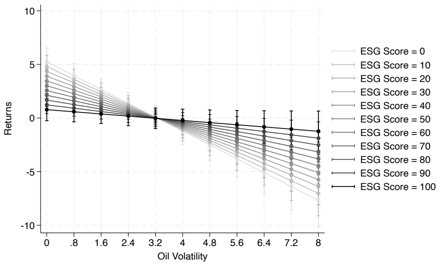
(h) E. Transportation: Oil Volatility over returns for different uncertainty levels



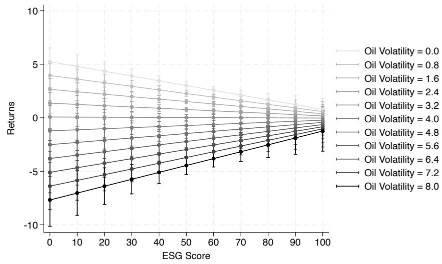
(a) F. Wholesale Trade: Oil Volatility over returns for different ESG levels



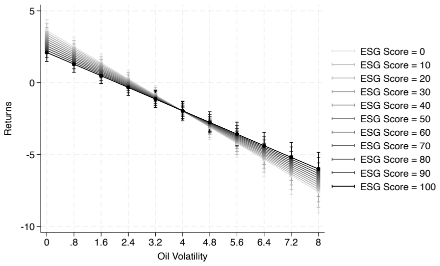
(b) F. Wholesale Trade: Oil Volatility over returns for different uncertainty levels



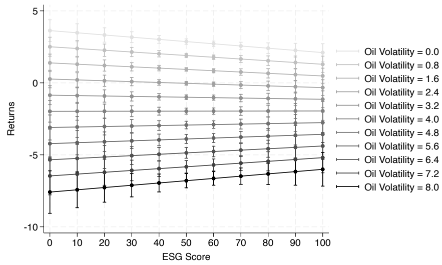
(c) G. Retail Trade: Oil Volatility over returns for different ESG levels



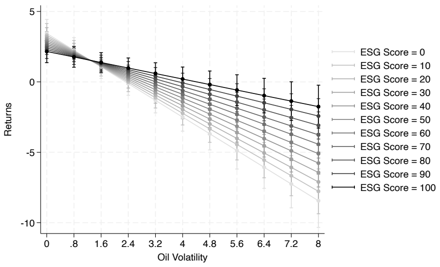
(d) G. Retail Trade: Oil Volatility over returns for different uncertainty levels



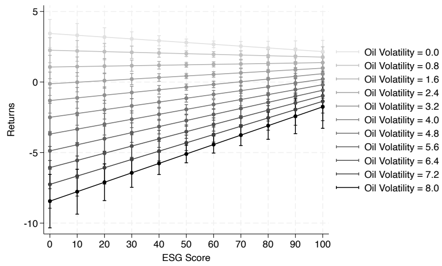
(e) H. Finance: Oil Volatility over returns for different ESG levels



(f) H. Finance: Oil Volatility over returns for different uncertainty levels



(g) I. Services: Oil Volatility over returns for different ESG levels



(h) I. Services: Oil Volatility over returns for different uncertainty levels

Effect of oil volatility over returns for different levels of ESG scores (left) and for different levels of volatility (right). The confidence levels are set to 95% and are represented by the vertical bars.

Table 3.7: SIC Divisions and Major Groups

SIC Division Name	Freq.	Percent
B. Mining	16	3.2
C. Construction	6	1.2
D. Manufacturing	203	40.6
E. Transportation, Communications, Electric, Gas And Sanitary Services	64	12.8
F. Wholesale Trade	12	2.4
G. Retail Trade	30	6
H. Finance, Insurance And Real Estate	96	19.2
I. Services	73	14.6
Total	500	100

SIC Major Group (A-H)	Freq.	Percent
Amusement And Recreation Services	2	0.4
Apparel And Accessory Stores	3	0.6
Apparel And Other Textile Products	3	0.6
Automotive Dealers And Service Stations	5	1
Building Materials And Garden Supplies	5	1
Business Services	54	10.8
Chemicals And Allied Products	39	7.8
Communications	9	1.8
Depository Institutions	19	3.8
Eating And Drinking Places	5	1
Electric, Gas, And Sanitary Services	36	7.2
Electronic And Other Electric Equipment	26	5.2
Engineering And Management Services	5	1
Fabricated Metal Products	6	1.2
Food And Kindred Products	21	4.2
Food Stores	1	0.2
Furniture And Homefurnishing Stores	1	0.2
General Building Contractors	4	0.8
General Merchandise Stores	5	1
Health Services	5	1
Heavy Contractors, Except Building	1	0.2

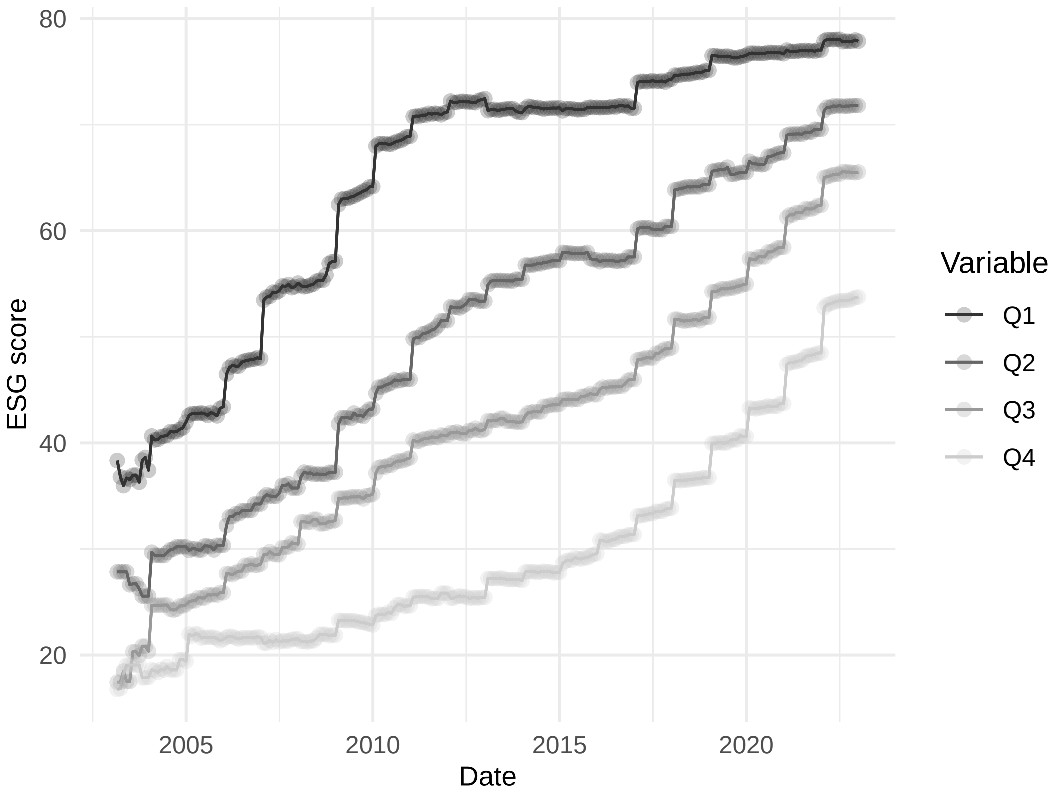
SIC Major Group (H-W)	Freq.	Percent
Holding And Other Investment Offices	28	5.6
Hotels And Other Lodging Places	6	1.2
Industrial Machinery And Equipment	27	5.4
Instruments And Related Products	41	8.2
Insurance Agents, Brokers And Service	5	1
Insurance Carriers	25	5
Leather And Leather Products	1	0.2
Metal Mining	3	0.6
Miscellaneous Manufacturing Industries	2	0.4
Miscellaneous Retail	5	1
Motion Pictures	1	0.2
Nondepository Institutions	3	0.6
Nonmetallic Minerals, Except Fuels	2	0.4
Oil And Gas Extraction	11	2.2
Paper And Allied Products	5	1
Petroleum And Coal Products	7	1.4
Primary Metal Industries	4	0.8
Printing And Publishing	1	0.2
Railroad Transportation	3	0.6
Real Estate	2	0.4
Rubber And Misc. Plastics Products	2	0.4
Security And Commodity Brokers	14	2.8
Special Trade Contractors	1	0.2
Textile Mill Products	1	0.2
Tobacco Products	2	0.4
Transportation By Air	6	1.2
Transportation Equipment	15	3
Transportation Services	4	0.8
Trucking And Warehousing	3	0.6
Water Transportation	3	0.6
Wholesale Trade - Durable Goods	7	1.4
Wholesale Trade - Nondurable Goods	5	1
Total	500	100

Table 3.7 presents a breakdown of the companies within the S&P 500 Index according to their respective Standard Industrial Classification (SIC) Divisions (2-digit codes) and SIC Major Groups (4-digit codes), as defined by the Securities and Exchange Commission (SEC) classification. The table includes the count of firms (Freq) and the corresponding percentage of these firms in relation to the total of 500 firms (Percent) for each Division and Major Group.

Quartile analysis

We further delve into the effectiveness of ESG practices in hedging the returns in times of rising volatility in the crude oil market by dividing the sample into four groups based on firms' ESG. The division is made by evaluating the average of the ESG performances of each firm over the period considered. These four groups each comprise 125 firms from the S&P 500 Index. Quartile 1 (Q1) consists of ESG leaders companies, with ESG scores ranging from 82.25 to 59.90. The second quartile (Q2) encompasses firms with ESG scores between 59.68 and 48.84. Quartile 3 (Q3) includes companies with ESG performance spanning from 48.83 to 39.76, while the ESG laggard firms are found in quartile 4 (Q4), characterised by ESG scores ranging from 39.75 to 15.15.

Figure 3.11: Quartile Analysis - Evolution of ESG Scores Across Time for All Firms by Quartile



Evolution of the ESG scores across time for all the firms, divided by quartile.

The evolution of the ESG scores of each quartile is presented in Figure 3.11 while Table 3.8 reports the descriptive statistics of the returns, the ESG scores, and the interaction effect of each quartile together with the descriptive statistics of the time series

Table 3.8: Quartile Analysis - Descriptive Statistics

Variable	Mean	Std. dev.	Min	Max	Obs
Returns (All Sectors)	0.8784	9.1364	-186.4615	127.9980	109122
Q1	0.8457	8.9322	-186.4615	123.8308	28060
Q2	0.8616	8.9772	-137.9244	69.1924	28055
Q3	0.8152	9.0199	-93.2409	127.9980	27091
Q4	0.9981	9.6327	-178.5359	114.0773	25916
Oil Volatility	2.1466	1.0258	0.6554	7.7563	237
with COVID-19 spike	2.3747	3.0741	0.6554	45.7646	239
ESG Score (All Sectors)	50.5666	20.2740	0.5986	95.1624	93614
Q1	67.4695	15.7993	5.8737	95.1624	25580
Q2	54.0960	16.8656	4.1783	93.6641	23595
Q3	44.7887	15.3120	3.2147	87.4099	23102
Q4	32.4854	14.8663	0.5986	84.3312	21098
Oil Volatility × ESG Score (All Sectors)	107.7505	70.9247	0.8062	715.7063	92387
Q1	121.5492	131.8894	0.7292	1947.6729	25578
Q2	93.4442	114.8726	0.6030	1851.3340	23593
Q3	75.8930	99.7448	0.4787	1782.3577	23100
Q4	52.8249	78.7796	0.2767	1679.7117	21096

Table 3.8 provides descriptive statistics for the primary variables of interest, organised by sector. Oil Volatility is analysed as a time series, while returns, ESG scores, and the interaction effect between ESG and oil volatility are examined as panel data. Returns and Oil Volatility are multiplied by 100.

of the crude oil volatility. The evolution of ESG scores within each quartile is visually displayed in Figure 3.11. Notably, all quartiles exhibit a steady increase in ESG scores over time. There are noteworthy spikes, such as those of Q2 and Q3 at the beginning of 2004 and of Q4 towards the end of the same year, indicating periods of rapid ESG score growth. Meanwhile, Table 3.8 presents descriptive statistics for returns, ESG scores, and the interaction effect within each quartile, along with statistics for the crude oil volatility time series. As expected, the mean values of both ESG scores and the interaction effect decline from Q1 to Q4. The deviation from the mean in ESG scores is relatively consistent across quartiles, with Q2 demonstrating the highest volatility. Surprisingly, Q4 stands out with the highest average returns, despite the generally similar average returns among the first three quartiles.

In our analysis based on ESG quartiles, our methodological approach remains

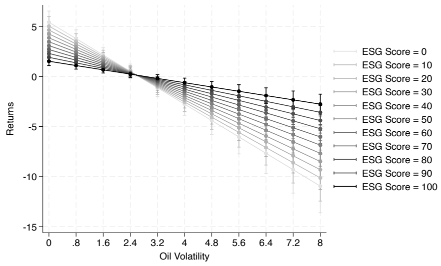
Table 3.9: Quartile Analysis - Regression Results

	Q1	Q2	Q3	Q4
Variables	Returns	Returns	Returns	Returns
Oil Volatility	-2.0472***	-2.3814***	-1.6743***	-1.4878***
	(0.2184)	(0.1456)	(0.1300)	(0.1027)
ESG Score	-0.0390***	-0.0462***	-0.0385***	-0.0367***
	(0.0077)	(0.0062)	(0.0066)	(0.0073)
Oil Volatility $\times$ ESG Score	0.0151***	0.0210***	0.0130***	0.0096***
	(0.0029)	(0.0022)	(0.0023)	(0.0023)
Constant	8.3625***	7.1681***	8.5599***	6.2099***
	(0.7439)	(0.7872)	(0.9157)	(0.9630)
Number of Observations	21,270	20,059	17,613	16,078
R-squared	0.1930	0.2196	0.2068	0.2013
Number of firms	125	124	125	122

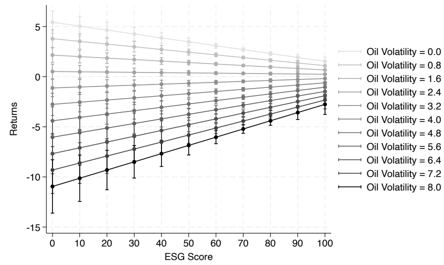
Table 3.9 reports the regression results of Equation 3.1 applied to the quartiles. For conciseness, only the results of the FE models with the micro and macro variables are included.
*** Significant at 1%, ** Significant at 5%, * Significant at 10%. The parenthesis represents the standard errors. Oil volatility and firms' returns are multiplied by 100.

consistent with the main research. We employ the same regression model, and the results are presented in Table 3.9. Furthermore, Figure 3.12 visualises the marginal effects of ESG and oil volatility on returns, mirroring what is presented in the main analysis. The breakdown of companies into ESG quartiles allows us to assess the efficacy of the ESG measure within each quartile. As can be noticed in the figures on the left side of Figure 3.12, as volatility increases (on the right side of each figure), the vertical difference in returns of the firms with different ESG scores is more pronounced in Quartile 2 and it diminishes in line with the increase in threshold, with Quartile 1 following, and subsequently, Quartile 3 and Quartile 4. These findings suggest that firms falling within Quartile 2 ESG range are more resilient to ESG-related risks due to their ESG activities.

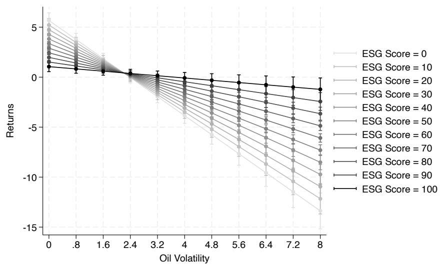
Figure 3.12: Quartile Analysis - Margin Plots



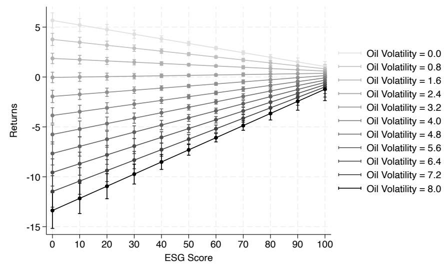
(a) Q1: Oil Volatility over returns for different ESG levels



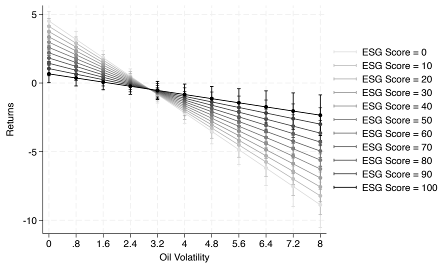
(b) Q1: Oil Volatility over returns for different uncertainty levels



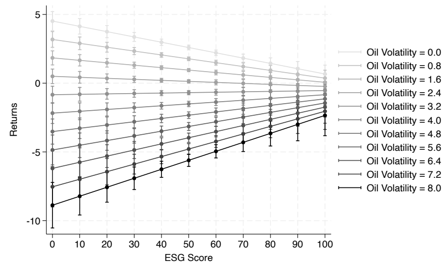
(c) Q2: Oil Volatility over returns for different ESG levels



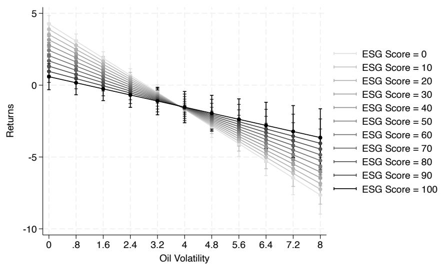
(d) Q2: Oil Volatility over returns for different uncertainty levels



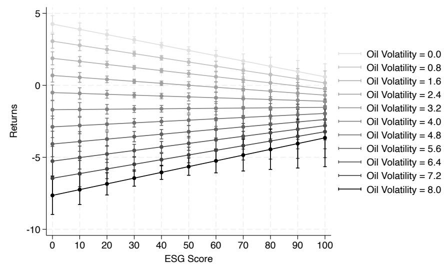
(e) Q3: Oil Volatility over returns for different ESG levels



(f) Q3: Oil Volatility over returns for different uncertainty levels



(g) Q4: Oil Volatility over returns for different ESG levels



(h) Q4: Oil Volatility over returns for different uncertainty levels

Effect of oil volatility over returns for different levels of ESG scores (left) and for different levels of volatility (right). The confidence levels are set to 95% and are represented by the vertical bars.

Robustness: Alternative volatility measurement

In this section, we present the results of a robustness test that comprises an alternative measure of volatility. Instead of our main approach to evaluate the crude oil volatility, where we compute volatility as the average of the WTI daily squared returns within the month, in this section we evaluate volatility as the sum of the squared returns within the month. This alternative formulation is commonly employed in financial research (Andersen and Bollerslev 1998; Boldanov et al. 2016; Hsu and Murray 2007; Liu and Gong 2020; Ma et al. 2017, 2018).

Specifically, in this section the crude oil volatility is assessed as follows:

$$\begin{aligned} EV_t &= \textstyle\sum_{i=1}^{d} r_i^2, \\ EVol_t &= \sqrt{EV_t} \times 100. \end{aligned} \tag{3.9}$$

Here, as in our primary analysis, $EVol_t$ represents the crude oil volatility of the month t, while r_t denotes the daily log-return on WTI on day i of month t.

Table 3.10 presents descriptive statistics for the volatility computed using the alternative measure described above, as well as the interaction effect between this volatility measure and ESG scores. In addition, Table 3.11 provides the regression results as outlined in the methodology section of this study. For a visual representation, Figure 3.13 illustrates the margin effect of volatility on returns across different levels of ESG scores, and Figure 3.14 depicts the margin effect of ESG performance on returns across various levels of volatility.

As expected, the alternative volatility formulation yields higher overall volatility values, as can be appreciated in Table 3.10. Comparing the outcomes presented in Table 3.2 for the main results and Table 3.11 for the robustness results, our study demonstrates the robustness of our primary findings. Notably, in the robustness analysis, we observe slightly smaller coefficients and a lower volatility threshold for ESG's hedging effect, compared to the main analysis. The latter implies that the hedging impact of firms' activities against ESG-related risks starts to manifest their effectiveness at a lower level of volatility. It is noticeable that the turning point of the robustness test (0.9732, calculated as $0.0109/0.0112$) differs from that of the main analysis (1.8929). Indeed, the turning point of the robustness test is smaller due to a significantly wider range of

Table 3.10: Alternative Volatility Measure - Descriptive Statistics

Variable	Mean	Std. dev.	Min	Max	Obs
Oil Volatility	1.2072	1.4916	0.0902	13.8368	237
with COVID-19 spike	3.1871	28.4298	0.0902	439.8235	239
Oil Volatility $\times$ ESG Score (All Sectors)	60.19	80.53	0.20	1276.78	92387
B. Mining	49.27	110.41	0.33	1808.77	2991
C. Construction	36.87	84.27	0.33	1441.34	960
D. Manufacturing	52.87	119.14	0.30	1872.22	38295
E. Transportation	46.02	105.79	0.20	1856.47	12265
F. Wholesale Trade	47.01	107.02	0.39	1606.99	1860
G. Retail Trade	53.38	117.23	0.38	1817.70	5794
H. Finance	50.76	114.01	0.23	1807.76	17808
I. Services	50.75	112.84	0.32	1947.67	13386

Table 3.10 provides descriptive statistics for the primary variables of interest, organised by sector. Oil Volatility is analysed as a time series, while the interaction effect between ESG scores and oil volatility is examined as panel data.
Returns and Oil Volatility are multiplied by 100.

volatility values. The volatility range derived from the robustness test is indeed notably higher. Specifically, the highest value within the volatility range of the main analysis stands at 7.7563, while in the robustness test, it reaches 13.8368, as shown in Table 3.10. However, the consistent directions, significance, and signs of these coefficients provide robust support for our primary findings.

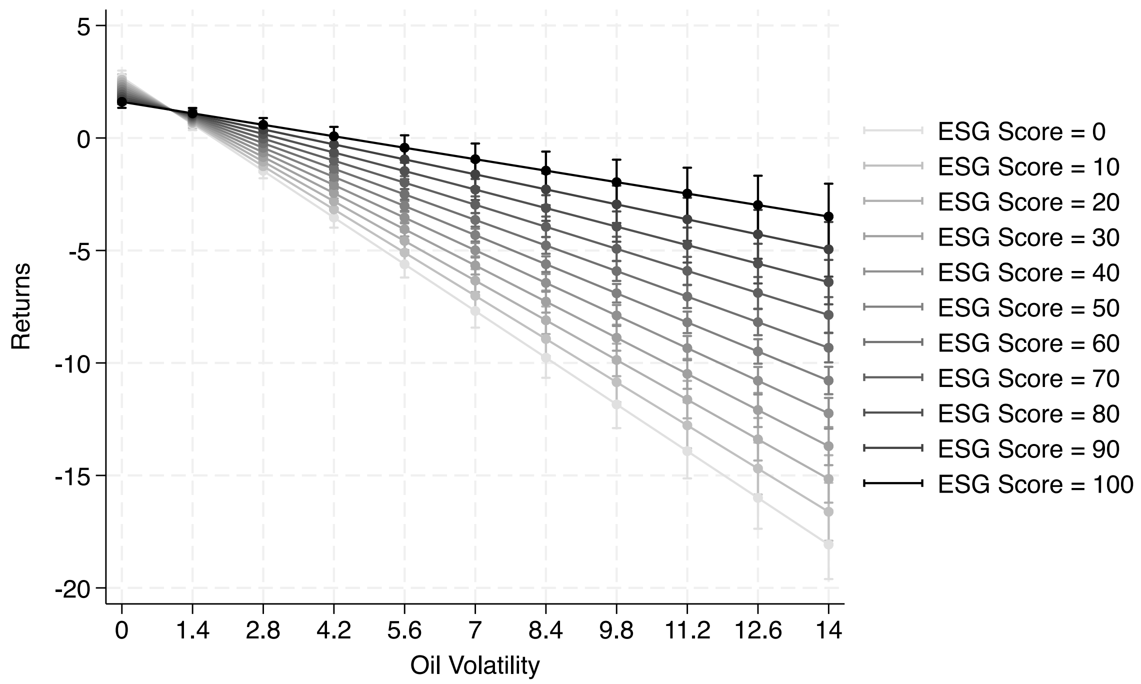
Table 3.11: Alternative Volatility Measure - Regression Results

	$r_{it} = \alpha + \beta_1\ OilVol_t + \beta_2\ ESGScore_{it_U} + \beta_3\ ESGScore_{it_U} \times OilVol_t + Controls + \varepsilon_{it}$					
	(1)	(2)	(1)	(2)	(1)	(2)
Variables	Returns	Returns	Returns	Returns	Returns	Returns
Oil Volatility	-1.4091***	-1.3969***	-1.3916***	-1.3918***	-1.4726***	-1.4834***
	(0.0509)	(0.0511)	(0.0639)	(0.0643)	(0.0596)	(0.0598)
ESG Score	-0.0115***	-0.0056**	-0.0129***	-0.0136***	-0.0100***	-0.0109***
	(0.0018)	(0.0023)	(0.0022)	(0.0030)	(0.0020)	(0.0028)
Oil Volatility × ESG score	0.0121***	0.0118***	0.0138***	0.0138***	0.0112***	0.0112***
	(0.0010)	(0.0010)	(0.0011)	(0.0011)	(0.0011)	(0.0011)
Constant	2.5271***	2.2211***	3.5761***	3.7551***	3.8267***	3.9444***
	(0.1004)	(0.1230)	(0.2699)	(0.3832)	(0.2504)	(0.3525)
Micro Controls	No	No	Yes	Yes	Yes	Yes
Macro Controls	No	No	No	No	Yes	Yes
Number of Observations	87,163	87,163	74,075	74,075	74,061	74,061
R-squared	0.0345	0.0342	0.0416	0.0399	0.0708	0.0688
Number of firms	497	497	496	496	496	496

Table 3.11 shows the regression results of Equation 3.1. Only the coefficients of the main variables and the intercept are reported; the coefficients of the control variables are in the Appendix. The sample period ranges from February 2003 to December 2022 and includes companies listed on the S&P 500 Index. Model (1) reports the OLS regression results, while model (2) accounts for fixed effects for firms. Initially, the models included only the main variables, then firm-level control variables were added, and finally, both firm- and macro-level control variables were included.

*** Significant at 1%, ** Significant at 5%, * Significant at 10%. The parentheses represent the standard errors.

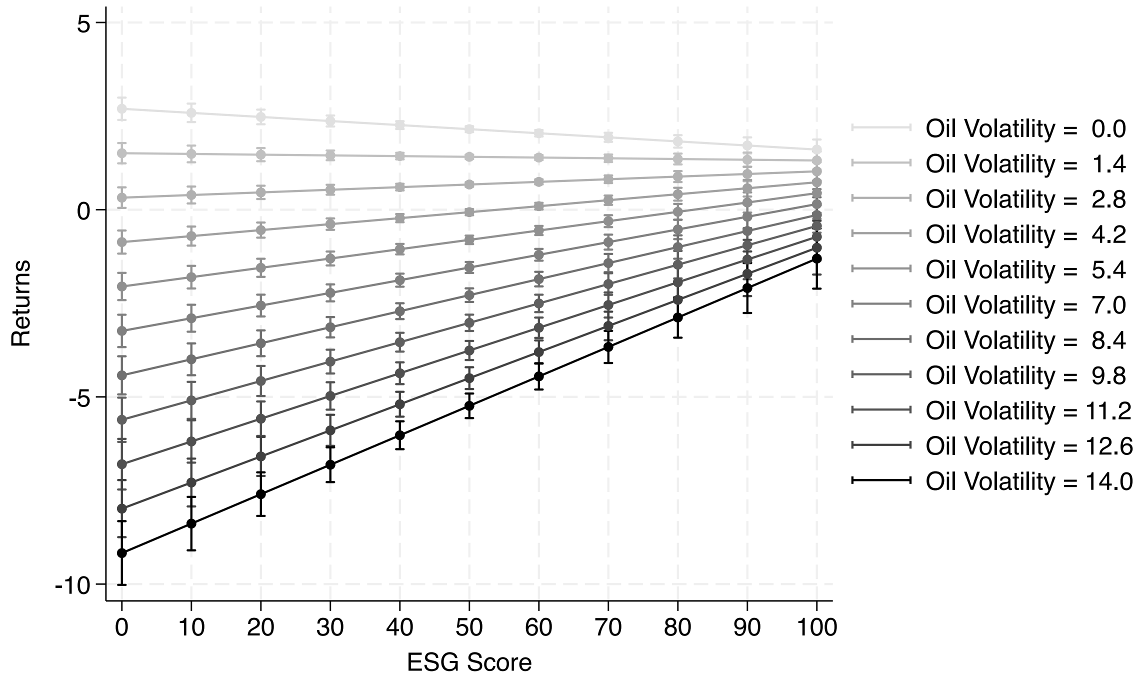
Figure 3.13: Alternative Volatility Measure - Margin Plot of the Returns Across Oil Volatility Levels at Different ESG Levels



Effect of oil volatility over returns for different levels of ESG Scores. The confidence levels are set to 95% and are represented by the vertical bars.

Figure 3.13 illustrates the margin effect of volatility on returns across various ESG score levels while Figure 3.14 displays the margin effect of ESG performance on returns across different volatility levels. A visual comparison between these two figures and those from the main analysis (Figures 3.6 and 3.8) shows no substantial differences, except for two notable aspects already mentioned previously. Focusing on Figure 3.13, it can be easily appreciated that the scale of volatility appears higher in the robustness check measure. Secondly, the turning point's lower magnitude, as indicated in Table 3.11, is more noticeable in this representation, despite its similarity to the main analysis. Nevertheless, the slopes of the curves in the graphs and the magnitudes of returns on the y-axis reveal that the level of the ESG hedging effect on returns during periods of increased volatility remains highly consistent between the main results and those from the robustness check.

Figure 3.14: Alternative Volatility Measure - Margin Plot of Returns Across ESG Levels at Different Oil Volatility Levels



Effect of ESG over returns for different levels of crude oil volatility. The confidence levels are set to 95% and are represented by the vertical bars.

3.6 Conclusion

The aim of this study is to explore the potential role of a high ESG score as a "safe haven" for firms during periods of high volatility in the crude oil market. The study focuses on companies listed in the S&P500 index, which are considered representative of firms in the United States, spanning from February 2003 to December 2022.

We collect the returns and the ESG scores for each firm while, in order to incorporate the crude oil market into the analysis, the study includes time series data on crude oil volatility, calculated as a monthly measure derived from daily prices of WTI crude oil. The crude oil uncertainty shows a spike related to the COVID-19 period, which is removed in the analysis.

This work finds its place among the strand literature that suggests that companies with high ESG performances tend to generate higher returns (Eccles et al. 2014; Edmans 2011; Zhang et al. 2022) and, more specifically, within the growing body of research examining ESG's role during times of crises (Broadstock et al. 2021). While previous studies have primarily explored ESG's impact in the context of broader economic downturns, this study extends the literature by examining its function in mitigating the financial effects of crude oil market volatility. By integrating insights from ESG-financial performance research with the emerging discussion on corporate resilience to commodity price fluctuations, this work is the first to empirically assess whether ESG scores shield firms from the adverse financial consequences of crude oil price volatility. Our findings reveal an interesting dynamic played by ESG activities in hedging firms' returns in times of uncertainty stemming from the crude oil market. Albeit the regression shows a direct negative relationship between ESG scores and returns, the overall analysis reveals a more complex and accurate picture. This negative relationship is offset by the interplay between ESG scores and crude oil volatility. ESG activities appear counterproductive for returns when crude oil volatility is low, but overall they act as a hedge when oil volatility rises. In essence, ESG activities can be likened to insurance during periods of heightened volatility in the crude oil market. In the main analysis, we identify a threshold of volatility below which ESG activities negatively affect returns, and above which they become a safeguard. This relatively low threshold means that only for low levels of volatility ESG activities lead to lower returns. After this turning point, the protective impact of ESG scores becomes more significant during high volatility, favouring ESG leaders over laggards. This suggests an overall positive link between ESG activities and a firm's ESG score, indicating that they effectively shield firms from the negative impacts of oil price volatility.

We further investigate this dynamic by dividing the firms into eight sectors based on the US Standard Industrial Classification (SIC) divisions, and also in four quartiles based on the firms' average ESG scores. Sectoral analysis reveals that while some industries experience an initial negative relationship between returns and ESG scores, this effect reverses beyond sector-specific volatility thresholds. Notably, industries more sensitive to crude oil price fluctuations have lower threshold values, suggesting that the protective effect of ESG is particularly relevant for firms operating in energy-intensive sectors. For the rest of the sectors, we find a consistent hedging effect of ESG scores for each level of volatility, stemming from the positive direct relationship between returns and ESG scores. In the quartile analysis, we observe a positive relationship between returns and ESG scores across all the quartiles, with a more pronounced effect in the second-highest and third-best quartiles. This implies that firms with ESG scores close to the average are better protected against crude oil uncertainty.

In conclusion, our research offers fresh insights into the intricate relationship between ESG activities, crude oil market volatility, and firm returns. While a negative correlation between ESG scores and returns is observed in the main analysis, this is offset by the interplay between ESG activities and increased volatility. ESG efforts initially appear to have a negative impact on returns when oil volatility is low but function as a protective hedge as volatility rises. This protective effect is more pronounced for ESG leaders, underlining the significance of ESG scores. Our sector and quartile analyses reveal diverse patterns, with some sectors having specific thresholds for this relationship, while most sectors exhibit a consistent hedging effect of ESG scores. In quanriles, firms with ESG scores near the average are better protected, possibly penalising those with exceptionally high ESG efforts. These findings highlight the multifaceted nature of ESG's impact on firm returns in the context of crude oil market volatility.

While crude oil volatility is considered as a negative externality, it is by no mean the sole one. While this study highlights ESG's role in mitigating the financial risks of crude oil volatility, future research could explore whether different ESG dimensions (Environmental, Social, or Governance) provide varying degrees of protection across different external shocks. For instance, investigating whether environmental initiatives shield firms more effectively from climate-related risks while governance structures mitigate financial crises would extend our understanding of ESG's risk-mitigation capabilities beyond commodity markets Additionally, while this study already incorporates sectoral analysis, a more granular approach could explore whether ESG resilience effects vary not only across industries but also within firms of different sizes, market positions, or regulatory environments within the same sector. Lastly, applying a dynamic approach — such as tracking changes in ESG performance before, during, and after crisis periods — could provide a clearer picture of how firms leverage ESG strategies for long-term risk management.

Despite its contributions, this study has certain limitations. First, ESG initiatives can vary significantly in scope, effectiveness, and strategic intent, ranging from genuine long-term sustainability commitments to compliance-driven or symbolic actions. Future research could explore whether the effectiveness of ESG in reducing financial risk depends on the depth and integration of ESG policies within firms, rather than relying solely on ESG scores as a broad measure of sustainability performance. Second, the study relies on existing ESG rating methodologies, which, despite increasing standardisation, may still suffer from subjectivity and reporting inconsistencies. Future research could integrate alternative ESG providers to assess whether differences in rating methodologies influence the observed relationship between ESG and financial resilience. Lastly, future research could incorporate sentiment analysis from corporate disclosures to better capture how firms communicate their ESG commitments and how these disclosures influence investor confidence and financial resilience. A longitudinal study tracking firms' ESG investments over multiple economic cycles could further clarify the sustainability of ESG-driven financial advantages.

3.7 Appendix A

Variables Definitions

In this appendix, we present two key tables: Table 3.12 provides the descriptive statistics, while Table 3.13 outlines the statistical information for the regression coefficients of the control variables. Additionally, we examine the categorisation of distinct firms listed in the S&P 500 Index based on the Standard Industrial Classification (SIC) sectors, as outlined by the Securities and Exchange Commission SEC. We categorise the companies listed in the S&P 500 Index according to the SIC Divisions and the SIC Major Groups. Table 3.7 presents a comprehensive breakdown of these classifications, detailing the count of companies encompassed within each classification as well as the corresponding percentage representation within the index[7].

Table 3.12: Control Variables - Descriptive Statistics

Variable	Mean	Std. dev.	Min	Max	Obs
Micro Controls					
Company Size	3.64E+10	9.22E+10	1.12E+07	2.90E+12	108178
Total Assets	5.66E+10	1.99E+11	3.33E+06	3.74E+12	112337
ROA	8.5482	12.4167	-240.9805	138.2316	110792
Board Size	10.9984	3.0400	1	138	93147
Board Gender Diversity	18.5196	10.1588	0	66.67	92779
Board Independence	81.2325	12.7695	0	100	88175
Board Meetings	8.1667	3.6762	1	43	92281
CSR Committee	0.5150	0.4998	0	1	93363
Macro Controls					
VIX	0.0003	0.2229	-0.6143	0.8526	239
GDP	0.0050	0.0145	-0.0887	0.0756	239
CPI	0.0020	0.0040	-0.0193	0.0136	239
IPI	0.0005	0.0131	-0.1437	0.0630	239
EPU	0.0002	0.1894	-0.6430	0.6842	239

Table 3.12 reports the descriptive statistics for the control variables.

Table 3.12 provides the descriptive statistics for the micro and macro control variables used in this study. The micro-level controls include variables such as company

[7]The very low minimum ROA values shown in Table 3.12 prompted further investigation, which revealed that these extreme negative values occurred only during the Global Financial Crisis (GFC). This finding is in line with research that shows the GFC had a major negative effect on company profitability, causing ROA to drop significantly and indicating the large financial losses companies experienced during that time (Akgün and Memiş Karataş 2023; Basten and Sánchez Serrano 2019; Yuen et al. 2022)

size, total assets, Return on Assets (ROA), board characteristics (size, gender diversity, independence, and number of meetings), and the presence of a Corporate Social Responsibility (CSR) committee. These variables exhibit substantial variability across firms, as indicated by their wide ranges, such as company size ranging from 1.12×10^7 to 2.90×10^{12} and ROA ranging from -240.9805 to 138.2316. The wide range of ROA reflects significant fluctuations in profitability, particularly during events like the Global Financial Crisis.

The macro-level controls, which are common across firms and have fewer observations due to their time-series nature, include variables such as the VIX (market volatility index), GDP growth, Consumer Price Index (CPI), Industrial Production Index (IPI), and Economic Policy Uncertainty (EPU). The number of observations for these variables is consistent at 239, with values reflecting monthly data aggregated over the sample period. The summary also highlights the variability in these indicators, with GDP growth ranging from -0.0887 to 0.0756 and CPI growth ranging from -0.0193 to 0.0136, illustrating the economic fluctuations during the analysed period.

Table 3.13: Control Variables - Regression Outcomes

Variables	(1) Returns	(2) Returns	(1) Returns	(2) Returns
$Size_t$	0.0000***	0.0000***	0.0000***	0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$TotalAssets_t$	-0.0000***	-0.0000***	-0.0000***	-0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ROA_t	-0.0190***	-0.0475***	-0.0183***	-0.0446***
	(0.0033)	(0.0049)	(0.0030)	(0.0045)
$BdSize_t$	-0.0563***	-0.0636***	-0.0560***	-0.0612***
	(0.0105)	(0.0185)	(0.0097)	(0.0171)
$BdGendDiv_t$	0.0046	0.0119**	0.0064**	0.0156***
	(0.0033)	(0.0047)	(0.0031)	(0.0044)
$BdIndep_t$	0.0003	0.0001	-0.0003	-0.0013
	(0.0028)	(0.0038)	(0.0026)	(0.0035)
$BdMeetings_t$	-0.0261***	-0.0124	-0.0221***	-0.0062
	(0.0087)	(0.0110)	(0.0081)	(0.0101)
CSR_t	-0.2757***	-0.2729***	-0.2635***	-0.2412***
	(0.0706)	(0.0980)	(0.0655)	(0.0902)
VIX_{t-1}			-13.1408***	-13.1141***
			(0.1227)	(0.1227)
GDP_{t-1}			-7.2144***	-7.6626***
			(1.6960)	(1.6967)
CPI_{t-1}			-69.4569***	-78.4944***
			(7.7803)	(7.8753)
IPI_{t-1}			-34.0933***	-34.2229***
			(2.1500)	(2.1501)
EPU_{t-1}			-1.3688***	-1.3546***
			(0.1455)	(0.1455)
$Constant$	5.4113***	5.5618***	5.4764***	5.6258***
	(0.3190)	(0.4211)	(0.2974)	(0.3889)
Micro Controls	Yes	Yes	Yes	Yes
Macro Controls	No	No	Yes	Yes
Number of Observations	74,075	74,075	74,061	74,061
R-squared	0.0416	0.0399	0.0708	0.0688
Number of firms	496	496	496	496

Table 3.13 shows the regression outcomes of Equation 3.1 for the control variables. The sample period ranges from February 2003 to December 2022. Model (1) reports the Ordinary Least Squares (OLS) regression results while model (2) accounts for fixed effects for firms.

*** Significant at 1%, ** Significant at 5%, * Significant at 10%. The parentheses represent the standard errors.

3.8 Appendix B

COVID-19 Spike Impact: Model Outliers Analysis

This section examines the impact of the COVID-19 spike on our model. Specifically, we take a closer look at two key outliers, pinpointed in March and April 2020, directly related to the pandemic period. During these months, the crude oil volatility series exhibited values of 13.06 and 45.76 respectively, which contrast sharply with the maximum value of 7.76 observed in the rest of the series. To effectively showcase the distinct impact these observations have on our model, we apply the same methodology we use in our primary research. The unique aspect here lies therefore in the inclusion of these two specific outlier-related data points within the volatility time series. Our primary objective is to shed light on the significant effect these outliers exert on the overall dataset. Moreover, we offer both a technical and an economic rationale to support our decision to remove these outliers.

Analysis

In this section, we apply a methodology identical to the one used in the primary analysis, but this time we integrate the outliers into the time series of crude oil volatility ($OilVol\_Spk_t$). Table 3.14 illustrates the regression output.

Table 3.14: COVID-19 Spike - Main Results

	$r_{it} = \alpha + \beta_1 \times OilVol\_Spk_t + \beta_2 \times ESGScore_{it_U} + \beta_3 \times ESGScore_{it_U} \times OilVol\_Spk_t + Controls + \varepsilon_{it}$					
	(1)	(2)	(1)	(2)	(1)	(2)
Variables	Returns	Returns	Returns	Returns	Returns	Returns
Oil Volatility Spike	-0.9319***	-0.9500***	-0.8111***	-0.8260***	-0.6992***	-0.7174***
	(0.0311)	(0.0312)	(0.0310)	(0.0312)	(0.0291)	(0.0292)
ESG Score	-0.0092***	-0.0026	-0.0062***	-0.0061**	-0.0061***	-0.0057**
	(0.0019)	(0.0023)	(0.0021)	(0.0030)	(0.0020)	(0.0028)
Oil Volatility Spike × ESG Score	0.0056***	0.0058***	0.0040***	0.0042***	0.0040***	0.0042***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Constant	2.8300***	2.5046***	3.6242***	3.8926***	3.5169***	3.7384***
	(0.1075)	(0.1277)	(0.2699)	(0.3881)	(0.2546)	(0.3601)
Micro Controls	No	No	Yes	Yes	Yes	Yes
Macro Controls	No	No	No	No	Yes	Yes
Number of Observations	88,145	88,145	75,042	75,042	75,028	75,028
R-squared	0.0345	0.0342	0.0416	0.0399	0.0708	0.0688
Number of firms	497	497	496	496	496	496
Number of firms	497	497	496	496	496	496

Table 3.14 shows the regression results of Equation 3.1 in which the crude oil volatility time series includes the COVID-19 spike ($OilVol\_Spk_t$). Only the coefficients of the main variables and the intercept are reported; the coefficients of the control variables are in the Appendix. The sample period ranges from February 2003 to December 2022 and includes companies listed on the S&P 500 Index. Model (1) reports the OLS regression results, while model (2) accounts for fixed effects for firms. Initially, the models included only the main variables, then firm-level control variables were added, and finally, both firm- and macro-level control variables were included.

*** Significant at 1%, ** Significant at 5%, * Significant at 10%. The parentheses represent the standard errors.

Comparing these results with the primary analysis, notable differences are observed in the form of less significant coefficients and an overall reduction in the value of the coefficients. It is intriguing to note that the signs of the coefficients align with the primary results. Therefore, we conduct a comparative exploration to identify the volatility threshold at which ESG activities negatively affect returns and act as a safeguard. We examine this threshold and compare it between this analysis and the primary one. We analyse partial derivatives as per Equations (3.10), (3.11), and (3.12) to establish the turning point in volatility. Comparing this new threshold with the one from the primary analysis, we find a relatively lower value in the volatility threshold (1.3571) compared to the primary analysis (1.8929).

$$\frac{\partial\, r_{it}}{\partial\, ESG_{it}} = -0.0057 + 0.0042\, OilVol_t. \tag{3.10}$$

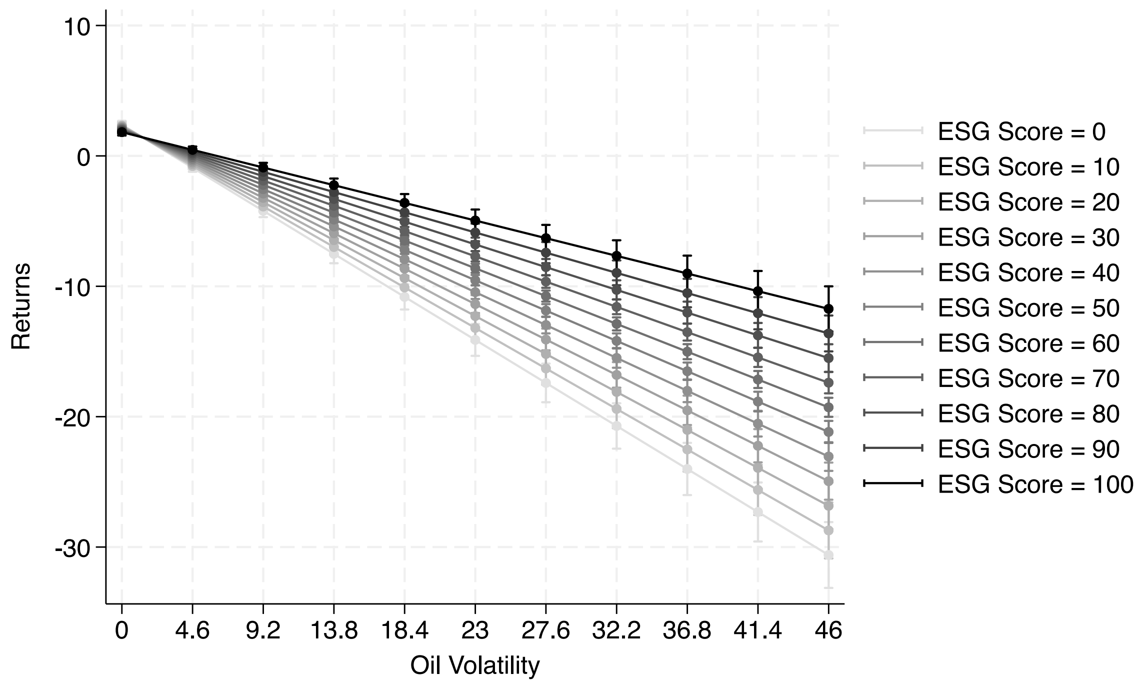
$$\frac{\partial\, r_{it}}{\partial\, OilVol_t} = -0.7174 + 0.0042\, ESG_{it}. \tag{3.11}$$

$$\begin{aligned} \frac{\partial\, r_{it}}{\partial\, ESG_{it}} &= 0, \\ -0.0057\ + 0.0042\, OilVol_t &= 0, \\ \frac{0.0057}{0.0042} &= 1.3571. \end{aligned} \tag{3.12}$$

Adopting the same structure used in the primary analysis, Figures 3.15, 3.16, and 3.17 visually represent the regression output, demonstrating the effects of oil volatility on returns for various ESG score levels. As per the main body, these illustrations respectively show the impact of oil volatility on returns across various ESG score levels, offer a closer examination of the proximity around the inflexion point, and present the effect of ESG scores over firms' returns at different levels of crude oil volatility.

Examining Figure 3.15, although the turning point is less pronounced due to the wider x-scale to include confidence levels, the light grey curves representing ESG laggards clearly shift, exhibiting higher returns before the threshold and declining returns afterwards as volatility increases. This observation aligns with the regression coefficients, where the ESG coefficient (β_2) is negative and the interaction effect (β_3) is positive, indicating a turning point, consistent with the findings in the primary analysis.

Figure 3.15: COVID-19 Spike - Margin Plot of the Returns Across Oil Volatility Levels at Different ESG Levels



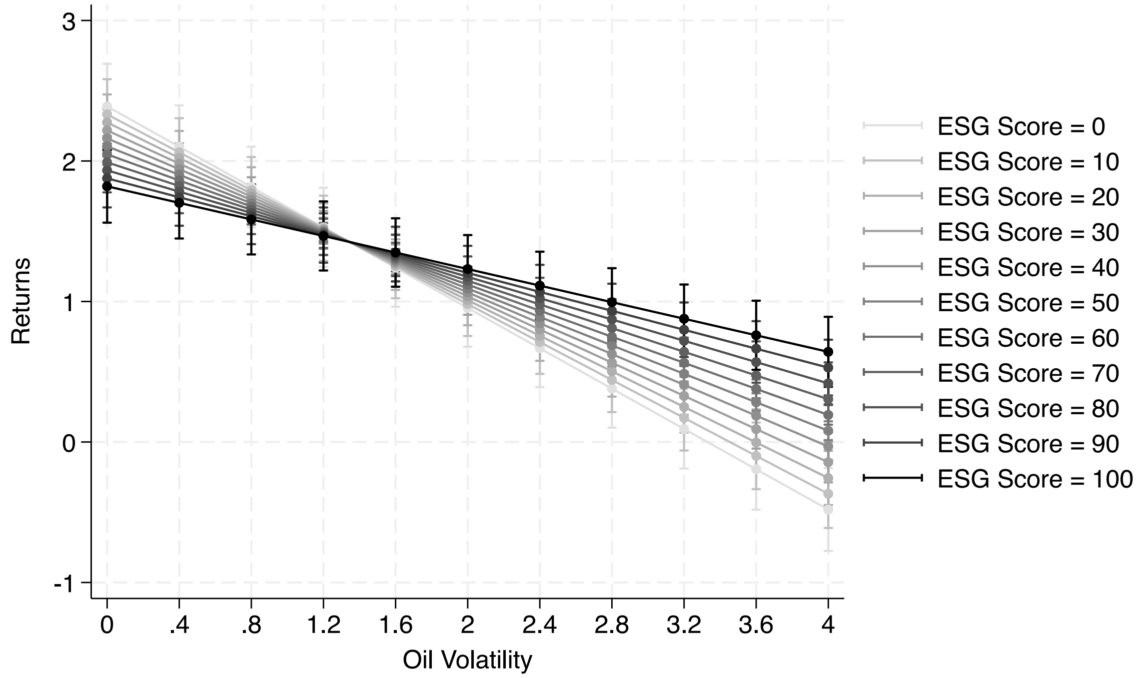
Effect of oil volatility over returns for different levels of ESG Scores. The confidence levels are set to 95% and are represented by the vertical bars.

In summary, the inclusion of the spike notably diminishes the magnitude and significance of the regression coefficients. Moreover, the revised model indicates that the ESG hedge against volatility risk from the crude oil market becomes effective at a considerably lower volatility level.

Theoretical background

On the technical side, the fundamental assumption of linearity underlying regression models implies that the relationship between variables can be effectively represented by a straight line. Outliers, particularly exceptionally large ones, can substantially disrupt this linearity, deviating the data from the linear model's intended scope. Consequently, the presence of such extreme values can significantly skew the estimated coefficients, altering the model's predictive capacity and undermining its reliability. The technical grounds for excluding the outlier stemmed from the acknowledgement that its disproportionate influence could distort the model's outcomes, potentially resulting in

Figure 3.16: COVID-19 Spike - Focus on Volatility Range Around Turning Point at Different ESG Levels



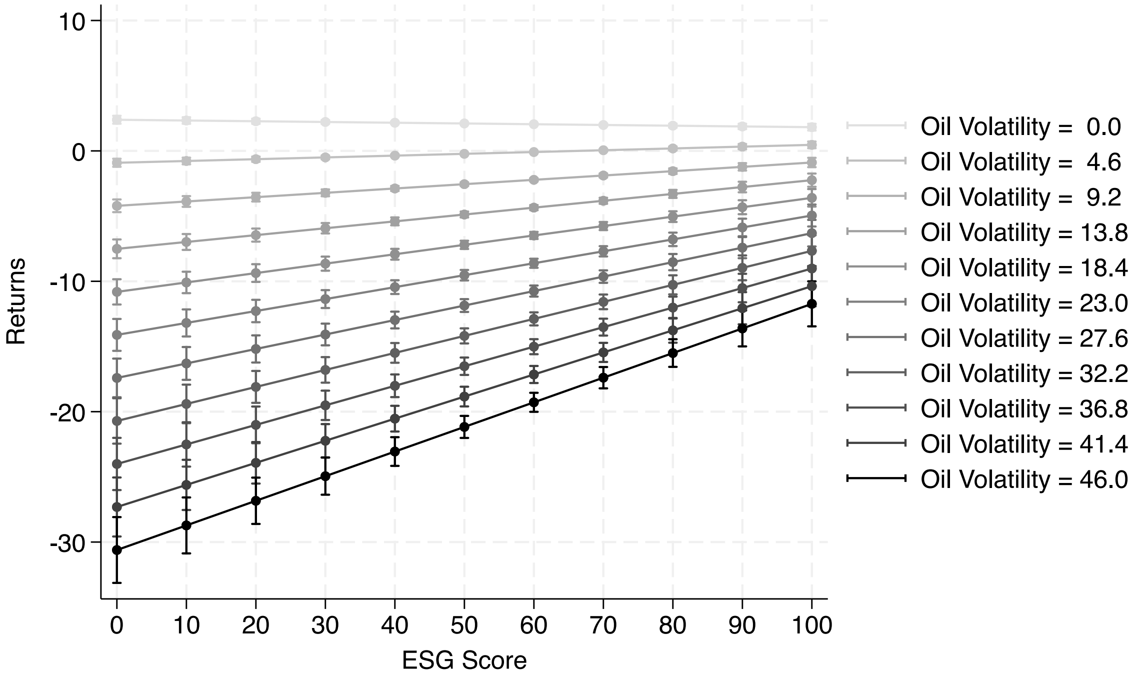
Focus on the range of volatility (0-3) around the turning point (1.3571). The confidence levels are set to 95% and are represented by the vertical bars.

misleading or less accurate predictions. By removing this outlier, we aim to preserve the integrity of the linear regression model within the valid data range, enabling a more robust and dependable analysis.

From an economic standpoint, the decision to exclude the outlier is rooted in the extraordinary circumstance of a negative price anomaly in the WTI crude oil market. The occurrence of the negative price anomaly in the WTI crude oil market is a highly unusual event that has a profound impact on the traditional dynamics of price and volatility behaviour within this market. It comes from an imbalance between supply and demand, resulting in an unprecedented scenario where surplus oil overwhelms storage capacities.

This particular event is not a reflection of the actual value of the commodity but is a consequence of specific market conditions prevailing at that time. The surplus of oil leads to storage costs exceeding the commodity's value, prompting an unconventional situation where it is economically favourable to pay someone to take surplus oil rather than incur storage expenses. This results in the observed negative price, an anomaly

Figure 3.17: COVID-19 Spike - Margin Plot of the Returns Across ESG Levels at Different Oil Volatility Levels



Effect of ESG over returns for different levels of crude oil volatility. The confidence levels are set to 95% and are represented by the vertical bars.

that diverges significantly from typical market behaviour.

Typically the convenience yield is a minor factor in price determination, representing the additional benefit derived from holding the physical commodity itself. However, during this period of the negative price anomaly, the convenience yield becomes a substantial driving force behind observed price dynamics. This unique influence of the convenience yield during the negative price episode reflected a scenario where the urgency to offload surplus oil takes precedence over usual price-determining factors. Consequently, the calculation of volatility during this period is significantly distorted by this aberration, resulting in a misleading depiction of market volatility.

Hence, the decision to exclude this outlier becomes critical as it no longer captures the genuine market volatility but signifies an extraordinary event driven by surplus supply and storage constraints. This economic rationale, in conjunction with the technical explanation, motivates the choice to eliminate this outlier, ensuring that the integrity of the volatility measure reflects the standard market behaviour rather than the exceptional circumstances observed during this atypical event.

CHAPTER 4

Empirical Chapter 3

Cost of Capital Resilience: Exploring ESG as a Hedge Against High Oil Price Volatility

4.1 Introduction

The integration of environmental, social, and governance (ESG) factors into corporate strategies has gained significant momentum in the modern financial landscape, with capital markets increasingly reflecting this shift towards sustainability. It is estimated that ESG assets managed will surpass $\$50$ trillion by 2025, making up more than one-third of worldwide assets, while the ESG debt market is also predicted to grow significantly, reaching $\$11$ trillion. In the past, the financial industry was slow to address sustainability issues, but after the 2008 financial crisis, there was a significant change in approach as institutions began focusing on ESG criteria to improve their resilience and growth. Initiatives such as the UN's "Who Cares Wins" have strengthened this change and influenced the corporate cost of capital (Programme 2004; Wang et al. 2021). Nevertheless, despite thorough research on the impact of ESG on stocks, the relationship between ESG elements and debt costs is still not substantially investigated.

Simultaneously, oil price volatility, a significant source of uncertainty, critically impacts firm decision-making, profitability, and valuations. Fluctuations in oil prices are a crucial factor in production, causing higher operational costs and economic instability. This results in postponed investments and increased borrowing costs due to perceived risk (Bernanke 1983; Sadorsky 2008). Understanding how ESG considerations and oil price volatility influence corporate debt costs is essential for firms aiming to navigate these financial challenges and enhance their long-term stability and investor confidence.

In this study, we investigate how Environmental, Social, and Governance (ESG) scores function as a hedging mechanism against the cost of debt, with a particular focus on their effectiveness in relation to crude oil market volatility. Employing firms listed on the Standard & Poor's 500 Index as a representative sample of the US market, our analysis covers the period from the first quarter of 2000 to the fourth quarter of 2023. We incorporate firm-level data on the cost of debt and ESG scores, while crude oil price volatility is included as a time series representing external volatility, uniform across firms.

Our findings demonstrate a negative relationship between firms' cost of debt and their ESG scores, suggesting that higher ESG scores are associated with lower debt costs. Additionally, there is a positive relationship between firms' cost of debt and crude oil price volatility, indicating that increased volatility leads to higher debt costs. Notably, we identify that firms with higher ESG scores experience a mitigating effect on the relationship between cost of debt and volatility. In essence, firms with robust ESG scores are less adversely impacted by oil price volatility compared to those with lower scores, effectively utilising ESG activities as a hedging strategy.

Further analysis, detailed in Appendix A, investigates potential non-linearities in the relationship between ESG scores and the cost of debt. Our polynomial analysis suggests a slight U-shaped relationship, implying that average levels of ESG engagement are most beneficial in reducing debt costs. Additionally, we examine the mitigating effect of ESG scores under different volatility regimes. By applying the Hodrick-Prescott filter to isolate the cyclical component of volatility, our results indicate that the hedging effect of ESG scores is consistent across low and mid-level volatility regimes but diminishes significantly during periods of high volatility.

This research contributes to the literature by corroborating the negative relationship between ESG scores and the cost of debt, aligning with the findings of Lee et al. (2022), Godfrey (2005), and Minor and Morgan (2011) among others. High ESG scores are linked to reduced borrowing costs due to decreased information asymmetry and enhanced reputational capital (Cui et al. 2018; Hoepner et al. 2016). These effects are consistent with signalling theory, which posits that ESG disclosures act as positive signals, reducing information asymmetries between firms and external stakeholders, including lending institutions. Studies such as those by El Ghoul et al. (2011) and Goss and Roberts (2011) have similarly reported that firms with robust ESG practices benefit from more favourable debt terms, reflecting the signalling effect of ESG disclosures (Nguyen et al. 2020).

Additionally, this study extends the literature on the impact of crude oil volatility on the cost of debt, supporting the financial intermediaries' constraint channel (Adrian et al. 2014; Brunnermeier and Pedersen 2009). Christoffersen and Pan (2018) find that crude oil price volatility exacerbates financial intermediaries' constraints, leading to higher borrowing costs for firms. This is consistent with the observation that increased market volatility results in tighter capital constraints for intermediaries, as evidenced by higher margins and reduced asset values (Jermann and Quadrini 2012; Korajczyk and Levy 2003). Our findings align with this mechanism, showing that heightened volatility translates into stricter lending criteria and elevated interest rates on corporate debt.

Despite extensive research on ESG and cost of debt, no prior study has examined how ESG activities mitigate the impact of oil price market volatility on firms' debt costs. This study addresses this gap by demonstrating that ESG scores function as an effective hedge against the adverse effects of volatility on the cost of debt. Specifically, our findings illustrate that higher ESG scores can buffer firms against the financial strain typically induced by increased volatility. This protective effect of ESG scores represents a significant extension to the existing literature, showcasing their strategic importance in stabilising firms' borrowing costs amidst fluctuating crude oil market conditions. Notably, while the hedging benefits of ESG activities are robust under moderate levels of oil price volatility, they tend to weaken as crude oil price volatility intensifies. Our analysis indicates that during periods of extreme volatility, the efficacy of ESG as a hedging mechanism is reduced.

We recommend that firms commit to sustained ESG performance, integrate ESG factors into their risk management strategies, and enhance ESG reporting and transparency. Sustaining robust ESG practices can reduce borrowing costs and bolster financial stability. Incorporating ESG considerations into risk management strategies is particularly crucial during volatile conditions. Improved ESG disclosures can diminish information asymmetry and consequently lower the cost of debt.

The remainder of this document is structured as follows: Chapter 2 reviews the literature, explaining the economic channels that link the variables under study and stating the hypotheses. Chapter 3 outlines the research methodology. Chapter 4 provides an overview of the dataset used in the investigation. Chapter 5 presents the research findings. Chapter 6 discusses the conclusions and proposes future research directions. Finally, Appendix A details the non-linearity analysis between ESG scores and cost of debt and the volatility regime analysis, while Appendix B explores different proxies for the cost of debt.

4.2 Review of the Literature

Old perceptions regarding corporate practices fostering environmental care and the well-being of employees and stakeholders view these activities solely as costs, without returns or profitability, and therefore to be minimised (Mahapatra 1984). While some recent studies, like Richardson and Welker (2001), initially supported this notion by finding a positive link between these practices and the cost of capital, the vast majority of contemporary research suggests a contrary perspective. The prevailing evidence opposes the outdated view, indicating that initiatives promoting environmental protection, connectivity, and enhancement of relationships with firms' stakeholders are indeed rewarded by financial markets.

Effect of ESG on the cost of debt

The relationship between corporate governance and the cost of debt financing has a long history. In this study, we concentrate on the correlation between ESG factors and the cost of debt, specifically examining the relationship following the widespread adoption of the United Nations Environment Programme's Statement by Banks on the Environment and Sustainable Development in 2012 (UNEP 2012). This can be seen as a pivotal moment when ESG considerations became crucial for financial institutions evaluating firms. Many institutions not only began incorporating ESG scores into their disclosure documents but, more importantly, in their assessments when determining whether to lend money to companies. It's worth noting that while some institutions had previously taken ESG into account in their evaluations (Thompson and Cowton 2004), the 2012 initiative marks a significant shift in the broader adoption of ESG criteria by money lenders.

As mentioned earlier, the literature lacks a clear consensus on whether there is a predominantly positive or negative relationship between firms' ESG scores and the cost of debt. Authors like Dhaliwal et al. (2011) propose a positive relationship, indicating that an increase in ESG scores leads to a higher cost of debt for companies. Conversely, researchers such as Gao et al. (2016) argue in favour of the idea that high ESG scores negatively impact debt financing, implying a negative relationship between ESG scores and the cost of debt.

The channels through which we disentangle the ESG-cost of debt relationship can be broken down into three theories: the signaling theory, the agency theory, and the tradeoff theory.

Signaling theory

The *signaling theory* highlights and explores the importance of the different levels of information that two parties are exposed to and have access to. In this context, the party who delivers the information, the sender of the signal, comprises the firms which are meant to share information about their ESG or Corporate Social Responsibility (CSR) activities. The other party is left not only with the passive act of receiving the signal but also with the active part of interpreting them. The focus of the signaling theory is therefore to analyse the difference, or asymmetry, of the information between the two parties (Spence 2002). In the context of the relationship between the ESG and the cost of debt, on the side of the receivers there are all the external shareholders including the lending money institutions.

The singaling theory can be used to address and explain the channel through which the ESG rating influences the cost of debt. ESG scores act as a signal for firms since sharing ESG information reduces information asymmetries as already mentioned in the previous section. On the other side, high ESG scores are a "green light" signal (Lee et al. 2022) for reputational capital (Friske et al. 2023; Minor and Morgan 2011; Zhu et al. 2014), building trust between managers and external shareholders (Godfrey 2005; Hoepner et al. 2016), reducing the firm's exposure to ESG risks (Li et al. 2024), and to effectively reduce information asymmetries (Cui et al. 2018). Moreover, the benefit of disclosure of information gives managers lesser pressing monitoring from lenders (Nguyen et al. 2020) and a longer less expensive debt. Overall, the singling theory therefore suggests a negative relationship between ESG scores and the cost of debt.

Agency theory

On the other side, the *agency theory* delves into the dynamics between managers and shareholders, including financial lenders, with a focus on managers' actions and responses in the pursuit of shareholders' interests. In examining the interplay between ESG scores and the cost of debt, the agency theory seeks to elucidate the strategies employed by managers to align with the concerns of lender institutions.

Specifically concerning the cost of debt, some authors highlight that as debt approaches renewal, managers typically undertake initiatives to fortify the company, rendering it more robust and attractive for lender evaluation. For instance, studies like Galant and Cadez (2017) observe managers enhancing the corporate side by augmenting employee salaries. Some authors propose instead that managers might boost eco-friendly initiatives, such as curbing CO2 emissions (Brown et al. 2006). Guided by the principle *"Primum non nocere"* (Minor and Morgan 2011), in this context these initiatives prove to be nothing but beneficial for the company. Actions like extending benefits to employees and contributing to environmental preservation enhance in turn the company across various dimensions — resulting in facing less stringent regulatory scrutiny and improving corporate reputation.

However, the agency theory warns that managers might be influenced by personal or company advantages that could outweigh the interests of shareholders. Managers may excessively engage in these actions to enhance their personal reputation, attract media attention (Jensen and Meckling 1976). This creates a counter-effect for the company, as an excessive focus on personal gains may divert resources from maximising shareholder value, potentially leading to sub-optimal financial performance, as previously discussed.

Excessive or deceitful ESG efforts could be perceived as attempts to manipulate public opinion rather than genuine commitments, eroding trust and potentially increasing the cost of debt due to concerns about managerial motivations and long-term sustainability.

Tradeoff theory

As already mentioned, ESG ratings play a crucial role in shaping the dynamics of the lending mechanism, serving as a pivotal factor considered by lenders when evaluating the creditworthiness of firms and as a means to convey information, or signals, from companies to shareholders. In essence, a high ESG score can be seen as synonymous with a firm's trustworthiness (Godfrey 2005; Yoon et al. 2006). A firm's trustworthiness shapes also the form of debt of the company (Hackbarth et al. 2007; Hege and Mella-Barral 2005). Indeed, firms' trustworthiness influences lenders' preferences towards establishing long-term debt relationships with such companies. The preference for long-term debt traduces not only to a lower cost of debt on the company side (Chava 2014), but also to a lower cost of monitoring from the lenders' side increasing their interest in lending money to these companies (Brockman et al. 2010). In contrast, the trustworthiness (or lack thereof) of firms introduces also another effect. Lenders opt for shorter agreements as a strategic measure to facilitate a more accessible exit from potentially precarious financial arrangements. This strategic move results in lenders imposing higher interest rates to counterbalance the perceived heightened risk associated with ESG laggards. This dynamic creates a financial scenario where firms with lower trustworthiness encounter challenges in securing favourable lending terms, leading to increased financial costs (Brockman et al. 2010; Datta et al. 2005).

The intricate interplay of various factors delineates a dynamic mechanism, driving the cost of debt in opposite directions suggesting a non-linear relationship between the cost of debt and the ESG rating, as observed in the research by Li et al. (2024). When engaging in ESG activities, akin to conventional investments, firms encounter an initial phase dominated by costs (Cappucci 2018). These initial costs, in turn, trigger an increase in risk, manifested through higher interest rates imposed by lenders and the preference for shorter lending contracts. However, as the returns on ESG investments materialise in the form of a favourable cost-benefit ratio, a cascading effect unfolds. Over the long term, this effect translates into improved financial performance, reduced idiosyncratic risk, and a diminished cost of capital.

All things considered, the *tradeoff theory* posits that the relationship between ESG and the cost of debt relies on many factors and can be described as a non-linear relationship. The tradeoff theory proposes that the relationship between ESG rating and the cost of debt evolves through distinct stages, suggesting a U-shaped relationship (Li et al. 2024). In the initial stages of adopting ESG practices, the upward slope of the curve signifies a period marked by significant investments, where costs may initially outweigh immediate benefits. This aligns with the tradeoff theory, suggesting that upfront ESG costs might lead to negative short-term financial performance. As the firm progress its ESG journey, a pivotal moment occurs where costs begin to align with and eventually give way to the accumulating benefits of sustained ESG efforts. This shift indicates the potential for reduced costs and improved financial performance. Moving forward, the downward slope of the U-shaped curve represents a phase where the benefits of ESG engagement become more evident, resulting in enhanced long-term financial performance. This later stage reinforces the tradeoff theory's proposition that a prolonged commitment to ESG practices can lead to a positive financial outlook, characterised by decreasing costs and increasingly favourable outcomes. Thus, the U-shaped curve can be viewed as a chronological representation of how ESG scores influence the cost of debt over time.

Empirical evidence

In this section, we approach the literature through a more analytical lens. Initially, we outline the various proxies utilised to assess the firms' cost of debt. Subsequently, we delve into the diverse methodological approaches employed to investigate the connection between ESG and the cost of debt. Our objective is to gain insight into the significance of the cost of debt proxies and the methodological approach in examining the relationship between the cost of debt and the ESG score.

Cost of debt proxies

One of the most commonly employed methodologies to assess a firm's cost of debt is the ratio between interest expenses and average debt. This methodology is grounded in the principles of accounting and extensively documented in the literature. Some authors advocate for the superiority of accounting-based measures over market-based ones. Houqe et al. (2020) indeed suggest that an accounting-based measure is able to capture private debt components with greater granularity. This perspective dovetails with the findings of Orlitzky et al. (2003), particularly in relation to examining the correlation between firms' cost of debt and ESG factors. Specifically, Orlitzky et al. (2003) suggest that this proxy is particularly suitable when ESG is considered as one of the independent variables. Their meta-analysis suggests indeed a stronger correlation between ESG scores and accounting-based proxies compared to market-based ones.

Another widely used way to build a proxy for the cost of debt is to evaluate the difference between the yields of a firm's bonds and the yield of a corresponding risk-free bond. This proxy has instead a market-oriented perspective. Indeed it reflects the premium that the market charges to borrowers above the risk-free rate for the risk that they may default on their debt obligations.

It is worth mentioning other proxies for the cost of debt, even if they are not widely employed. Sengupta (1998), for instance, utilises two proxies. One of these proxies is conceptually similar to the ratio between interest expenses and debt, as it represents the total interest cost that the firm pays on its first debt issue in the following year $(t + 1)$. The other proxy used in the paper is the yield to maturity of the first debt issue of the following year $(t + 1)$. This latter proxy is also subsequently employed by Gao et al. (2016).

A relatively noticeable number of authors employ the net weighted average cost of debt (WACC of Debt) derived from Bloomberg as a proxy for the cost of debt. [1]

Raimo et al. (2021) supports the accuracy of Bloomberg's evaluation compared to the interest-to-debt ratio stating that "the realised interest costs measure is considered to be too noisy due to the effect of borrowings and non-adjustment for the new bond issue

[1](Bloomberg 2013: p. 18) evaluates the cost of debt as: "the weighted average cost of debt for the security, calculated using government bond rates, a debt adjustment factor, and the proportions of short and long term debt to total debt. The debt adjustment factor represents the average yield above government bonds for a given rating class. The lower the rating, the higher the adjustment factor. The debt adjustment factor (AF) is only used when a company does not have a fair market curve (FMC). When a company does not have a credit rating, an assumed rate of 1.38 (the equivalent rate of a BBB + Standard and Poor's long term currency issuer rating) is used".

$$CoD = [[(SD/TD) \times (CS \times AF)] + [(LD/TD) \times (CL \times AF)]] \times [1 - TR]$$

Where SD = short-term debt, TD = total debt, CS = pre-tax cost of short-term debt, AF = debt adjustment factor, LD = long-term debt, CL = pre-tax cost of long-term debt, and TR = effective tax rate.

(Pittman and Fortin 2004; Shaw 2012)". The Bloomberg evaluation method is widely acknowledged in academic literature, as emphasised in Raimo et al. (2022) referencing the study by Caragnano et al. (2020).

Methodologies

In Table 4.1, we summarise the various approaches employed by authors to analyse the relationship between ESG and the cost of debt. In doing so, we pay particular attention to whether they utilise a linear analysis or allow for a non-linear relationship. The table indicates that non-linear attempts to identify a U-shaped relationship are notably successful. This reinforces our decision to incorporate a non-linear approach into our analysis as well. Indeed, there appears to be a discernible trend wherein non-linear approaches uncover a U-shaped relationship that ties ESG and the cost of debt together.

Table 4.1: Overview of Proxies for Cost of Debt in ESG Studies

Paper	CoD Evaluation	Methodology	ESG-CoD Relationship
Menz (2010)	yield to maturity	linear	positive
Goss and Roberts (2011)	yield spread	non-linear	U-shaped
Oikonomou et al. (2014)	yield spread	linear	negative
Ge and Liu (2015)	yield spread	linear	negative
Gao et al. (2016)	yield to maturity	non-linear	U-shaped
Hoepner et al. (2016)	yield spread	linear	insignificant
Eliwa et al. (2021)	interest exp over debt ratio	linear	negative
Apergis et al. (2022)	yield spread	linear	negative
Gigante and Manglaviti (2022)	yield spread	linear	negative
Li et al. (2024)	interest exp over debt ratio	non-linear	U-shaped

Table 4.1 presents a summary of several papers, including the evaluation methods utilised for the cost of debt (CoD), the approach taken in analysing the relationship between ESG score and the cost of debt (linear or non-linear), and the reported findings regarding this relationship.

Negative relationship findings

As previously discussed theoretically, signaling theory provides a conceptual framework through which ESG practices can help companies reduce their cost of debt. This reduction occurs by mitigating information asymmetries and consequently fostering greater trust between firms and investors as well as minimising exposure to ESG-related risks. Empirical research supports this theoretical underpinning, as many scholars identify a negative correlation between ESG scores and the cost of debt. This suggests that engaging in ESG activities positively influences a firm's ability to secure debt financing. Studies by scholars such as Oikonomou et al. (2014), Ge and Liu (2015), Eliwa et al. (2021), and Apergis et al. (2022) provide evidence supporting this notion, consistently finding a negative relationship between ESG performance and the cost of debt.

U-shaped relationship findings

Further exploration of the ESG-cost of debt relationship focussing on the methodological approaches reveal an evident pattern wherein attempts to seek a non-linear relationship often unveil an inverted U-shaped pattern. These findings are supported by the trade-off theory, as previously mentioned.

Goss and Roberts (2011) explore the relationship between corporate social responsibility (CSR) and the cost of debt by distinguishing between CSR strengths, a measure of firms' proactive CSR activities, and CSR concerns. Through the application of an interaction effect between these two dimensions, the study reveals that while CSR strengths alone are statistically insignificant, the positive coefficient of CSR concerns and the negative coefficient of the interaction effect indicate an inverted U-shaped relationship between CSR concerns and the cost of debt. This suggests that as CSR concerns increase, the cost of debt rises, while high CSR strengths lower the cost of debt. However, the study also highlights that attempts by firms to manipulate stakeholders through "greenwashing" strategies towards increasing the ESG score rather than enhancing sustainability practices are identified and penalised by money lenders. This highlights that non-genuine initiatives are unlikely to succeed.

Gao et al. (2016), instead, use a dummy variable to isolate companies that fall into the Dow Jones Sustainability Index (DJSI), considered as companies with high CSR performances, from the ones that do not, considered as firms with low CSR rating. Their analysis suggests that companies with high CSR scores benefit from better pricing in terms of a lower cost of debt, making the CSR disclosure more effective while low CSR-scored companies suffer from higher cost of debt. Similar results can be found in the work of Gigante and Manglaviti (2022) which employs a sharp Regression Discontinuity

(RD) model. The design of their research involves a sharp RD model designed to discriminate companies based on their ESG score. Indeed, the several attempts to set different bandwidths for the running variable (ESG) suggest that the marginal effect of the ESG performance on the cost of debt changes sign between below the average and above, moving from positive for companies with an ESG score below the average and negative for firms with ESG above the mean. This finding strongly suggests a non-linear relationship between the two variables with ESG laggards facing a higher cost of debt while ESG leaders benefit from a reduction in the cost of debt financing.

Li et al. (2024) find similar results also. In their analysis they employ a model that encompasses the ESG score variable solely in level and another model in which the ESG variable is considered in its level as well as squared to introduce non-linearity. While in the first model, the ESG variable is not statistically significant, in the latter formulation, the coefficients are instead significant and they unravel a non-linear relationship. Indeed, the coefficient for the level is positive while the one for the non-linear is on the opposite sign finding analytical support for the inverted U-shaped relationship between ESG scores and firms' cost of debt. In other words, the findings of the paper suggest that the cost of debt is positively correlated with firms with low levels of ESG scores while it is negative, even if weakly, for companies that show higher levels of commitment to ESG activities.

Positive relationship and insignificant findings

On the other side the agency theory, as mentioned previously, supports the idea that there might exist a positive relationship between firms' cost of debt and ESG scores. Although the theoretical side is appealing and worth mentioning, analytically, just a few researchers find a positive relationship. The work of Menz (2010) is one of the few showing indeed a positive, even if weak, relationship between the cost of debt and ESG scores. It must be said though that the scope of the analysis is slightly different since the author focuses on the corporate bond market rather than on the firms' cost of debt. It is also worth mentioning the work of Hoepner et al. (2016) which finds a positive correlation between ESG and cost of debt but fails to find significance in the ESG coefficient in the main model which comprises all the control variables and the fixed effects.

In summary, while the proxy for the cost of debt may not play a crucial role in defining the relationship with the ESG, the choice of the methodology is very relevant instead, suggesting an inverted U-shaped relationship between the two variables when non-linear models are employed.

While the literature on the relationship between ESG rating and cost of debt presents contradictory findings, it offers valuable insights into the complex nature of this relationship. Building on this existing body of research, we aim to deepen the understanding by exploring the potential relationship between ESG scores and cost of debt proposing the following hypothesis:

Hypothesis 4.1. *ESG scores and cost of debt have a negative relationship.*

Effect of crude oil volatility on the cost of debt

The association between the crude oil market and the equity market boasts a longstanding tradition, with seminal research by Jones and Kaul (1996) and Sadorsky (1999) laying foundational groundwork[2]. Since these early contributions, numerous seminal works have further enriched the topic. In exploring the impact of crude oil market volatility on the equity market, the pivotal work of Kilian (2009) and Kilian and Park (2009) stands as an essential cornerstone in the exploration of the impact of crude oil market volatility on the equity market. The latter particularly underscores the significance of the nature of crude oil shocks, emphasising that demand shocks play a more substantial role in explaining equity market movements than supply shocks. That being said, the channel in which crude oil volatility affects the cost of financing is not examined yet.

In this section, we analyse the relationship by considering the impact of oil price volatility on the constraints of financial intermediaries, due to the spillover effects between oil price and equity volatilities. We argue that heightened constraints on financial intermediaries are transferred to firms, resulting in higher borrowing costs or reduced access to credit.

[2]While Hamilton (1983)'s work does not comprehensively cover the oil market's relationship with the equity market, it stands as one of the initial investigations into the broader macroeconomic repercussions of oil price fluctuations, offering insights into how oil shocks can impact the overall economy, including the stock market.

Oil price volatility and market volatility

The connection between oil price volatility and equity market volatility is complex and not directly evident, as highlighted by studies such as those by Richards (1995), Dimpfl (2014), and Dimpfl and Peter (2018), which found no fundamental economic linkage between volatilities. To address this gap, literature proposes several theories. Notably, Kodres and Pritsker (2002) introduce the cross-market rebalancing theory, suggesting a contagion mechanism whereby shocks in one market lead to investor rebalancing across markets. Another theory, the social learning channel proposed by Trevino (2020), posits that even in the absence of a direct financial link, a crisis in one sector can incite fear among investors, concerned about potential crises in other markets.

Empirical evidence supports the presence of volatility transmission between the oil market and the equity market, particularly in specific regions and sectors. Malik and Hammoudeh (2007) and Maghyereh and Awartani (2016) document such transmissions in Middle Eastern countries. Similarly, Malik and Ewing (2009) observe this phenomenon in various sectors in the US, including financial, industrial, consumer services, healthcare, and technology sectors. El Hedi Arouri et al. (2011) find volatility spillovers between the crude oil market and equity markets in Europe and the US, with no significant spillover in the opposite direction. Awartani and Maghyereh (2013) discover that in the Gulf Cooperation Council (GCC) countries, the volatility transmission channel is predominantly influenced by the crude oil market.

Further analysis conducted by Maghyereh et al. (2016) utilises a set of tools specifically designed to disentangle the direction of volatility spillovers between markets. These methodologies, developed by Diebold and Yilmaz (2012), Diebold and Yılmaz (2014), and Diebold and Yılmaz (2015), reveal a bi-directional relationship between crude oil and equity volatility. However, during the recovery period following the Global Financial Crisis, crude oil volatility is more pronounced in dominating the transmission channels.

Market volatility and cost of debt

We support the financial intermediaries' constraint channel as a mechanism linking market volatility to firms' cost of debt. Evidence from Christoffersen and Pan (2018) demonstrates that crude oil price volatility significantly impacts the constraints faced by financial intermediaries. Their research builds upon the foundational work of Brunnermeier and Pedersen (2009), who identifies a correlation between market volatility and the capitalisation of intermediaries. Financial intermediaries must finance trading either through their own capital or via collateralised borrowing from other financiers. High market volatility leads to increased margins, resulting in tighter capital constraints for intermediaries. Similarly, during market downturns, financial intermediaries are more likely to face capital constraints. Therefore, when market volatility is elevated, financial intermediaries become more constrained due to higher margins, declines in portfolio values, or both.

Christoffersen and Pan (2018) extend this framework by demonstrating that higher crude oil price realised volatility, associated with increased uncertainty and negative market returns following financialisation, transmits positive shocks to the stock market. According to Adrian et al. (2014), the marginal value of wealth for financial intermediaries is a key determinant of pricing kernel dynamics. Building on this idea, Christoffersen et al. show that such shocks reduce the risk-bearing capacity of intermediaries. Increased volatility leads to higher margins or lower asset values for intermediaries, tightening speculators' funding constraints, reducing market liquidity, and amplifying risk premia.

When the risk-bearing capacity of intermediaries is reduced due to increased volatility, intermediaries become more risk-averse, leading to stricter lending criteria and higher interest rates for firms seeking debt financing. With higher margins and reduced asset values, intermediaries face tighter funding constraints, which are passed on to firms as higher borrowing costs or reduced access to credit. Additionally, as volatility leads to higher risk premia, the overall cost of financing increases for firms because investors demand higher returns to compensate for the increased risk, resulting in higher interest rates on corporate debt.

Building on the preceding discussion, this study proposes the following hypothesis:

Hypothesis 4.2. *Crude oil volatility and cost of debt have a positive relationship.*

ESG as hedge from oil price volatility for firms' cost of debt

As mentioned earlier, we address the existing research gap by integrating two strands of literature: the body of work that analyses the effect of ESG ratings on the cost of debt and the literature on the impact of crude oil volatility on the cost of debt.

Our approach aligns with the findings of Chen and King (2014), who explore the impact of corporate hedging on the cost of debt and identify a negative relationship, suggesting that hedging strategies lead to a reduction in the cost of debt. In our context, we view ESG activities as a form of hedging strategy for companies, in line with the perspective of Gonçalves et al. (2022). Gonçalves et al. support the idea that ESG activities, formalised in ESG rankings, act as a kind of "insurance" against ESG-related risks.

Expanding on the work of Chen and King, we generalise the concept, assuming that companies' hedging also correlates negatively with the cost of debt. Additionally, we consider crude oil price volatility as the source of risk meant to be hedged by ESG scores, suggesting that ESG activities act as a hedge for firms' cost of debt during times of heightened volatility.

In essence, ESG practices serve as a hedging strategy aiming to shield the cost of debt of firms during periods of increased volatility stemming from the crude oil market. Formalising our hypothesis based on this rationale:

Hypothesis 4.3. *ESG scores act as a hedge for the cost of debt during heightened crude oil price volatility.*

Building on these theoretical foundations, this study extends the literature by explicitly linking ESG practices to firms' cost of debt in the context of crude oil price volatility. While prior research has explored the independent effects of ESG scores on financing costs and crude oil volatility on debt markets, these strands of literature have not been integrated to assess whether ESG acts as a financial hedge against oil-induced uncertainty. This research bridges this gap by investigating whether firms with higher ESG scores experience lower borrowing costs during periods of heightened crude oil price volatility, effectively positioning ESG as a risk mitigation tool within corporate debt markets.

By framing ESG activities as a financial hedging mechanism, this study provides a novel empirical contribution to both ESG and commodity risk literature. Unlike prior research that predominantly considers general risk management strategies (e.g., Chen and King (2014)) or ESG's role as a reputational shield (Gonçalves et al. 2022), this study empirically tests whether ESG scores directly offset the impact of crude oil price fluctuations on the cost of debt. In doing so, it offers new insights into how sustainability-related financial policies influence corporate risk exposure in volatile market environments.

4.3 Methodology

In this chapter, we utilise a regression analysis following the methodology proposed by Ozdagli (2017). Our model indeed focuses on the interaction effect between firms' ESG scores and market volatility to examine their combined impact on the cost of debt, as specified in Equation (4.1):

$$\begin{aligned} CoD_{it} = \alpha \ + \ \beta_1 \, ESGScore_{it_U} \ + \ \beta_2 \, OilVol_t \\ + \beta_3 \, ESGScore_{it_U} \times OilVol_t \ + \ ControlVariables + \varepsilon_{it}. \end{aligned} \tag{4.1}$$

In this equation, i denotes variables that are related to each single firm, while t represents the quarter of each observation. The subscription t_U variable signifies that the ESG scores remain constant between assessments, with the most recent ESG score applied at each time t.

We tailor the selection of firm-level control variables to align with the recommendations found in the literature on the cost of debt (Buallay 2019; Datta et al. 2005; Eliwa et al. 2021; Gigante and Manglaviti 2022; Houqe et al. 2020). Similarly, we choose macro-level control variables to be consistent with existing studies on crude oil price volatility. The complete list of control variables utilised in this chapter is presented in Equation (4.2):

$$\begin{aligned} ControlVariables_{it} = \{TotalAssets_{it}, \ Leverage_{it}, \\ + \ ROE_{it}, \ VIX_{t-1}, \ GPD_{t-1}, \ CPI_{t-1}, \ IPI_{t-1}\}. \end{aligned} \tag{4.2}$$

In this equation, the variables that show an it subscript are controls at a firm level, specific to each firm (i) for each observation (t). Macro-level controls are included with a one-quarter lag ($t-1$) to account for heterogeneity and are uniform across all firms.

To further elucidate the interaction effects on the cost of debt, we employ margin plots to further delve into the interaction effect on the cost of debt. The margin plot provides a graphical representation of the partial derivatives outlined in Equations (4.3) and (4.4):

$$\frac{\partial\, CoD_{it}}{\partial\, ESG_{it}} = \beta_2 + \beta_3\, OilVol_t. \tag{4.3}$$

$$\frac{\partial\, CoD_{it}}{\partial\, OilVol_t} = \beta_1 + \beta_3\, ESG_{it}, \tag{4.4}$$

4.4 Data Description

Sample section and data source

In this research project, we primarily utilise data from Bloomberg and LSEG[3][4]. These sources are widely recognised and commonly employed in the literature due to their established reliability and accuracy.

Our dataset includes firm-level data for each company listed in the Standard & Poor's 500 Index. For each of these companies, we evaluate the cost of debt, ESG scores, and control variables. Additionally, we incorporate some macroeconomic-level variables. This macro-level data includes a proxy for crude oil price volatility which constitutes one of the main variables of our analysis, and macro-level control variables.

The timeframe of our project spans from the beginning of 2000 to the end of 2023. We opt for quarterly data because our main variable, the cost of debt, is reported in firms' financial statements, which are typically released on a quarterly basis.

[3] In January 2021, LSEG acquired Refinitiv and subsequently rebranded the database as "LSEG" (LSEG 2022). Prior to this, on October 1, 2018, Blackstone acquired 55% of the Financial & Risk business from Thomson Reuters, leading to the renaming of the database from "Thomson Reuters" to "Refinitiv" (Reuters 2018).

[4] We utilise Bloomberg solely for their proxy of the cost of debt in Appendix B when comparing different cost of debt proxies.

Dependent variables

In this project, our focus lies in examining the response of the cost of debt. Our calculation of the cost of debt aligns with established literature, determined as the interest expenses a firm encounters at time t divided by the debt held by the company. Our approach is in line with the literature in terms of its evaluation (Gray et al. 2009; Houqe et al. 2020; Pittman and Fortin 2004), but also from the perspective of utilising an accounting-based approach. As already mentioned, the effectiveness of an accounting-based perspective becomes evident particularly when ESG scores are included as independent variables in the regression model. Indeed, Orlitzky et al. (2003) and Eliwa et al. (2021) find that the accounting-based measures for the cost of debt tend to be more correlated to the ESG scores.

In Figure 4.1, we provide a detailed examination of our proxy for the cost of debt. This figure dissects the various components employed in its evaluation, as delineated in Equation (4.5), to identify the primary drivers of the proxy. The variables presented in the graphs represent the average values across the 500 firms in the index.

$$CoD_t = \frac{Interest\ Expenses}{Debt}. \tag{4.5}$$

The top graph illustrates the expenses related to debt (the numerator of the formula)[5]. The middle graph displays the level of debt (the denominator of the formula). Both variables exhibit similar overall trends. Notably, fluctuations in the interest rate are prominently displayed, whereas the debt level demonstrates less volatility, thereby moderating the average behaviour of the cost of debt.

In essence, the interest rate drives the fluctuations in the cost of debt, while variations in the debt level adjust the overall level of the proxy. The sharp increase in the proxy towards the end of the series, starting from the end of the first quarter of 2022, reflects both the rise in the interest rate and the decline in the debt level. The bottom graph of the figure represents the proxy for the cost of debt, evaluated as expenses related to debt over the level of debt, as per Equation (4.5).

Figure 4.2 provides a detailed examination of our proxy of the cost of debt (CoD),

[5]Unfortunately, we were unable to obtain further details about the debt structure in terms of fixed and floating debt composition of the companies.

Figure 4.1: Cost of debt breakdown.

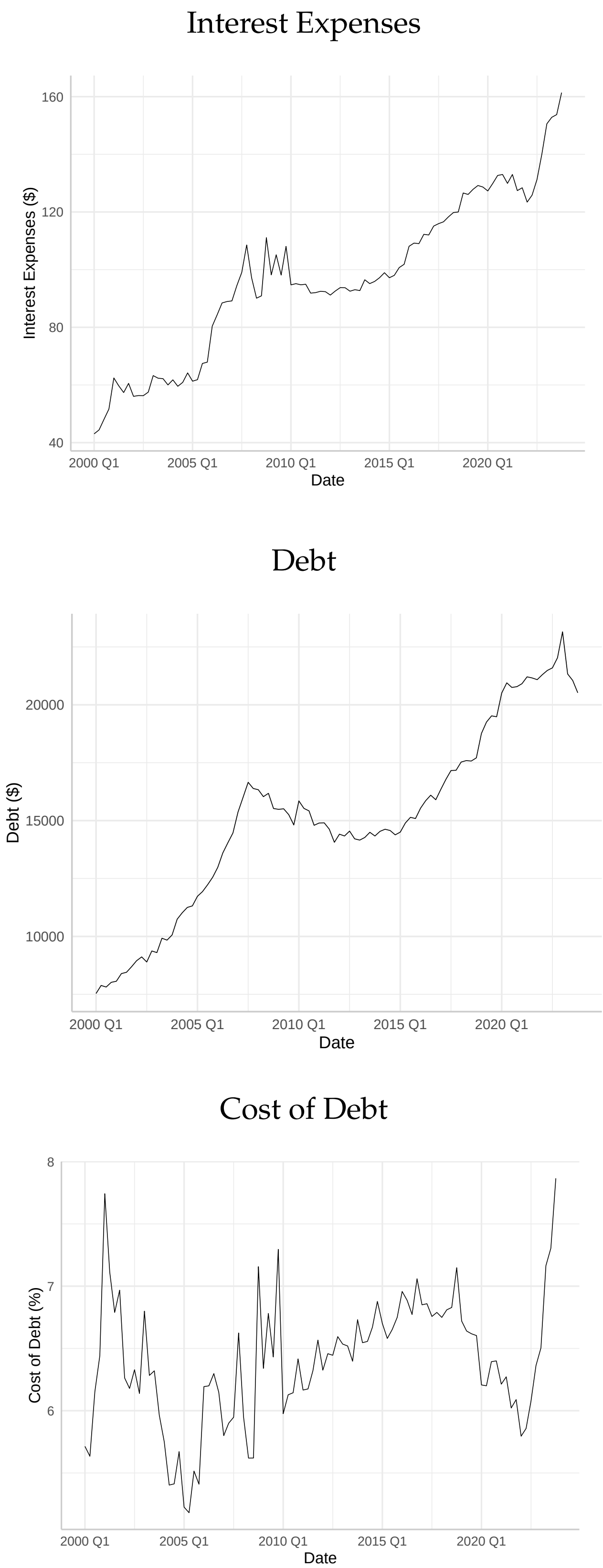
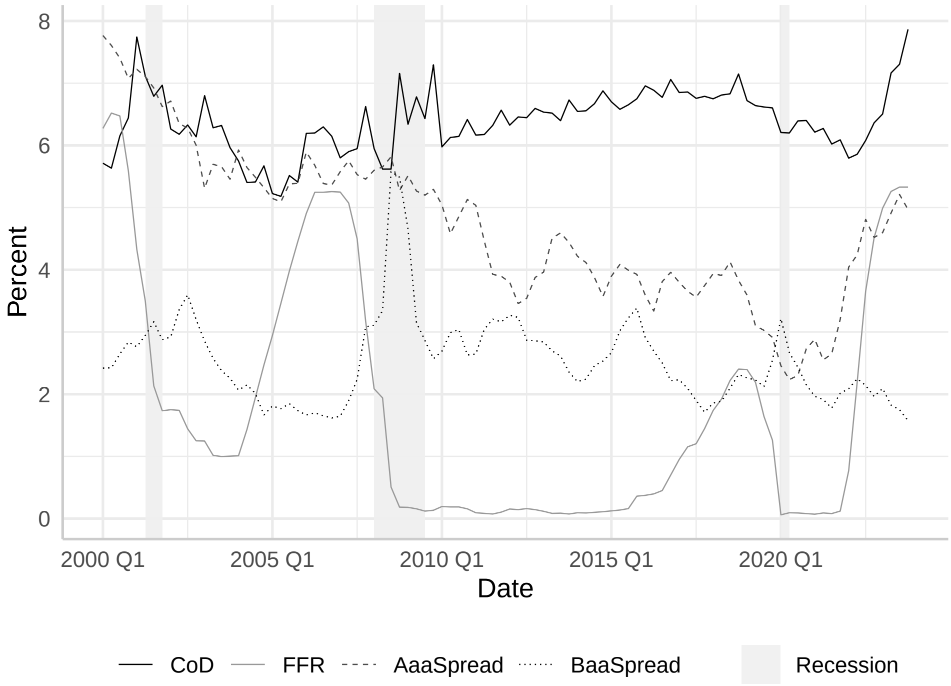


Figure 4.1 illustrates the components of the proxy utilised for the cost of debt. It displays the interest expenses and the debt, along with the cost of debt calculated according to Equation (4.5).
The figures are arranged vertically to help the comparison keeping the x-axis, which represents the dates, consistent.

Figure 4.2: Cost of Debt, Corporate Bonds Spreads, and Federal Fund Rate



The figure illustrates the proxy for the cost of debt (CoD), the spread between AAA corporate bonds and the 10-year Treasury Constant Maturity yield (AaaSpread), and the spread between BAA corporate bonds and the 10-year Treasury Constant Maturity yield (BaaSpread) as reported by FRED, along with the Federal Funds Rate (FFR). Shaded areas denote periods of economic recessions.

the spreads between AAA and BAA corporate bonds and the 10-year Treasury Constant Maturity yield (AaaSpread and BaaSpread), and the Federal Funds Rate (FFR). This figure captures the evolution of these variables across major economic events, including the Dot-com Bubble Burst, the Global Financial Crisis (GFC), the Federal Reserve rate hike starting in 2016, and the COVID-19 pandemic.

During the Dot-com Bubble Burst (2000–2001), the behaviour of corporate bond spreads diverges significantly based on credit quality. The spread between AAA corporate bonds and the 10-year Treasury yield decreases, indicating that investors perceive highly rated bonds as relatively safer investments during the economic turmoil. Conversely, the spread for BAA corporate bonds increases, reflecting heightened risk premiums for lower-rated bonds as investors demand greater compensation for perceived risks. Despite the Federal Reserve's efforts to reduce the Federal Funds Rate to stimulate the economy, the overall cost of debt exhibits a slight increase. This suggests that elevated risk aversion among investors lead to higher borrowing costs for corporations, particularly those with lower credit ratings.

During the Global Financial Crisis (GFC) of 2007–2009, the spread between highly rated (AAA) corporate bonds and the 10-year Treasury yield initially increases but generally shows a slight decrease toward the end of the crisis. In contrast, the spread for lower-rated (BAA) corporate bonds increases sharply, peaking in late 2008, reflecting heightened credit risk perceptions. Despite the Federal Reserve's substantial reduction of the Federal Funds Rate to near-zero levels, intended to alleviate the financial turmoil, the overall cost of debt for corporations rises significantly. This increase in borrowing costs is driven by soaring credit spreads and heightened market volatility, which significantly raises the risk premiums demanded by investors. This period underscores the severe pressure on corporate financing conditions, with lower-rated firms experiencing pronounced increases in borrowing costs.

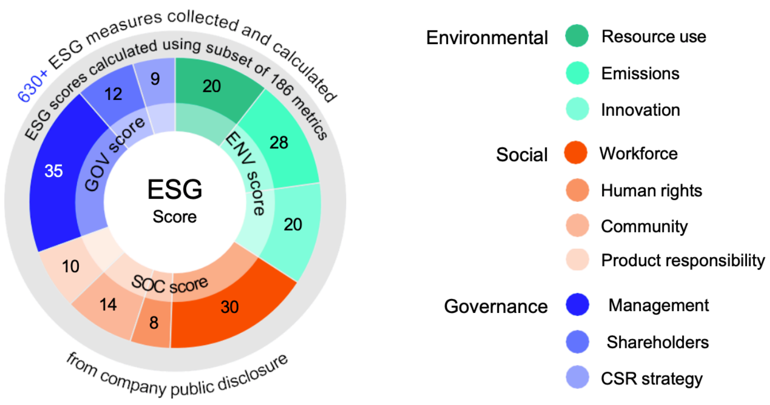
Starting in late 2016, the Federal Reserve initiates a series of rate hikes to normalise monetary policy, reflected in the gradual increase in the Federal Funds Rate from 0.70% to approximately 2.40% by the end of 2018. During this period, the cost of debt for corporations shows a moderate increase, rising from around 7.06% to about 7.15%. The spread between highly rated (AAA) corporate bonds and the 10-year Treasury yield slightly decreases, indicating a stable risk perception for high-quality bonds despite the rising interest rates. In contrast, the spread for lower-rated (BAA) corporate bonds remains relatively stable with a slight increase, suggesting that risk premiums for lower-rated bonds is less affected by the rate hikes. This moderate rise in the cost of debt aligns with Bräuning et al. (2023) findings, which show that changes in the Federal Funds Rate do not fully or immediately affect corporate borrowing costs. This is because most corporate debt has fixed rates and is refinanced gradually over time. As a result, the increase in borrowing costs during this period is less severe than in earlier times of economic stress, indicating a steady adjustment of corporate debt to the new interest rate conditions.

The COVID-19 pandemic in early 2020 causes significant economic disruption, leading to a notable increase in the spreads between corporate bonds and the 10-year Treasury yield, especially for lower-rated bonds. The spread for lower-rated corporate bonds surges, reflecting heightened risk premiums as credit markets react to the unprecedented uncertainty. This is accompanied by a slight rise in the spread for highly rated bonds. Despite the Federal Reserve's swift reduction of the Federal Funds Rate to near-zero levels, as depicted by the steep drop in the FFR, the overall cost of debt remains relatively stable but elevated.

Following the COVID-19 pandemic, starting in late 2021, the Federal Reserve implements substantial interest rate hikes to counter rising inflation, resulting in a sharp increase in the Federal Funds Rate from 0.12% in Q4 2021 to approximately 5.33% by Q4 2023. This period experiences a significant rise in the cost of debt for companies, which increases from around 6.09% to about 7.87%. This rise is primarily driven by increased interest expenses relative to debt levels, with the most notable jump occurring in the second half of 2023, where the cost of debt surges nearly two percentage points within six months. This escalation in borrowing costs can be largely attributed to the delayed impact of the Federal Reserve's rate hikes on the average cost of corporate debt. According to Bräuning et al. (2023), this phenomenon is due to the relatively small proportion of corporate debt that is floating rate, which adjusts more directly in line with changes in the Federal Funds Rate. Instead, the majority of corporate debt is fixed-rate and subject to staggered refinancing schedules, which delays the full effect of rising interest rates on the overall borrowing costs for firms. During the pandemic and subsequent recovery, firms issue a substantial volume of fixed-rate bonds, extending the average maturity of their debt and contributing to this delayed pass-through effect during the rate-hiking cycle.

The spread between highly rated (AAA) corporate bonds and the 10-year Treasury yield also reflects this dynamic. The AAA spread peaks at 5.21% in Q3 2023 before slightly decreasing to 4.97% by Q4 2023, indicating that even the most creditworthy bonds face heightened risk premiums as the market adjusts to the new interest rate environment. Similarly, the spread for lower-rated (BAA) corporate bonds fluctuates but generally stabilises towards the end of 2023, showing a peak at 2.25% in Q2 2022 and then declining to 1.57% by Q4 2023. These trends in the spreads underscore the broader impact of the Federal Reserve's monetary policy on credit risk perceptions and borrowing costs across different credit ratings.

Figure 4.3: LSEG Database: ESG Score Evaluation



Evaluation methodology for ESG scores of companies as per the LSEG ESG scores guide (LSEG 2023).

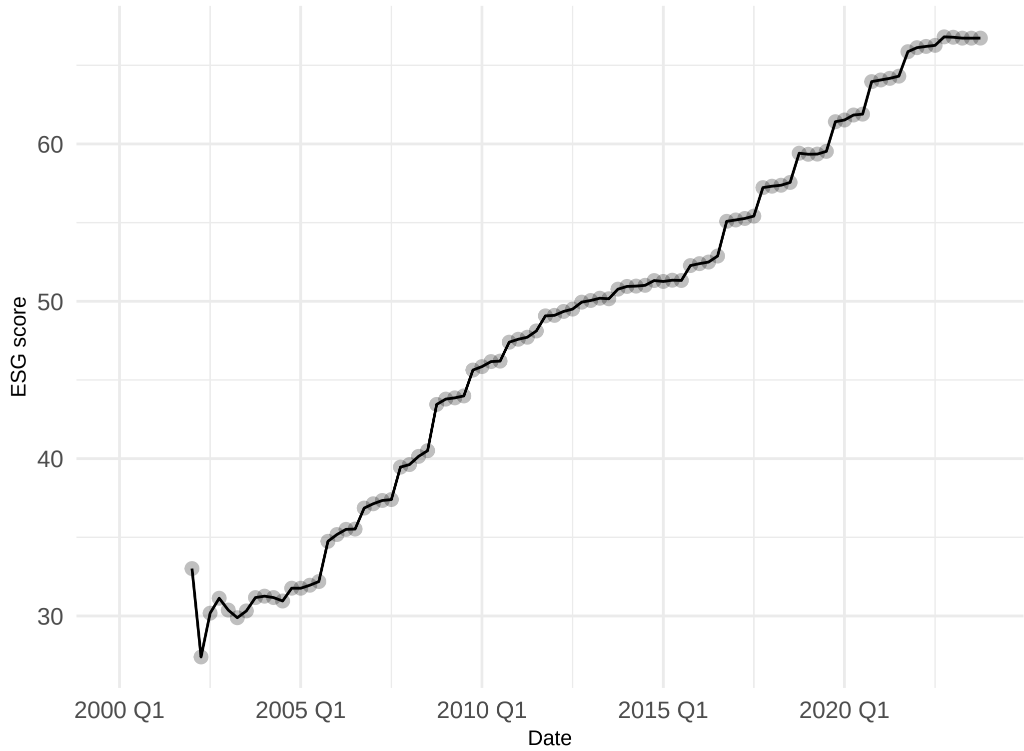
Independent variables

The independent variables utilised in this study encompass firms' ESG scores and the time series of crude oil price volatility, both sourced from the LSEG database.

The LSEG database classifies public information reported by the firms into ten categories. These ten categories serve as foundational elements for each of the single Environmental, Social, and Governance pillars. Figure 4.3, taken from the LSEG ESG scores guide (LSEG 2023), illustrates that out of the ten categories, three contribute to the Environmental, three to the Governance pillars, and the remaining four to the Social pillar. The weights of these categories vary according to the industry in which firms operate for the environmental and social pillars, while they remain constant for the governance pillar. The overall ESG score is therefore evaluated as a combination of these three pillar scores. Ultimately, the ESG scores are normalised to a 0-100 scale for clarity and comparability purposes.

The other independent variable is the time series of the crude oil price volatility, which we refer to as empirical volatility. Consistent with the methodology used in other chapters of this thesis, this measure is calculated as the average of daily squared returns within each quarter, aligning with the quarterly data used in this chapter. To ensure

Figure 4.4: ESG Scores: Firms' Average



Evolution of the average ESG scores of the firms comprising the S&P 500 Index.

consistency, daily West Texas Intermediate (WTI) prices are collected, transformed into logarithmic differences, and aggregated to derive quarterly volatility.

$$EV_t = \frac{1}{d}\sum_{i=1}^{d} r_i^2, \quad EVol_t = \sqrt{RV_t} \times 100. \tag{4.6}$$

As per the equation above indeed, r_t indicates the daily log-return on the WTI related to the day i of the quarter t. Consequently, d represents the number of trading days of the quarter t. It is worth noticing that, consistently with the previous chapters, the crude oil empirical volatility enters into our analysis as an external variable. This means that the time series of the oil volatility remains constant for each firm.

In line with the analysis conducted in the second chapter of this thesis, two observations are excluded from the crude oil volatility time series due to the notable positive spike in 2022Q1 and 2022Q2 attributed to the impact of COVID-19. This spike significantly influences the overall series, as evident in Table 4.2 and Figure 4.7. The positive surge during the first half of 2020, driven by the effects of COVID-19, dominates the statistical characteristics of the series. Table 4.2 provides a detailed summary, highlighting how the spike elevates the average and standard deviation, along with increasing the maximum value from 6.25 to 26.30. Likewise, Figure 4.7 offers a visual representation, underscoring the influence of the spike on the overall series, complementing the insights presented in Table 4.2[6].

Table 4.2: Descriptive Statistics for Key Variables

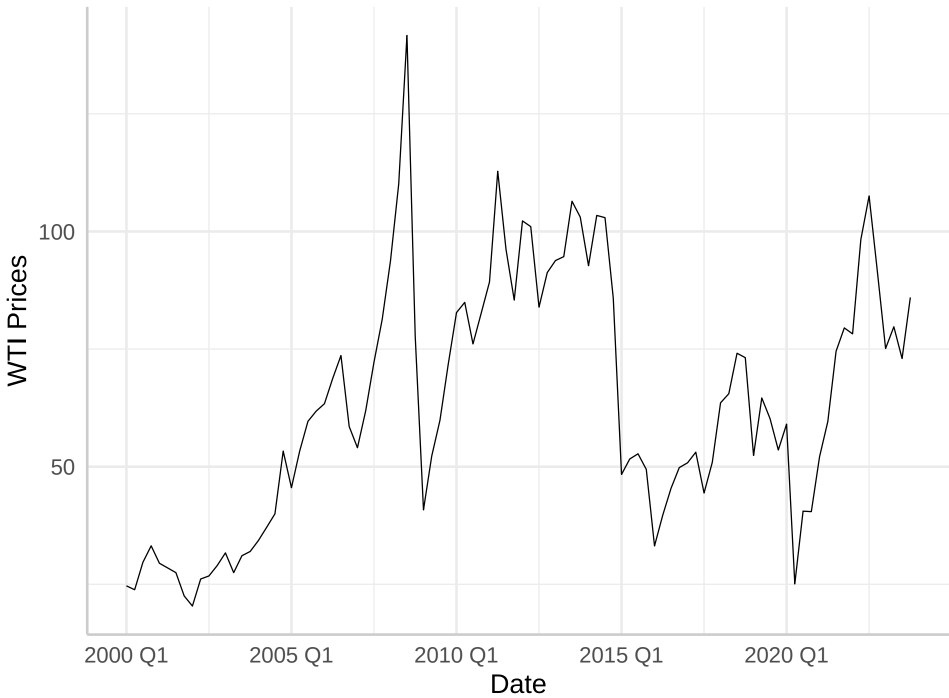
Variable	Mean	Std. dev.	Min	Max	Obs
Cost of Debt	0.0318	1.2782	0	142.1563	40,359
Oil Volatility	2.2396	0.8310	0.8329	6.2502	94
with COVID-19 spike	2.5462	2.6291	0.8329	26.2970	96
ESG Score	51.8019	20.2691	0.5986	95.1624	34,034
Oil Volatility × ESG Score	112.3857	63.8873	1.0464	576.7292	33,048

Table 4.2 presents descriptive statistics for the primary variables under examination. Oil Volatility is analysed as a time series, while firms' cost of debt, ESG scores, and the interaction effect between ESG and oil volatility are examined as panel data. Oil Volatility is multiplied by 100.

It is worth noticing that the Figures 4.4, 4.5, 4.6, and 4.7 are quarterly representations of the variables already described in the second chapter of this thesis. Although these variables are employed on a monthly basis in the second chapter, the shift in time frequency does not alter the fundamental evolution of the variables.

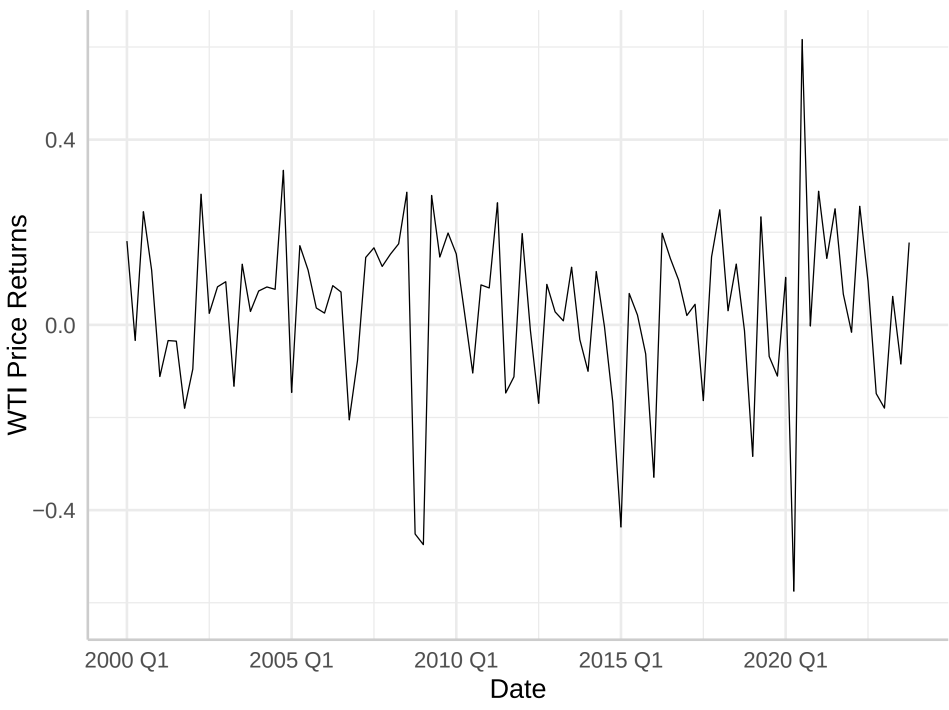
[6]A comprehensive explanation, including both analytical and economic justifications for this adjustment, is provided in Appendix B of the second empirical chapter of this thesis.

Figure 4.5: WTI Prices



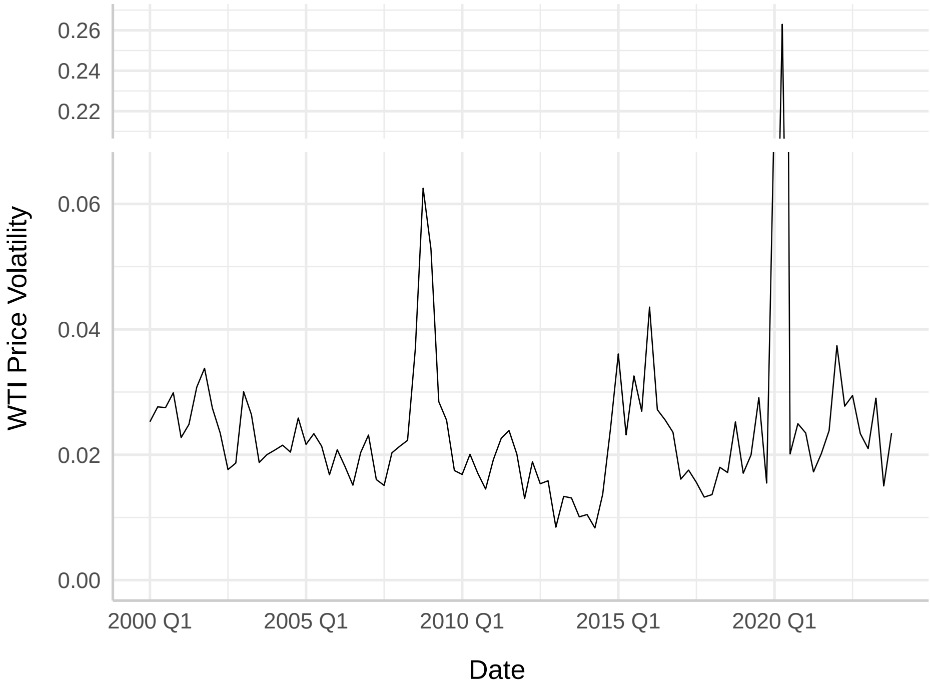
Evolution of the West Texas Intermediate (WTI) prices.

Figure 4.6: WTI Prices: Returns



Evolution of the WTI returns.

Figure 4.7: WTI Prices: Empirical Volatility



Evolution of the crude oil empirical volatility.

4.5 Control variables

The control variables employed in this study are categorised into firm-level (or micro-level) variables and macro-level variables. The selection of control variables aligns with the principal literature in the field (Buallay 2019; Datta et al. 2005; Eliwa et al. 2021; Gigante and Manglaviti 2022; Houqe et al. 2020)[7].

Micro-level variables

The micro-level data encompass the information collected for each firm including:

Total Assets. This variable represents the company's reported total assets. In the absence of reported data, it is derived by summing Total Current Assets and Total Non-Current Assets.

Leverage. Leverage is calculated as the ratio of Total Debt to Total Assets, offering insights into the financial leverage utilised by the company.

Profitability (ROE). Return on Equity (ROE) is obtained by the formula: (Net Income

[7]It should be noted that there is some overlap between the control variables employed in this chapter and those used in the second empirical or third chapter of this thesis.

before Preferred Dividends - Preferred Dividend Requirement) / Average of Last Year's and Current Year's Common Equity $\times$ 100.

Macro-level variables

Macro-level data are exogenous to individual firms as they pertain to macroeconomic variables consistent across all entities. These variables are considered in terms of their changes and include:

VIX Index (Chicago Board Options Exchange Volatility Index). The VIX Index functions as a financial benchmark, providing real-time estimations of expected volatility in the S&P 500 Index. This index is calculated using the midpoint between real-time S&P 500 Index (SPX) option bid and ask quotes, as outlined by Koçak et al. (2022).

GDP (Gross Domestic Product). This variable includes the United States' Real Gross Domestic Product (GDP) figures, measured in constant prices and chained to 2009, to reflect the nation's economic performance. To integrate quarterly GDP data into the monthly dataset, we maintain a consistent log change value for each quarter. The data is sourced from the Energy Information Administration, United States.

CPI (Consumer Price Index). This index measures changes in consumer prices for a basket of goods and services, serving as a proxy for inflation in the United States. The Consumer Price Index, expressed as a percentage, is obtained from the Bureau of Labor Statistics, U.S. Department of Labor.

IPI (Industrial Production Index). The Industrial Production Index quantifies overall industrial production, presented in percentage terms. The data is sourced from the Federal Reserve of the United States.

EPU (Economic Policy Uncertainty Index). The Economic Policy Uncertainty (EPU) Index, derived from business surveys, assesses the level of economic policy uncertainty. This baseline overall index is expressed as a percentage and is sourced from Economic Policy Uncertainty, United States. The methodological framework for this variable is based on the study by Koçak et al. (2022).

Table 4.3 provides an overview of the descriptive statistics for the control variables used in this analysis. The micro-level controls include firm-specific characteristics such as Total Assets, Leverage, and ROE, while the macro-level controls represent broader economic indicators like the VIX, GDP, CPI, IPI, and EPU.

Table 4.3: Control Variables - Descriptive Statistics

Variable	Mean	Std. dev.	Min	Max	Obs
Micro Controls					
Total Assets	5.51E+10	1.96E+11	6.05E+05	3.74E+12	44281
Leverage	161.9506	966.4969	0.0000	1134.7777	40853
ROE	19.0281	565.5125	-348.7411	457.8139	42134
Macro Controls					
VIX	0.2514	0.3202	0.0120	1.3572	96
GDP	0.0052	0.0129	-0.0822	0.0747	96
CPI	0.0063	0.0062	-0.0232	0.0230	96
IPI	0.0013	0.0208	-0.1372	0.0897	96
EPU	0.0049	0.1718	-0.3955	0.3912	96

Table 4.3 reports the descriptive statistics for the control variables.

The micro-level variables demonstrate variability across firms, with Total Assets showing a wide range, reflecting the inclusion of both large and smaller firms in the dataset. The macro-level variables, consistent across all firms, highlight key economic trends during the period under study, such as the stability of GDP growth and the relatively moderate fluctuations in the CPI and IPI indices.

Correlation analysis

The Pearson (1896) correlation matrix presented in Table 4.4 provides an overview of the relationships between the variables used in our analysis. It captures the degree of linear association among key variables influencing the cost of debt, ESG scores, and other macroeconomic and firm-level factors.

The correlation between the cost of debt (CoD) and ESG scores is negative (-0.1532), suggesting that higher ESG scores are associated with lower costs of debt. This relationship aligns with the literature, indicating that firms with strong ESG performance may benefit from reduced borrowing costs due to improved risk management and reputation.

Oil price volatility shows a very weak positive correlation with CoD (0.0055) and a negligible correlation with ESG scores (0.0102). This minimal relationship suggests that fluctuations in oil prices have a limited direct impact on both the cost of debt and ESG performance in the firms analysed.

Total assets exhibit a negative correlation with CoD (-0.1137), implying that larger firms tend to have lower costs of debt, which may reflect economies of scale or bet-

Table 4.4: Pearson Correlation Matrix

	CoD_t	ESG $Scores_t$	Oil $Volatility_t$	$TotalAssets_t$	$Leverage_t$	ROE_t
CoD_t	1					
ESG $Scores_t$	-0.1532	1				
Oil $Volatility_t$	0.0055	0.0102	1			
Total $Assets_t$	-0.1137	0.1737	-0.0066	1		
$Leverage_t$	0.0007	0.0171	0.0041	0.015	1	
ROE_t	-0.0133	0.017	-0.0009	-0.0007	0.0546	1
VIX_{t-1}	-0.0048	0.0027	0.0834	0.0011	-0.0052	0.0048
GDP_{t-1}	-0.0125	0.0149	-0.1353	0.0019	0.0004	-0.0011
CPI_{t-1}	-0.0601	0.1072	-0.0375	0.0192	-0.0086	0.0106
IPI_{t-1}	-0.0003	0.0019	-0.3004	0.0017	-0.0054	0.0008
EPU_{t-1}	0.0147	-0.021	0.1256	-0.0063	-0.0019	0.0002

~	VIX_{t-1}	GDP_{t-1}	CPI_{t-1}	IPI_{t-1}	EPU_{t-1}
CoD_t					
VIX_{t-1}	1				
GDP_{t-1}	-0.057	1			
CPI_{t-1}	0.1269	0.3442	1		
IPI_{t-1}	0.0876	0.8798	0.4306	1	
EPU_{t-1}	0.4091	-0.3695	-0.1199	-0.2815	1

Table 4.4 presents the Pearson correlation matrix for the key variables under examination, including cost of debt (CoD), ESG scores, oil volatility, total assets, leverage, and return on equity (ROE), along with macroeconomic variables.

ter creditworthiness. Total assets are positively correlated with ESG scores (0.1737), indicating that larger firms may be more likely to invest in ESG initiatives.

Leverage has a negligible positive correlation with CoD (0.0007) and ESG scores (0.0171), indicating that leverage does not significantly affect these variables in our sample. Return on equity (ROE) has a slightly negative correlation with CoD (-0.0133), suggesting that higher profitability might be associated with lower costs of debt. The correlation between ROE and ESG scores is also minimal (0.017), indicating little direct relationship.

For the macro-level variables, the lagged VIX shows a very weak negative correlation with CoD (-0.0048), indicating that market volatility has a minimal impact on borrowing costs. It has a slightly positive correlation with ESG scores (0.0027), suggesting a limited association with ESG performance. The lagged GDP growth rate is negatively correlated with CoD (-0.0125) and positively with ESG scores (0.0149), implying that better economic conditions are weakly associated with lower borrowing costs and higher ESG scores. The lagged Consumer Price Index (CPI) shows a negative correlation with CoD (-0.0601) and a positive correlation with ESG scores (0.1072), suggesting that inflation might slightly influence these variables.

The Industrial Production Index (IPI) shows a negligible correlation with CoD (-0.0003) and a very weak positive correlation with ESG scores (0.0019). Lastly, the lagged Economic Policy Uncertainty (EPU) index exhibits a very slight positive correlation with CoD (0.0147) and a small negative correlation with ESG scores (-0.021), indicating that economic policy uncertainty has a minimal effect on both variables.

In summary, the correlation matrix highlights that ESG scores and total assets have the most notable negative correlations with the cost of debt, suggesting that higher ESG performance and larger firm size are associated with lower borrowing costs. The other variables exhibit generally weak correlations, indicating limited direct interactions with the cost of debt and ESG scores in the context of our analysis.

4.6 Empirical Evidence

In this section, we present our main results. Table 4.5 details the regression results obtained using the approach outlined in the methodology section. We examine the impact of two independent variables, firms' ESG scores and crude oil price volatility, and their interaction effect on the cost of debt for each firm, as outlined in Equation (4.1).

In the table, three models are presented, differing in the inclusion of control variables. The first two columns represent the model with no control variables, the following pair of columns display the model fitted solely with firm-level control variables (Micro Controls), and the final pair of columns depict the full model incorporating both firm-level control variables and macro-level variables (Macro Controls).

For each pair of columns, corresponding to each model, the first column (1) exhibits the coefficients from the pooled regression, while the second column (2) reveals the outcomes of the fixed-effect model for firms[8].

[8]As can be observed in Figure 4.1, the number of firms included in the regression analysis decreases from the initial sample of 500. The model without control variables excludes 34 firms due to missing ESG scores. When micro-level control variables are introduced, a further 2 firms are excluded because of incomplete data for these variables.

Table 4.5: Impact of ESG Scores and Oil Volatility on Cost of Debt (Main Results)

	$CoD_{it} = \alpha + \beta_1\ ESGScore_{it_U} + \beta_2\ OilVol_t + \beta_3\ ESGScore_{it_U} \times OilVol_t + Controls + \varepsilon_{it}$					
	(1)	(2)	(1)	(2)	(1)	(2)
Variables	CoD	CoD	CoD	CoD	CoD	CoD
ESG Score	-0.0080***	-0.0081***	-0.0071***	-0.0072***	-0.0071***	-0.0072***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Oil Volatility	0.0411***	0.0409***	0.0518***	0.0518***	0.0512***	0.0515***
	(0.0116)	(0.0116)	(0.0117)	(0.0117)	(0.0122)	(0.0122)
ESG Score × Oil Volatility	-0.0012***	-0.0012***	-0.0014***	-0.0014***	-0.0011***	-0.0011***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Constant	-4.2404***	-4.1877***	-4.2658***	-4.2009***	-4.2305***	-4.1695***
	(0.0408)	(0.0288)	(0.0415)	(0.0292)	(0.0414)	(0.0299)
Micro Controls	No	No	Yes	Yes	Yes	Yes
Macro Controls	No	No	No	No	Yes	Yes
Number of Observations	28,917	28,917	27,533	27,533	27,533	27,533
R-squared	0.0660	0.0660	0.0687	0.0687	0.0730	0.0730
Number of firms	466	466	464	464	464	464

Table 4.5 shows the regression results for the equation shown on the top row. Only the coefficients of the main variables and the intercept are reported. Model (1) reports the OLS regression results, while model (2) accounts for fixed effects for firms. Initially, the models included only the main variables, then firm-level control variables were added, and finally, both firm- and macro-level control variables were included.

*** Significant at 1%, ** Significant at 5%, * Significant at 10%. The parentheses represent the standard errors.

Table 4.5 supports our initial hypotheses. Across all models utilised in this analysis, a consistent negative relationship emerges between firms' cost of debt and ESG scores. This indicates that firms with higher ESG scores tend to have lower costs of debt[9]. This finding confirms our Hypothesis 4.1. Furthermore, our findings align with Hypothesis 4.2. We consistently observe a positive relationship between crude oil price volatility and the cost of debt. This indicates that as crude oil price volatility increases, so does the cost of debt. The negative sign stemming from the interaction effect between the oil volatility and ESG scores suggests that also our Hypothesis 4.3 is confirmed. Indeed this implies that the combined effect between the two variables reduces the cost of debt financing for firms. In other words, this indicates that ESG scores act as a hedging strategy for the cost of debt during times of high volatility in the crude oil market.

Focusing on the coefficients from the model incorporating all controls and fixed effect, the coefficient for ESG scores is -0.0072, which implies that a one-unit increase in ESG scores corresponds to a decrease in the cost of debt by approximately $exp(-0.0072)-1 \approx -0.0072$ or -0.72%. This finding indicates that higher ESG scores directly lead to lower borrowing costs.

Our findings are consistent with the signalling theory, which posits a negative relationship between firms' cost of debt and their ESG scores (Friske et al. 2023; Godfrey 2005; Lee et al. 2022; Li et al. 2024; Zhu et al. 2014). When examining the magnitude of this relationship, our results align with those reported in existing research, despite the variability in coefficient sizes across studies. For instance, Eliwa et al. (2021) report coefficient magnitudes ranging from -0.011 to -0.018, while Lavin and Montecinos-Pearce (2022) find values between -0.003 and -0.007. Similarly, Alves and Meneses (2024) present a coefficient of approximately -0.005. Li et al. (2024) identify a non-significant linear relationship but reports a coefficient of 0.059 in a non-linear context. Our results fall within this spectrum, reinforcing the robustness of the negative correlation between ESG performance and the cost of debt across different methodological approaches and datasets.

The coefficient for the crude oil price volatility is 0.0515, suggesting that a one-unit increase in volatility results in an increase in the cost of debt by approximately $exp(0.0515) - 1 \approx 0.0528$ or 5.28%. This result highlights the sensitivity of the cost

[9] Additional analysis exploring potential non-linear effects further confirms this trend. Refer to Appendix A for additional evidence.

of debt to the crude oil market conditions, showing that heightened crude oil price volatility significantly raises borrowing costs.

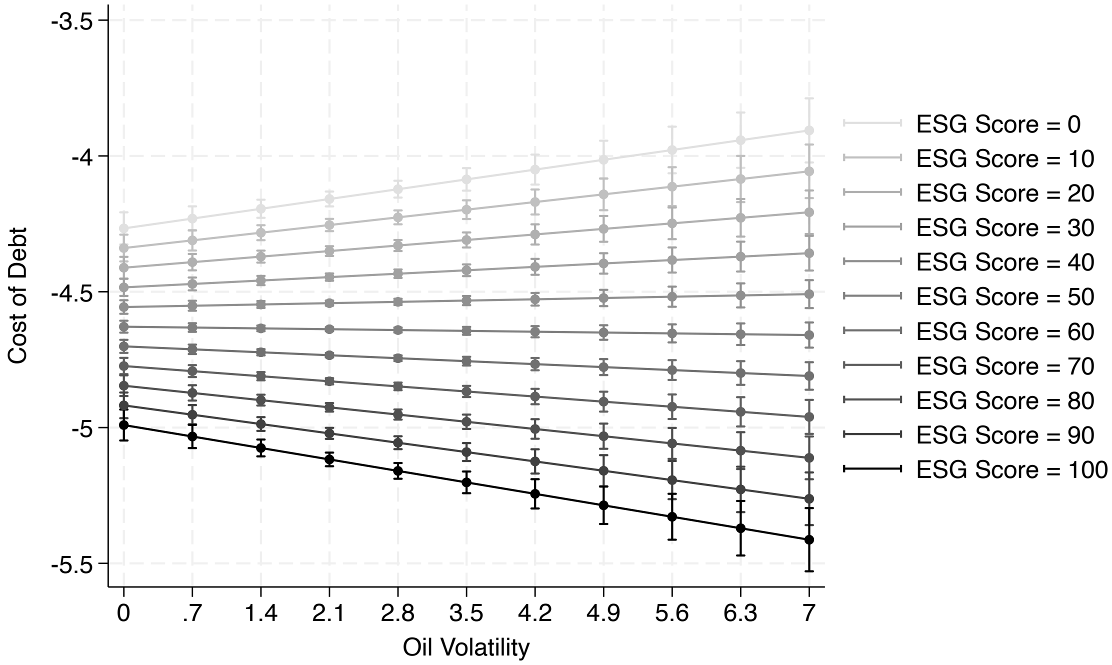
The interaction term between ESG scores and oil price volatility, with a coefficient of -0.0011, indicates that the negative effect of volatility on the cost of debt is mitigated by improved ESG performance. Specifically, each unit increase in ESG scores reduces the effect of volatility on the cost of debt by approximately $exp(-0.0011) - 1 \approx -0.0011$ or -0.11%. This interaction suggests that firms with higher ESG scores experience a reduced increase in borrowing costs in response to market volatility.

For example, at an ESG score of 50, the mitigating effect of the interaction term adjusts the cost of debt downwards in response to an initial volatility-induced increase of 5.28%. The combined impact is calculated as $exp(0.0515 - 0.0011 \times 50) - 1 \approx -0.35\%$. This indicates that firms with an ESG score of 50 would experience a slight reduction in the cost of debt rather than an increase, effectively neutralising the impact of volatility. Similarly, at an ESG score of 80, the adjustment can be computed as $exp(0.0515 - 0.0011 \times 80) - 1 \approx -3.58\%$, suggesting a significant reduction in the cost of debt as opposed to the increase from volatility alone. Conversely, for an ESG score of 30, the adjustment is $exp(0.0515 - 0.0011 \times 30) - 1 \approx 1.87\%$, showing that the cost of debt would still increase but by a lesser amount compared to the effect of volatility alone.

The observation that firms with an ESG score of 30 experience an increase in the cost of debt, rather than a decrease, is consistent with the insights derived from Figure 4.8. The figure shows that firms with low ESG scores face rising costs of debt as volatility increases. This trend aligns with a critical ESG threshold, where firms with an ESG score of approximately 47 ($46.82 = 0.0515/0.0011$) are neutral to volatility levels. This threshold suggests that only firms with ESG scores around 47 show consistency in debt costs irrespective of volatility levels. Consequently, firms with and ESG score below this threshold, such as those with an ESG score of 30, do not benefit from the mitigating effects of ESG on the cost of debt and hence experience increased borrowing costs in volatile market conditions.

Overall, while the direct effect of ESG in reducing the cost of debt is more substantial at 0.72% per unit increase, the interaction term provides an additional buffering effect against the cost escalations induced by market volatility. These results underscore the dual role of ESG performance: it not only directly lowers borrowing costs but also

Figure 4.8: Margin Plot: Cost of Debt Across Oil Volatility Levels at Different ESG Levels



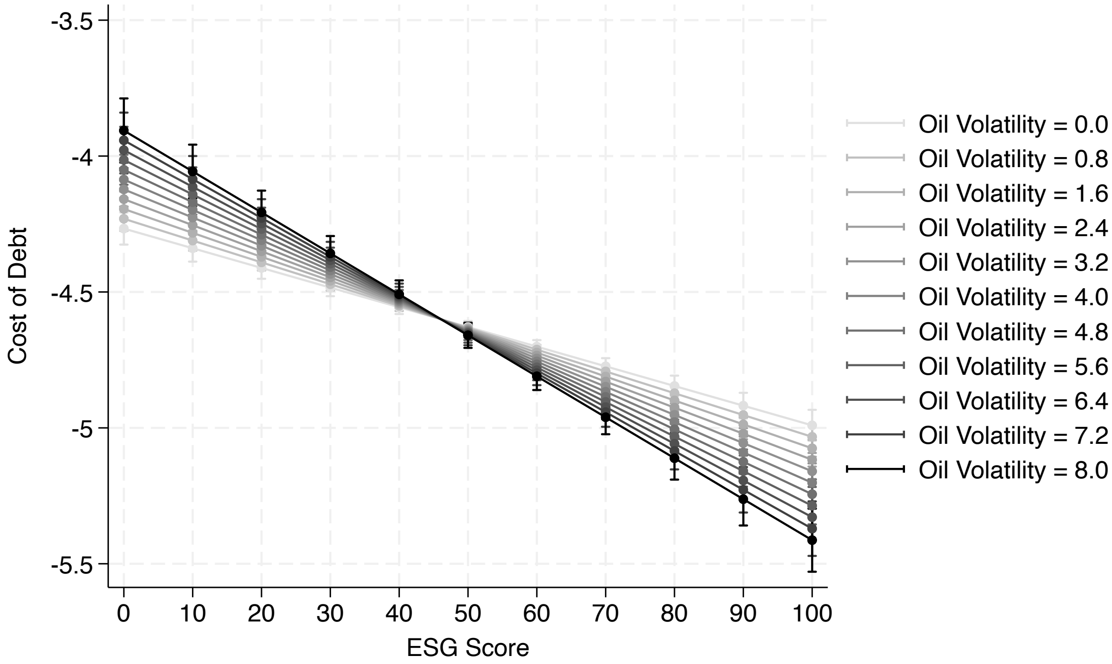
Effect of oil volatility over the cost of debt for different levels of ESG scores. The confidence levels are set to 95% and are represented by the vertical bars. Negative values on the y-axis reflect the log transformation. The critical ESG threshold for neutralising the impact of volatility on the cost of debt is approximately 47.

mitigates the adverse financial impacts of crude oil market instability.

Figures 4.8 and 4.9 delve into the marginal effect of the interaction term between ESG scores and crude oil volatility on firms' cost of debt. Specifically, Figure 4.8 shows that firms with lower ESG scores experience a higher cost of debt when the volatility of the crude oil market increases. The brighter lines represent ESG laggards, and it is evident that, moving to the right side of the graph, the cost of debt for these firms rises. The opposite happens for the darker lines representing the ESG leaders. This indeed can be appreciated by looking at the vertical difference between the value of the cost of debt on the left side of the graph, representing periods of low volatility in the crude oil market, and the value of the cost of debt that the same company faces when the volatility in the crude oil market gets its maximum, hence on the right hand side of the figure. As it can be seen indeed, firms with high ESG scores indeed show a stark reduction in the cost of debt as the volatility increases while ESG laggards experience an increase in the cost of debt.

Figure 4.9 illustrates the variations in firms' cost of debt based on ESG scores at

Figure 4.9: Margin Plot: Cost of Debt Across ESG Levels at Different Oil Volatility Levels



Effect of ESG over the cost of debt for different levels of crude oil volatility. Negative values on the y-axis reflect the log transformation. The confidence levels are set to 95% and are represented by the vertical bars.

different levels of crude oil volatility. The figure corroborates previous findings, and from this perspective, it's noteworthy that ESG leaders, depicted on the right side of the figure, experience significantly lower costs of debt when volatility reaches higher values, as indicated by the darker curves compared to lower volatility scenarios in the crude oil market. Consistently, for firms with an ESG score higher than 47, as previously indicated as the pivotal threshold, ESG leaders (on the right side of the graph) face lower costs of debt when crude oil volatility is at its minimum (brighter curves). Conversely, ESG laggards (on the left side of the graph) experience lower costs of debt when crude oil volatility is at its minimum.

These results suggest that ESG leaders tend to experience a notable reduction in the cost of debt during periods of heightened volatility in the crude oil market. This inference is based on the negative and statistically significant coefficient of the interaction effect between firms' ESG scores and crude oil volatility, as observed in Table 4.5. The graphical representations provided by Figures 4.8 and 4.9 further underscore this trend, illustrating that companies with high ESG scores exhibit a consistent decrease in the cost of debt as the volatility in the crude oil market intensifies.

4.7 Conclusion

This chapter makes a novel contribution to the literature by investigating whether ESG scores mitigate the cost of debt during periods of heightened crude oil price volatility, a dimension that has not been extensively explored in prior research. Leveraging a comprehensive dataset from LSEG database, encompassing firms listed in the S&P 500 index from the first quarter of 2000 to the fourth quarter of 2023, we test three hypotheses: H4.1: ESG scores and cost of debt have a negative relationship, H4.2: Volatility and cost of debt have a positive relationship, and H4.3: ESG scores act as a hedging mechanism during periods of increased volatility.

Our findings support H4.1 and H4.2. Higher ESG scores are associated with reduced borrowing costs, consistent with the signalling theory, which posits that ESG scores serve as a signal of firm quality, thereby reducing information asymmetry between firms and external stakeholders. By signalling reduced exposure to ESG risks and enhancing reputational capital, high ESG scores lower perceived risk by lenders, resulting in decreased borrowing costs. This aligns with the hypothesis that firms with higher ESG scores benefit from enhanced stability and financial performance, which is reflected in their lower cost of debt.

Testing for the validity of H4.2, we find that increased oil price volatility correlates with higher costs of debt. We propose that the channel linking crude oil market volatility to the cost of debt operates through spillovers from crude oil volatility to equity market volatility. Specifically, high volatility in the crude oil market leads to high volatility in the equity market. This heightened equity market volatility is also positively related to the cost of debt, consistent with the financial intermediaries' constraint theory. According to this theory, volatility imposes constraints on financial intermediaries, who, facing higher risks and uncertainties, pass these constraints on to firms in the form of higher borrowing costs or reduced access to credit. The heightened risk environment forces lenders to tighten credit conditions, leading to increased costs of debt for firms. This relationship underscores the impact of market volatility on financial intermediaries and the subsequent effect on firm-level financing costs.

To address H4.3, we examine the interaction between ESG scores and crude oil price volatility. Our results confirm that firms with superior ESG scores (ESG leaders) experience a significant reduction in the cost of debt during volatile periods, demonstrating the hedging effect of ESG activities. This finding extends previous research on ESG and debt financing by introducing crude oil price volatility as a key moderating factor, highlighting that ESG serves not just as a risk-mitigation tool but specifically as a stabilizer against commodity market-driven financial distress.

In Appendix A, we explore the potential non-linearity of the ESG-cost of debt relationship using both polynomial regression models and a Sharp Regression Discontinuity (RD) model. The polynomial analyses reveals significant quadratic terms and interaction effects, suggesting a complex U-shaped relationship where the benefits of high ESG scores in reducing the cost of debt diminish at higher levels. Conversely, the Sharp RD model does not corroborate these findings, indicating a lack of non-linearity. This divergence highlights the complexity of the relationship and suggests that the non-linear effects might not be robust across different analytical approaches.

Furthermore, we analyse the impact of different crude oil volatility regimes on the ESG-cost of debt relationship using various decomposition techniques. The Hodrick-Prescott (HP) filter-based model provides the most robust and consistent results, affirming the significant role of ESG scores in reducing the cost of debt across different volatility regimes. The consistent negative coefficients for ESG across models reinforce its effectiveness in lowering borrowing costs, particularly in high-volatility contexts.

In summary, this chapter makes a significant contribution to the literature by providing empirical evidence that ESG activities serve as an effective hedging mechanism against the cost of debt in volatile crude oil market conditions. This study is among the first to empirically validate the interaction between ESG and commodity market volatility in the context of corporate borrowing costs, offering new insights into the role of sustainability in financial risk management. While the non-linear analysis presents mixed results, the overall evidence strongly supports the strategic importance of maintaining high ESG standards for enhancing financial stability and resilience.

Building on the findings of this research, firms are advised to make a sustained commitment to high ESG performance to maximise financial benefits and enhance resilience. Maintaining long-term, robust ESG practices can significantly reduce borrowing costs and provide stability during volatile market conditions. Integrating ESG considerations into risk management strategies is crucial, as it allows firms to proactively mitigate financial risks and leverage ESG strengths in their overall risk frameworks. Furthermore, firms should prioritise ESG initiatives that specifically address vulnerabilities exacerbated by market volatility, focusing on resilience-enhancing activities that safeguard against financial instability. Enhancing ESG reporting and transparency remains essential; clear and comprehensive disclosures can reduce information asymmetry, improve lender perceptions, and consequently lower the cost of debt. By adhering to these strategic recommendations, firms can effectively align their ESG efforts with financial performance objectives and market demands.

This study provides valuable insights into the relationship between ESG scores and the cost of debt, particularly in the context of crude oil price volatility. Given the novelty of this approach, several avenues for future research could deepen our understanding of this dynamic. One potential extension is to examine how the cost of debt varies across different types of ESG-linked financial instruments, such as green bonds or sustainability-linked loans, to determine whether firms with stronger ESG commitments benefit from more favourable borrowing conditions. Another promising direction would be to assess how market conditions influence the ESG–debt cost relationship, investigating whether the financial benefits of ESG performance persist during periods of monetary tightening, economic downturns, or heightened credit market volatility.

While this study takes a quantitative approach to ESG measurement, future research could integrate qualitative perspectives, such as interviews with institutional investors and lenders, to better understand the subjective factors influencing ESG-related financing decisions. Another valuable extension would be to explore the long-term effects of sustained ESG performance on corporate borrowing costs, particularly over extended economic cycles or structural shifts in financial markets. Furthermore, examining the evolution of ESG perceptions among creditors could provide a dynamic perspective on how changes in ESG disclosures affect borrowing conditions in real time. Employing high-frequency financial data or textual analysis of credit rating agency reports could help capture these evolving dynamics.

Another critical aspect that calls for further exploration is the role of firm-specific governance structures in shaping ESG-financing relationships. ESG factors are typically assessed collectively, yet governance mechanisms — such as board independence, executive compensation structures, or shareholder activism — may independently influence how creditors perceive firm risk. Investigating these governance effects separately could offer a clearer understanding of their relative significance compared to broader ESG considerations in determining debt costs.

Additionally, incorporating sentiment analysis from lenders and investors could provide further insights into the behavioural and strategic drivers behind ESG-linked financing decisions. Understanding how investor perceptions and risk assessments evolve in response to ESG commitments would broaden the discussion on sustainability and financial performance, reinforcing the strategic importance of ESG integration in corporate finance.

4.8 Appendix A

Robustness Checks and Additional Results

In this section, we explore the relationship between the firms' cost of debt and ESG looking for a potential non-linear relationship, as suggested by most of the literature. We employ two approaches. We start by set up a polynomial regression in which we fit the model with a non-linear parameter for the ESG score, specifically, we square the ESG variable (ESG^2), following the work of Li et al. (2024). Secondly, we employ a sharp Regression Discontinuity (RD) model in the spirit of Gigante and Manglaviti (2022) in which we set the ESG as the running variable and we split the sample using the ESG mean as the cutoff point. We apply the RD model to both, the model of polynomial order 1 and 2.

On the other side, we also analyse non-linearity in oil price volatility, proposing different methods to identify periods of high, middle, and low volatility. The first method involves determining the values of the crude oil volatility time series that fall into the lower 25% quartile, the middle 50%, and the upper 25% quartile. We also extract the cyclical and trend components from the level of crude oil volatility using the Hodrick and Prescott (1997) filter and the Hamilton (2018) filter, defining volatility regimes based on the high and low 25 quartiles of the cyclical component generated by these filters.

Cost of debt and ESG scores non-Linear analysis

ESG descriptive statistics

We start by presenting more detailed statistics on the ESG variable which include descriptive statistics and a histogram to provide a comprehensive overview of the distribution of ESG scores across companies.

Table 4.6 briefly reports the descriptive statistics for the ESG variables while Figure 4.10 shows how the variable is spread across different ranges of ESG scores.

The histogram illustrates the density distribution of the ESG variable, with the y-axis representing the density corresponding to each bar and the x-axis displaying the ESG

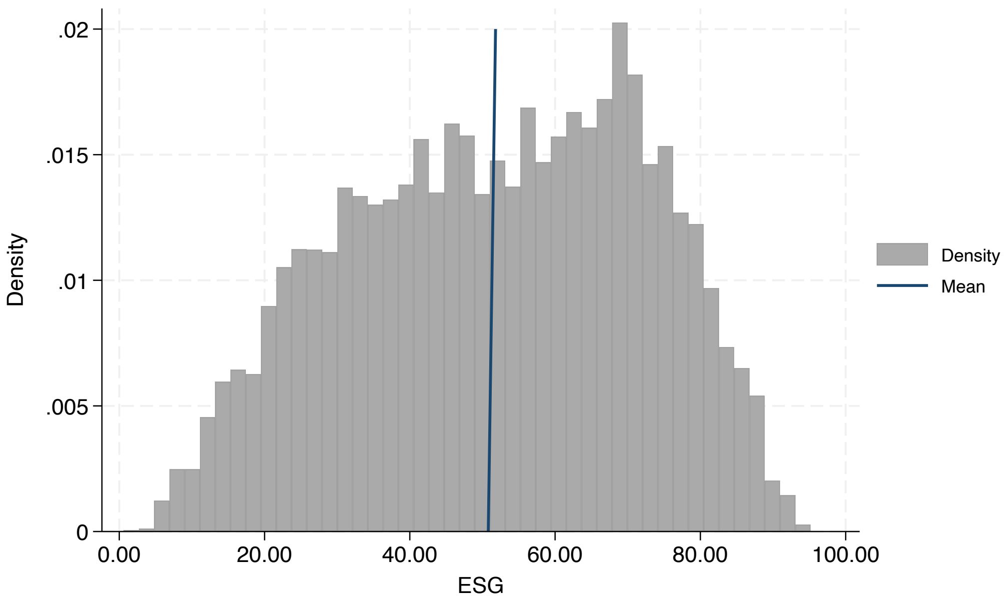
Table 4.6: Non-Linear Analysis - Descriptive Statistics for ESG variable

Variable	Mean	Std. dev.	Min	Max	Obs
ESG Score	51.8019	20.2691	0.5986	95.1624	34034

Table 4.6 briefly presents the descriptive statistics for the ESG variable.

scores. The histogram comprises 45 bars, each representing a range of ESG scores. A blue vertical line is drawn at the average ESG score of 51.08, providing a reference point for the following cutoff for the RD model. The distribution exhibits slightly higher density on the right side, particularly around the ESG score of 70, which is depicted by a peak. This suggests that there is a concentration of observations with ESG scores close to 70, indicating a potential skewness or clustering of data towards higher ESG scores in the dataset.

Figure 4.10: Non-Linear Analysis - ESG Histogram



Histogram of the ESG variable with a blue vertical line indicating the average ESG score of 51.08. This line serves as a reference point for the cutoff used in the Regression Discontinuity (RD) model.

Model testing

In this section, we explore the potential non-linearity of the relationship between the cost of debt and the ESG scores within our sample.

Polynomial Analysis

To investigate the possible non-linear nature of the link between firms' cost of debt and ESG scores, we start with a polynomial analysis.

Table 4.7 presents the results of multiple regression models analysing the non-linear relationship between ESG scores and the cost of debt. Models (1) and (2) incorporate solely the ESG score and both the ESG score and its squared term (ESG^2), respectively, as the only independent variables. Notably, these models do not incorporate the volatility term and are included as initial exploration. Specifically, the linear term of ESG scores of indicates a significant negative relationship (-0.0108^{***}), being in line with the main body of this research. Model (2) adds the squared term of ESG scores, yet the quadratic term itself is not significant, suggesting no immediate non-linearity at this level of analysis.

The focus on non-linearity becomes more evident in Models (3) to (5), where additional variables and interaction effects are incorporated. Model (3), which represents the main model applied in the primary analysis, is included here for comparison. Models (4) and (5) examine non-linearity by including the squared ESG term. Both models demonstrate significant coefficients for the squared ESG term (-0.0001^{***}), as well as significant interaction terms, confirming the non-linear relationship. Although the coefficients for the squared ESG scores are low, their negative values suggest a slight sign of a U-shaped relationship between ESG scores and the cost of debt. This indicates that while higher ESG scores generally lead to lower costs of debt, the marginal benefit decreases at higher ESG scores.

Table 4.7: Non-Linear Analysis - ESG and Cost of Debt Relationship

Variables	(1) CoD	(2) CoD	(3) CoD	(4) CoD	(5) CoD
ESG Score	-0.0108***	-0.0108***	-0.0072***	-	0.0000
	(0.0002)	(0.0011)	(0.0005)	-	(0.0026)
ESG Score^2	-	0.0000	-	-0.0001***	-0.0001***
	-	(0.0000)	-	(0.0000)	(0.0000)
Oil Volatility	-	-	0.0515***	0.0231***	0.1210***
	-	-	(0.0122)	(0.0080)	(0.0255)
Oil Volatility $\times$ ESG Score	-	-	-0.0011***	-	-0.0044***
	-	-	(0.0002)	-	(0.0011)
Oil Volatility $\times$ ESG Score^2	-	-	-	0.0000***	0.0000***
	-	-	-	(0.0000)	(0.0000)
Constant	-4.1477***	-4.1487***	-4.1695***	-4.3196***	-4.3213***
	(0.0321)	(0.0385)	(0.0299)	(0.0197)	(0.0614)
Number of Observations	29,815	29,815	27,533	27,533	27,533
R-squared	0.0662	0.0662	0.0730	0.0702	0.0733
Number of firms	466	466	464	464	464

In Model (1), only the ESG variable is considered. Model (2) incorporates the ESG variable with polynomial terms of the first and second orders. Models (3) to (5) present the comprehensive model, which encompasses the interaction effects and control variables. Specifically, Model (3) is employed in the primary analysis, Model (4) includes the squared ESG scores, and Model (5) integrates both ESG and ESG squared terms along with their interaction terms.

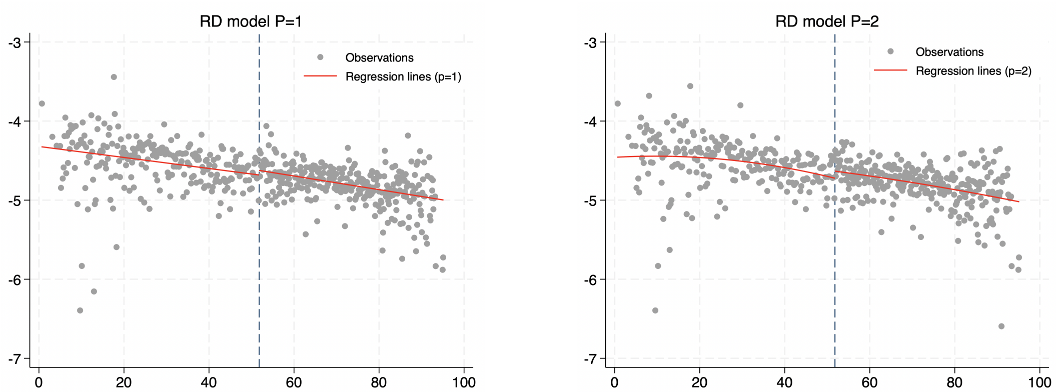
*** Significant at 1%, ** Significant at 5%, * Significant at 10%. The parentheses represent the standard errors.

Sharp RD model

To assess the non-linearity of the relationship between firms' cost of debt and ESG scores, we also employ a sharp Regression Discontinuity (RD) model approach. ESG is utilised as the running variable in both specifications of our model: one considering ESG with a polynomial order of 1, and the other with a polynomial order of 2. The sample is divided into two sections based on the ESG average of 51.80.

Figure 4.11 presents a graphical depiction of the RD models. The left panel illustrates the model with a polynomial order of $p = 1$, while the right panel displays the model with a polynomial order of $p = 2$. In each graph, the two red lines represent the regression lines corresponding to the sample partitions, divided by the blue vertical dashed line indicating the ESG average used for sample splitting. The dots signify individual observations, with 570 dots plotted to represent the total observations of $29,815$, clustered into 570 bins.

Figure 4.11: Non-Linear Analysis - Sharp RD Models



The scatter plot on the left shows the model fitted with ESG of polynomial order 1, while the plot on the right depicts the model fitted with ESG of polynomial order 2.

Upon initial inspection, the analysis via the sharp RD model appears to indicate a lack of non-linear relationship between firms' cost of debt and ESG scores. In both scatter plots of Figure 4.11, the regression lines exhibit a negative correlation. A non-linear relationship would typically manifest as an inversion of the slope of the regression line between the two partitions, as demonstrated in the study by Gigante and Manglaviti (2022).

Conclusion

This appendix offers a detailed examination of the potential non-linear relationship between ESG scores and the cost of debt. The polynomial regression models reveal significant quadratic terms and interaction effects, indicating a complex relationship. While the primary linear relationship is negative and significant, as discussed in the main body of this research, these additional models show that higher ESG scores not only decrease borrowing costs but also exhibit diminishing marginal benefits at higher levels. The low, negative coefficients for the squared ESG terms suggest a U-shaped relationship, where the marginal benefits of high ESG scores diminish at higher levels, consistent with literature suggesting such a relationship (Gao et al. 2016; Goss and Roberts 2011; Li et al. 2024).

In contrast, the Sharp Regression Discontinuity (RD) model analysis suggests an absence of non-linearity between ESG scores and the cost of debt. The regression lines in the scatter plots of Figure 4.11 consistently show a negative correlation, without the expected inversion of slope between the partitions that would indicate non-linearity.

In conclusion, while polynomial regression models suggest a slight non-linear relationship, the Sharp RD model does not corroborate this finding. The divergence in results between these methodologies highlights the complexity of assessing the impact of ESG scores on the cost of debt.

Crude oil price volatility regimes analysis

In this section, we propose different ways to identify periods of high, middle, and low volatility to investigate whether the mitigating effect of having a high ESG score provides different levels of protection to different levels of volatility.

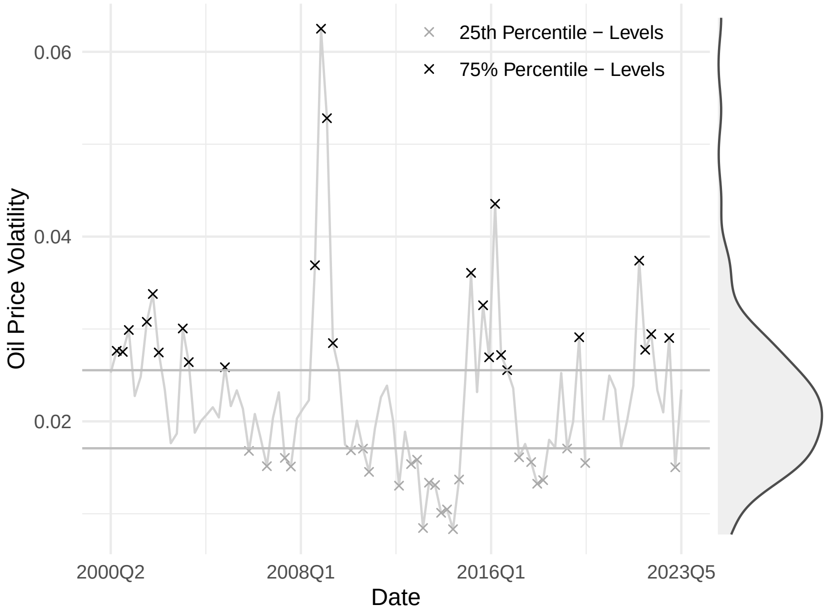
Quartiles identifications

We evaluate the volatility regimes utilising different techniques:

Levels

The first method for identifying the quartiles involves determining the values of the crude oil volatility time series that fall into the lower quartile (the lower 25%), the

Figure 4.12: Non-Linear Analysis - Level: Oil volatility quartiles



Crude oil price volatility values corresponding to the lowest 25% and highest 25% quartiles of volatility levels. This graph highlights periods of extreme absolute high and low volatility.

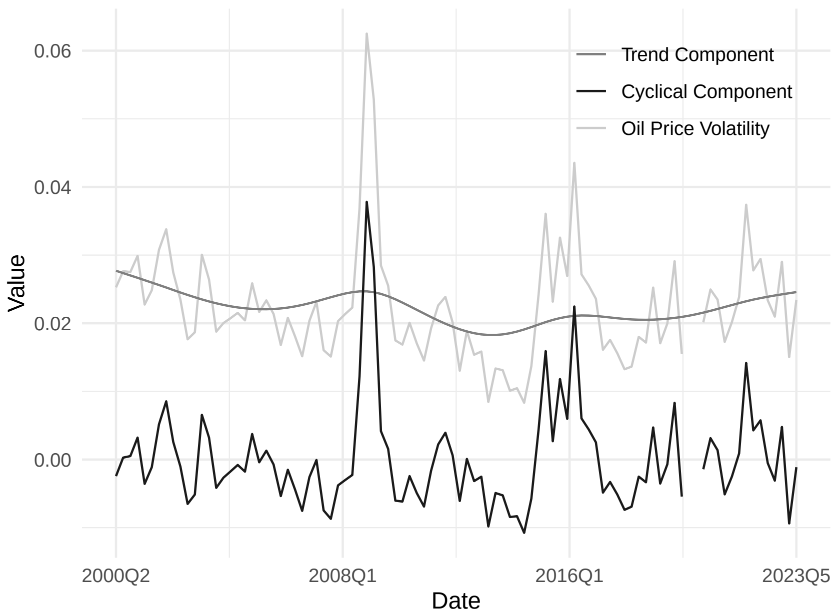
middle 50%, and the upper quartile (the upper 25%). In this analysis, the lower quartile represents the left tail of the distribution, while the upper quartile corresponds to the right tail. This approach solely considers the level of oil price volatility. Figure 4.12 illustrates this distinction, with the dark crosses indicating the values in the upper quartile, while the grey crosses represent the values in the lower quartile.

Hodrik-Prescott filter

Another method we employ involves using the Hodrick and Prescott (1997) filter (HP) to separate the trend and cyclical components from the oil price volatility levels. In this approach, the volatility regimes are based on the upper and lower quartiles (the top 25% and bottom 25%) of the cyclical component generated by the filter.

The trend component represents the long-term progression of the data, capturing the underlying direction over an extended period, while the cyclical component captures the short-term fluctuations around the long-term trend. In our analysis, we consider periods of high volatility, during which the volatility levels deviate significantly from the trend component, resulting in high cyclical values, and periods of low volatility, during which the actual levels and the trend are closely aligned, resulting in low cyclical

Figure 4.13: Non-Linear Analysis - HP Filter: Trend and Cyclical Components



Trend and cyclical components of crude oil price volatility, derived using the Hodrick-Prescott filter. This analysis highlights the long-term trend and short-term fluctuations in volatility.

values.

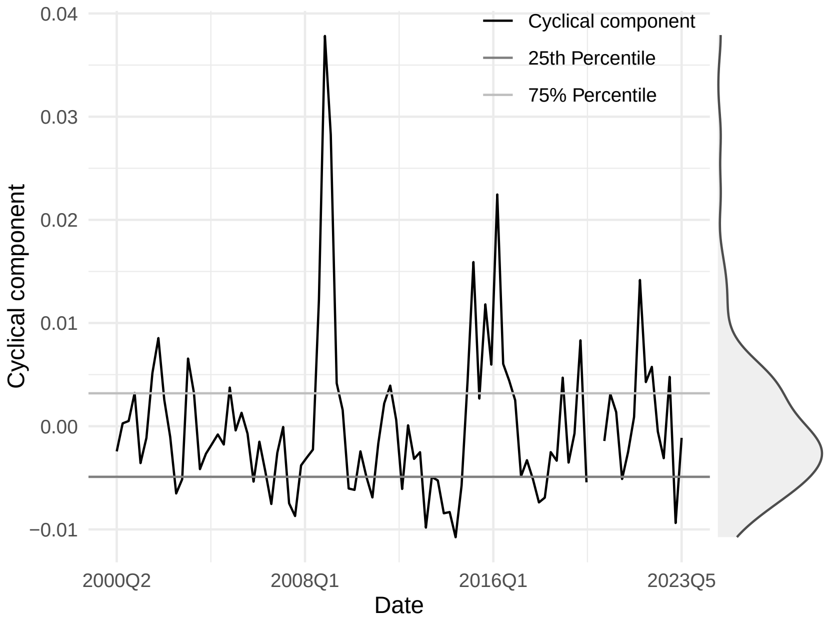
The application of the Hodrick-Prescott filter to a volatility series is supported by Bloom (2009), as published in Econometrica. This filter requires the specification of a single parameter, the smoothing factor λ. For our analysis, we set the smoothing parameter λ to 1600, as advised by Ravn and Uhlig (2002) for quarterly data.

Figure 4.13 illustrates the decomposition of oil price volatility into its trend and cyclical components, with the oil volatility level included in light grey for reference.

Focusing on the cyclical component, we divide its values into the upper and lower quartiles (the top 25% and bottom 25%), and the middle 50%. Figure 4.14 illustrates the evolution of the cyclical component in black, while the quartiles lines are depicted in grey. Additionally, a frequency distribution is presented on the right side of the graph to enhance clarity.

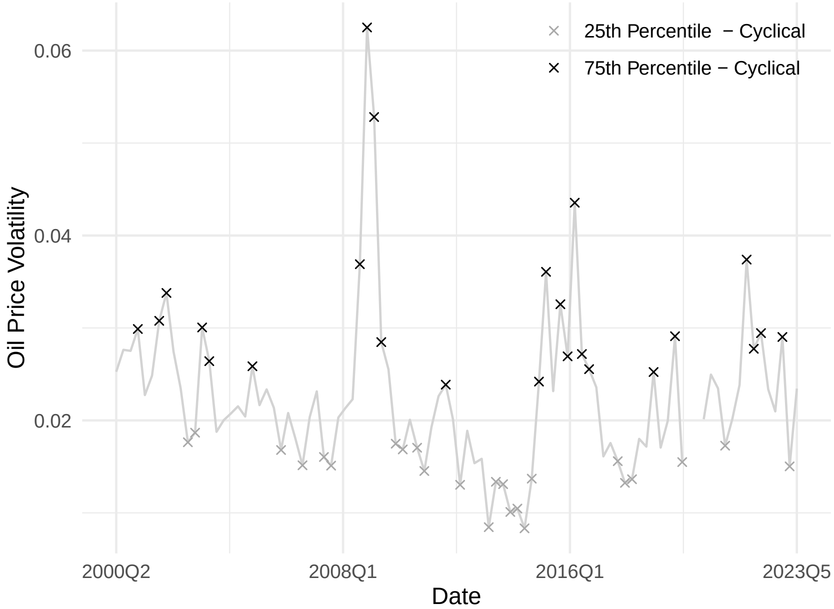
Once we identify the values that fall into the quartiles of the cyclical component distribution, we select the corresponding oil price volatility levels. These values are depicted by the crosses in Figure 4.15, where black crosses represent values associated with the upper quartile, indicating periods of high volatility, and grey crosses represent values associated with the lower quartile, indicating periods of low volatility.

Figure 4.14: Non-Linear Analysis - HP Filter: Cyclical Component



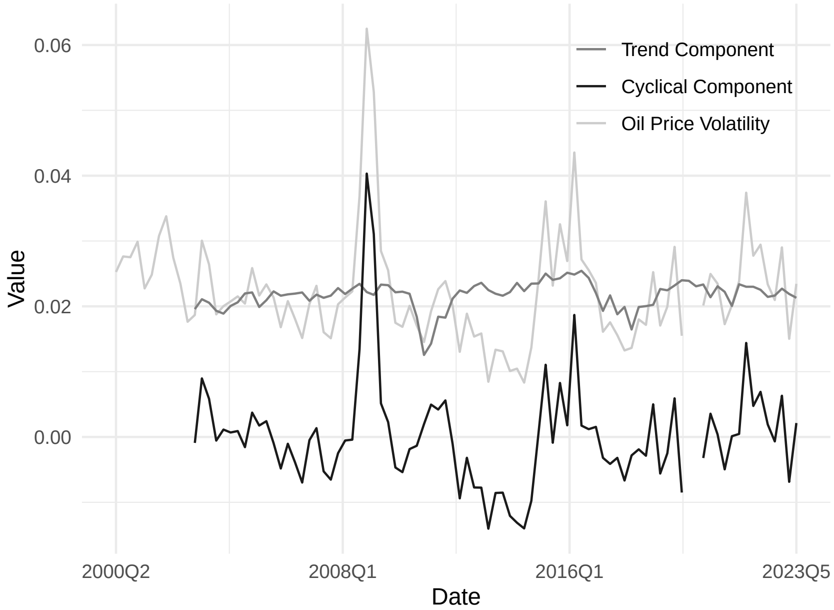
Evolution of the spread between the trend and cyclical components of crude oil price volatility, derived using the Hodrick-Prescott filter. The spread indicates periods of significant deviation from the long-term trend.

Figure 4.15: Non-Linear Analysis - HP Filter: Oil Volatility Quartiles



Crude oil price volatility values corresponding to periods of extreme high and low volatility. These periods are identified when the cyclical components, derived using the Hodrick-Prescott filter, fall within the lowest 25% and highest 25% quartiles.

Figure 4.16: Non-Linear Analysis - Hamilton Filter: Trend and Cyclical Components



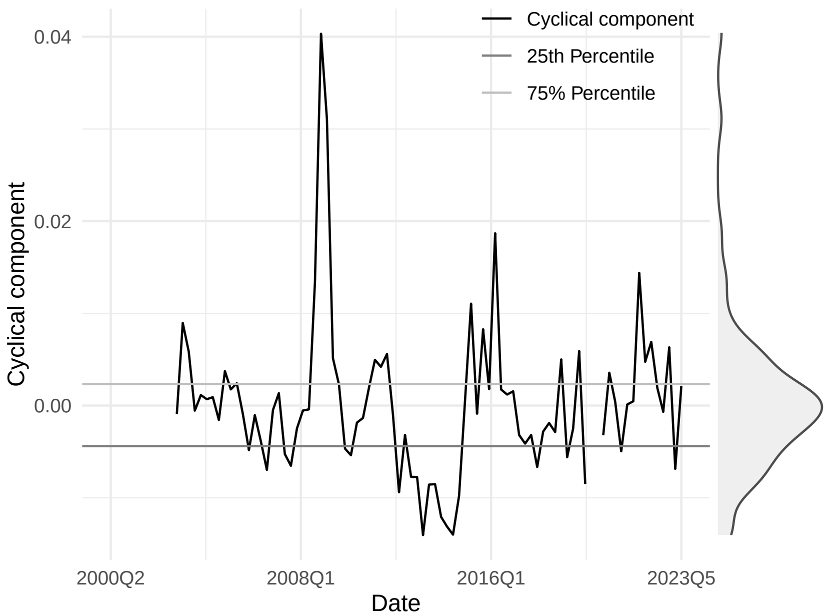
Trend and cyclical components of crude oil price volatility, derived using the Hamilton filter. This analysis highlights the long-term trend and short-term fluctuations in volatility.

Hamilton filter

We extend our analysis by applying the same methodological approach, but this time utilising the Hamilton (2018) filter. As outlined in Hamilton's seminal work, the Hamilton filter is generally favoured for its robustness in mitigating the spurious dynamics often associated with the Hodrick-Prescott filter. This advantage arises from the regression-based nature of the Hamilton filter, which, unlike the Hodrick-Prescott filter, does not rely solely on a pre-specified smoothing parameter (λ). Instead, it allows for a more empirically grounded selection of model parameters, reducing the likelihood of overfitting and enhancing the filter's capacity to capture meaningful economic cycles.

While the regression-based nature of the Hamilton filter provides a significant advantage in terms of empirical flexibility and robustness, one inherent limitation is the loss of initial observations. Following the methodology of Jönsson (2020) and Schüler (2020), we address this by setting the filter regression parameters to include lags from the previous year (four lags, given our quarterly data) and a forecast horizon of two years. The loss of initial observations is evident in Figure 4.16, where the trend and cyclical component series begin with a slight delay.

Figure 4.17: Non-Linear Analysis - Hamilton Filter: Cyclical Component

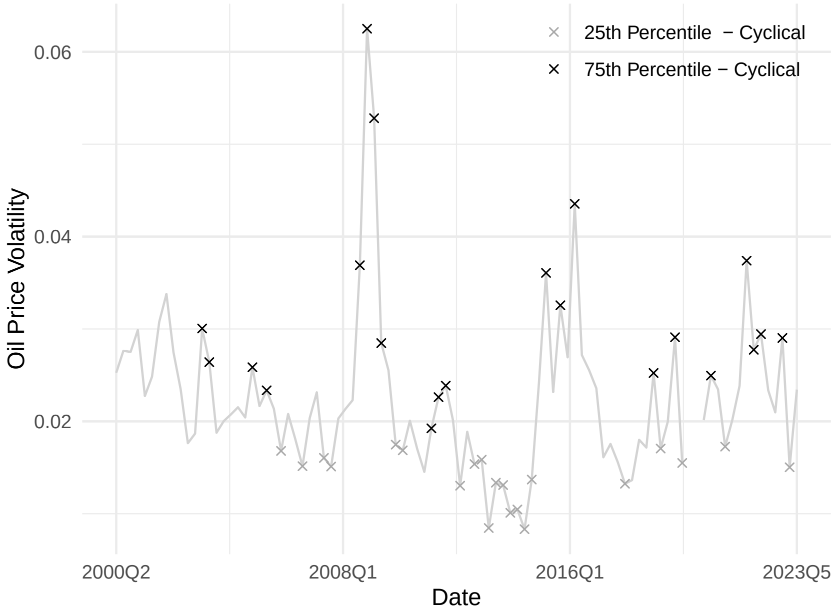


Evolution of the spread between the trend and cyclical components of crude oil price volatility, derived using the Hamilton filter. The spread indicates periods of significant deviation from the long-term trend.

As with the Hodrick-Prescott filter, we identify periods of low and high volatility based on the quartiles of the cyclical component. Figure 4.14 displays the quartile division and the evolution of the cyclical component, along with the frequency distribution on the right side of the figure.

Finally, we select the corresponding oil price volatility levels. These values are depicted by the crosses in Figure 4.18, where, consistent with our approach using the HP filter, the black crosses denote values in the upper quartile, which correspond to periods of high volatility, while the grey crosses denote values in the lower quartile, which correspond to periods of low volatility.

Figure 4.18: Non-Linear Analysis - Hamilton Filter: Oil Volatility Quartiles



Crude oil price volatility values corresponding to periods of extreme high and low volatility. These periods are identified when the cyclical components, derived using the Hamilton filter, fall within the lowest 25% and highest 25% quartiles.

Results

Levels-based Quartiles

In the levels-based quartile regressions, volatility regimes are defined simply by the quartiles of volatility levels. The results indicate that during periods of high volatility (right tail), there is a significant positive relationship with the CoD ($\beta = 0.1953^{***}$), implying that high volatility leads to an increased cost of debt. In contrast, the middle quartile shows a significant positive coefficient ($\beta = 0.1475^{**}$), suggesting that moderate volatility also increases the CoD, albeit to a lesser extent. Low volatility periods (left tail) have a significant positive impact ($\beta = 0.0547^{**}$), but the effect is much smaller.

The ESG scores variable consistently shows a negative coefficient, indicating that ESG activities generally reduce the cost of debt. For high volatility periods, the coefficient is $\beta = -0.0044^{**}$, for medium volatility, it is $\beta = -0.0037$, and for low volatility, it is $\beta = -0.0068^{***}$. The interaction terms reveal that a high ESG rating mitigates the effect of high volatility on the CoD ($\beta = -0.0023^{**}$), although this effect is less pronounced compared to the other regimes. Specifically, the interaction related to medium volatility ($\beta = -0.0025^{**}$) is more significant, while the interaction for low volatility is not significant.

HP Filter-based Cyclical Components

In this section, we analyse the results stemming from utilising the HP filter to extract the cyclical component of volatility to evaluate the volatility regimes. This approach yields the most significant results. High volatility periods exhibit a significant positive impact on the CoD ($\beta = 0.0645^{***}$), indicating that elevated volatility significantly raises the cost of debt. Medium volatility periods also show a positive effect ($\beta = 0.1385^{***}$), while low volatility periods are associated with a significant positive impact ($\beta = 0.1607^{***}$), suggesting that even low cyclical volatility can influence the CoD.

The ESG variable remains negative across all regimes: $\beta = -0.0058^{***}$ for high volatility, $\beta = -0.0041^{***}$ for medium volatility, and $\beta = -0.0040^{***}$ for low volatility. Importantly, the interaction effects are significant across all regimes. ESG ranking significantly reduces the impact of high volatility on the CoD ($\beta = -0.0013^{***}$), with the effect being most pronounced during medium and low volatility periods ($\beta = -0.0023^{***}$ and $\beta = -0.0022^{*}$, respectively). This indicates that ESG strategies are particularly effective in mitigating the cost of debt across varying volatility regimes.

Hamilton Filter-based Cyclical Components

We apply the Hamilton filter to define volatility regimes in this section. Here, high volatility periods are associated with a significant negative impact on the CoD ($\beta = 0.2002^{***}$), which contrasts with the expected positive relationship observed in the other models. Medium volatility periods also show a significant negative relationship ($\beta = -0.0961^{**}$), while low volatility periods do not present a significant impact.

The ESG scores variable shows strong negative coefficients across all regimes, indicating its consistent role in reducing the cost of debt: $\beta = -0.0125^{***}$ for high volatility, $\beta = -0.0071^{***}$ for medium volatility, and $\beta = -0.0127^{***}$ for low volatility. The interaction terms suggest that ESG activities do not significantly mitigate the impact of high volatility on the CoD in this case, as indicated by the non-significant interaction coefficient for high volatility periods ($\beta = 0.0018$). However, ESG ranking is effective during low volatility periods ($\beta = 0.0020^{*}$).

Table 4.8: Non-linear Analysis - Regression Results for Different Volatility Levels

Variables	(1) CoD	(2) CoD	(3) CoD
ESG Score	-0.0044**	-0.0037	-0.0068***
	(0.0020)	(0.0025)	(0.0016)
Oil Volatility RT	0.1953***	-	-
	(0.0752)	-	-
Oil Volatility M	-	0.1475**	-
	-	(0.0696)	-
Oil Volatility LT	-	-	0.0547**
	-	-	(0.0228)
Oil Volatility RT × ESG Score	-0.0023*	-	-
	(0.0013)	-	-
Oil Volatility M × ESG Score	-	-0.0025**	-
	-	(0.0012)	-
Oil Volatility LT × ESG Score	-	-	-0.0006
	-	-	(0.0004)
Constant	-4.4362***	-4.3610***	-4.4706***
	(0.1141)	(0.1485)	(0.0842)
Number of Observations	8,476	13,044	6,013
R-squared	0.0578	0.0833	0.1224
Number of firms	460	464	461

This table presents the regression results for crude oil price volatilities evaluated as quartiles of the volatility levels. The oil volatilities are categorised into the lowest 25% and highest 25% quartiles of volatility levels. The models include all control variables. Model (1) is based on the lowest 25% quartile values, Model (2) includes values not in the extremes, and Model (3) is based on the highest 25% quartile values. The dependent variable is CoD (Cost of Debt).

*** Significant at 1%, ** Significant at 5%, * Significant at 10%. The parentheses represent the standard errors.

Table 4.9: Non-linear Analysis - HP Filter: Regression Output

Variables	(1) CoD	(2) CoD	(3) CoD
ESG Score	-0.0058***	-0.0041***	-0.0040**
	(0.0012)	(0.0014)	(0.0020)
Oil Volatility RT	0.0645***	-	-
	(0.0183)	-	-
Oil Volatility M	-	0.1385***	-
	-	(0.0392)	-
Oil Volatility LT	-	-	0.1607**
	-	-	(0.0674)
Oil Volatility RT × ESG Score	-0.0013***	-	-
	(0.0003)	-	-
Oil Volatility M × ESG Score	-	-0.0023***	-
	-	(0.0007)	-
Oil Volatility LT × ESG Score	-	-	-0.0022*
	-	-	(0.0012)
Constant	-4.2836***	-4.3709***	-4.4550***
	(0.0633)	(0.0812)	(0.1128)
Number of Observations	8,142	13,449	5,942
R-squared	0.0753	0.0841	0.0902
Number of firms	460	464	460

This table presents the regression results for crude oil price volatilities evaluated as quartiles of the volatility levels. In this model, the Hodrick-Prescott (HP) filter is used to evaluate the oil price volatility values corresponding to periods of extreme high and low volatility. These periods are identified when the spread between trend and cyclical components, derived using the HP filter, falls within the lowest 25% and highest 25% quartiles. The models include all control variables. Model (1) is based on the lowest 25% quartile values, Model (2) includes values not in the extremes, and Model (3) is based on the highest 25% quartile values. The dependent variable is CoD (Cost of Debt). *** Significant at 1%, ** Significant at 5%, * Significant at 10%. The parentheses represent the standard errors.

Table 4.10: Non-linear Analysis - Hamilton Filter: Regression Output

Variables	(1) CoD	(2) CoD	(3) CoD
ESG Score	-0.0125***	-0.0071***	-0.0127***
	(0.0034)	(0.0017)	(0.0017)
Oil Volatility RT	-0.2002***	-	-
	(0.0631)	-	-
Oil Volatility M	-	-0.0961**	-
	-	(0.0476)	-
Oil Volatility LT	-	-	-0.0230
	-	-	(0.0642)
Oil Volatility RT × ESG Score	0.0018	-	-
	(0.0011)	-	-
Oil Volatility M × ESG Score	-	-0.0008	-
	-	(0.0008)	-
Oil Volatility LT × ESG Score	-	-	0.0020*
	-	-	(0.0011)
Constant	-3.5050***	-3.8150***	-4.0627***
	(0.1936)	(0.1040)	(0.0937)
Number of Observations	7,514	13,206	6,795
R-squared	0.0902	0.0863	0.0905
Number of firms	461	464	462

This table presents the regression results for crude oil price volatilities evaluated as quartiles of the volatility levels. In this model, the Hamilton filter is used to evaluate the oil price volatility values corresponding to periods of extreme high and low volatility. These periods are identified when the spread between trend and cyclical components, derived using the Hamilton filter, falls within the lowest 25% and highest 25% quartiles. The models include all control variables. Model (1) is based on the lowest 25% quartile values, Model (2) includes values not in the extremes, and Model (3) is based on the highest 25% quartile values. The dependent variable is CoD (Cost of Debt). *** Significant at 1%, ** Significant at 5%, * Significant at 10%. The parentheses represent the standard errors.

Conclusion

The analysis demonstrates that the HP filter-based model provides robust and consistent results, highlighting the significant impact of volatility on the cost of debt across different regimes. Our findings indicate that while ESG scores generally mitigate borrowing costs, this mitigating effect is less pronounced at higher levels of volatility. Specifically, the interaction between ESG scores and high volatility (Volatility RT) reveals a reduced ability of ESG scores to lower the cost of debt in highly volatile environments. In contrast, the mitigating effect of ESG scores remains relatively stable when volatility is at medium (Volatility M) and low (Volatility LT) levels, suggesting that ESG activities are more effective in moderating borrowing costs in these less extreme conditions.

In contrast, the levels-based and Hamilton filter-based models show some inconsistencies, particularly with the latter displaying an unexpected negative relationship between high volatility and the cost of debt. These discrepancies underscore the importance of selecting an appropriate method for volatility decomposition. The HP filter's ability to separate trend and cyclical components makes it a superior tool for analysing the effects of volatility on the cost of debt, providing clearer insights into the dynamics of financial risk and debt costs.

The consistent negative coefficients of the ESG variable across all models demonstrate its role in reducing the cost of debt. Additionally, the interaction effects in the HP filter-based model highlight the effectiveness of ESG activities in periods of high, medium, and low volatility, making it a critical strategy for managing financial risk.

4.9 Appendix B

Alternative Proxies for the Cost of Debt

In this section, we consider different proxies to evaluate the cost of debt. For each of them, we graphically compare their evolution within the time frame of this analysis. We also report some descriptive statistics and the outcomes of the main model in which the alternative proxies enter the mode as the dependent variable.

Variables descriptions

We start the description of alternative proxies for the cost of debt by outlining their evaluation methods. Equations (4.7)-(4.11) present the evaluations for each proxy.

$$CoD_p = \frac{Interest\ Expenses}{Average\ Period\ Debt}. \tag{4.7}$$

$$CoD_y = \frac{Interest\ Expenses}{Average\ Year\ Debt}. \tag{4.8}$$

$$CoD_{IA} = \frac{Interest\ Expenses}{Total\ Assets}. \tag{4.9}$$

$$CoD_{IL} = \frac{Interest\ Expenses}{Total\ Liabilities}. \tag{4.10}$$

$$CoD_{BB} = [[(SD/TD) \times (CS \times AF)] + [(LD/TD) \times (CL \times AF)]] \times [1 - TR]\,.^{10} \tag{4.11}$$

As can be seen, both CoD_p and CoD_y, Eq. (4.7) and Eq. (4.8) respectively, are calculated as ratios between interest expenses and debt. However, they differ in the method of evaluating debt. For CoD_p, debt is averaged over four quarters: the three preceding the expense observation and the current quarter. In contrast, for CoD_y, debt is averaged over the year corresponding to the interest expenses.

[10]Where SD = short-term debt, TD = total debt, CS = pre-tax cost of short-term debt, AF = debt adjustment factor, LD = long-term debt, CL = pre-tax cost of long-term debt, and TR = effective tax rate.

In Equations (4.9) and (4.10), we put total assets and total liabilities into the denominator. Additionally, we include evaluations for the cost of debt provided by Bloomberg. The Bloomberg evaluation has been previously discussed and is briefly reiterated here.

A brief statistic description of the variables can be found in Table 4.11 and is analysed below.

Analysis of alternative cost of debt proxies

Starting with CoD_p and CoD_y, which represent ratios of interest expenses to debt, we observe relatively low mean values. For instance, the mean for CoD_p is 2.51%, indicating that, on average, firms incur a small fraction of their debt as interest expenses. The standard deviation for CoD_p is 0.8881, suggesting considerable variability among firms. For CoD_y, the mean is 1.81% with a standard deviation of 0.1283, indicating that while the average cost of debt is lower than CoD_p, there is less variability in the interest expenses relative to debt among firms.

Table 4.11: Alternative Proxies - Descriptive Statistics for CoD

Variable	Mean	Std. dev.	Min	Max	Obs
CoD_p	0.0251	0.8881	0	152.6808	40,819
CoD_y	0.0181	0.1283	0	9.1208	40,920
CoD_{IA}	3.38e-09	4.29e-09	0	2.75e-07	42,119
CoD_{IL}	5.31e-09	8.89e-09	0	7.45e-07	42,105
CoD_{BB}	2.8045	1.5505	0	10.3435	42,838

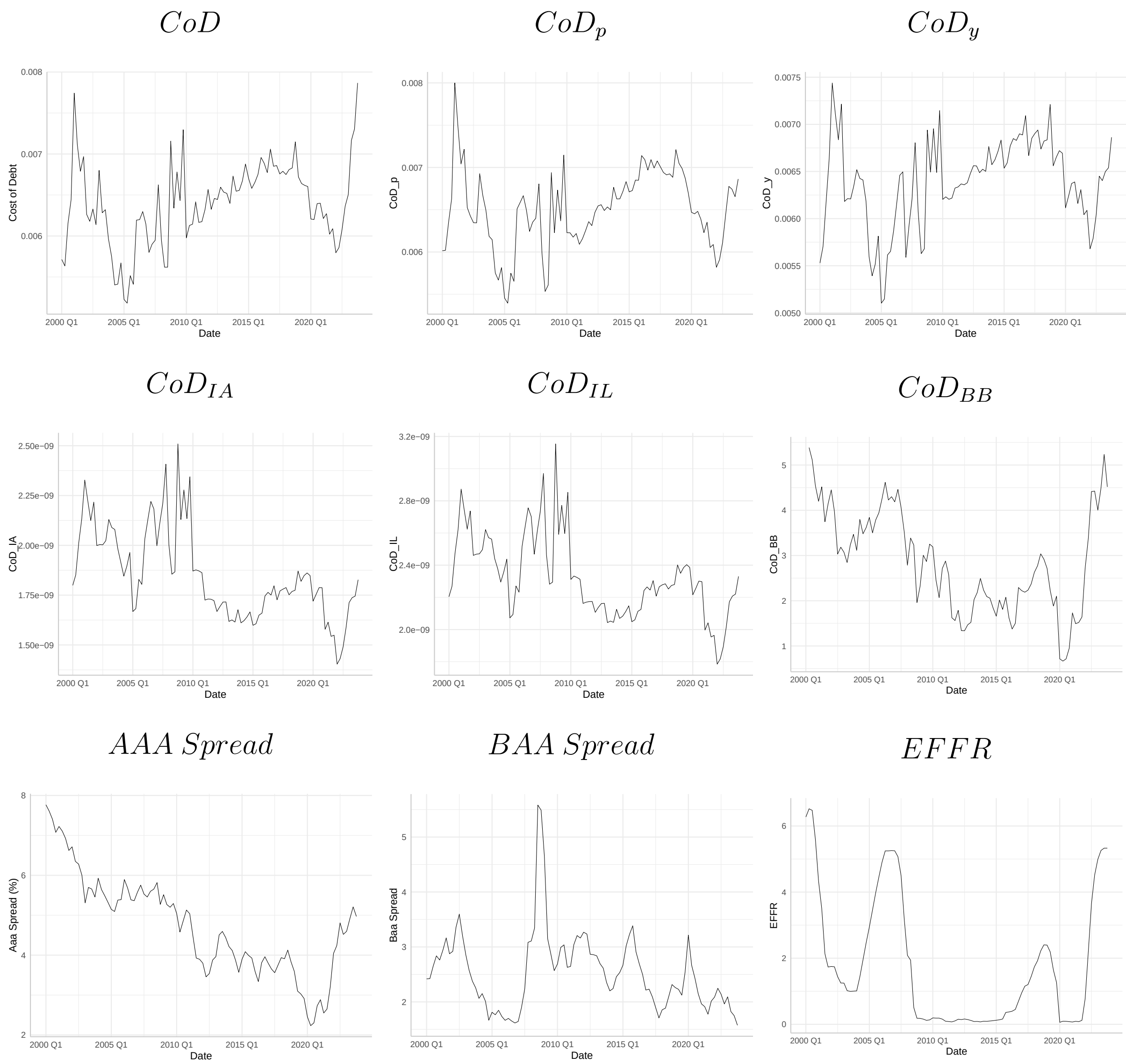
Table 4.11 briefly presents the descriptive statistics for the different proxies of the cost of debt.

Moving on to CoD_{IA} and CoD_{IL}, we encounter much smaller mean values. For instance, the mean for CoD_{IA} is 3.38×10^{-9}, and the mean for CoD_{IL} is 5.31×10^{-9}, indicating substantially lower costs of debt compared to the previous proxies. The small range between the minimum and maximum values reflects low heterogeneity in debt levels and financial positions across firms.

Next, we consider CoD_{BB}, sourced from Bloomberg. The mean is 2.8045, with a standard deviation of 1.5505, suggesting moderate variability among firms.

Figure 4.19 presents the evolution of various proxies analysed in this section, alongside the primary proxy utilised in the main analysis (CoD), the spread between AAA

Figure 4.19: Alternative Proxies - Comparison of Proxies Used in the Analysis.



The plots in this figure show the evolution of the alternative proxies analysed in this section. The main proxy utilised in the main analysis (CoD) and the AAA and BAA firms' bond and US Treasury bonds spread as reported as well to facilitate the comparison.

and BAA corporate bonds and US Treasury bills, and the US effective rate.

The primary proxy (CoD) and the first two proxies in the figure (CoD_p and CoD_y), which vary in their debt evaluation, show notable similarities. Specifically, both CoD_p and CoD_y emphasise interest expenses in capturing proxy fluctuations, while debt outlines the general trend, mirroring the behaviour described for CoD in the main analysis section. This similarity underscores the consistent role of interest expenses in driving cost of debt metrics.

CoD_{AI} and CoD_{IL} also exhibit similarities with the primary proxy, as well as with CoD_p and CoD_y, particularly in the latter part of the sample. However, in the earlier part of the sample, these proxies appear more affected by the turbulence caused by the Global Financial Crisis (GFC), with both CoD_{IA} and CoD_{IL} displaying a significant positive spike during this period. It is noteworthy that the values of CoD_{AI} and CoD_{IL}, including the spikes, are considerably smaller, as reflected by the reduced scale of the y-axis. This divergence underscores the sensitivity of these proxies to economic shocks, albeit on a comparatively smaller scale than the primary proxy.

These variables track the US effective interest rate's trajectory. Following the post-Dot-Com Bubble Burst recovery, the accommodative monetary policy measures implemented by the US Federal Reserve results in a decline in debt costs across all proxies, including CoD. Subsequent tightening monetary policy measures from 2004 until the Global Financial Crisis (GFC) are mirrored by an overall rise in debt costs. During this period, the primary proxy CoD and the alternative proxies (CoD_p, CoD_y, CoD_{IA}, and CoD_{IL}) all exhibit increases, although CoD_{IA} and CoD_{IL} show more pronounced spikes, reflecting its higher sensitivity to economic turbulence. The decrease in interest rates associated with the GFC appears persistent in the proxies, indicating a prolonged high cost of debt which lasts until around the first quarter of 2010. However, while CoD and CoD_p show more gradual declines, CoD_{IA} and CoD_{IL} exhibit sharper decreases, underscoring their higher responsiveness to monetary easing.

Similarly, the post-COVID-19 period reveals a sustained period of high cost of debt following the Fed's interest rate reduction in the first quarter of 2020. This decline occurs gradually until reaching a low in the first quarter of 2022. Our proxies also capture the spike in interest rates applied by the Fed to mitigate inflationary pressures during the post-pandemic recovery. The notable positive spike in our proxies from the second half of 2022 until the end of the sample appears to mirror the sustained rise in interest rates. The primary proxy CoD and the alternative proxies (CoD_p, CoD_y, CoD_{IA}, and CoD_{IL}) all reflect this trend. The comparative analysis highlights that while all proxies generally follow the same trends as CoD.

The Bloomberg proxy (CoD_{BB}) shows distinctive behaviour compared to the primary proxy (CoD) and other alternative proxies (CoD_p, CoD_y, CoD_{IA}, and CoD_{IL}). During the Global Financial Crisis (GFC), CoD_{BB} rises sharply, mirroring the increase in US interest rates and reflecting heightened credit risk, similar to other proxies but with quicker adjustments. Post-GFC, CoD_{BB} maintains higher volatility and sensitivity to market changes. The COVID-19 pandemic sees CoD_{BB} surge, stabilising at elevated levels, like CoD and other proxies, but with more pronounced fluctuations.

Non-linearity analysis

Table 4.12 and Figure 4.20 delve into the potential non-linear relationship between the cost of debt and firms' ESG scores. We explore this by introducing the square root of the ESG variable and applying the Regression Discontinuity model to each proxy.

Analysing the ESG^2 term in Table 4.12 and the slopes of the regression lines before and after the ESG mean in Figure 4.20, we find little to no evidence supporting non-linearity between the variables, consistent with the primary analysis. Notably, CoD_{IA} and CoD_{IL} show significance for the ESG^2 term but the coefficient is zero. Similarly, the Bloomberg proxy (CoD_{BB}) is the only one displaying a positive and statistically significant coefficient for the ESG^2 term, albeit of small magnitude, as depicted in Table 4.12.

Focusing on the graphs of CoD_{IA} and CoD_{IL} in Figure 4.20, we observe a slight change in sign for the polynomial of order 1, shifting from negative on the left-hand side of the figure to slightly positive on the right-hand side. The graph depicting the polynomial of order 2 reveals a more intriguing pattern, suggesting that the cost of debt generally has a negative relationship with low ESG values, and this negative relationship culminates around ESG scores of 50, increasing before decreasing again at the highest ESG scores. However, this finding does not seem to be supported when examining the Regression Discontinuity (RD) model explicitly illustrated in Figure 4.20, which indicates an absence of non-linearity.

Table 4.12: Alternative Proxies - Polynomial Analysis of ESG and Cost of Debt

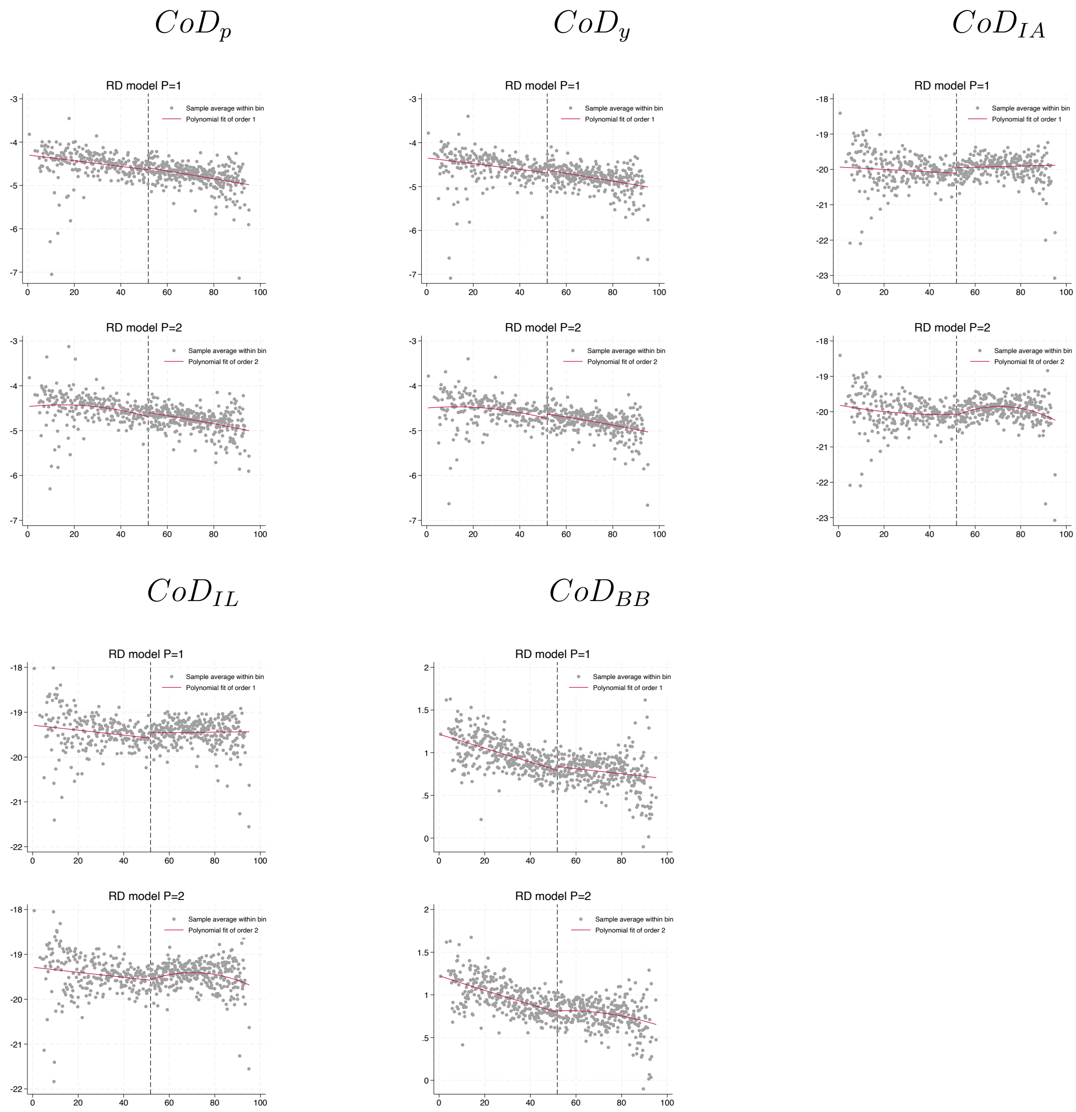
Variables	(1) CoD_p	(2) CoD_p	(1) CoD_y	(2) CoD_y
ESG	-0.0108***	-0.0097***	-0.0106***	-0.0099***
	(0.0002)	(0.0011)	(0.0002)	(0.0011)
ESG^2	-	0.0000	-	0.0000
	-	(0.0000)	-	(0.0000)
Constant	-4.0996***	-4.1231***	-4.1601***	-4.1732***
	(0.0317)	(0.0381)	(0.0314)	(0.0382)
Number of Observations	29,996	29,996	30,006	30,006
Number of firms	466	466	466	466

Variables	(1) CoD_{IA}	(2) CoD_{IA}	(1) CoD_{IL}	(2) CoD_{IL}
ESG	0.0002	-0.0037***	-0.0022***	-0.0041***
	(0.0003)	(0.0011)	(0.0002)	(0.0011)
ESG^2	-	0.0000***	-	0.0000*
	-	(0.0000)	-	(0.0000)
Constant	-20.0499***	-19.9703***	-19.3843***	-19.3470***
	(0.0536)	(0.0582)	(0.0471)	(0.0516)
Number of Observations	30,233	30,233	30,230	30,230
Number of firms	467	467	467	467

Variables	(1) CoD_{BB}	(2) CoD_{BB}
ESG	-0.0068***	-0.0140***
	(0.0002)	(0.0008)
ESG^2	-	0.0001***
	-	(0.0000)
Constant	1.1995***	1.3483***
	(0.0118)	(0.0202)
Number of Observations	32,382	32,382
Number of firms	497	497

In Model (1), only the ESG variable is considered. Model (2) includes the ESG variable with polynomial orders of 1 and 2.
*** Significant at 1%, ** Significant at 5%, * Significant at 10%. The parentheses represent the standard errors.

Figure 4.20: Alternative Proxies - Sharp RD models.



The scatter plot on the left shows the model with ESG of polynomial order 1, while on the right, the model fitted with ESG of polynomial order 2 is depicted.

Results

In this section, we employ the methodology we apply in the primary analysis to the alternative proxies, aiming to provide a comparative assessment.

The different proxies utilised lead to different outcomes. Indeed, the primary proxy (CoD) and the two proxies where the debt feature in the denominator (CoD_p and CoD_y) exhibit a similar narrative, as can be observed in Tables 4.13 and 4.14. While there are minor differences in the coefficients' significance and magnitude, their consistency remains clear. Overall, the findings confirm the ones of the main analysis, showing that periods of heightened volatility coincide with a decrease in firms' cost of debt. Additionally, ESG rankings appear to influence firms' debt financing costs, offering advantages to those with stronger ESG commitments. The interaction effect further deepens this dynamic relationship; the negative coefficient suggests that during periods of elevated volatility, the cost of debt for ESG-leading firms is lower compared to ESG laggards, attributable to the beneficial impact of higher ESG scores on debt costs. This analysis reinforces the robustness of the primary conclusions.

As depicted in Table 4.15, the CoD_{IA} proxy exhibits positive coefficients for both the direct impact of crude oil price volatility and ESG scores on the cost of debt, indicating that firms with higher ESG scores or during periods of high volatility experience higher debt costs. However, the interaction effect between ESG scores and oil price volatility has a negative coefficient, suggesting that the positive impact of ESG scores on the cost of debt is mitigated during periods of high volatility.

As shown in Table 4.16, CoD_{IL} demonstrates a consistent lack of significance for the ESG coefficient across various model specifications, while a positive relationship is observed between firms' cost of debt and oil price volatility, alongside a negative interaction effect.

Notably, the Bloomberg proxy (CoD_{BB}) shows a consistent negative relationship between the cost of debt and ESG scores. However, the significance of the coefficients for oil price volatility and the interaction effect diminishes when accounting for macro-level control variables.

Table 4.13: Alternative Proxies - Regression Results for Main Model (p)

Variables	(1) $lny91\_CoD_p$	(2) $lny91\_CoD_p$	(1) $lny91\_CoD_p$	(2) $lny91\_CoD_p$	(1) $lny91\_CoD_p$	(2) $lny91\_CoD_p$
Oil Volatility	0.0349***	0.0348***	0.0374***	0.0269**	0.0258*	0.0258*
	(0.0115)	(0.0115)	(0.0130)	(0.0130)	(0.0135)	(0.0135)
ESG Score	-0.0083***	-0.0084***	-0.0031***	-0.0013**	-0.0017**	-0.0017**
	(0.0005)	(0.0005)	(0.0007)	(0.0007)	(0.0007)	(0.0007)
Oil Volatility $\times$ ESG Score	-0.0011***	-0.0011***	-0.0012***	-0.0009***	-0.0008***	-0.0008***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Constant	-4.1776***	-4.1424***	-3.9207***	-3.4451***	-3.4565***	-3.4565***
	(0.0404)	(0.0285)	(0.0598)	(0.0584)	(0.0592)	(0.0592)
Micro Controls	No	No	Yes	Yes	Yes	Yes
Macro Controls	No	No	No	No	Yes	Yes
Number of Observations	29,094	29,094	22,998	22,998	22,998	22,998
R-squared	0.0671	0.0671	0.1016	0.1016	0.1036	0.1036
Number of firms	466	466	462	462	462	462

This table shows the regression results for the equation shown on the top row. For conciseness, we only reported the coefficients of the main variables and the intercept. Model (1) reports the OLS regression results while model (2) accounts for fixed effect for firms. We initially tested the models including only the main variables, then we added the firm-level control variables, and ultimately comprised both firm- and macro-level control variables.

*** Significant at 1%, ** Significant at 5%, * Significant at 10%. The parentheses represent the standard errors.

Table 4.14: Alternative Proxies - Regression Results for Main Model (y)

Variables	(1) lny92_CoD_y	(2) lny92_CoD_y	(1) lny92_CoD_y	(2) lny92_CoD_y	(1) lny92_CoD_y	(2) lny92_CoD_y
Oil Volatility	0.0485***	0.0482***	0.0512***	0.0406***	0.0404***	0.0404***
	(0.0118)	(0.0118)	(0.0134)	(0.0133)	(0.0139)	(0.0139)
ESG Score	-0.0075***	-0.0076***	-0.0031***	-0.0012*	-0.0015**	-0.0015**
	(0.0005)	(0.0005)	(0.0007)	(0.0007)	(0.0007)	(0.0007)
Oil Volatility $\times$ ESG Score	-0.0013***	-0.0013***	-0.0013***	-0.0011***	-0.0010***	-0.0010***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Constant	-4.2688***	-4.2261***	-3.9650***	-3.4745***	-3.4834***	-3.4834***
	(0.0407)	(0.0293)	(0.0612)	(0.0601)	(0.0609)	(0.0609)
Micro Controls	No	No	Yes	Yes	Yes	Yes
Macro Controls	No	No	No	No	Yes	Yes
Number of Observations	29,104	29,104	22,990	22,990	22,990	22,990
R-squared	0.0604	0.0604	0.0922	0.0922	0.0935	0.0935
Number of firms	466	466	462	462	462	462

This table shows the regression results for the equation shown on the top row. For conciseness, we only reported the coefficients of the main variables and the intercept. Model (1) reports the OLS regression results while model (2) accounts for fixed effect for firms. We initially tested the models including only the main variables, then we added the firm-level control variables, and ultimately comprised both firm- and macro-level control variables.

*** Significant at 1%, ** Significant at 5%, * Significant at 10%. The parentheses represent the standard errors.

Table 4.15: Alternative Proxies - Regression Results for Main Model (IA)

Variables	(1) lny93_CoD_IA	(2) lny93_CoD_IA	(1) lny93_CoD_IA	(2) lny93_CoD_IA	(1) lny93_CoD_IA	(2) lny93_CoD_IA
Oil Volatility	0.0489***	0.0489***	0.0532***	0.0533***	0.0291**	0.0293**
	(0.0123)	(0.0123)	(0.0122)	(0.0121)	(0.0127)	(0.0126)
ESG Score	0.0022***	0.0022***	0.0024***	0.0023***	0.0019***	0.0019***
	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Oil Volatility × ESG Score	-0.0009***	-0.0009***	-0.0010***	-0.0010***	-0.0007***	-0.0007***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Constant	-20.1573***	-20.0969***	-20.1396***	-20.0756***	-20.0856***	-20.0236***
	(0.0600)	(0.0304)	(0.0567)	(0.0302)	(0.0561)	(0.0310)
Micro Controls	No	No	Yes	Yes	Yes	Yes
Macro Controls	No	No	No	No	Yes	Yes
Number of Observations	29,333	29,333	27,784	27,784	27,784	27,784
R-squared	0.0006	0.0006	0.0047	0.0047	0.0073	0.0073
Number of firms	467	467	464	464	464	464

This table shows the regression results for the equation shown on the top row. For conciseness, we only reported the coefficients of the main variables and the intercept. Model (1) reports the OLS regression results while model (2) accounts for fixed effect for firms. We initially tested the models including only the main variables, then we added the firm-level control variables, and ultimately comprised both firm- and macro-level control variables.

*** Significant at 1%, ** Significant at 5%, * Significant at 10%. The parentheses represent the standard errors.

Table 4.16: Alternative Proxies - Regression Results for Main Model (IL)

Variables	(1) lny94_CoD_IL	(2) lny94_CoD_IL	(1) lny94_CoD_IL	(2) lny94_CoD_IL	(1) lny94_CoD_IL	(2) lny94_CoD_IL
Oil Volatility	0.0434***	0.0435***	0.0499***	0.0501***	0.0303**	0.0305***
	(0.0114)	(0.0114)	(0.0114)	(0.0114)	(0.0119)	(0.0119)
ESG Score	-0.0002	-0.0002	0.0004	0.0004	0.0001	0.0000
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Oil Volatility × ESG Score	-0.0009***	-0.0009***	-0.0010***	-0.0010***	-0.0007***	-0.0007***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Constant	-19.4808***	-19.4410***	-19.4670***	-19.4235***	-19.4185***	-19.3771***
	(0.0533)	(0.0283)	(0.0516)	(0.0283)	(0.0513)	(0.0290)
Micro Controls	No	No	Yes	Yes	Yes	Yes
Macro Controls	No	No	No	No	Yes	Yes
Number of Observations	29,330	29,330	27,780	27,780	27,780	27,780
R-squared	0.0036	0.0036	0.0074	0.0074	0.0101	0.0101
Number of firms	467	467	464	464	464	464

This table shows the regression results for the equation shown on the top row. For conciseness, we only reported the coefficients of the main variables and the intercept. Model (1) reports the OLS regression results while model (2) accounts for fixed effect for firms. We initially tested the models including only the main variables, then we added the firm-level control variables, and ultimately comprised both firm- and macro-level control variables.

*** Significant at 1%, ** Significant at 5%, * Significant at 10%. The parentheses represent the standard errors.

Table 4.17: Alternative Proxies - Regression Results for Main Model (BB)

Variables	(1) lny95_CoD_BB	(2) lny95_CoD_BB	(1) lny95_CoD_BB	(2) lny95_CoD_BB	(1) lny95_CoD_BB	(2) lny95_CoD_BB
Oil Volatility	-0.0994***	-0.1010***	-0.0973***	-0.1029***	-0.0138	-0.0138
	(0.0084)	(0.0084)	(0.0100)	(0.0100)	(0.0100)	(0.0100)
ESG Score	-0.0090***	-0.0095***	-0.0058***	-0.0054***	-0.0025***	-0.0025***
	(0.0004)	(0.0004)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Oil Volatility $\times$ ESG score	0.0016***	0.0017***	0.0014***	0.0015***	0.0002	0.0002
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Constant	1.3884***	1.4244***	1.3987***	1.5921***	1.4550***	1.4550***
	(0.0215)	(0.0207)	(0.0382)	(0.0451)	(0.0437)	(0.0437)
Micro Controls	No	No	Yes	Yes	Yes	Yes
Macro Controls	No	No	No	No	Yes	Yes
Number of Observations	31,400	31,400	24,951	24,951	24,951	24,951
R-squared	0.0396	0.0396	0.0388	0.0388	0.1195	0.1195
Number of firms	497	497	494	494	494	494

This table shows the regression results for the equation shown on the top row. For conciseness, we only reported the coefficients of the main variables and the intercept. Model (1) reports the OLS regression results while model (2) accounts for fixed effect for firms. We initially tested the models including only the main variables, then we added the firm-level control variables, and ultimately comprised both firm- and macro-level control variables.

*** Significant at 1%, ** Significant at 5%, * Significant at 10%. The parentheses represent the standard errors.

CHAPTER 5

Conclusions

This thesis explores how crude oil market dynamics affect a range of macroeconomic and financial variables across three distinct but interconnected chapters. Central to each analysis is crude oil price volatility, which serves as the consistent link uniting these chapters.

The first empirical chapter, presented as the second chapter of this thesis, bridges finance and economics, exploring how crude oil exporter and importer countries react differently to crude oil returns and volatility shocks. The second and third empirical chapters delve into corporate finance, examining how ESG activities can respectively safeguard firms' returns and lower their borrowing costs during times of high crude oil price volatility. This conclusion section brings together the insights from each chapter, underscoring the key themes and broader implications of the research.

5.1 Summary of Key Findings

Empirical Chapter 1: Asymmetric Reactions to Crude Oil Returns and Uncertainty Shocks

The first empirical chapter explores the asymmetric reactions of crude oil exporter and importer countries to crude oil returns and uncertainty shocks, using a set of nine countries, including three exporters (Norway, Canada, Mexico) and six importers (United States, United Kingdom, Germany, Italy, Spain, Sweden). By employing a

Vector Autoregressive (VAR) model with exogenous shocks from crude oil returns and volatility, the analysis captures the dynamic relationships between key economic country variables such as crude oil trade balances, real exchange rates, policy rates, inflation (proxied by the Consumer Price Index, CPI), and output (measured by the Industrial Production Index, IPI).

The findings indicate that crude oil return shocks generally lead to an increase in trade balances and an appreciation of real exchange rates in both exporter and importer countries. This suggests that, while exporters may benefit from increased oil revenues, importers adjust their macroeconomic conditions in ways that partially offset the anticipated negative impact. Volatility shocks, however, cause declines in these variables, reflecting the dampening effects of uncertainty on economic stability. A notable exception is observed in the United States, where the USD appreciates following a volatility shock, likely due to its role as a global safe-haven currency.

An important contribution of this chapter lies in its analysis of central bank policy responses to oil price shocks. The findings reveal that return shocks tend to initially lead to a decrease in policy rates, followed by an increase as central banks adjust to manage inflationary pressures. Conversely, volatility shocks often prompt an immediate increase in policy rates, which later decline as central banks respond to the economic slowdown caused by heightened uncertainty. These results suggest that monetary policy adjustments in response to oil price fluctuations are not fundamentally different between exporters and importers, highlighting a broader, shared macroeconomic response to crude oil market instability.

Despite some differences, the study finds that the effects of crude oil market fluctuations are largely symmetrical across exporter and importer countries. Both types of countries commonly implement defensive measures, such as adjusting policy rates and managing exchange rates, to mitigate the impacts of crude oil price volatility, suggesting that similar economic strategies may be effective across different contexts. This challenges the assumption that exporters and importers respond in fundamentally different ways and instead suggests that crude oil price volatility represents a systemic risk, requiring similar macroeconomic stabilisation strategies across different economic contexts.

This chapter extends the literature by demonstrating that oil price volatility affects both oil-exporting and importing economies in more comparable ways than previously assumed. While previous studies have focused on the impact of oil price shocks on trade balances and exchange rates (Baumeister and Peersman 2013; Hamilton 2009), this research provides new insights into how policy rates, inflation, and output adjustments exhibit similar patterns across economies with different oil trade positions. This has important implications for monetary and fiscal policymakers, as it suggests that crude oil price volatility requires coordinated economic policies across exporting and importing nations to stabilise inflation, maintain exchange rate stability, and manage macroeconomic uncertainty.

Empirical Chapter 2: ESG Activities as a Safe Haven for Firm Returns During Crude Oil Volatility

The second empirical chapter investigates the role of ESG activities in protecting firms' returns during periods of high crude oil market volatility, using a panel dataset of companies listed in the S&P 500 Index. The analysis focuses on the interaction between crude oil price volatility, ESG scores, and firm returns, while controlling for firm-level and macroeconomic variables.

The main findings show a negative direct relationship between ESG scores and firm returns, indicating that firms with higher ESG scores tend to have lower returns under normal market conditions. However, this relationship does not fully reflect ESG's role in volatile environments. The central contribution of this study lies in demonstrating that ESG serves as a risk-mitigating factor during heightened crude oil price volatility. Specifically, ESG activities exhibit a conditional hedging effect, meaning that while ESG scores may appear to reduce returns under normal market conditions, they provide a financial buffer when crude oil volatility rises.

A threshold effect related to crude oil volatility is identified, indicating that below a certain volatility level, ESG scores negatively impact returns, reinforcing the overall direct relationship. However, once crude oil volatility surpasses this threshold, the interaction between ESG and volatility reverses the effect, mitigating the negative consequences of market fluctuations. In high-volatility conditions, ESG activities function as a hedge, protecting firms against financial instability. This hedging effect strengthens as volatility rises, confirming that ESG scores provide an insurance-like benefit when crude oil market uncertainty escalates.

Overall, the findings suggest that while ESG activities do not directly enhance returns, they play a crucial role in mitigating risk during high-volatility periods. As market uncertainty increases, ESG's protective effect becomes more pronounced, reinforcing its strategic importance in stabilising firm performance. This insight underscores the value of ESG as a dynamic risk management tool, particularly for firms operating in industries exposed to commodity price fluctuations.

Empirical Chapter 3: ESG Activities and the Cost of Debt During Crude Oil Price Volatility

The third empirical chapter examines whether ESG activities can mitigate the cost of debt for firms during periods of heightened crude oil price volatility, using a panel dataset of companies listed in the S&P 500 Index. The study analyses the relationships between firms' ESG scores, crude oil price volatility, and the cost of debt, placing particular emphasis on their interaction effects.

The findings indicate a clear negative relationship between ESG scores and the cost of debt, suggesting that firms with higher ESG scores tend to have lower borrowing costs. This supports the view that high ESG performance signals lower risk to lenders, leading to more favourable financing conditions. Conversely, there is a positive relationship between crude oil price volatility and the cost of debt, indicating that higher market uncertainty results in increased borrowing costs.

A novel contribution of this study is the analysis that uncovers a significant interaction effect between ESG scores and crude oil volatility. While prior research has examined ESG's influence on corporate finance, this study is among the first to demonstrate that ESG performance actively shields firms from volatility-induced financial distress. Specifically, while firms with lower ESG scores experience rising borrowing costs as volatility increases, firms with higher ESG scores experience a reduced impact or even a reduction in debt costs. This suggests that ESG activities provide a hedging benefit, acting as a buffer against the financial impact of crude oil market volatility.

A notable finding is the identification of a threshold ESG score, around 47, above which firms begin to experience the protective effect of ESG on borrowing costs during volatile market conditions. This threshold highlights the dual role of ESG: directly lowering borrowing costs and providing protection against volatility-induced cost increases. Firms with ESG scores exceeding this threshold are better positioned to manage financial risks, demonstrating the strategic importance of strong ESG performance in mitigating the effect of crude oil market volatility on corporate debt financing.

These findings extend prior work on ESG and corporate finance by offering empirical evidence that ESG initiatives are not just passive indicators of firm quality but active risk-mitigating mechanisms. This insight is valuable for corporate treasurers, financial managers, and policymakers, as it suggests that firms investing in ESG not only benefit from lower direct borrowing costs, but also enhance their resilience against external economic shocks.

5.2 Integrated Implications

As discussed, the insights from these chapters underscore the crucial role of crude oil market dynamics on various economic and financial variables. The research highlights several important findings that contribute to the broader literature on macroeconomic stability, corporate finance, and ESG-driven risk management strategies.

1. **Symmetrical Responses to Crude Oil Shocks:** Contrary to the initial hypothesis of asymmetric responses between crude oil exporter and importer countries, the findings of our first empirical chapter suggest that the reactions of these economies are more similar than previously assumed. While theoretical expectations suggest that exporters would benefit from rising oil prices while importers would face adverse effects, the empirical evidence indicates that both groups adjust in comparable ways to crude oil volatility. This has important policy implications for both exporting and importing nations. The symmetrical responses indicate that both types of countries may need to implement similar stabilisation policies during periods of crude oil volatility. These findings contribute to the broader literature that examines the macroeconomic effects of oil price shocks. For instance, studies such as those by Hamilton (2009) and Baumeister and Peersman (2013) suggest that oil price shocks have significant macroeconomic impacts, which are often similar across different types of economies. This suggests that both crude oil exporting and importing countries should consider enhancing their domestic

economic resilience through targeted fiscal policies and strategic reserves management. By focusing on strengthening internal economic buffers, countries can better absorb the shocks from crude oil price volatility and maintain economic stability.

2. **Protective Role of ESG Activities:** The second and third empirical chapters focus on corporate finance, investigating the extent to which ESG activities serve as a hedge against crude oil price volatility. Findings indicate that firms with strong ESG performance experience reduced financial risk exposure during periods of heightened crude oil volatility, both in terms of stock returns and borrowing costs. These results provide empirical support for the role of ESG as a conditional hedge, meaning that its risk-mitigating benefits are not uniform but become more pronounced during extreme market fluctuations. Specifically, firms with robust ESG practices experience less negative impact on their stock returns during periods of high volatility, likely due to stronger stakeholder trust, improved risk management, and enhanced operational efficiency. Additionally, high ESG scores are linked to lower borrowing costs, as they signal reduced environmental and social risks to lenders, who, in turn, perceive these firms as safer investments. This research builds upon existing studies on ESG and financial stability, aligning with the findings of Giese et al. (2019), who demonstrate that ESG factors contribute to lower risk and better performance, and Broadstock et al. (2021), who show that firms with strong ESG performance are more resilient during crises. By extending this literature, our findings reveal that ESG's stabilising effect is not uniform across all market conditions but becomes more pronounced in periods of heightened volatility, underscoring its role as a conditional risk-mitigation tool.

3. **Sectoral and Quartile Variations:** The variation in the protective effects of ESG activities across sectors and firm reveals important nuances that suggest ESG strategies should be tailored rather than applied uniformly. Our findings indicate that sectors more exposed to crude oil volatility exhibit lower volatility thresholds, meaning they experience ESG's risk-mitigating benefits earlier than less exposed sectors. This insight is particularly relevant for corporate strategy and policy formulation. Firms need to align their ESG initiatives more closely with their specific risk exposures and operational characteristics rather than adopting a

one-size-fits-all ESG approach. In sectors where the impact of crude oil volatility is more pronounced, a well-integrated ESG strategy can significantly mitigate adverse financial effects. This aligns with previous research, particularly the sector-specific analysis conducted by Dhaliwal et al. (2011), which underscores the importance of stakeholder awareness in understanding the financial impact of ESG practices. It also aligns with the findings of Henisz et al. (2019), who explore how ESG value creation differs across sectors, highlighting the need for sector-specific ESG strategies to effectively manage risks and leverage opportunities. From a policy perspective, this suggests that regulatory frameworks should be flexible enough to account for sector-specific risks and promote sector-specific ESG practices.

4. **Broader Economic and Financial Stability:** Beyond firm-level analysis, the research emphasizes that crude oil price volatility is a critical risk factor not only for individual firms but also for broader economic and financial stability. The ability of high ESG scores to mitigate financing costs during periods of heightened oil volatility suggests that ESG engagement has the potential to contribute to macroeconomic stability by lowering systemic credit risk during turbulent market conditions. This has important policy implications for financial regulators and central banks. If ESG performance reduces borrowing costs in high-volatility environments, financial institutions could integrate ESG risk assessments into stress-testing frameworks and lending policies. Encouraging strong ESG engagement could enhance financial market stability, particularly in economies heavily reliant on volatile commodities like crude oil. These findings contribute to ongoing discussions on sustainability-driven financial strategies and economic resilience (Chava 2014; El Ghoul et al. 2011), reinforcing the argument that ESG considerations should be incorporated into financial stability assessments at both the micro and macro levels. Policymakers may consider encouraging ESG standards as a strategic component of financial market stability, particularly in economies that are heavily reliant on volatile commodities like crude oil. By incentivising ESG integration, governments can help create a more stable financial environment that mitigates the economic disruptions caused by commodity price shocks.

5.3 Future Research and Limitations

Building on the findings of this thesis, several avenues for future research can further explore the complex interactions between crude oil volatility, ESG factors, and financial performance. Additionally, certain limitations in this study present opportunities for methodological improvements and broader applicability in future research.

Future Research Directions

- **Cross-Commodity Analysis:** While this study focuses on the crude oil market, future research could examine whether similar effects are observed in other commodity markets. Extending the analysis to assets such as gold, wheat, or industrial metals could provide insights into whether ESG strategies influence corporate resilience during periods of economic uncertainty. A comparative approach could further elucidate whether commodity-specific characteristics influence financial risk mitigation strategies.

- **Temporal Dynamics:** Focusing on the corporate finance aspect of this thesis, future research could explore the long-term effects of ESG activities on financial performance. Examining whether sustained ESG engagement consistently enhances firm value or if its impact diminishes over time could offer insights into its true effectiveness. This would also help assess whether ESG initiatives reflect genuine long-term strategies or managerial actions influenced by external pressures. Such an analysis could provide empirical evidence to challenge or support agency theory, which suggests that firms and managers may engage in ESG initiatives for motives that do not necessarily align with long-term shareholder value.

- **Investor and Market Perception of ESG Commitments:** While this thesis primarily utilises quantitative ESG measures, future research could incorporate sentiment analysis from corporate disclosures, media reports, or analyst assessments to better capture how markets react to ESG initiatives. Understanding the role of public perception and market sentiment could refine the assessment of ESG as a risk mitigation tool in financial markets.

Study Limitations

- **Data Scope and Market Coverage:** A limitation of this study is its focus on firms listed in the S&P 500 Index, which primarily consists of large, well-established companies in developed markets. As a result, the findings may not be fully applicable to smaller firms, privately held businesses, or companies operating in emerging economies. Future research could extend this analysis by incorporating a broader range of firms across different market conditions and regulatory environments to enhance the relevance of the results.

- **Data and Methodological Constraints:** The reliance on existing ESG rating providers, while standardised, introduces challenges related to rating inconsistencies and subjective assessment methodologies. An avenue for further exploration could focus on integrating alternative sources, such as firm-specific ESG disclosures or AI-driven sentiment analysis, to improve measurement accuracy and comparability.

- **Focus on Short-Term Effects:** This study primarily examines ESG's impact during high-volatility periods, but the long-term financial implications remain less explored. A potential direction for future work may consider adopting a longitudinal approach to assess whether firms with sustained ESG performance experience enduring benefits in financial stability and cost of capital over extended time horizons.

By addressing these limitations and pursuing the suggested research directions, future studies can build on this thesis to further refine the understanding of crude oil market dynamics, ESG factors, and their broader financial implications.

The advancement of this ambitious research agenda now awaits the dedicated efforts of future scholars.

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