# Financing and investment decisions in times of uncertainty

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# Abstract

This thesis presents three studies on uncertainty spillovers and their effects on corporate sectors' investment and financing decisions.

The second chapter examines the impact of international capital flows on the Chinese real economy during the Chinese Corporate Debt Crisis. It exploits an extensive dataset on Chinese firm-level characteristics and international cross-border flows between 2005 and 2016. It finds that capital inflows expand the capital availability of Chinese banks and result in more credit, especially to more risky firms – with lower profitability and a higher risk of insolvency. These results indicate a risk-taking channel originating from banks' greater liquidity during capital inflow surges. I recommend stricter supervision of Chinese banks in times of capital inflow surges and more targeted macroprudential policies.

The third chapter, motivated by the sovereign debt crisis and based on a dataset including bilateral Foreign Direct Investment (FDI) holdings, investigates the implications of sovereign and bank-related risk on FDI in the Eurozone. In this chapter, strikingly, I discover that only banking risk in the country of origin impacts FDI choices. On the contrary, sovereign risk in both origin and host countries appears to have effects. These results suggest that although poor financial discipline by host governments has been widely blamed as the primary factor likely to frighten off overseas investors, it is amongst FDI supplying nations that the effects of sovereign yields seem most pronounced.

The fourth chapter, building on Wright et al. (2016), explores the effect of uncertainty spillovers of Brexit on UK PE activity and the channels that transmit uncertainty to the PE market. In this chapter, employing a novel dataset on PE targets and non-targets over the 2010–2019 period, I find that uncertainty, especially Brexit-related uncertainty, negatively affects the UK's PE activity. Moreover, the transmission of such uncertainty occurs primarily through the real-options channel and tension arising from prolonged interim periods of PE deals. These

results imply that ongoing uncertainty in Brexit policy will continue to depress PE activity and, by extension, investment and growth in the UK.

This thesis proposes that the domestic real economy is very "fragile" and sensitive to the global economic condition and uncertainty in geographies far from the domestic borders. Therefore, identifying better ways to support economic resilience and prevent cross-country spillovers have never been more crucial.

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## Disclaimer

Hereby, I declare that this thesis is an original artefact of my research and has not been submitted for any previous degree, another degree, or other professional qualification. I have also made appropriate referencing to acknowledge all supporting previous literature and resources adopted in the writing of this thesis. The thesis work is entirely my own, except for the collaborative contributions acknowledged throughout.

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# 1 Introduction

Uncertainty plays a vital role in shaping political decisions and discourses, everyday choices, and the global economic conjecture and outlook. Particularly in the period when I am writing this thesis, uncertainty about the severity of epidemiological factors related to the Covid-19 pandemic has vastly shaped political, academic and press debates about the determinants of uncertainty, its associated costs and the impact of policymakers' inaction vs reaction to it. Despite the peculiarity of these circumstances, some important questions posed in this context of Covid-19 uncertainty are innately similar to those arising in most uncertainty settings (see Baker et al., 2016). These questions relate to uncertainty on *who* will make (is entitled to make) decisions, *what* decisions will be taken and *when*, or, of course, *until when* this uncertainty (and policies) will last, and *the effects* of policy action, or inaction.

Nevertheless, arguably uncertainty takes various forms in different circumstances. Therefore, the prevalence of one or more of these questions might affect the 'type' of uncertainty in consideration and, therefore, how it propagates to the economic agents in question. Understanding the type of uncertainty in consideration is indeed essential to be able to answer the previously mentioned questions.

Several studies tried to get a better understanding of uncertainty in its various forms. Early work from Rowe (1994) provides a broad definition of uncertainty and the variability of information that it embeds. The author documents four broad categories of uncertainty: (i) temporal (i.e., about future or past states); (ii) structural (i.e., that arises from models/reality complexity); (iii) metrical (i.e., in the measurement of uncertainty itself or variables in a particular state); and (iv) translational (i.e., uncertainty in explaining/translating its effects).

These categories of uncertainty are independent up to a certain extent. In a particular context, one or more (even all of them) might co-exist at a given point in time, in the same context (economy) or different ones (e.g., in other countries). However, each of them will have various causal factors and propagation mechanisms.

Rowe (1994) suggests that temporal uncertainty about the future, typically pending events, causes anxiety that often leads to a greater propensity to gamble in the agents affected by it. Differently, uncertainty about the past arising from a perceived information loss can cause recrimination and different forms of denial (ibid.). Similarly, he proposes that the information overload of structural uncertainty can lead to bewilderment and undue conservative responses. Metrical uncertainty arising from measurement difficulties can bring frustration and result in the forced estimation of its outcomes (ibid.). As opposed to situations of translational uncertainty, whereby policymakers cannot estimate its effects because of the diversity of the economic agents it affects, which might lead to favouring one party over another (ibid.).

During the Covid-19 pandemic, we experienced several if not all these forms of uncertainty. At the start of the pandemic, temporal uncertainty was at its peak since nobody could anticipate how long it would last or the extent of the economic costs it would bring. Policymakers of several countries expressed concerns over measuring the Covid-19 patients and, on several occasions, suggested the under-reporting of many nations (i.e., some degree of temporal uncertainty about the past). Still, today, differences in the reporting of cases between different countries exist as well as concerns over countries' previous calculations and adaptations in the reporting schemes.

Therefore, I would argue that, to some extent, we observed all these forms of uncertainty and many of its predicted effects over the past several months. These categories and features, however, are not characteristic of the Covid-19 pandemic alone. On the contrary, they also appear relevant in several other uncertain events we have observed in the past decade. In this Section (and thesis), we consider uncertainty propagation in the context of three major recent uncertainty events.

In the aftermath of the Global Financial Crisis (GFC), most advanced economies central banks adopted unconventional monetary policies to facilitate their domestic economic recovery. In this context, the low interest rate environment and elevated uncertainty about the length of these easing policies led to significant spillovers to emerging market countries. That caused a considerable growth in corporate debt, which eventually resulted in the case of China in the so-called Corporate Debt Crisis (i.e., uncertainty about the future created risk-taking incentives).

In Europe instead, this same uncertainty, combined with the vast central bank purchase of government bonds, encouraged banks to reduce credit and substantially increase their exposure to their domestic economy sovereign bonds (i.e., "flight to quality" in response to structural uncertainty). This exposure of banks led to severe consequences once the Sovereign Debt Crisis unfolded, sovereign bonds depreciated, and their balance sheets suddenly shrunk. In this context, we might argue that, to a certain extent, also temporal uncertainty about the past and metric uncertainty played a crucial role. That is because of the role of the "smoking gun" of this crisis, typically associated with the discovery of the Greek government under-reporting of debt and deficit level in October 2009.

Not surprisingly, once structural and metrical uncertainty arose, these ultimately caused severe austerity policy in the periphery of the Euro Area (EA), strong under-investment, and an instead much quicker recovery of the EA's core countries (i.e., they resulted in a conservative response).

Ultimately, uncertainty related to the 2016 UK Brexit Referendum led to an unprecedented and controversial Brexit vote in June 2016. At least to some extent, this result has been affected by the complexity of the referendum implications, the vast diversity of needs of different agents and British citizens involved in the vote. After the referendum result, uncertainty about the future negotiations between Britain and the EU and the outcome of these negotiations had an even more devasting effect on British and EU businesses, which resulted in a substantial reduction in investment in the UK (both from companies and institutional investors).

Bringing these few important uncertainty events into Rowe (1994) uncertainty frameworks, these seem to do a "good job" in providing a qualitative description of the consequences of uncertainty for companies and policymakers. However, the model remains silent on the transmission channels of this uncertainty, its duration and its effects on the real economy. This thesis aims to fill these gaps by focusing on uncertainty propagation mechanisms or, in economic terms, on the transmission channels of uncertainty. By studying its propagation, of course, it also provides an assessment of its effects (i.e., an estimation), explains its duration, and tries to shed light on policies that can mitigate it. In particular, focusing on the three previously mentioned uncertainty events (i.e., Chinese Corporate Debt Crisis, Sovereign Debt Crisis and Brexit Referendum), this thesis analyses the impact of uncertainty on the financing behaviour of banks and the investment decisions of firms affected by these uncertainty types.

In Chapter 2, I analyse the impact of cross-country investment in China on the real economy and find that this results in increases in Chinese firms’ corporate debt levels.

The unprecedented nature of monetary policies adopted after the GFC, the slow growth of many advanced economies after the crisis, and the unclear length of time for which these policies would remain in place created strong capital flight incentives that led to a substantial increase in investment in emerging markets. Spillovers of advanced economies financial conditions had the effect of constraining emerging markets monetary policy choices (and independence), leading to the build-up of vulnerabilities. In the case of China, its record growth observed in the aftermath of the GFC made it one of the leading emerging market recipients of capital inflows from advanced economies.

Many scholars and policymakers argued that in China, among other emerging countries, monetary policy and financial spillovers caused a rapid and vast increase in debt. In more detail, the BIS and the IMF estimated that Chinese corporate debt increased from 80 per cent of its GDP in 2008 to 175 per cent in 2015, posing an unprecedented threat to financial stability (Maliszewski et al., 2016) when spillovers vulnerabilities spillback to their countries of origin.

This chapter inspects the transmission of international capital flows to the Chinese real economy and the resulting increase in corporate debt. Its methodology leverages the idea that capital inflows, like loosening monetary policies, expand domestic liquidity and drive banks' risk-taking. Several studies find non-trivial evidence of resources misallocation during capital inflow regimes (Dinger and te Kaat, 2015; Disyatat and Rungcharoenkitkul, 2017; BIS, 2015; Bruno and Shin, 2017). To investigate this phenomenon for China and contextualise it with existing evidence on growth in private sector debt, I look at firms' leverage and their fundamentals. In particular, I try to understand whether having a healthier balance sheet increases (or decreases) their likelihood of receiving a loan during periods of high capital inflows.

Moreover, I split firms according to their industry and size, as they hugely matter during expanded liquidity regimes. I argue that mining, construction, and real estate industries are more heavily reliant on debt and more capital intensive; hence, they will ask for more credit. Likewise, small firms tend to have a much more robust synchronisation with the domestic business cycle because of their more significant funding constraints. Hence, they have a stronger incentive to exploit cheaper and more accessible financing (Begenau and Salomao, 2018; Gertler and Glichrist, 1994).

I find a positive relationship between capital inflows and credit growth in China in all regression models. In particular, a 1 percent increase in capital inflows-over-GDP leads to a more than double growth in firms' leverage ratio. Secondly, I observe that capital inflows are associated with increased banks' lending to less profitable firms. For the overall period, I find that the geometric mean of debt financing (scaled by assets) of less profitable firms' is about 32 per cent higher than that of profitable ones (using the industry median as the benchmark). Moreover, the marginal effect of a 1 percent increase in capital inflows is an additional 4 percent lending to less profitable firms. Ultimately, I observe that the credit expansion arising from capital inflow surges has a significantly stronger effect on smaller firms and capital-intensive industries due to their more challenging access to capital in normal times and their greater reliance on debt financing.

In Chapter 3, instead, I focus on the Euro Area (EA) context and explore how uncertainty arising from the Sovereign Debt Crisis affected inward Foreign Direct Investment (FDI) in its member countries. The Euro Area has historically been a key recipient of FDI investments and an important FDI supplier. That has been attributed not only to the elimination of transaction costs and exchange risk in the reallocation of capital between members of the monetary union (Lane & Milesi-Ferretti, 2008; Darvas et al., 2013) but also to an increase in international investors' confidence in its financial institutions and supervisory bodies (Shatz & Venables, 2000). In the aftermath of the Global Financial Crisis (GFC), worries about fiscal sustainability in the EA intensified (Merler and Pisani-Ferry, 2012; Arghyrou & Kontonikas, 2012; Bernoth & Erdogan, 2012; Afonso et al., 2014, 2018) as risks in the banking sector fed back to the sovereign position and vice versa, generating a detrimental cycle (De Bruyckere et al., 2013; Acharya et al., 2014; Delatte et al., 2017). As a result, in the run-up of the sovereign debt crisis, the EA experienced significant capital outflows. In this context, the chapter examines how sovereign and banking sector risks that accumulated during the crises affected FDI in the EA. More specifically, I dissect the effect of sovereign and banking risk in origin (foreign investors) and host countries (EA), which I consider as the main drivers of investors' capital allocation in the analysis period. Therefore, this approach extends the empirical literature on FDI that typically considers domestic factors as drivers for foreign investment (e.g., Carril-Caccia & Pavlova, 2018; Dellis et al., 2016; Razin & Sadka, 2007). By contraposing banking and sovereign stress in the country where FDI originates (i.e., the origin country) with the corresponding recipient country of FDI (i.e., the host), the chapter isolates the impact that EA countries' sovereign and banking risk have on their ability to attract FDI from other factors, whilst also considering the relative importance of origin countries' domestic risk.

Moreover, I provide evidence on cross-country spillovers arising from sovereign and banking sectors' stress and the transmission to the Euro Area through FDI. I argue that modelling the effects of FDI in the EA context constitutes *per se* an ideal setting for this empirical analysis. Since all countries in the European Monetary Union (EMU) have a common currency and monetary policy, that mutes the effect from the monetary transmission and allows for a cleaner identification of variations in the financial account of the Balance of Payments. The empirical analysis employs a large panel dataset from the IMF Coordinated Foreign Direct Investment Survey (IMF CDIS) on 112 countries FDI stock positions between 2009 and 2016, which I use to identify inward FDI in the EA. The chapter's empirical work yields three main findings. Firstly, I observe that an increase in non-performing loans-over-total loans – widely employed in the banking literature (see Aiyar & Monaghan, 2015) to test banking sector stability – in the origin country leads to a decrease in FDI. However, importantly, changes in the corresponding bank risk in host countries leave inward-FDI unaffected. Secondly, I find that FDI responds negatively to upturns in sovereign yields both in origin as well as host countries, arguing that (i) an increase in origin country sovereign yield encourages corporate sector Multinational Enterprises (MNEs) to engage in less risk-taking, whilst (ii) an increase in host country yield implies that other destinations appear more attractive.

Additionally, when the EA sample is separated into subsamples of non-stressed and stressed (GIIPS: Greece, Ireland, Italy, Portugal and Spain) countries[1], these findings are confirmed, reinforcing my confidence regarding the identified transmission channels. In a nutshell, I find that economic conditions – including financial stability – in origin countries particularly matters for FDI. A core achievement of this chapter is the identification of a spillover effect of risk in origin countries to the Euro Area through FDI. Finally, I re-affirm findings in the literature related to the importance of economic and financial ties in investment and financing decisions, embedded in standard gravity variables.

In Chapter 4, I consider another well-known recent event of elevated uncertainty, the Brexit referendum. In particular, I examine the effects of uncertainty from the Brexit referendum results in June 2016 on private equity investment in the UK.

Private equity (PE) is a very popular and economically relevant category of investment in the UK context. The size of its PE market is the largest in all the European continent, and leveraged buyouts (LBOs) account for three-quarters of the UK merger and acquisition (M&A) deals (CMBOR, 2016). Moreover, its economic relevance has been vastly documented by the relevant literature. Benefits arising from PE investment include enhancement in corporate governance practices (see, e.g., Jensen, 1989; Acharya et al., 2013); improvement in firms' efficiency (see, e.g., Kaplan and Strömberg, 2009) and productivity (see, e.g., Lerner et al., 2011; Davis et al., 2019); and, employment opportunities of portfolio firms' workers (see, e.g., Kaplan, 1989; Davis et al., 2014; Agrawal and Tambe, 2015).

However, anecdotal evidence suggests that many PE investors disinvested from the UK in the years of post-referendum negotiations between the UK and the EU because of the elevated uncertainty. In this context, many commentators also argued that uncertainty might

[1] Note that a vast body of literature identifies in the context of the sovereign debt crisis Euro Area GIIPS countries as stressed, and non-GIIPS countries as non-stressed (see, e.g., Acharya et al., 2018; Afonso et al., 2018).

have a persistent effect on the UK economic activity and strongly quested for a fast resolution of this uncertainty (Wright et al. 2016; Kadiric and Korus, 2019).

Therefore, in Chapter 4, building on the work of Wright, co-authors, and other existing literature on PE (e.g., Leslie and Oyer, 2009; Lerner et al., 2011; Kaplan and Strömberg, 2009; Hotchkiss et al., 2011; Cumming et al., 2020; for an excellent review see Gilligan and Wright, 2020), I investigate two associated research questions: firstly, what is the effect of uncertainty and, in particular, Brexit-related uncertainty, on PE activity in the UK? And secondly, what are the channels that operationalise the transmission of uncertainty to the PE market? In terms of measuring activity, I follow others (e.g., Wright et al., 2016) in defining PE as the 'risk capital employed to finance the acquisition of mature businesses via a leveraged buyout (LBO).' Less straightforward is identifying an appropriate analytical framework, given that the conceptualisation and measurement of uncertainty is a non-trivial task. To circumvent this, I employ a set of uncertainty measures, including the Bloom et al. (2019) Brexit Uncertainty Index (BUI) and the Baker et al. (2016) Economic Policy Uncertainty Index (EPU).

This chapter's analyses a novel dataset that I construct by conflating several data sources. I collect data on buyout investors and targets from S&P Market Intelligence and Capital IQ, identifying UK targets acquired by PE buyout firms over the 2010-2019 period and following standard deal classification criteria from the existing literature (see Axelson et al., 2013; Faccio and Hsu, 2017). Subsequently, I employ Capital IQ, Compustat Global and Orbis databases to obtain data for the necessary accounting and financial fundamentals of the constructed sample targets. After matching targets to available accounting data, I obtain a sample of 765 UK targets. Moreover, to provide a suitable control group to these targets, I consider all UK firms with analogous size characteristics, generating a final dataset of 290,022 firms.

To derive appropriate hypotheses, I follow Bonaime et al. (2018) and Adra et al. (2020) in drawing on related literature, including: work positing that uncertainty will increase the real option to delay investment (cf. Quigg, 1993; Gulen & Ion, 2015); notions of an interim risk channel of uncertainty (see Bhagwat et al., 2016), where periods of high uncertainty widen the interim period occurring between announcement and completion of an acquisition (or buyout deal); and principal-agent theory, whereby greater uncertainty can lead to increased moral hazard if limited partners (principals) ability to control general partners (agents) is impaired. In doing so, the investigation of this Chapter sheds light on the impact of uncertainty for PE and entrepreneurial finance (e.g., Wright et al., 2016; Cumming and Zahra, 2016; Brown et al., 2019), the general economic and financial effects of uncertainty (e.g., Baker et al., 2016; Gulen and Ion, 2016; Drobetz et al., 2018; Bonaime et al., 2018), and related issues of effective policy for supporting investment during periods of higher uncertainty due to exogenous shocks.

I find that Brexit uncertainty negatively affects UK PE activity, primarily arises from policy, FX and CFOs (firm-level) uncertainty and transmits through real-options and interim risk channels. These results imply that industries most deeply affected rely on fixed assets, durable goods, or are heavily exposed to the EU because of their export/import activities. I also find that the impact and transmission of uncertainty vary according to the different nature of uncertainty itself. Different types of uncertainty have different degrees of persistence or lead to longer deal interim periods, therefore "scaring off" potential PE investors. These considerations lead me to urge policymakers to address uncertainty arising from Brexit whilst encouraging a more holistic view of uncertainty 'types' and channels.

## 1.1 Contribution to the extant literature

The broad contribution of this thesis is in identifying the several, crucially important, channels through which uncertainty spillovers to the real economy. Our work starts by the consideration of some of the most dramatic uncertainty events of the last decade (at least before the start of the Covid-19 pandemic) and, by exploring these events, tries to come up with a unified view of how uncertainty affects multinational enterprises (MNEs) through several financing and investment channels.

Both Chapters 2 and 3 aim to provide a link between risk (and uncertainty from which it originates) on a global scale and its effect on MNEs financing conditions. Chapter 4 instead conceptualises uncertainty in its many forms and studies the impact of domestic uncertainty on (domestic and foreign) investors' behaviour.

Chapter 2 contributes to a vast body of literature on the caveats of prologued liquidity easing and its destructive effects on financial stability (Minsky, 1992; Bernanke and Blinder, 1992; Jiménez et al., 2012; Ioannidou et al., 2014). The findings of these studies, merely focusing on a domestic-induced liquidity easing, document greater banks' risk-taking in this context. The driver for this risk-taking channel pass through banks' capital availability and suggest that as banks' capital availability increases, banks reduce their lending standards, hence take more risk. Perhaps, surprisingly, we observe a similar bank behaviour once the liquidity injection comes from abroad. Larger capital availability of banks leads to greater risk-taking or more lending to firms with worse economic fundamentals. Following the Bernake and Gertler (1990) definition of financially fragile firms by looking at the borrowers "net worth" relative to the size of their investment "project". We hypothesise that firms with these characteristics of fragility (i.e., small firms or firms in capital intensive industries) would receive more credit if a risk-taking channel is in play. Our results sustain this hypothesis and confirm the existence of a 'leverage channel' through which banks' risk-taking incentives transmit more substantially to firms more heavily relying on external finance, hence increasing the corporate sector financial fragility. This finding contributes to fast-growing literature on the importance of credit cycles for the real economy (Bernanke & Gertler, 1990; Bordo & Jeanne, 2002; Chen et al., 2012) and the need of policymakers to tame them.

Chapter 3 makes then a "step forward" by linking financing conditions with investment patterns. Both chapters show that both foreign and domestic resilience matters for a "sound" domestic real economy. Interestingly, Chapter 3 emphasises how foreign risk factors affect the domestic real economy, to some extent, even more than the corresponding domestic ones. As investment dynamics, particularly those related to FDI, involve large capital expenditures (e.g., purchasing a large pull of shares in the target company or elevated costs associated with investment abroad), banks capital availability once more plays an important role. In other words, by determining the foreign MNEs ability to invest in the EA, in this chapter, we find evidence of how foreign economic (and financial) conditions transmit across the border through the 'leverage channel' channel previously discussed. This work contributes to a substantial body of work on FDI flows (Carril-Caccia & Pavlova, 2018; Dellis et al., 2016; Razin & Sadka, 2007; Damgaard et al., 2018; Haufler et al., 2018; Egger et al., 2018) that however focuses just on the domestic country risk factor by highlighting the role of global factors.

Chapter 4 instead takes a slightly different approach. Without losing its specificity, it provides a unified view of uncertainty (including its estimation, duration, and propagation mechanisms) analysing a single event, Brexit. That aims to contribute to a substantial effort of the relevant literature exploring uncertainty and its transmission channels (see, e.g., Rowe, 1994; Baker et al., 2016; Bloom et al., 2018; 2019; Bhagwat et al., 2016). Second, it assesses uncertainty propagation with a specific focus on investment dynamics. It suggests multiple transmission channels of uncertainty to the private equity industry, and by doing so, it adds a solid theoretical and empirical contribution to the findings of Chapter 3 as well as to the relevant literature on uncertainty's effects on the private equity industry (Ljungqvist et al., 2020; Malenko and Malenko, 2015).

Ultimately, Chapter 5 concludes by drawing the policy-relevant implications of this thesis, some relevant take-aways for MNEs and indicating future research avenues for finance and economics scholars studying uncertainty spillovers.

# 2 International capital flows and corporate debt growth in China[2]

## 2.1 Introduction

After the Global Financial Crisis (GFC), there has been a significant increase in academic interest in capital market frictions and their connection to debt and financial crises (see Reinhart and Rogoff, 2008; Gourinchas and Obstfeld, 2012; Dell'Ariccia et al., 2012; Broner et al., 2013). Capital market frictions originating from Western countries (especially from the US) unconventional monetary policies (UMPs) have received particularly elevated academic and policy makers' attention (see, e.g., Obstfeld, 2019). That is because of the extensive evidence of global spillovers to emerging markets, resulting in tremendous boosts in asset prices (especially property prices) and credit, drastically increasing the risk of another event of global instability (see, e.g., Scheubel et al., 2019; Obstfeld, 2021). Particular concerns over monetary policy spillovers and their related risks were expressed for China, whose corporate debt levels increased from 80 percent of its GDP in 2008 to 175 percent in 2015 (Maliszewski et al., 2016), leading to the so-called Chinese Corporate Debt Crisis. Although the literature suggested several reasons to explain the extraordinary growth in Chinese corporate debt, such as credit-based development in upstream industries such as steel and copper, its rapid growth in domestic infrastructure (Song and Xiong, 2018; Maliszewski et al., 2016), or the growing inefficiencies of Chinese State-Owned Enterprises (SOEs). This phenomenon has received vast press[3],

[2] This Chapter benefits from the supervision and guidance of Michael Lamla, which I acknowledge by using the pronouns: “we”, “us”, “our”; rather than: “I”, “me”, “my”.
[3] Chinese debt has attracted significant newspapers attention, which defined it as a 'Lehman moment' (Reuters.com and FT.com). China's private sector debt has been growing significantly more than its GDP, and companies have been found unable to service their debt obligations in many cases. Among the several dangerous effects, the excessive corporate sector debt led to China's downgrade by Moody's on the 24th of May 2017 (Moody's investor's service, 2017). Real estate (with the highest credit risk), consumers, manufacturing and small businesses appear to be the most endangered industries (FT.com). Not surprisingly, also the housing market bubbled (see FT.com, FT.com, FT.com).

academic[4], and policymakers' attention[5] in the period of the crisis. Still, it receives extensive interest now that the Covid-19 pandemic seems to bring this debt bubble to a bust (see Bloomberg link).

In this context, this paper explores how financial spillovers from advanced economies after the GFC enhanced China's corporate debt and build-up a less resilient Chinese corporate sector. In our analysis, we exploit firms demand for credit to scrutinise the effect of capital inflow surges in China on firm-level access to external finance. We build upon several strands of the relevant literature on the expansive effects of cross-country capital flows on host countries' economic fundaments (e.g., Shin, 2012; Rey, 2013; Blanchard et al., 2017; Obstfeld, 2019; Banti and Bose, 2021), on firms' patterns of external financing over the business cycle (Korajcyk and Levy, 2003; Jermann and Quadrini, 2006; Covas and Den Haan, 2011; Begenau and Salomao, 2018), and banks' response to regimes of liquidity easing (Minsky, 1992; Acharya and Naqvi, 2012; Ioannidou et al., 2014). This approach extends substantially the findings of the relevant literature on international capital flows that typically focuses on the macroeconomic effects and financial assets responses (e.g., Fratzscher et al., 2017; MacDonald, 2017; Dedola et al., 2017; Ahmed et al., 2017; Anaya et al., 2017; Ayala et al., 2017; Bowman et al., 2015; Lim et al., 2014; MacDonald, 2017; Milesi-Ferretti and Tille, 2011). By considering factors affecting Chinese firms' demand for credit and fundamentals (such as firms' industry, size, investment opportunities, profitability and solvency), and controlling for domestic credit-supply factors (such as the monetary policy stance, banks' characteristics) as well as time-varying effects, this paper isolates the impact of a foreign-driven liquidity expansion on the domestic credit condition and its consequent effects on the corporate sector.

[4] E.g., see Ahamed and Mallick (2017); Ahmed et al. (2017); Dedola et al. (2017).
[5] E.g., see McCauley et al. (2015a,b); BIS Quarterly Review (2015); Kock (2015).

We depart from prior literature, studying the macroeconomic effects of international capital flows comparing several developed and emerging countries, as focusing on the Chinese context alone brings this study several advantages. First, despite several authors found common ("push") factors as the main drivers of global capital flows, recent literature on emerging markets found country-specific, mainly institutional ("pull") factors, as highly significant in explaining countries' ability to attract foreign investment (see, e.g., Cerutti et al., 2015; Fratzscher, 2011). Since this paper aims to identify the real effects of capital flow propagation, rather than the drivers of foreign investors' capital allocation choices, focusing on one country allows keeping "pull" factors constant and have a cleaner identification of the relevant microeconomic effects. China not only is the second-largest economy globally, but also its elevated central government control the balance of payments make capital flow surges and their consequent amplification of credit substantially more unlikely than in other more liberal countries. Despite that, the relevant literature found China post-GFC as the country with the most incredible volume of capital inflows (see Maliszewski et al., 2016; MacDonald, 2017). Ultimately, the peculiarity of the Chinese institutional environment, dominated by state-owned firms and banks, allows this paper to answer important questions which would be harder to answer elsewhere. For example, considering that state-owned and politically connected firms' funding comes directly from China's government and its financial institutions, would a non-domestic-driven liquidity expansion still result in a credit expansion? Is this expansion a value-creating or destroying (considering the implicit bailout guarantee enjoyed by firms and banks)? And, what are the risks involved?[6] Focusing on China offers a unique setting to address these

[6] Note that in China, governmental institutions are responsible for monitoring SOEs (Guo et al., 2017). Moreover, SOEs are encouraged to use their business operations to serve the public interest and promote social welfare. As such, the existence of strong “financial rigidities” imposed on SOEs (including the banking sector) could counteract the transmission of international capital flows (passing through state-owned banks), i.e. not resulting in a debt bubble, and/or create rather than destroy value for Chinese firms.

questions and observe a lower bound effect of spillovers of global financial imbalances on host countries' credit growth and the real economy.

Our empirical approach employs a fixed-effect panel regression model à la Fazzari et al. (1988). It exploits quarterly consolidated data collected from Wind on 2968 Chinese listed firms between 2005 and 2016, supplemented by numerous macroeconomic control variables to isolate the effect of international capital flows from other potential drivers of firms' leverage (see Appendix A.3, for a more detailed description). This period coincides with the initial Chinese government effort to start opening the balance of payment, approximately the end of the crisis, but most importantly, the entire period of US government zero-interest rates monetary policies. These policies have been vastly blamed to be the main source of spillovers to EMEs (see, e.g., Rey, 2013).

Our work yields three main findings. First, we find that a 1 percent increase in capital inflows (scaled by GDP) leads to about a 2.3 percent increase in corporate sector debt, a result which we find robust in several empirical settings (e.g., splitting the sample by size, industry, and age). Second, benchmarking our sample of Chinese firms to their industry or size peers (according to numerous risk and profitability measures), we also find that the least profitable firms are those receiving more credit during surges in capital inflows. In particular, we find that a one percent marginal increase in capital inflows leads to about 4 percent greater lending to less profitable (than the benchmark). That leads not only to a more significant domestic debt (as found by Rey, 2013; Shin, 2012; and many others), but also to higher risk-taking of banks (as proposed by Minsky, 1992; Acharya and Naqvi 2012; and Ioannidou et al., 2014). That suggests a loosening of banks' lending standards, typical of periods of expanded domestic liquidity (as proposed by Minsky, 1992; Acharya and Naqvi, 2012; and, Ioannidou et al., 2014).

Ultimately, separating firms according to their size and industry, this effect becomes significantly stronger for smaller firms and capital-intensive industries. This phenomenon suggests the existence of a 'leverage channel' through which cross-country capital flows transmit to the real economy. Whereby firms with either a low level of net worth in absolute terms (small firms) or relative to the value of their investment "project" (firms in capital-intensive industries) have to borrow from banks to finance investment. Therefore, the industries most affected are those heavily relying on business cycle expansion for accessing banks' capital (i.e., small firms) or those that heavily rely on debt financing (i.e., operating in capital-intensive industries).

The main takeaway of this study is that it highlights the prominent role of advanced economies in causing financial vulnerabilities in China (that ultimately resulted in China's corporate debt crisis). On a broader level, it shows the easiness through which financial and economic imbalances transmit cross-border. This result finds vast support in the relevant literature (see, e.g. Shin, 2012; Rey, 2013; Ahmed et al., 2017; Anaya et al., 2017; Ayala et al., 2017). In particular, this paper emphasises two important transmission channels through which international liquidity results in real economy vulnerabilities differently from the previously mentioned literature. First, we propose a risk-taking channel of banks, which lead not only to greater credit accumulation, as suggested by Rey (2013), Cerutti et al. (2015) and others but to more "toxic" credit. Second, we introduce a 'leverage channel' that results in industry-level asymmetries in international liquidity transmission. Most importantly, higher debt levels are reached by firms with lower net worth relative to their investment values – i.e., causing financial fragility (see Bernanke and Gertler, 1990).

Our paper relates to four main strands of the literature. Firstly, our paper contributes to all the literature on the transmission of unconventional monetary policy (UMP) spillovers to Emerging Markets Economies (Bruno and Shin, 2014; Fratzscher et al., 2017; MacDonald, 2017; Dedola et al., 2017; Ahmed et al., 2017; Anaya et al., 2017; Ayala et al., 2017; Bowman et al., 2015; Dahlhaus and Vasishtha, 2014; Eichengreen and Gupta, 2015; Forbes and

Warnock, 2012; Lim et al., 2014; MacDonald, 2017; Milesi-Ferretti and Tille, 2011; Moore et al., 2013; Neely, 2015; Ghosh et al., 2014). Their identified macro-transmission, passing either through financial intermediaries (Dinger and te Kaat, 2015; Cerutti et al., 2015; Bowman et al., 2015; Bruno and Shin, 2017; Cohen et al., 2016; Koch, 2015; Maliszewski et al., 2016; McCauley et al., 2015b; Baskaya et al., 2017) or financial markets (Bruno and Shin, 2014; Fratzscher et al., 2017; Ayala et al., 2017; Ahmed et al., 2017; Mizen et al., 2012; McCauley et al., 2015a) enable us to picture the cross-country transmission of global liquidity and to link it with the observed response of corporate sector fundamentals. Secondly, this paper contributes to the risk-taking channel literature, which identified a softening in banks' lending standards (i.e., an increase in risk-taking) during periods of low central bank rates (see Minsky, 1992; Bernanke and Blinder, 1992; Jiménez et al., 2012; Ioannidou et al., 2014). These studies identify the expansion in domestic liquidity as the main cause for the increase in risky loans observed after a loose monetary policy. Eventually, we contribute to the literature on firms' financing over the business cycle. That points to higher and heterogeneous risk-taking of firms during business cycle expansion, which results in higher debt financing (see Korajcyk and Levy, 2003; Jermann and Quadrini, 2006; Covas and Den Haan, 2011; Begenau and Salomao, 2018), especially of small firms. Our paper finds indeed very similar results.

The rest of our paper is structured as follows. In Section 2, we present the hypotheses of this study; Section 3 explains our identification strategy and the empirical model used for the analysis. Section 4 analyses the composition of our dataset and describes the construction of the variables used in the empirical analysis. In Section 5, we provide detailed summary statistics. Section 6 discloses our empirical findings. Section 7 adds several robustness tests of baseline results. Eventually, Section 8 concludes by summarising the contribution of the paper and the implications of our findings.

### 2.2 Hypotheses

Although access to international financial markets gives China numerous benefits (for instance, facilitating the funding of its fast-developing corporate sector, creating diversification opportunities and supporting the accumulation of foreign reserves to hedge its international positions). It also brings significant challenges and new risks for its macroeconomic stability. A vast body of literature on global capital flows suggest that these tend to amplify the business cycle (Aruajo et al., 2017; Disyatat and Rungcharoenkitkul, 2017), reinforcing the effect of government and monetary policy in the domestic economy. Rey (2013) argues that greater financial integration and the emerging markets greater reliance on the US dollar significantly amplified the effect of US monetary policy spillovers, causing ample capital inflows in these countries that led to fast credit growth and bank leverage. Shin (2013), in particular, examines the role of banking flows in the transmission of external vulnerabilities to open emerging economies. They find that banks play a major role in this transmission since international capital flows passing through banks lead to quick expansions (or contractions) of credit to the corporate sector of the countries where the banks are incorporated (c.f. Cerutti et al., 2015; for an excellent study on capital flows transmission through the banking system). In line with this literature, we develop the following hypothesis:

**HP 1:** Foreign capital inflows in China expand its corporate sector leverage

Academic and policymakers work have often connected expansions of domestic liquidity with substantial risk-taking incentives of banks. Previous studies on the risk-taking channel from Paligorova and Santos (2017), Dinger and te Kaat (2015), and te Kaat (2017), in particular, analyse the risk-taking incentives of banks by comparing the volume of bank lending received by safe firms, as opposed to unsafe ones. They find that during periods of expanded domestic liquidity (e.g., because of loosening monetary policies), banks lend to firms with worse accounting fundamentals, hence take a greater risk. Similarly, Dell'Ariccia and Marquez (2006), studying banks' risk-taking in times of liquidity expansions, find a reduction in banks' lending standards arising from an increased information asymmetry in these periods. In particular, they theorise that when liquidity eases, banks face an increase in demand from loans from unknown borrowers. As the portion of unknown borrowers increases, banks' screening costs significantly increase, making it more convenient for banks not to charge any collateral requirement. In other words, Dell'Ariccia and Marquez (2006) find that greater information asymmetries reduce the screening incentives of banks, hence, leading to a softening of their lending standards. In this study, we adopt a very similar argument to that of the relevant literature. As capital inflows increase, greater banks' capital availability substantially reduces their screening incentives and incite banks to maximise their earnings. As a result, that causes greater lending to firms with worse economic fundamentals than those observed in periods with lower capital inflows. The banking literature strongly supports this idea that credit becomes more "toxic" in times of expanded liquidity (see, e.g. Ioannidou et al., 2014). Therefore, our second hypothesis suggests that:

**HP 2:** Higher capital inflows result in more significant corporate debt, particularly in the less creditworthy firms.

In line with the literature on cross-country capital flows (Rey, 2013; Broner, 2013; Shin, 2012), capital inflows positively correlate with domestic country credit growth, but credit growth tends to be very heterogeneous across industries. Capital intensive industries and real estate are well-known for their greater procyclicality and sensitivity to capital inflows patterns (Borio, 2014; Borio and Disyatat, 2015; Drehmann et al., 2012). Because of their higher reliance on external funding and the higher associated risk of these industries (high debt-financed), their performance is highly correlated with the business cycle (Covas and Den Haan, 2011). As a result, we hypothesise that corporate debt in industries with greater procyclicality and capital intensity will experience a greater sensitivity to capital inflows if capital flows expand domestic credit.

**HP 3:** Capital inflows expand corporate sector leverage, especially for firms in highly procyclical and capital-intensive industries.

Alike capital-intensive industries, credit to small businesses is also significantly correlated with the domestic business cycle. Because of the lack of collateral of small firms (e.g., a start-up), the high uncertainty about their future cash flows, and in many cases, the lower financial sophistication, these firms' financing ability highly depends on the state of the economy. In other words, small firms have their credit capacity significantly expanded (relative to normal times) when in times of economic boom and vice versa contracted in recessions. Because of the expansionary effect of capital inflows, we assume that small firms will experience greater access to credit, i.e., greater leverage, in times of more significant capital inflows. In line with this argument, we formalise our last hypothesis as follows:

**HP 4:** Capital inflows expand corporate sector leverage, particularly for small firms.

## 2.3 Empirical identification

### 2.3.1 *The Chinese context*

While many studies argued the importance of capital inflows in stimulating credit growth (e.g., Rey, 2013; Cerutti et al., 2015; Banti and Bose, 2020), we know much less of their transmission to the real economy, hence the micro-transmission of capital inflows. Because of the scarce availability of data on international positions of Chinese firms and the vast opacity (and under-reporting) of Chinese authorities, the focus of previous studies has been primarily on the aggregate macroeconomics transmission and asset prices implications of capital flows (Horn et al., 2020). However, Song and Xiong (2018) suggest that commonly used approaches for assessing Western countries' financial risk might not apply to the Chinese context because of the peculiar role of the government and government-owned entities as a market clearing mechanism (Behr et al., 2018; Bruno et al., 2016; Gounopoulos et al., 2020). Therefore, this section provides a short overview of the Chinese financial sector infrastructure and explains how this plays a crucial role in our identification strategy.

The Chinese government developed the current financial system to fund the fast economic growth and reforms in China at the beginning of the 1980s-1990s. This aim, according to many commentators, shaped in many aspects its model and ownership structure.

Economic reforms in the early '80s have led to the fast economic growth of the Chinese economy over the past 40 years. The core of this growth is creating a private sector and allowing the co-existence of SOEs, previously representing the entire Chinese economy (the so-called "dual-track reform"). Contemporarily with these reforms, in the early '80s, a financial sector was also progressively created in China. However, contrary to the business sector, the liberalisation of the financial sector in China took substantially longer. In the '80s, the Chinese government created a banking sector by splitting the People's Bank of China (PBC) into four state-owned banks (the Big Four) to support state-owned enterprises financially. In the early '90s, the Shanghai and Shenzhen stock exchanges were created; the interbank market in 1996 and the other existing bond market in 2007. However, in all these markets, the favouritism of SOEs over private companies is ubiquitous in China (Gounopoulos et al., 2020; Cao et al., 2019; Chen et al., 2011). Until recently, private companies were excluded from equity and bond markets, and listing or issuance in these markets was an exclusive right of SOEs (Allen et al., 2005). To date, SOEs have priority, private companies have quotas on their bond issuances, and all major banks are state-owned.

Because of all these reasons, financial frictions in China, such as those coming from foreign investors, are vastly under the central government's control. Four state-owned banks (the Big Four) vastly dominate the Chinese financial sector (Allen, et al., 2005; Firth et al., 2016) and alone account for 40 percent of total deposits in 2018 (Song and Xiong, 2018). Together, the bond and equity market contribute to only a fifth of the credit to non-financial firms in 2018 (ibid.). Moreover, in the analysis period, the balance of payment is only partially liberalised; in particular, only "Qualified Institutional Investors" (eligibility criteria tightly defined by the central government) are allowed to invest in Chinese financial markets. Therefore, other than foreign direct investment (FDI)[7], financial inflows in China almost entirely pass through state-owned banks. These banks (like other state-owned entities) enjoy explicit and implicit government guarantees on their lending (or borrowing) that induce significant misallocations (credit mispricing). That is because when either of these parties suffers substantial losses, domestic and international creditors expect that the government would bail them out, hence are willing to keep lending to these firms without increasing the price of these funds. That causes the build-up of further leverage, further inefficiencies, and greater risk of the Chinese financial system, which we test in this paper.

### 2.3.2 *Identification*

To assess the impact of capital inflows in China on the creation of firms' leverage and the build-up of the previously mentioned inefficiencies, we start from a recent study by Blanchard et al. (2017). The authors theoretically modelled the transmission of capital inflows to Emerging

[7] Note that FDI in China is mostly of "brownfield" nature and involving SOEs.

Markets' bond market and "non-bonds" assets (foreign direct investment, domestic equity market, and bank lending). The authors show that in Emerging Markets, non-bond flows (mainly constituted by interbank lending) have a more noticeable impact on the recipient economy than the bond counterparts because of "the relatively primitive financial system" (Blanchard et al., 2017:8) of these economies. Specifically, Blanchard et al. (2017) find that capital inflows have an expansionary effect on EMEs. They decrease the cost of credit for a given central bank rate and could lead to credit booms and expanded domestic output. Despite the broad macroeconomic focus of this study, its implications are of great value and very applicable to the Chinese context. The only partial liberalisation of foreign investment in (and out of) China in the period of analysis and the presence of a financial sector vastly dominated by a few state-owned banks makes the transmission of capital inflows inevitably passing through banks and in a similar way to that observed by Blanchard et al. (2017). This characteristic of the Chinese economy, hence its reliance on banks for domestic and foreign liquidity transmission, facilitates us in identifying cross-country liquidity transfers to the private sector. Moreover, it permits us to overcome some limitations of previous studies using aggregated data, hence the lack of disaggregated data on state-owned banks' positions or firms' positions in China.

Therefore, we start from existing evidence on the expansionary features of capital inflows and, subsequently, we resort to the banking literature to identify their transmission. We argue that significant capital inflows in banks’ balance sheet, similar to an expansive monetary policy, reduce the cost of loanable funds, improving banks' profit opportunities and risk-taking. In China's case, the government guarantee on banks' credit arguably makes greater risk-taking and the associated greater returns significantly safer.

Our work is not the first to connect expansions of domestic liquidity with the risk-taking incentives of banks. Previous literature has associated this phenomenon with financial institutions rebalancing their portfolios to achieve a nominal return target (Bonizzi, 2017); with an understatement of borrowers' risk when interest rates are low (Ioannidou et al., 2014); or with more intense 'agency problems' (Acharya and Naqvi, 2012; Dinger and te Kaat, 2015). Paligorova and Santos (2017), among others, explored the risk-taking channel during regimes of expanded liquidity. Their analysis compares credit risk premia charged by banks to firms with different risk levels. They isolated demand factors using bank-year fixed effects. They find that greater information asymmetries reduce banks' screening incentives, leading to a softening of their lending standards. However, Dinger and te Kaat (2015) is perhaps the first study adopting this concept to study banks' risk-taking in the Euro Area (EA) during capital inflow. They hypothesise that the higher the capital inflows, the more unknown borrowers are for domestic banks, lead to more acerbated information asymmetries, which reduce banks' risk aversion. Accordingly, they find that countries characterised by strong capital inflows experienced sizeable bank lending, arising primarily from weakly capitalised or more insolvent banks.

This paper adopts a similar identification strategy to study the increase in corporate sector leverage through greater implicit bank risk-taking. Therefore, like Paligorova and Santos (2017), Dinger and te Kaat (2015), and te Kaat (2017), we identify risk-taking of banks by looking at publicly available accounting indicators of risk and then comparing the volume of bank lending received by safe firms, as opposed to unsafe ones. In particular, we look at the quantity, rather than the price, of loans made to firms with higher risk during periods of expanded liquidity (more significant capital inflows) instead of the overall analysis period. We argue the existence of a risk-taking channel if firms with worse credit fundamentals receive greater lending than other comparable firms during capital inflow surges (*vice versa*, if instead firms with better accounting metrics receive more credit). Like previous studies, since the risk-taking channel implies a bank-driven transmission, we use several fixed effects (firm-year, industry-year, size-year, or age-year) to compare the volume of credit issued to firms with similar characteristics (but with different levels of risk). Using this approach, we manage to mitigate the effect of demand-driven channels (e.g., the interest rate or balance sheet channels).

We argue that the Chinese economic centralisation allows a neater identification of capital flows transmission, despite bringing unsurmountable data availability and opacity issues. Unlike the previously mentioned studies in the US and European context (i.e., with a liberalised balance of payment and banking sector), the almost monopoly role of state-owned banks in the transmission of foreign liquidity in China allows this study to rule out heterogeneities in the diffusion of foreign capital implicitly flows to the Chinese corporate sector. Also, it will enable us to minimise the bias arising from the heterogeneity in banking sector financing choices which is characteristic of a liberal economic infrastructure.

### 2.3.3 *Methodology*

As baseline models of our study, we use a fixed-effect regression model à la Covas and Den Haan (2011).

Therefore, we regress gross capital inflows on the log-change in external debt financing (scaled by total assets) to test their association with the change in banks' lending to the private sector. In particular, we assess whether larger inflows improve lending to more profitable firms, solvent, and with a higher Tobin's q than their industry (or size) peers[8]. To benchmark individual firms (*i*) variables with those of firms with similar characteristics, we firstly computed the industry and size (*j*) median profitability (cash flows), solvency (z-score), and Tobin's q. We defined highly profitable, highly solvent, or high Tobin's q companies (at each given quarter) as those entities with respectively cash flow, z-score, or Tobin's q exceeding the

[8] In their paper, Covas and Den Haan (2011) were studying external financing over the business cycle. Therefore, they were not looking at capital inflows but instead at the cyclical component of GDP.

industry median. Finally, we interact the calculated industry or size dummy variables with capital inflows to observe whether, during capital inflow surges, companies receiving more loans are also those with high profitability (or vice versa if they are less profitable). This analysis enables us to argue whether international capital inflows affect the growth in private sector leverage and whether this can be associated with higher risk-taking of banks.

$$\Delta \log(\frac{D_{i,t}}{A_{i,t-1}}) = \alpha_i + \alpha_j + \alpha_s + \alpha_t + \beta_1 \log(\frac{CIF}{GDP})_{t-1} + \beta_2 dZ_{i,t-1} + \beta_3 dProf_{i,t-1} +$$

$$\beta_4 dQ_{i,t-1} + \beta_5 dZ_{i,t-1} \; x \log(\frac{CIF}{GDP})_{t-1} + \beta_6 dProf_{i,t-1} \; x \log(\frac{CIF}{GDP})_{t-1} +$$

$$\beta_7 dQ_{i,t-1} \; x \log(\frac{CIF}{GDP})_{t-1} + \beta_8 \varepsilon_{D.\log(mpi)_t} + \beta_n \log(X)_t + \varepsilon_{i,t} \quad \text{[Equation 2.1]}$$

In our baseline model, $\Delta \log(\frac{D_{i,t}}{A_{i,t-1}})$ stands for the log-change in Chinese firms' debt financing, where *i* represent individual firms and *t* is time. $\log(\frac{CIF}{GDP})_{t-1}$ represents instead the first lag of capital inflows scaled by GDP and is our main explanatory variable. Therefore, looking at the coefficient $\beta_1$, we can assess whether capital inflow regimes can be considered as associated with the dramatic increase in Chinese firms' debt (as in McCauley et al., 2015; BIS, 2015; Ahamed and Mallick, 2017; Koch, 2015; Dedola et al., 2017) through an increase in domestic liquidity leading to an increase in banks' lending. Afterwards, we include several controls for firms' profitability, solvency and Tobin's q (respectively $dProf_{i,t-1}$, $dZ_{i,t-1}$, and $dQ_{i,t-1}$) and for the domestic monetary policy ($MP$) (see Appendices A.2.5 and A.2.6 for details on its computation). Since we contrapose individual firms' risk against that of comparable firms, having analogous industry and size characteristics, we use $dProf_{i,t-1}$, $dZ_{i,t-1}$ and $dQ_{i,t-1}$; dummy variables taking value of 1 if the considered firm (*i*) at a given time exceed the industry (or size group) median profitability, solvency, or Tobin's q, and zero otherwise.

In mathematical terms, at first $dProf_{i,t-1} = 1$ if $\frac{CF_{i,t-1}}{A_{i,t-2}} - \frac{\widetilde{CF_{J,t-1}}}{A_{j,t-2}} > 0$, $dZ_{i,t-1} = 1$ if instead $z_{i,t-1} - \widetilde{z_{J,t-1}} > 0$, and $dQ_{i,t} = 1$ if $Q_{i,t-1} - \widetilde{Q_{J,t-1}} > 0$, whilst they take value of zero otherwise. Depending on the regression specification, $j$ identifies the size or industry peers of firm $i$.

In order to assess whether during capital inflows surges lending is more (or less) dependent on firms' balance sheet fundamentals, we interacted the three previously mentioned dummies with our capital inflows variable. Therefore, looking at the sign and magnitude of $\beta_5$, $\beta_6$ and $\beta_7$, we can observe whether having a healthier balance sheet increases (or decreases) firms' likelihood of receiving a loan during periods of greater capital inflows, as opposed to overall. Hence, we can conclude whether capital inflows, expanding domestic liquidity, enhance banks' risk-taking, creating a misallocation of loans to less creditworthy firms. Ultimately, $\log{(X)_t}$ is the log of our bank-level and macroeconomic control variables, $\varepsilon_{i,t}$ is instead the white-noise error term of the fixed effect regression.

## 2.4 Data

To obtain accounting data on Chinese listed firms between 2005 and 2016, we exploit the database Wind, a well-known data provider of consolidated accounting data on Chinese corporations. Wind allows us to obtain quarterly data on many accounting variables for 2968 Chinese listed firms. Instead, we use data from the IMF to calculate quarterly gross capital in(out-)flows in (from) Mainland China.

### 2.4.1 *Dependent variable*

The dependent variable in our paper is the log-change in debt financing of a sample of 2968 Chinese listed firms that we compute subtracting from firms' book value of liabilities, their account payables, and deferred tax liabilities[9]. Eventually, as in Covas et al. (2011), we used the first lag of individual firms' book value assets to benchmark this variable. This ratio helps us preserve our model's integrity by minimising the potential endogeneity arising from the considered firm-level variables.

As motivated in Section 2.3, we assume that Chinese firms' debt variations are due to changes in banking sector lending standards (i.e., they are due to variations in banks' risk attitude). This assumption is not new to the relevant literate. For example, te Kaat (2017), trying to analyse corporate debt in bank-based Euro Area countries, uses the same assumption to identify the micro-transmission of international capital flows.

### 2.4.2 *Independent variables*

Our paper includes three sets of independent variables. Firstly, we create an international capital inflow variable, the main variable of our baseline model. Then, we collect a series of accounting control variables, included in the Fazzari et al. (1988) model, relating firms' financing decisions to their profitability and Tobin's q. Thirdly, we resort to the banking literature to identify a set of financial and macro-economic control variables. The variables explain the macroeconomic drivers of the observed increase in bank lending. Finally, we interact our capital flow variable with firms' profitability, solvency, and Tobin's q to assess whether banks show an increase in risk-taking during capital inflow regimes.

#### *2.4.2.1 Capital inflows*

As standard in the literature on international capital flows, we build our capital inflow variable using quarterly data gathered from the IMF International Financial Statistics (IMF IFS).

[9] The paper several times uses the word ‘log’ or ‘logarithm’. In all these instances, we refer to the natural logarithm of the variable into consideration.

Moreover, we assume them to be exogenous, as mainly driven by pull factors independent from China's economic condition (see Rey, 2016; Broner, 2013; Ayala et al., 2017, Fratzscher et al., 2017; Bowman et al., 2015; Giardin et al., 2017).

Data from the IMF IFS consist of three types of international capital flows, such as Direct Investment (assets and liability), Portfolio Investment (assets and liability), Other Investments (assets and liabilities). These measures identify different types of international investment, with several features of risk, duration, and objectives. Direct Investment (FDI) includes a category of global investment that reflects the purpose of a resident entity in one country to obtain a lasting interest in an enterprise resident of another country[10]. Given the long-term nature of this investment, previous literature often associates FDI with host country economic growth (see Barrel, 1997; Contessi and Weinberger, 2009; Dellis et al., 2017). Portfolio investment is a return-driven form of international investment. Unlike FDI, it does not imply a long-lasting interest in the host country company or an active role in the management of the host country firm – it is a speculative investment. In particular, the instruments included in its portfolio investment classification are equity, debt securities, and derivatives assets. As a result, this category comprises risky and short-term cross-border investments targeting the host country. Finally, another investment is a residual category, containing financial instruments not included in neither of the previous variables. Its composition comprises trade credits, loans, currency and deposits, and other assets and liabilities (IMF, 2016)[11].

About these flow variables, the IMF IFS disclose flow data comprehensive of new transactions, revaluations, and changes in outstanding volumes of assets and liabilities (IMF, 2016). Therefore, each of the capital inflow observations represents a quarter-to-quarter

[10] Specifically, the investment is classified as "direct investment" if the direct investor owns at least 10 percent or more of the ordinary shares or voting power (IMF, 2016).
[11] See Appendix A.2.1 for a more detailed description of our capital inflows components.

variation in outstanding liability volumes of China against the rest of the World at a given point in time. This feature of our data comes very handy for country intertemporal comparison. Our measure indeed already comes adjusted for exchange rate and valuation effects arising from changes in assets' market values.

We compute gross capital inflows from foreign countries in China as the sum of gross: Portfolio Investment liabilities (both in the form of debt securities and equities), other investment liabilities (mainly including bank loans, trade credit, and deposits), and Foreign Direct Investment (FDI) (see Figure 2.2).

[Insert Figure 2.2 around here]

#### *2.4.2.2 Firm Control Variables*

Following Fazzari, Hubbard, and Petersen (1988) and Covas and Den Haan (2011), we added several control variables, accounting for firms' profitability, solvency, and Tobin's q, as well as for size and industry. We identify firms' profitability using their cash flows, which we compute as the difference between gross profit, interest expense, and corporate taxes[12]. Moreover, we control for firms' insolvency using Altman Z-score, which we compute following De Nicoló et al. (2006) and Iosifidi and Kokoas (2015) (see Appendix A.2.3). These profitability and solvency measures have been used as identifiers of firms' creditworthiness to test whether a surge in capital inflow results in higher risk-taking, hence in lending to less creditworthy customers. Eventually, since firms could borrow to finance investment and growth, we add firms' Tobin's q as a proxy for firms' investment opportunities, which we compute following Huang and Mazouz (2018) (see Appendix A.2.3).

[12] Differently from Fazzari, Hubbard and Petersen (1988), we used gross profit instead of EBITDA. This decision is due to the many missing values for the variable EBITDA. Considering the similarity of the two measures, we hardly believe that the results would be affect by the inclusion of either one or the other.

#### 2.4.2.3 The creation of size portfolios

In line with well-known literature on external financing over the business cycle (Korajcyk and Levy, 2003; Jermann and Quadrini, 2006; Covas and Den Haan, 2011; Begenau and Salomao; 2018) and different liquidity regimes (see Gertler and Glichrist, 1994). We use a percentile approach to split Chinese firms into seven-size portfolios according to their book value of assets ($BV\ Assets_{i,t}$). That is a crucial step, as firms' size impacts their financing ability both in surge and retrenchment periods of capital flows. The underlying reason is that easing and tightening of financing conditions have a different impact on firms according to their size. For instance, the greater access to direct financing of large firms than small ones makes the latter much more sensitive to variations in banks' lending constraints. Also, since banks typically deem smaller firms riskier, they are normally charged higher lending rates than their larger counterparts. Therefore, everything else constant, less risk-averse banks would proportionally lend more to small firms than to large ones, because of the greater earning potential.

#### 2.4.2.4 The creation of industry portfolios

We also divide our sample firms according to their industry (see Appendix A.2.2, for details on the Chinese industrial classification). That is also an important step, as firms' industry determines their reliance on external debt and their likelihood of receiving a loan during periods of expanded liquidity. In particular, several scholars such as Rey (2013), Shin (2012) found evidence of a boost in asset prices during capital inflow surges. That could decrease the risk of some procyclical industries and increase their profitability, raising their likelihood of receiving bank lending. We also collect industry data from Wind for all the firms in our sample.

### *2.4.2.5 Financial and macroeconomic control variables*

We also included several financial and macroeconomic control variables that could affect bank lending, hence explain the variation in debt financing not explained by capital inflows and accounting variables. Macroeconomic control variables include controls for domestic monetary policy[13], Consumer Price Index (CPI), and 10-year sovereign bond yields (which we collected from CEIC). We argue that higher sovereign risk will harm bank lending. That is because higher yields directly transmit to the banking sector through the collateral channel. An increase in yields decreases the value of banks' bond holdings and the value of government guarantees, increasing banks' risk of default (Acharya et al., 2014), which inevitably feeds back to the private sector through lower loans. Likewise, Acharya et al. (2014) also hypothesised a similar relationship, identifying an almost one-to-one relationship between sovereign risk and domestic banks' insolvency risk.

We also add the banking sector and financial sector's specific control variables such as Chinese banks' profitability (ROA) (available from the CEIC) and Chinese stock market fundamentals (also gathered from CEIC). For the latter set of variables, we include as fundamentals Chinese stock market capitalisation (computed as the sum in Shanghai and Shenzhen end-of-quarter stock market capitalisations) and volatility (standard deviation of end-of-the-day stock market capitalisation in each quarter).

## 2.5 Summary Statistics

In this Section, we provide a detailed overview of the data adopted in our study. To assess the relationship between capital inflows and debt financing growth, we start by performing a correlation analysis of debt financing, capital inflows, and our key control variables (see Table

[13] Since China uses a mix of price- and quantity-based monetary policies. We created an indicator of Chinese monetary policy following Girardin et al. (2017). For more details on the calculation of this variable see Appendices A.2.5 and A.2.6.

2.1). Afterward, we analyse the pairwise correlation between debt financing and capital inflows in China, splitting our sample into seven size portfolios and ten industry groups (see Tables 2.2 and 2.3). We also provide standard summary statistics on the variables adopted in our study, which we display in Appendix A.2.4.

In Table 2.1, we observe a positive correlation between capital inflows and domestic monetary policy. Higher capital inflows lead PBOC to tighten its monetary policy and negatively correlated with stock market indicators, both capitalisation, and volatility. That is consistent with the idea that foreign investors buy when investment is cheap and low volatility. As predicted by the capital flows' literature, they are positively correlated with both Bank ROA, coherently with a risk-taking channel, while negatively correlated with Chinese economic fundamentals and inflation. We observe a negative correlation between our monetary policy variable and stock market measures and inflation, as well as with Chinese fundamentals. Stock market fundamentals appear instead negatively correlated with bank's ROA, suggesting a substitution effect between debt and equity financing, and positively correlated with Chinese inflation. Ultimately, also the remaining correlation coefficients reveal as significant and with the expected signs.

Table 2.2 analyses the pairwise correlation between debt growth and capital inflows at the industry level. Coherently with the literature on cross-country capital flows (Rey, 2013; Broner, 2013; Shin, 2012), capital inflows are positively correlated with domestic country credit growth, but credit growth tends to be very heterogeneous across industries. In our study, we do not find a significant correlation (at 5 percent level) between debt financing growth and capital inflows for 'agriculture, forestry and fishing' ('1'), 'finance and insurance activities' ('6'), and other service activities' ('10'). On the contrary, more cyclical industries[14] that are well-known to receive more significant investment when risk appetite increases have high

[14] Such as mining, construction, manufacturing, IT, and real estate.

correlation coefficients, which appears consistent with hypothesised greater "risk-taking channel." The remaining industries react to capital inflow surges by increasing their debt, but their correlation coefficients are smaller (about 8 percent).

We also assess the correlation between debt financing and capital inflows controlling for firms' size (see Table 2.3). We observe positive and significant correlation coefficients across all size percentiles except the top one, which implies a considerable heterogeneity in financing across size groups. In particular, we observe that the lowest quartile has the highest correlation coefficient (about 13 percent), hence three times higher than the average (4 percent). Eventually, correlation coefficients are not significant in the largest-size portfolios. Overall, exploring the relationship between leverage and firms' size, we find a significant negative correlation between the two variables. Similar works also pointed to a relatively higher synchronisation of small firms' external debt financing with domestic liquidity and the business cycle (see Gertler and Glichrist, 1994; Jermann and Quadrini, 2006; Covas and Den Haan, 2011; Begenau and Salomao, 2018).

[Insert Tables 2.1, 2.2, and 2.3 around here]

## 2.6 Findings

Following the approach outlined in Section 2.4, we analyse firms' financing behaviour during capital inflow surges. Since both financing and banks' funding depend on the size and industry characteristics of the credit recipient, when performing this analysis, we benchmark each firm's attributes to the median of the industry portfolio to which the firm belongs (see Table 2.4) and their relative size (see Table 2.5).

In Table 2.4, we present the results obtained by estimating Equation [2.1], exploiting industry-level differences in median performance. We find that growth in debt financing (scaled by assets) is positively associated with capital inflows-over-GDP with a coefficient of about 2.3 percent in all our regressions (see Table 2.4 columns (1), (2), and (3)). Afterward, we compare firms' financing decisions with their accounting fundamentals to gain an insight into evidence of more significant banks' risk-taking. We find that firms with lower profitability (expressed in terms of lower cash flows-over-assets) receive higher credit over the whole period than their industry peers. In particular, switching from non-profitable to profitable firms, we can observe a decrease in the geometric mean of debt financing (scaled by assets) of about 32 percent. Looking at the interaction term between capital inflows and firms' fundamentals, hence at whether during capital inflow surges firms with more robust accounting fundamentals receive more credit, we find a negative marginal effect (of about -4 percent). That implies less profitable firms are more likely to receive credit during capital inflow surges. These appear significantly in line with what we anticipated in the correlation analysis (Section 2.3.3). The remaining control variables of solvency measure or investment opportunities are instead insignificant. These results provide evidence of a link between foreign capital inflows in China and its build-up of corporate sector debt. As hypothesised, during capital inflow surges, riskier companies receive more credit than their safer industry-level counterparts. In columns (3) and (4), we supplement our baseline regression with several macroeconomic, financial, and banking sector control variables.

Macroeconomic control variables enable us to control for the domestic monetary policy stance (the MPI), hence addressing endogeneity concerns that could arise from the impact of PBOC monetary policy on banks' credit growth. Financial control variables help us control the cost of direct financing in equity markets (Shanghai and Shenzen Stock Exchanges). Variables of bank performance (Banks ROA) instead provide a "litmus test" for our story. Since the lower is the aggregate profitability of the Chinese banking sector, the higher would be banks' incentive to exploit greater foreign liquidity for profit maximisation. Almost all the variables' coefficients appear statistically significant and with the expected signs. PBOC monetary policy is negatively associated with debt financing, with a coefficient of about -34 percent in column (3) and -25 percent in column (4). We do not find evidence of a switch between debt and equity financing, as our stock market capitalisation variable has a positive and significant coefficient in column (3). At the same time, it is instead non-significant in column (4), and stock market volatility is also non-significant. These results are not rare in periods of expanded liquidity, as both bank credit and risk appetite contemporaneously grow and share prices boom. Finally, we included 10-year government bond yields (representing Chinese credit risk), which inversely move with Chinese bonds' prices, directly affecting banks' collateral values, hence their central bank loans or loans from other banks in the interbank market. Therefore, as expected, this measure has a negative and significant sign, as higher yields imply lower loanable capital and vice versa.

[Insert Table 2.4 around here]

Calculating Equation [2.1] this time benchmarking firms with their closest size peers, we find very similar results to those just described (see Table 2.5). In all specifications, capital inflows positively affect firms' increases in debt. The coefficients are statistically and economically significant with a magnitude of 2.3 percent (as in Table 2.4). Greater profitability (than other firms with similar size) appears negative and significant with a coefficient of about -30 percent. Once we interact this variable with international capital inflows (scaled by GDP), the interaction coefficient is still negative and significant, with a value of about -4 percent. Therefore, increases in capital inflows in China lead to a marginal increase in lending to less profitable firms in the analysis period. As in Table 2.4, control variables for firms' solvency and Tobin's q are not significant. Likewise, financial and macroeconomic control variables yield qualitatively the same results as those reported in Table 2.4. We also tested several more specifications of this model, and all of them produce similar results.

[Insert Table 2.5 around here]

### 2.6.1 *Capital inflows and leverage developments in procyclical and capital-intensive industries*

In this subsection, we assess the impact of capital inflows on corporate debt in the industries displaying the most outstanding procyclicality and capital intensity.

We start by defining procyclicality as the average correlation between the average leverage of firms in each industry and China's GDP growth. We consider procyclical industries with a correlation between leverage and business cycle in the top quartile ([75;100 percent]). Afterwards, we re-estimate Equation [2.1] for this group of firms. As in all our baseline regressions, when looking at firms' leverage, we benchmark it to the medial leverage of firms in the same industry (Table 2.6) or the same size (Table 2.7) of those in consideration.

In Table 2.6, we find that a one percent increase in capital inflows lead to an almost double increase in leverage (the coefficient of 'CIF' is slightly smaller than the corresponding for the whole sample). We find an average negative correlation between profitability and solvency, and leverage. In particular, more significant capital inflows lead to more credit to less solvent firms (the interaction between profitability and capital inflows is not significant in this setting). Greater investment opportunities (Tobin's Q) lead to greater leverage (i.e., more obtained financing). Firms with better investment opportunities receive 5 percent more credit during capital inflows surges than their less attractive counterparts. Overall, there seems to be some evidence of "toxic" credit to insolvent firms in times of high capital inflows. Still, the effect of capital inflows on firms' leverage in procyclical industries appears comparable to (and not more substantial than) that observed for the whole sample.

The effect appears much stronger than that observed for the whole sample when considering capital-intensive industries, characterised by firms with an average PPE-to-asset ratio in the top quartile. In Table 2.6, capital inflows affecting these firms lead to an average of about two and a half times more leverage growth in firms operating in capital intensive industries. A one percent increase in capital inflows leads to an eleven percent more debt to less profitable firms. That provides strong evidence of credit misallocation, remarkably stronger in firms operating in capital intensive industries. Less intense instead for firms operating in procyclical industries (as stated in HP 3).

Our results are unchanged in both statistical and economic significance if we benchmark firms accounting fundamentals to the firm's size peers rather than industry ones (see Table 2.7). We find support for a positive effect of international capital flows on creating corporate sector leverage both in procyclical and capital-intensive industries. The result, though, is substantially less strong for procyclical industries than for capital intensive ones. Insolvent firms and firms with higher investment opportunities in procyclical industries receive more credit than their more solvent size peers (profitability is not significant) when capital inflows increase. In capital intensive industries, greater capital inflows lead less profitable firms to receive substantially more credit than profitable ones of similar size. Also, in this case, we find support for greater credit to more capital-intensive industries (as hypothesised in HP 3). We find less conclusive evidence for a stronger transmission of capital inflows to procyclical industries instead. Again, we observe clear evidence of credit misallocation that appears consistent with banks' greater risk-taking and confirm our second hypothesis.

[Insert Tables 2.6 and 2.7 around here]

### 2.6.2 *Capital inflows and leverage of small and large firms*

Ultimately, in Table 2.8, we separately estimate Equation [2.1] for each size percentile available in our dataset. As hypothesised in HP 4, we find that the expansive effect of capital inflows leads to a significantly higher corporate debt growth in small firms (except for firms in the [90-95] percentile). Firms in the bottom 25 percent group experience the most remarkable increase in leverage in response to capital inflows. Except for the firms in the [90-95] percentile, we observe that capital inflows are associated with smaller and smaller increases in leverage as the firm size increases. That culminates with a negative and economically significant coefficient of -2.4 percent increase in leverage associated with a one percent capital inflow growth that we observe for the top 1 percent size portfolio. That indicates that different from what we observe for small firms, where capital inflow are associated with greater access to debt financing (procyclical debt financing), the external financing behaviour of the largest firms display a counter-cyclical behaviour. That provides strong support for our hypothesised more extraordinary transmission of an expansion in credit availability to the smallest firms categories and with previous findings on the pro- (counter-)cyclicality of debt financing of small (large) firms (Covas and Den Haan, 2011; Begenau and Salomao, 2018).

[Insert Tables 2.8 around here]

## 2.7 Robustness checks

This section presents several of the robustness checks that we perform to validate our baseline results.

We start by testing the validity of our results to an alternative measure of capital inflows, i.e., current account imbalances (see Tables 2.9 and 2.10). Similar to capital inflows, a current account surplus expands the recipient country domestic liquidity or, at least, it contributes to the creation of an income stock that the recipient country can use to finance its investment in the following periods[15]. This makes it commonly used to assess financial integration and cross-country capital inflows[16]. Therefore, we re-estimated Equation [2.1], replacing CIF-to-GDP with the quarterly change in the current account balance (CAB)-to-GDP

[15] In the standard balance of payments (BOP) structure, a net current account value corresponds to an equivalent value arising in the country capital account (capital and financing accounts in IMF data)

[16] In this paper, we share the view that current account imbalances are imperfect measure of capital inflows, popular in current debate of the relevant literature on the topic. We agree that "current account patterns are largely silent about the role a country plays in international borrowing, lending and financial intermediation" (Borio and Disyatat, 2015:1), since the current account reveals the saving pattern of a country, not its financing. Moreover, as argued by the authors, investment is not driven by countries' savings, but their financing, which is a gross measure, not a net one. Therefore, looking at the current account, it is possible to see whether a country attracts from (or release resources to) foreign investors, but we cannot assess whether the spending is financed from home or abroad (Borio and Disyatat, 2015). Therefore, we chose to use gross capital inflows in our baseline regression.

(we kept all the other variables unchanged). Examining the results of Tables 2.9 and 2.10, we can argue that our previous findings are confirmed. Therefore, we find evidence of a link between capital inflows (i.e., negative variations of Chinese current account balance) and credit growth. In particular, we find that an increase in the current account deficit leading to an almost 3 percent credit growth in the private sector (see columns (1) and (2) of Tables 2.9 and 2.10). This finding is in line with previous work from Reinhart and Rogoff (2008), Gourinchas and Obstfeld (2012), pointing to a strong relationship between current accounts deficit and credit growth (widely associated with financial and banking crises). Assessing the theorised risk-taking channel, using our previous dummy variables for firms' profitability, solvency, and investment opportunities, which we benchmark to firms' industry and size peers. We find slightly different results from those of the previous section. Therefore, we still find banks to lend to firms that are less profitable than their benchmark in the whole period. However, looking at the interaction term, we also observe a marginal increase in lending to profitable firms when capital inflows rise. This coefficient is significant in columns (2) and (3) of Table 2.6, while just in column (2) of Table 2.10. On the contrary, in both Tables, we find that more significant capital inflows increase lending to more insolvent firms (with a lower z-score). In particular, a one percent increase in capital inflows is associated with a 4 percent greater of banks' lending to entities closer to bankruptcy than the size or industry benchmark. That is consistent with the previous findings of our baseline regressions.

[Insert Tables 2.9 and 2.10 around here]

We also robustify our results by adding several more variables identifying profitability and risk. Following Iosifidi and Kokoas (2015), as additional performance measures, we included firms' return on assets (ROA) and the natural logarithm of firms' market value of equity, a forward-looking indicator of firms' performance. As measures of risk, we computed the volatility of firms' return on assets, calculated as a 12-quarters rolling standard deviation of

ROA, and firms' premium for risk (Sharpe ratio). Our conclusions again are unchanged. Capital inflows are indeed still highly positively correlated with an increase in firms' debt in all our regressions, with a coefficient of 2.3 in both Table 2.11 and Table 2.12. We find that banks lend to less profitable firms on average, and a marginal increase in capital inflows worsens this phenomenon ($\beta_6$ is negative and about -4 percent). We also observe that more profitable firms" have a lower geometric mean of debt financing of about 4 percent in both Tables; the coefficients are, however, not significant. Firm risk, proxied by the standard deviation of ROA, is significant and positive, both in the whole period and in moments of growth in capital inflows. A one percent increase in capital inflows is associated with more lending to firms with more volatile ROA (the coefficient is 2 percent in Table 2.11 and about 3 percent in Table 2.12). Both these measures support the existence of a risk-taking channel.

[Insert Tables 2.11 and 2.12 around here]

To further support a supply-driven change in debt financing of Chinese firms, we re-run our baseline regressions instrumenting CIF-over-GDP with Chinese banks loans to the non-financial sector (see Table 2.13). Therefore, we exclude from this regression also all firms in the financial industry. The results are consistent with our baseline findings. Current bank loans are associated with higher debt growth over assets of Chinese firms in all our regressions. In particular, a 1 percent increase in bank loans lead to about 0.7 percent growth in firms' debt-over-assets. The coefficient has a lower magnitude than that of capital inflows-over-GDP in Tables 2.4 and 2.5. Still, it presents an identical sign, implying that a significant amount of private-sector debt is intermediated through bank loans (approximately 70 percent, as stated in Song and Xiong, 2018). Our baseline regressions used several dummy variables to compare individual firms with their industry peers. As far as firm fundamentals are concerned, our profitability dummy is again the variable with the highest explanatory power since neither the Z-score nor Tobin's q is significant in any regressions. In particular, interacting *d_prof* with the log of bank loans, we can observe that the marginal effect of an increase in bank loans leads to higher lending to firms with better fundamentals. That suggests that higher bank lending (i.e., with higher private sector debt) in standard times is associated with better accounting fundamentals. That leads us to conclude that, in normal times, lending does not seem driven by risk-taking incentives, different to periods of capital inflow surges, when firms with lower profitability receive instead more credit.

[Insert Table 2.13 around here]

Ultimately, to add further robustness to our results, we test whether the hypothesised risk-taking channel is more present during episodes of procyclicality of cross-country capital inflows to the business cycle. Several scholars and policymakers, including Araujo et al. (2017) and Shin (2016), found gross capital inflows to ease domestic lending standards in the host country, especially when capital flows are procyclical. Other authors (see Behn et al. (2016), Danielsson et al. (2001), Kashyap and Stein (2004), Repullo and Suarez (2012)) explained the procyclicality of lending as linked to capital requirements regulation, establishing capital charges on banks as based on institutions' asset risk. Therefore, as asset risk is sensitive to the economic condition, this implies that banks' capital availability (and thus lending) is more accessible (as capital charges are lower) in periods of economic expansion than in recession periods. When gross capital inflows are procyclical, these expand the business cycle and boost asset prices (Rey, 2013). That increases banks' lending capacity through Behn et al.'s (2016) regulatory-driven procyclicality of banks' financing. Therefore, evidence of a positive relationship between the cyclical component of capital inflows and corporate debt would support a bank-driven transmission channel.

To compute procyclicality, we firstly retrieved the cyclical components of capital inflows (CIF) and of quarter-to-quarter GDP growth (since CIF is a quarter-to-quarter flow measure) using a Hodrick-Prescott filter (with $\lambda$=1600) – see Figure 2.3. As evident from

Figure 2.3, the two variables have a positive correlation, which equals 58.28 percent, significant at 1 percent level. Secondly, we computed the 12 quarters rolling window correlation between CIF and GDP growth, which we substituted our baseline regression model instead of the first lag of *log(CIF/GDP)*. Eventually, we re-run our baseline regressions[17].

The results presented in Table 2.14 are coherent with our hypotheses. Greater capital inflows procyclicality is associated with greater firms' leverage. Moreover, the marginal effect of an increase in procyclicality is more lending to firms with weaker fundamentals (less profitable and more insolvent). This finding is confirmed both across industry and size. In other words, we conclude that capital inflow procyclicality stimulates a risk appetite of banks, which lend to more risky customers. The observed change increase in private sector leverage is very likely bank-driven, as opposed to firm-driven.

[Insert Figure 2.3 around here]

[Insert Table 2.14 around here]

We perform several additional robustness specifications, even if we do not display the results in the manuscript. These include estimations using variations in the fixed-effect structure; estimates of our baseline regression using firms' age rather than size, or sectors rather than industries; the consideration of stock rather than flow measures of capital inflows, or of net capital flows (calculated as capital inflows minus outflows) rather than capital inflows. The results are in all specifications unaffected.

## 2.8 Conclusions

Using an extensive firm-level panel dataset, this paper analyses international capital flows in China between 2005 and 2016. Starting from previous evidence on the relationship between

[17] In the regressions, we computed the Z-score using Leaven and Levine (2009) formula. This would help us to avoid multicollinearity arising from an identical rolling-window computation of most of our explanatory variables.

capital inflows, expanded domestic liquidity, and risk-taking, our main contribution lies in developing a methodology that empirically found an association between foreign capital inflows and corporate sector debt during the Chinese Corporate Debt Crisis. In other words, this study provides an insight into the real effects of global capital inflows on the Chinese corporate sector.

Specifically, we find that a 1 percent increase in capital inflows (scaled by GDP) leads to about a 2.3 percent increase in corporate sector debt, a result which we find robust in several empirical settings (e.g., splitting the sample by size, industry, and age). This result, we believed to be driven by an expansion of domestic liquidity (as suggested by Blanchard et al. (2017)). That leads not only to a more significant domestic debt (as found by Rey (2013), Shin (2012), and many others), but also to higher risk-taking of banks (as proposed by Minsky (1992), Acharya and Naqvi (2012), and Ioannidou et al., (2014)). To assess risk-taking and inefficiencies arising from the Chinese government implicit guarantee, we individually benchmark our sample of Chinese firms to their industry or size peers according to numerous risk and profitability measures. Our results are that less profitable firms receive more credit both overall and during surges in capital inflows. In particular, we find that a marginal increase in capital inflows leads to about 4 percent greater lending to less profitable (than the benchmark). All our regressions find support for this result. We also performed several robustness tests. We included additional profitability and risk measures (e.g., ROA, the standard deviation of firms ROA, and market value of equity) and replaced capital inflows with current account imbalances. Our findings are still unchanged.

Overall, our paper closely relates to the previous literature on capital flows, such as Rey (2013) and Shin (2012), among others. In the peculiar Chinese context, heavily relying on a few state-owned banks for liquidity transmission, we argue that capital inflow surges unsustainably expand banks' loanable funds leading to the build-up of excessive corporate sector debt. The combination of greater bank liquidity from foreign investors and the implicit bailout guarantee of most Chinese banks leads to greater lending, especially to less credit-worthy customers. Therefore, our results suggest that the excessive credit in China, vastly discussed by academics and policymakers, could result from a risk-taking channel originating from banks' greater liquidity during capital inflow surges and enhancing the corporate sector's credit risk. That suggests the need for stricter supervision of banks' credit when capital inflows intensify.

We also acknowledge the limitations of our methodology. As a matter of fact, despite the many robustness tests, the lack of loan-level data for China do not allow this study (or any other study) a precise identification of banks' lending volumes to the private sector. Iosifidi and Kokoas (2015) did excellent work identifying firm-bank lending transactions and the potential risks involved. Their identification strategy relies on a dataset of US syndicated loans available from DealScan, matched with firms' accounting risk measures. Unfortunately, the vast under-reporting and opacity of Chinese state-owned entities make this data impossible to obtain for China. That makes research on this topic much scarcer and more difficult. Therefore, greater transparency is quintessential for a better knowledge of international capital flows transmission to the real economy and for a better understanding of the impact of central government coordination and implicit guarantees on the build-up of unsustainable corporate debt levels.

# Tables

**Table 2.1 Correlation Analysis**

Table 2.1 presents the correlations matrix containing our key country-level explanatory variables: capital inflows-over-GDP, stock market capitalisation and volatility, Banks ROA, Inflation, Sovereign Bond Yields and our key explanatory and control variables. Underneath the Table, we explain how we assigned the stars reported next to the correlation coefficients. Coefficients have been marked with ***, **, and * when significant at 10, 5, and 1 percent levels.

| | CIF | mpi | Stock Mkt Cap | Mkt vol | Banks ROA | Sov. Yields | Δlog(CPI) |
|---|---|---|---|---|---|---|---|
| CIF | 1 | | | | | | |
| mpi | 0.090*** | 1 | | | | | |
| Stock Mkt Cap | -0.344*** | -0.338*** | 1 | | | | |
| Mkt vol | -0.634*** | -0.001** | 0.503*** | 1 | | | |
| Banks ROA | 0.211*** | 0.070*** | -0.207*** | -0.244*** | 1 | | |
| Sov. Yields | 0.106*** | -0.541*** | -0.052*** | -0.183*** | -0.551*** | 1 | |
| Δlog(CPI) | -0.176*** | -0.290*** | 0.773*** | 0.209*** | 0.259*** | -0.322*** | 1 |

**Table 2.2 Pair-wise correlation between leverage growth and capital inflows (split by industry)**

Table 2.2 reports pair-wise correlations between the debt financing of firms and the first lag of capital inflows-over-GDP. In the Table, we split firms according to their industry to observe the correlation between the two variables taking into account the impact of firms' industry on their received lending. Finally, we marked with two stars correlation coefficients that are significant at 5 percent level.

| Industry | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| corr (CIF, Lev. ratio) | 0.05 | 0.08** | 0.08** | 0.08** | 0.08** | 0.05 | 0.06** | 0.08** | 0.08** | 0.06 |

**Table 2.3 Pair-wise correlation between leverage growth and capital inflows (split by size)**

Table 2.3 reports pair-wise correlation coefficients between firms' debt financing and the first lag of capital inflows-over-GDP. Using a percentile approach, we allocated firms to one of the seven size groups reported in the Table at each point in time. Splitting firms according to their size, we observe the correlation between the two variables considering the impact of firm size on debt financing. Finally, we marked with two stars correlation coefficients that are significant at 5 percent level.

| Size | [0-0.25] | [0.25-0.5] | [0.5-0.75] | [0.75-0.9] | [0.9-0.95] | [0.95-0.99] | [0.99-1] |
|---|---|---|---|---|---|---|---|
| corr (CIF, Lev. ratio) | 0.129** | 0.076** | 0.044** | 0.016 | 0.006 | -0.001 | 0.026 |

**Table 2.4 Baseline regression – industry-level results**

Table 2.4 reports Equation 2.1 results, which we present decomposed into four columns. In column 4, we display the estimation results, including all control variables and fixed effects in the regression. However, we omit the coefficients of our control variables and fixed effects for graphical reasons but only present those of our main explanatory variables. d_prof, d_Z, and d_Q are calculated respectively as the difference between a firm profitability, solvency, and investment opportunities and the corresponding industry median. In this regression, we add to our variables of interest several macro-economic control variables and firm, time, and size fixed effects. Note that, in Appendix A.2.3, we describe all the variables displayed in this Table and their calculation. We also report the coefficients' standard errors in round-brackets underneath each regression coefficient. Finally, coefficients have been marked with ***, **, and * when significant at 10, 5, and 1 percent levels.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Lev. ratio | Lev. ratio | Lev. ratio | Lev. ratio |
| CIF | 2.334*** | 2.335*** | 2.302*** | 2.298*** |
| | (0.033) | (0.034) | (0.033) | (0.033) |
| *Core firm fundamentals:* | | | | |
| d_prof | | -0.324*** | -0.323*** | -0.314*** |
| | | (0.048) | (0.047) | (0.047) |
| d_prof * CIF | | -0.043*** | -0.043*** | -0.041*** |
| | | (0.011) | (0.010) | (0.010) |
| d_Z | | -0.024 | -0.010 | -0.010 |
| | | (0.046) | (0.045) | (0.045) |
| d_Z * CIF | | -0.004 | -0.002 | -0.001 |
| | | (0.010) | (0.010) | (0.010) |
| d_Q | | -0.016 | -0.014 | -0.014 |
| | | (0.046) | (0.045) | (0.045) |
| d_Q* CIF | | -0.004 | -0.003 | -0.003 |
| | | (0.010) | (0.010) | (0.010) |
| Constant | 9.398*** | 9.495*** | -91.203*** | 18.141 |
| | (0.159) | (0.163) | (10.281) | (17.450) |
| Firm FE | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes |
| Size FE | No | No | No | Yes |
| Fin. markets fundamentals controls | No | No | Yes | Yes |
| Macroeconomic fundamentals controls | No | No | No | Yes |
| Obs | 78,469 | 78,469 | 64,607 | 64,607 |
| R-squared | 0.208 | 0.215 | 0.090 | 0.091 |

**Table 2.5 Baseline regression – size-level results**

Table 2.5 reports Equation 2.1 results, which we present decomposed into four columns. In column 4, we display the estimation results, including all control variables and fixed effects in the regression. However, we omit the coefficients of our control variables and fixed effects for graphical reasons but only present those of our main explanatory variables. d_prof, d_Z, and d_Q are calculated respectively as the difference between a firm profitability, solvency, and investment opportunities and the corresponding median of firms in the same size percentile. In this regression, we add to our variables of interest several macro-economic control variables and firm, time, and size fixed effects. Note that, in Appendix A.2.3, we describe all the variables displayed in this Table and their calculation. We also report the coefficients' standard errors in round-brackets underneath each regression coefficient. Finally, coefficients have been marked with ***, **, and * when significant at 10, 5, and 1 percent levels.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Lev. ratio | Lev. ratio | Lev. ratio | Lev. ratio |
| CIF | 2.334*** | 2.335*** | 2.297*** | 2.297*** |
| | (0.033) | (0.034) | (0.033) | (0.033) |
| *Core firm fundamentals:* | | | | |
| d_prof | | -0.339*** | -0.319*** | -0.319*** |
| | | (0.048) | (0.047) | (0.047) |
| d_prof * CIF | | -0.047*** | -0.043*** | -0.043*** |
| | | (0.011) | (0.010) | (0.010) |
| d_Z | | 0.013 | 0.025 | 0.025 |
| | | (0.046) | (0.045) | (0.045) |
| d_Z * CIF | | 0.005 | 0.007 | 0.007 |
| | | (0.010) | (0.010) | (0.010) |
| d_Q | | -0.032 | -0.012 | -0.011 |
| | | (0.046) | (0.045) | (0.045) |
| d_Q* CIF | | -0.008 | -0.003 | -0.003 |
| | | (0.010) | (0.010) | (0.010) |
| Constant | 9.398*** | 9.489*** | -91.460*** | 18.507 |
| | (0.159) | (0.163) | (10.282) | (17.456) |
| Firm FE | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes |
| Industry FE | No | No | No | Yes |
| Fin. markets fundamentals controls | No | No | Yes | Yes |
| Macroeconomic fundamentals controls | No | No | No | Yes |
| Obs | 78,469 | 78,469 | 64,607 | 64,607 |
| R-squared | 0.208 | 0.214 | 0.090 | 0.090 |

**Table 2.6 Baseline regression – industry-level results**

Table 2.6 reports Equation 2.1 results estimated for procyclical and capital-intensive industries. In column 4, we display the estimation results, including all control variables and fixed effects in the regression. However, we omit the coefficients of our control variables and fixed effects for graphical reasons but only present those of our main explanatory variables. d_prof, d_Z, and d_Q are calculated respectively as the difference between a firm profitability, solvency, and investment opportunities and the corresponding industry median. In this regression, we add to our variables of interest several macro-economic control variables and firm, time, and size fixed effects. Note that, in Appendix A.2.3, we describe all the variables displayed in this Table and their calculation. We also report the coefficients' standard errors in round-brackets underneath each regression coefficient. Finally, coefficients have been marked with ***, **, and * when significant at 10, 5, and 1 percent levels.

| | Procyclical Industries Leverage | | | | Capital Intensive Industries Leverage | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (1) | (2) | (3) | (4) |
| | Lev. ratio | Lev. ratio | Lev. ratio | Lev. ratio | Lev. ratio | Lev. ratio | Lev. ratio | Lev. ratio |
| CIF | 1.743*** | 1.741*** | 1.056*** | 1.077*** | 2.397*** | 2.412*** | 2.430*** | 2.424*** |
| *Core firm fundamentals:* | | | | | | | | |
| d_prof | | -0.263* | -0.269* | -0.253* | | -0.630*** | -0.769*** | -0.761*** |
| d_prof * CIF | | -0.038 | -0.040 | -0.035 | | -0.092*** | -0.117*** | -0.115*** |
| d_Z | | -0.287** | -0.206 | -0.196 | | -0.017 | 0.055 | 0.056 |
| d_Z * CIF | | -0.062** | -0.044† | -0.041 | | -0.003 | 0.013 | 0.013 |
| d_Q | | 0.231* | 0.189 | 0.191 | | 0.064 | -0.033 | -0.031 |
| d_Q* CIF | | 0.049* | 0.043 | 0.043 | | 0.015 | -0.008 | -0.007 |
| Constant | 6.645*** | 6.693*** | 11.244 | -35.484 | 10.208*** | 10.433*** | -90.442*** | 25.704 |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Size FE | No | No | No | Yes | No | No | No | Yes |
| Fin. markets fundamentals controls | No | No | Yes | Yes | No | No | Yes | Yes |
| Macroeconomic fundamentals controls | No | No | No | Yes | No | No | No | Yes |
| Obs | 10,417 | 10,417 | 8,256 | 8,256 | 27,501 | 27,501 | 21,497 | 21,497 |
| R-squared | 0.189 | 0.193 | 0.035 | 0.038 | 0.172 | 0.186 | 0.141 | 0.141 |

**Table 2.7 Baseline regression – size-level results**

Table 2.7 reports Equation 2.1 results estimated for procyclical and capital-intensive industries. In column 4, we display the estimation results, including all control variables and fixed effects in the regression. However, we omit the coefficients of our control variables and fixed effects for graphical reasons but only present those of our main explanatory variables. d_prof, d_Z, and d_Q are calculated respectively as the difference between a firm profitability, solvency, and investment opportunities and the corresponding industry median. In this regression, we add to our variables of interest several macro-economic control variables and firm, time, and size fixed effects. Note that, in Appendix A.2.3, we describe all the variables displayed in this Table and their calculation. We also report the coefficients' standard errors in round-brackets underneath each regression coefficient. Finally, coefficients have been marked with †, ***, **, and * when significant at 15, 10, 5, and 1 percent levels.

| | Procyclical Industries Leverage | | | | Capital Intensive Industries Leverage | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (1) | (2) | (3) | (4) |
| | Lev. ratio | Lev. ratio | Lev. ratio | Lev. ratio | Lev. ratio | Lev. ratio | Lev. ratio | Lev. ratio |
| CIF | 1.743*** | 1.745*** | 1.095*** | 1.095*** | 2.397*** | 2.431*** | 2.450*** | 2.450*** |
| *Core firm fundamentals:* | | | | | | | | |
| d_prof | | -0.282** | -0.287** | -0.288** | | -0.714*** | -0.831*** | -0.831*** |
| d_prof * CIF | | -0.041 | -0.044 | -0.044 | | -0.113*** | -0.133*** | -0.133*** |
| d_Z | | -0.318** | -0.235* | -0.235* | | -0.050 | -0.014 | -0.014 |
| d_Z * CIF | | -0.069** | -0.050† | -0.050 | | -0.012 | -0.004 | -0.004 |
| d_Q | | 0.236* | 0.248* | 0.249* | | 0.068 | 0.056 | 0.056 |
| d_Q* CIF | | 0.053* | 0.053* | 0.053* | | 0.017 | 0.013 | 0.013 |
| Constant | 6.645*** | 6.718*** | -34.864 | -35.202 | 10.208*** | 10.509*** | 25.769 | 25.766 |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry FE | No | No | No | Yes | No | No | No | Yes |
| Fin. markets fundamentals controls | No | No | Yes | Yes | No | No | Yes | Yes |
| Macroeconomic fundamentals controls | No | No | No | Yes | No | No | No | Yes |
| Obs | 10,417 | 10,417 | 8,256 | 8,256 | 27,501 | 27,501 | 21,497 | 21,497 |
| R-squared | 0.189 | 0.193 | 0.034 | 0.034 | 0.172 | 0.186 | 0.140 | 0.140 |

**Table 2.8 Baseline regression for each size group**

Table 2.8 reports Equation 2.1 results, which we estimate separately for each of the defined size percentiles. Each regression includes all control variables and fixed effects. However, we omit the coefficients of our control variables and fixed effects for graphical reasons but only present those of our main explanatory variables. d_prof, d_Z, and d_Q are calculated respectively as the difference between a firm profitability, solvency, and investment opportunities and the corresponding industry median. In this regression, we add to our variables of interest several macro-economic control variables and firm, time, and size fixed effects. Note that, in Appendix A.2.3, we describe all the variables displayed in this Table and their calculation. We also report the coefficients' standard errors in round-brackets underneath each regression coefficient. Finally, coefficients have been marked with †, ***, **, and * when significant at 15, 10, 5, and 1 percent levels.

| Size groups | [0-25%] | [25-50%] | [50-75%] | [75-90%] | [90-95%] | [95-99%] | [99-100%] |
|---|---|---|---|---|---|---|---|
| | Lev. ratio | Lev. ratio | Lev. ratio | Lev. ratio | Lev. ratio | Lev. ratio | Lev. ratio |
| CIF | 3.271*** | 2.125*** | 1.872*** | 0.313** | 3.078*** | -0.154 | -2.386*** |
| *Core firm fundamentals:* | | | | | | | |
| d_prof | -0.438*** | -0.424*** | -0.137* | -0.301*** | -0.270* | -0.291 | -0.051 |
| d_prof * CIF | -0.044 | -0.065*** | -0.009 | -0.045* | -0.036 | -0.048 | -0.010 |
| d_Z | -0.041 | -0.135 | -0.010 | -0.006 | -0.158 | -0.021 | 0.118 |
| d_Z * CIF | -0.005 | -0.033* | -0.003 | -0.003 | -0.035 | -0.005 | 0.024 |
| d_Q | 0.154 | -0.083 | 0.112 | -0.018 | 0.065 | -0.120 | 0.274 |
| d_Q* CIF | 0.032 | -0.017 | 0.025 | 0.001 | 0.013 | -0.027 | 0.066 |
| Constant | 52.241* | 253.355*** | -552.523*** | 546.967*** | -1.331 | -384.304*** | 1,084.950*** |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Fin. markets fundamentals controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Macroeconomic fundamentals controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Obs | 14,905 | 15,996 | 16,227 | 10,171 | 3,463 | 2,741 | 1,104 |
| R-squared | 0.194 | 0.094 | 0.053 | 0.018 | 0.189 | 0.033 | 0.352 |

**Table 2.9 Baseline regression using current account balance – industry-level results**

Table 2.9 reports Equation 2.1 results, which we present decomposed into four columns. In column 4, we display the estimation results, including all control variables and fixed effects in the regression. However, we omit the coefficients of our control variables and fixed effects for graphical reasons but only present those of our main explanatory variables. d_prof, d_Z, and d_Q are calculated respectively as the difference between a firm profitability, solvency, and investment opportunities and the corresponding industry median. In this regression, we add to our variables of interest several macro-economic control variables and firm, time, and size fixed effects. Note that, in Appendix A.2.3, we describe all the variables displayed in this Table and their calculation. We also report the coefficients' standard errors in round-brackets underneath each regression coefficient. Finally, coefficients have been marked with ***, **, and * when significant at 10, 5, and 1 percent levels.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Lev. ratio | Lev. ratio | Lev. ratio | Lev. ratio |
| CIF_CA | -2.908*** | -2.946*** | -2.560*** | -2.561*** |
| | (0.032) | (0.036) | (0.035) | (0.035) |
| *Firm fundamentals:* | | | | |
| d_prof | | -0.272*** | -0.130*** | -0.135*** |
| | | (0.022) | (0.020) | (0.020) |
| d_prof * CIF_CA | | 0.171*** | 0.031 | 0.035* |
| | | (0.021) | (0.020) | (0.020) |
| d_Z | | 0.028 | 0.049** | 0.048** |
| | | (0.021) | (0.019) | (0.019) |
| d_Z * CIF_CA | | -0.024 | -0.049*** | -0.048*** |
| | | (0.020) | (0.019) | (0.019) |
| d_Q | | -0.017 | -0.029 | -0.028 |
| | | (0.021) | (0.019) | (0.019) |
| d_Q* CIF_CA | | 0.015 | 0.030 | 0.029 |
| | | (0.020) | (0.019) | (0.019) |
| Constant | 2.126*** | 2.216*** | 49.966*** | 46.018*** |
| | (0.046) | (0.049) | (1.699) | (5.068) |
| Firm FE | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes |
| Size FE | No | No | No | Yes |
| Fin. markets fundamentals controls | No | No | Yes | Yes |
| Macroeconomic fundamentals controls | No | No | No | Yes |
| Obs | 93,419 | 93,419 | 79,550 | 79,549 |
| R-squared | 0.214 | 0.218 | 0.091 | 0.092 |

**Table 2.10 Baseline regression using current account balance – size-level results**

Table 2.10 reports Equation 2.1 results, which we present decomposed into four columns. In column 4, we display the estimation results, including all control variables and fixed effects in the regression. However, we omit the coefficients of our control variables and fixed effects for graphical reasons but only present those of our main explanatory variables. d_prof, d_Z, and d_Q are calculated respectively as the difference between a firm profitability, solvency, and investment opportunities and the corresponding median of firms in the same size percentile. In this regression, we add to our variables of interest several macro-economic control variables and firm, time, and size fixed effects. Note that, in Appendix A.2.3, we describe all the variables displayed in this Table and their calculation. We also report the coefficients' standard errors in round-brackets underneath each regression coefficient. Finally, coefficients have been marked with ***, **, and * when significant at 10, 5, and 1 percent levels.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Lev. ratio | Lev. ratio | Lev. ratio | Lev. ratio |
| CIF_CA | -2.908*** | -2.964*** | -2.555*** | -2.555*** |
| | (0.032) | (0.036) | (0.035) | (0.035) |
| *Firm fundamentals:* | | | | |
| d_prof | | -0.278*** | -0.122*** | -0.122*** |
| | | (0.022) | (0.020) | (0.020) |
| d_prof * CIF_CA | | 0.180*** | 0.025 | 0.025 |
| | | (0.021) | (0.020) | (0.020) |
| d_Z | | 0.042** | 0.060*** | 0.061*** |
| | | (0.021) | (0.020) | (0.020) |
| d_Z * CIF_CA | | -0.043** | -0.064*** | -0.064*** |
| | | (0.020) | (0.019) | (0.019) |
| d_Q | | -0.057*** | -0.038* | -0.037* |
| | | (0.021) | (0.020) | (0.020) |
| d_Q* CIF_CA | | 0.057*** | 0.040** | 0.040** |
| | | (0.020) | (0.019) | (0.019) |
| Constant | 2.126*** | 2.234*** | 50.011*** | 46.935*** |
| | (0.046) | (0.049) | (1.699) | (5.065) |
| Firm FE | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes |
| Industry FE | No | No | No | Yes |
| Fin. markets fundamentals controls | No | No | Yes | Yes |
| Macroeconomic fundamentals controls | No | No | No | Yes |
| Obs | 93,419 | 93,419 | 79,550 | 79,549 |
| R-squared | 0.214 | 0.218 | 0.091 | 0.091 |

**Table 2.11 Baseline regression using additional risk and profitability measures – industry-level results**

Table 2.11 reports Equation 2.1 results, which we present decomposed into five columns. In column 5, we display the estimation results, including all control variables and fixed effects in the regression. However, we omit the coefficients of our control variables and fixed effects for graphical reasons but only present those of our main explanatory variables. d_prof, d_Z, and d_Q are calculated respectively as the difference between a firm profitability, solvency, and investment opportunities and the corresponding industry median. As 'Additional firm fundamentals', we include in this Table d_σ(ROA), d_Sharpe, and d_ROA; dummy variables that take a value of 1 if a firm is more profitable (or risky) than the corresponding industry median. In this regression, we add to our variables of interest several macro-economic control variables and firm, time, and size fixed effects. Note that, in Appendix A.2.3, we describe all the variables displayed in this Table and their calculation. We also report the coefficients' standard errors in round-brackets underneath each regression coefficient. Finally, coefficients have been marked with ***, **, and * when significant at 10, 5, and 1 percent levels.

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | Lev. ratio | Lev. ratio | Lev. ratio | Lev. ratio | Lev. ratio |
| CIF | 2.334*** | 2.332*** | 2.325*** | 2.287*** | 2.283*** |
| | (0.033) | (0.034) | (0.035) | (0.034) | (0.034) |
| *Core firm fundamentals:* | | | | | |
| d_prof | | -0.323*** | -0.323*** | -0.323*** | -0.314*** |
| | | (0.048) | (0.048) | (0.047) | (0.047) |
| d_prof * CIF | | -0.043*** | -0.043*** | -0.043*** | -0.041*** |
| | | (0.011) | (0.011) | (0.010) | (0.010) |
| d_Z | | 0.040 | 0.041 | 0.049 | 0.050 |
| | | (0.044) | (0.044) | (0.043) | (0.043) |
| d_Z * CIF | | 0.009 | 0.009 | 0.011 | 0.011 |
| | | (0.010) | (0.010) | (0.009) | (0.009) |
| d_Q | | -0.045 | -0.068 | -0.062 | -0.059 |
| | | (0.044) | (0.046) | (0.045) | (0.045) |
| d_Q* CIF | | -0.011 | -0.016 | -0.014 | -0.013 |
| | | (0.010) | (0.010) | (0.010) | (0.010) |
| Constant | 9.398*** | 9.474*** | 9.438*** | -91.223*** | 18.321 |
| | (0.159) | (0.163) | (0.167) | (10.282) | (17.451) |
| Firm FE | Yes | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes |
| Size FE | No | No | No | No | Yes |
| Additional firm fundamentals | No | No | No | No | Yes |
| Fin. markets fundamentals controls | No | No | Yes | Yes | Yes |
| Macroeconomic fundamentals controls | No | No | No | Yes | Yes |
| Obs | 78,469 | 78,469 | 78,469 | 64,607 | 64,606 |
| R-squared | 0.208 | 0.215 | 0.215 | 0.091 | 0.091 |

**Table 2.12 Baseline regression using additional risk and profitability measures – size-level results**

Table 2.12 reports Equation 2.1 results, which we present decomposed into five columns. In column 5, we display the estimation results, including all control variables and fixed effects in the regression. However, we omit the coefficients of our control variables and fixed effects for graphical reasons but only present those of our main explanatory variables. d_prof, d_Z, and d_Q are calculated respectively as the difference between a firm profitability, solvency, and investment opportunities and the corresponding median of firms in the same size percentile. As 'Additional firm fundamentals', we include in this Table d_σ(ROA), d_Sharpe, and d_ROA; dummy variables that take a value of 1 if a firm is more profitable (or risky) than the corresponding size group median. In this regression, we add to our variables of interest several macro-economic control variables and firm, time, and size fixed effects. Note that, in Appendix A.2.3, we describe all the variables displayed in this Table and their calculation. We also report the coefficients' standard errors in round-brackets underneath each regression coefficient. Finally, coefficients have been marked with ***, **, and * when significant at 10, 5, and 1 percent levels.

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | Lev. ratio | Lev. ratio | Lev. ratio | Lev. ratio | Lev. ratio |
| CIF | 2.334*** | 2.339*** | 2.310*** | 2.274*** | 2.274*** |
| | (0.033) | (0.034) | (0.035) | (0.034) | (0.034) |
| *Core firm fundamentals:* | | | | | |
| d_prof | | -0.340*** | -0.337*** | -0.319*** | -0.319*** |
| | | (0.048) | (0.048) | (0.047) | (0.047) |
| d_prof * CIF | | -0.047*** | -0.046*** | -0.043*** | -0.043*** |
| | | (0.011) | (0.011) | (0.010) | (0.010) |
| d_Z | | 0.032 | 0.029 | 0.033 | 0.033 |
| | | (0.044) | (0.044) | (0.043) | (0.043) |
| d_Z * CIF | | 0.004 | 0.004 | 0.005 | 0.005 |
| | | (0.010) | (0.010) | (0.009) | (0.009) |
| d_Q | | -0.065 | -0.104** | -0.073 | -0.074 |
| | | (0.044) | (0.046) | (0.045) | (0.045) |
| d_Q* CIF | | -0.016 | -0.024** | -0.017* | -0.016* |
| | | (0.010) | (0.010) | (0.010) | (0.010) |
| Constant | 9.398*** | 9.498*** | 9.366*** | -91.598*** | 17.696 |
| | (0.159) | (0.163) | (0.168) | (10.281) | (17.456) |
| Firm FE | Yes | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes |
| Industry FE | No | No | No | No | Yes |
| Additional firm fundamentals | No | No | No | No | Yes |
| Fin. markets fundamentals controls | No | No | Yes | Yes | Yes |
| Macroeconomic fundamentals controls | No | No | No | Yes | Yes |
| Obs | 78,469 | 78,469 | 78,469 | 64,607 | 64,606 |
| R-squared | 0.208 | 0.215 | 0.215 | 0.091 | 0.091 |

**Table 2.13 Bank lending behaviour unaffected by capital inflows**

Table 2.13 reports Equation 2.1 results, in which we substituted the variable CIF with log(Bank Loans). In columns 3 and 6, we display the estimation results, including all control variables and fixed effects in the regression. However, we omit the coefficients of our control variables and fixed effects for graphical reasons but only present those of our main explanatory variables. d_prof, d_Z, and d_Q are calculated respectively as the difference between a firm profitability, solvency, and investment opportunities and the corresponding median of firms in the same industry or size percentile. As 'Additional firm fundamentals', we include in this Table d_σ(ROA), d_Sharpe, and d_ROA; dummy variables that take a value of 1 if a firm is more profitable (or risky) than the median of the corresponding industry or size group. In this regression, we add to our variables of interest several macro-economic control variables and firm, time, and size fixed effects. Note that, in Appendix A.2.3, we describe all the variables displayed in this Table and their calculation. We also report the coefficients' standard errors in round-brackets underneath each regression coefficient. Finally, coefficients have been marked with ***, **, and * when significant at 10, 5, and 1 percent levels.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Lev. ratio | Lev. ratio | Lev. ratio | Lev. ratio | Lev. ratio | Lev. ratio |
| | | **Industry Split** | | | **Size Split** | |
| log(Bank Loans) | 0.753*** | 0.684*** | 0.672*** | 0.753*** | 0.683*** | 0.665*** |
| | (0.011) | (0.013) | (0.013) | (0.011) | (0.012) | (0.013) |
| *Core firm fundamentals:* | | | | | | |
| d_prof | | -0.898*** | -0.906*** | | -0.937*** | -0.938*** |
| | | (0.064) | (0.064) | | (0.063) | (0.064) |
| d_prof * log(Bank Loans) | | 0.082*** | 0.082*** | | 0.086*** | 0.086*** |
| | | (0.007) | (0.007) | | (0.007) | (0.007) |
| d_Z | | 0.067 | 0.020 | | -0.075 | -0.005 |
| | | (0.056) | (0.062) | | (0.056) | (0.062) |
| d_Z * log(Bank Loans) | | -0.007 | -0.002 | | 0.008 | 0.001 |
| | | (0.006) | (0.007) | | (0.006) | (0.007) |
| d_Q | | -0.078 | -0.010 | | 0.042 | -0.008 |
| | | (0.056) | (0.062) | | (0.056) | (0.062) |
| d_Q* log(Bank Loans) | | 0.008 | 0.001 | | -0.004 | 0.001 |
| | | (0.006) | (0.007) | | (0.006) | (0.007) |
| Constant | -7.650*** | -6.936*** | -6.796*** | -7.650*** | -6.904*** | -6.733*** |
| | (0.105) | (0.118) | (0.125) | (0.105) | (0.117) | (0.126) |
| Obs | 93,608 | 93,608 | 93,608 | 93,608 | 93,608 | 93,608 |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Size FE | No | Yes | No | No | No | No |
| Industry FE | No | No | No | No | Yes | No |
| Additional firm controls | No | No | Yes | No | No | Yes |
| Fin. markets controls | No | No | Yes | No | No | Yes |
| Macroeconomic controls | No | No | Yes | No | No | Yes |
| Obs | 93,608 | 93,608 | 93,608 | 93,608 | 93,608 | 93,608 |
| R-squared | 0.141 | 0.149 | 0.149 | 0.141 | 0.149 | 0.149 |

**Table 2.14 Debt financing in periods of procyclical capital inflows**

Table 2.14 reports Equation 2.1 results, in which we substituted the variable CIF with the correlation between capital inflows and the quarter-to-quarter change in Chinese GDP [corr (CIF, ΔGDP)]. In columns 2 and 3, we display the estimation results, including all control variables and fixed effects in the regression. However, we omit the coefficients of our control variables and fixed effects for graphical reasons but only present those of our main explanatory variables. d_prof, d_Z, and d_Q are calculated respectively as the difference between a firm profitability, solvency, and investment opportunities and the corresponding median of firms in the same industry or size percentile. In this regression, we add to our variables of interest several macro-economic control variables and firm, time, and size fixed effects. Note that, in Appendix A.2.3, we describe all the variables displayed in this Table and their calculation. We also report the coefficients' standard errors in round-brackets underneath each regression coefficient. Finally, coefficients have been marked with ***, **, and * when significant at 10, 5, and 1 percent levels.

| | (1)<br>Lev. ratio | (2)<br>Lev. ratio | (3)<br>Lev. ratio |
|---|---|---|---|
| | | **Industry Split** | **Size Split** |
| corr(CIF, ΔGDP) | 0.056*** | 0.056*** | 0.056*** |
| | (0.001) | (0.001) | (0.001) |
| *Core firm fundamentals:* | | | |
| d_prof | | -0.112*** | -0.114*** |
| | | (0.008) | (0.008) |
| d_prof * corr(CIF, ΔGDP) | | -0.002*** | -0.002*** |
| | | (0.000) | (0.000) |
| d_Z | | 0.021** | 0.011 |
| | | (0.009) | (0.009) |
| d_Z * corr(CIF, ΔGDP) | | -0.001*** | -0.001* |
| | | (0.000) | (0.000) |
| d_Q | | -0.009 | -0.004 |
| | | (0.007) | (0.007) |
| d_Q* corr(CIF, ΔGDP) | | 0.000 | 0.001* |
| | | (0.000) | (0.000) |
| Constant | -1.774*** | -1.690*** | -1.685*** |
| | (0.021) | (0.022) | (0.022) |
| Firm FE | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes |
| Fin. markets controls | No | No | Yes |
| Macroeconomic controls | No | No | Yes |
| Obs | 95,242 | 95,242 | 95,242 |
| R-squared | 0.144 | 0.151 | 0.151 |

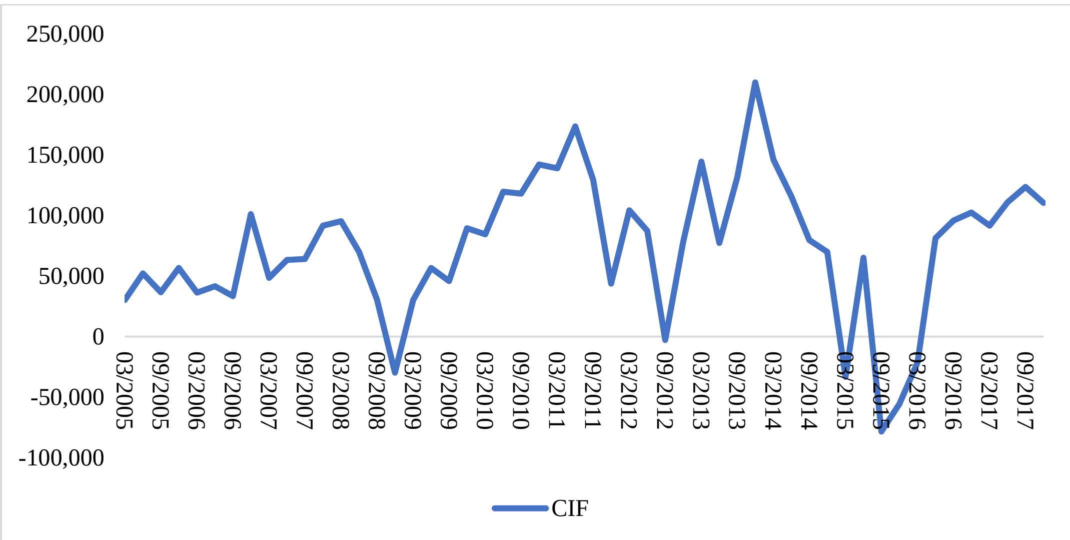
# Figures

**Figure 2.1 Assets and Liabilities positions of Chinese banks**


*Notes.* Figure 2.1 represents global cross-country positions of the World vis-à-vis China taking place in the form of foreign banks' claims on China – left-hand side graph – and Chinese financial institutions credit – on the right-hand side.

*Sources:* BIS Consolidated Banking Statistics (LHS graph), BIS Credit to the non-financial sector (RHS graph). Units: millions of US dollars (LHS graph), billions of RMB (RHS graph).

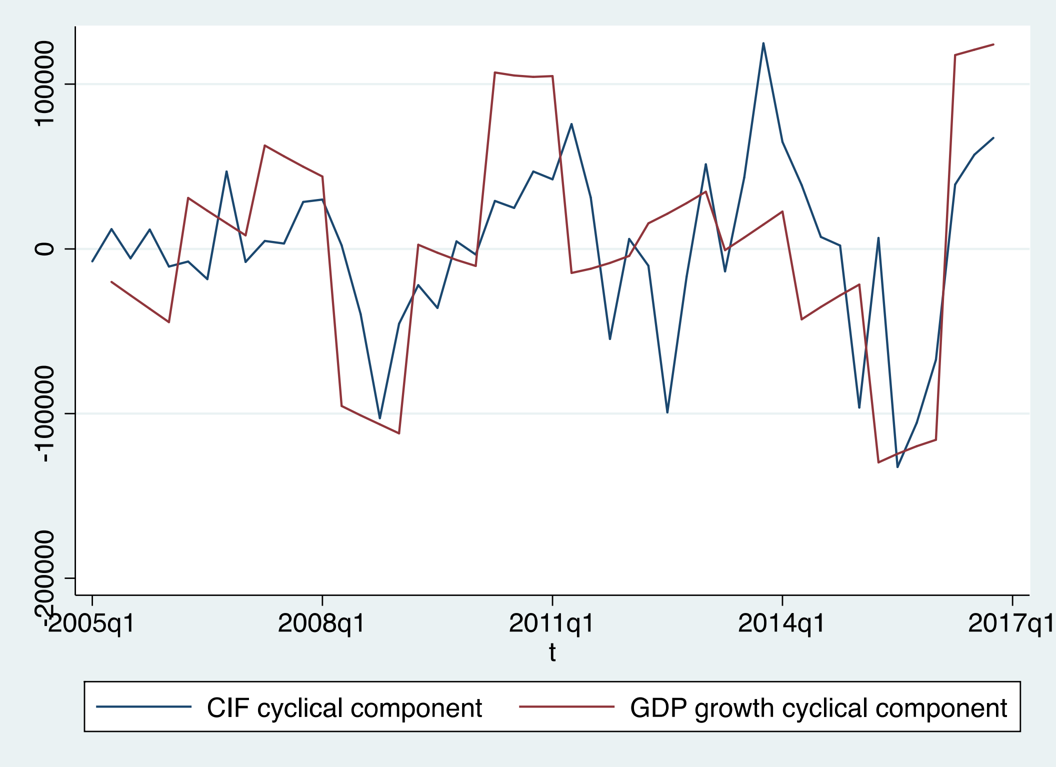
**Figure 2.2 Capital Inflows in China**




*Notes.* Figure 2.2 pictures international capital inflows in Mainland China. In the graph, the blue line represents Capital Inflows (liabilities of China) denominated in millions of USD.

*Sources.* IMF IFS and author's own calculations.

**Figure 2.3 Capital Inflows in China vis-à-vis China's business cycle**




*Notes.* In Figure 2.3, we show the Hodrick-Prescott cyclical components of CIF and quarter-to-quarter GDP growth from the beginning of 2005 to the end of 2016.

*Sources.* IMF IFS and author's own calculations.

# 3 Risk, Financial Stability and FDI[18]

## 3.1 Introduction

Over the past decade, Foreign Direct Investment (FDI) stock has grown markedly, rising almost 65% at a global level. This led to an increasing awareness on behalf of policymakers as to its role as a source of economic growth. For example, in 2016, FDI accounted for 35% of global GDP (Carril-Caccia & Pavlova, 2018; Neto & Veiga, 2013). The Euro Area (EA) has been both a key recipient of FDI investments and an important FDI supplier. This has been attributed not only to the elimination of transaction costs and exchange risk in the reallocation of capital between members of the monetary union (Lane & Milesi-Ferretti, 2008; Darvas et al., 2013), but also to an increase in international investors' confidence in its financial institutions and supervisory bodies (Shatz & Venables, 2000). In the aftermath of the Global Financial Crisis (GFC), worries about fiscal sustainability in the EA intensified (Merler and Pisani-Ferry, 2012; Arghyrou & Kontonikas, 2012; Bernoth & Erdogan, 2012; Afonso et al., 2014, 2018) as risks in the banking sector fed back to the sovereign position and *vice versa*, generating a detrimental cycle (De Bruyckere et al., 2013; Acharya et al., 2014a; Delatte et al., 2017). As a result, in the run-up of the sovereign debt crisis, the EA experienced significant capital outflows.

In this context, our paper examines how sovereign and banking sector risks that accumulated during the crises affected FDI in the EA. More specifically, we dissect the effect of sovereign and banking risk in origin (foreign investors) and host countries (EA), which we consider as main drivers of investors' capital allocation in the period of analysis. We draw from several strands of the literature on FDI in scenarios of crisis (e.g., Milesi-Ferretti & Tille, 2010;

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[18] The work of this Chapter is based on the article ,"Risk, Financial Stability and FDI" published in the Journal of International Money and Finance by myself, Neil Kellard, Alexandros Kontonikas, Michael Lamla and Geoffrey Wood (DOI: https://doi.org/10.1016/j.jimonfin.2020.102232).

Weitzel et al., 2014; Darvas et al., 2013; Habib and Venditti, 2018; Acharya et al., 2007; Carril-Caccia & Pavlova, 2018; Sondermann & Vansteenkiste, 2019), as well as work on investment allocation during the sovereign debt crisis (e.g., Beck et al., 2016; Weitzel et al., 2014). However, our approach extends the empirical literature on FDI that typically considers just domestic factors as drivers for foreign investment (e.g., Carril-Caccia & Pavlova, 2018; Dellis et al., 2016; Razin & Sadka, 2007). By contraposing banking and sovereign stress in the country where FDI originates (i.e., the origin country) with the corresponding recipient country of FDI (i.e., the host), our paper isolates the impact that EA countries' sovereign and banking risk have on their ability to attract FDI from other factors, whilst also considering the relative importance of origin countries' domestic risk. Moreover, we provide evidence on cross-country spillovers arising from sovereign and banking sectors' stress and the transmission to the Euro Area through FDI. From a methodological perspective, we argue that the modelling of the EA constitutes *per se* an ideal setting for our empirical analysis, given all countries in the European Monetary Union (EMU) have a common currency and monetary policy, which mutes the effect from monetary transmission and allows for a cleaner identification of variations in the financial account of the Balance of Payments.

The empirical analysis employs a large panel dataset from the IMF Coordinated Foreign Direct Investment Survey (IMF CDIS) on 112 countries FDI stock positions between 2009 and 2016, which we adopt to identify inward FDI in the EA. The main advantage of this dataset is that disaggregating countries' FDI positions using their immediate counterpart, the CDIS data allows for a cross-country and over time comparison of FDI positions (Damgaard & Elkjaer, 2017). We subsequently match the obtained data on bilateral FDI positions with bank and sovereign risk measures for host and origin countries. Additionally, we control for all the standard gravity variables commonly used in extant literature on international FDI (e.g., Martin & Rey, 2004; Portes & Rey, 2005; Daude & Fratzscher, 2008).

Our empirical work yields three main findings. Firstly, we observe that an increase in non-performing loans-over-total loans – widely employed in the banking literature (see Aiyar & Monaghan, 2015) to test banking sector stability – in the origin country leads to a decrease in FDI. However, importantly, changes in the corresponding bank risk in host countries leaves inward-FDI unaffected. Secondly, we find that FDI responds negatively to upturns in sovereign yields both in origin as well as host countries, arguing that (i) an increase in origin country sovereign yield encourages corporate sector Multinational Enterprises (MNEs) to engage in less risk-taking, whilst (ii) an increase in host country yield implies that other destinations appear more attractive. Additionally, when the EA sample is separated into subsamples of non-stressed and stressed (GIIPS: Greece, Ireland, Italy, Portugal and Spain) countries, these findings are confirmed, reinforcing our confidence regarding the identified transmission channels. In a nutshell, what we find is that economic conditions – including financial stability – in origin countries particularly matters for FDI. Here, the key point is the identification of a spillover effect of risk in origin countries to the Euro Area through FDI. Finally, we re-affirm findings in the literature related to the importance of economic and financial ties in investment and financing decisions, embedded in standard gravity variables.

Overall, we identify four main strands of the FDI literature to which our work relates. Firstly, there is a wide range of literature affirming the importance of economic and financial ties in investment and financing decisions, embedded in standard gravity models. These results find a common root in both the literature on institutional affinity (see Shukla & Cantwell, 2018), or on transaction costs, whereby *ceteris paribus*, countries' geographical closeness or common cultural background considerably reduces informational and transaction costs, therefore affecting FDI decisions (Martin & Rey, 2004; Portes & Rey, 2005; Daude & Fratzscher, 2008; Beck et al., 2016; Lane & Milesi-Ferretti, 2008; Sondermann & Vansteenkiste, 2019). Other factors similarly popular in this literature consist of proxies for institutional quality (see Dellis et al., 2017), as well as identifiers of incentives for regulatory or tax evasion (see Damgaard et al., 2018; Haufler et al., 2018; Egger et al., 2018). In our paper, we include standard gravity variables adopted by the previous literature, as well as additional variables which are specific to the context of crisis under consideration. Secondly, we draw from a limited number of studies that consider the response of FDI to macroeconomic shocks arising during crises. These include studies on the Asian financial crisis (Aguiar and Gopinath, 2005; Acharya et al., 2007), the Latin American financial crisis (Krugman, 2000), other emerging markets crises (Alquist et al., 2013), and the GFC and sovereign debt crisis (Demertzis & Pontuch, 2013; Forster et al., 2011; Darvas et al., 2013; Beck et al., 2016; Sondermann & Vansteenkiste, 2019). Thirdly, we contribute to studies on the sovereign debt crisis and determinants of euro-area sovereign bond yield spreads (vs. German bunds), which are commonly viewed as key indicators of crisis intensity (Arghyrou & Kontonikas, 2012; Bernoth & Erdogan, 2012; Afonso et al., 2014, 2018). Such studies investigate the role of banking risk in transforming the GFC into sovereign debt crisis, and consequently, the nexus between banking risk and sovereign risk (De Bruyckere et al., 2013; Acharya et al., 2018; Delatte et al., 2017). Finally, a set of studies on FDI considers the EMU membership and its impact on the ability of its composing countries to attract FDI (see Shatz & Venables, 2000; Carril-Caccia & Pavlova, 2018; Sondermann & Vansteenkiste, 2019).

The rest of the paper is structured as follows: in Section 3.2 we further explore the theoretical and empirical background that motivates our study. In Section 3.3, we explain the proposed methodology. In Section 3.4, we provide an exhaustive description of our dataset and the underlying literature justifying our choices. The empirical results are presented in Section 3.5. In Section 3.6, we present robustness tests and, in Section 3.7, the conclusions.

## 3.2 Theoretical and empirical background

The recent crises experienced by countries in the Euro Area, as well as the GFC, provided non-trivial evidence on the effect of bank credit cycles on economic growth, and fiscal and financial stability (Shin, 2012; Rey, 2013; Habib & Venditti, 2018). The build-up (and subsequent decline) of bank credit growth has been detrimental for domestic economies and a crucial predictor of crisis, and also largely synchronised on a global scale (Shin, 2012; Rey, 2013; Banti & Phylaktis, 2019). Similarly, in the context of the sovereign debt crisis, sovereign yields increased in numerous countries and regions. Several authors found evidence of contagion arising from spillovers from stressed EA countries sovereign risk across the EA (see Claeys & Vašícek, 2014) and other advanced and emerging economies (Beirne & Fratzscher, 2013).

In light of the above evidence, it becomes interesting to distinguish between origin and host countries' financial conditions when analysing the determination of inward FDI in the Euro Area. To do so, our paper newly hypothesises that both host and origin countries' conditions are relevant determinants of cross-country transmission of global FDI. In particular, we posit that greater risk in the origin country's banking sector (observed using the outstanding amount of non-performing loans as a ratio of total bank loans) is expected to depress FDI in the EA. This can be interpreted as a 'leverage channel', whereby firms borrow from banks *in their home country* to finance investment, including FDI. This effect will be stronger for firms wishing to invest overseas where imperfect knowledge considerations are greater. According to this argument, credit availability[19] is an important determinant of FDI. The importance of credit cycles for the real economy (Bernanke & Gertler, 1990; Bordo & Jeanne, 2002; Chen et al., 2012) has led to attempts by policymakers to tame them. Similarly, we assume that in origin

[19] Arguments related to the importance of credit availability for M&As, also called brownfield FDI, have been put forward by Harford (2005), amongst others. As described by Harford (2005), brownfield FDI could depend on industry, technological and regulatory shocks, which in the latter case included Basel regulation on banks' capital requirements, but also on the availability of "capital liquidity to accommodate the asset reallocation" (Harford, 2005, p. 530).

countries, greater sovereign credit risk (observed by examining the yields of 10-year national government bonds) will encourages the corporate sector MNEs to engage in less risk-taking. This is due to a stronger motive for companies to hoard cash for precautionary motives (see Akguc & Choi, 2013). Different precautionary motives have been explored by the finance literature, such as higher uncertainty about future cash flows (Bacchetta et al., 2014) or the future macro-economic conditions (Gao & Grinstein, 2014). Analogously, recent work has identified higher cash holdings and less investment generally due to financial crises (Campello et al., 2010; Pinkowitz et al., 2013; Song & Lee, 2012).

As far as the host country is concerned, we assume that greater banking risk (i.e., greater banks' non-performing loans) will also discourage foreign investment in the EA. In this respect, a comprehensive literature already exists on the impact of host countries economic fundamentals on inward FDI (Cai et al., 2018; Bevan and Estrin, 2004; Bellak et al., 2009; Dellis et al., 2017; for a review see Antonakakis and Tondl, 2011). Analogously, we hypothesise that periods of high sovereign yields will lead to lower inward FDI in the EA, via a credit risk channel. This is consistent with existing evidence, which uses sovereign credit ratings as a proxy for sovereign risk, and shows that rating changes affect investment (Chen et al., 2013) and direct investment (Cai et al., 2018). In other words, we expect that when credit risk is higher, this will make investment in the EA less attractive to foreign investors than investments in other, less risky foreign countries. Both our measures of banking and sovereign risk have been widely used by academics, practitioners and policy makers in their periodic assessment of a country credit risk (and financial stability) – especially during the years of the sovereign debt crisis and immediately afterwards. Therefore, these provide an ideal proxy for investors' assessment (both of origin and host countries) of the outstanding financial stability risk in the EA for our sample period.

## 3.3 Methodology

To analyse the effects of risk and financial stability on FDI, we build a panel dataset including all available bilateral holdings of origin and host countries. Specifically, the dataset contains information on the end-of-the-year positions of 112 foreign direct investor countries in 16 EA countries[20] over the period ranging from 2009 to 2016. We take the logarithm of our dependent variable[21], as well as our proxy variables for sovereign and banking risk, and equations (3.1) and (3.2) below show our chosen regression specification:

$$\log\left(FDI_{ih,t}\right) = \alpha + \beta_0 t + \beta_1 \log(Banking\ Risk_t) + \beta_2 G_{ih} + \beta_3 OC_{ih} + \beta_4 \log\left(Taxes_{h,t}\right) + \varepsilon_{ih,t} \qquad \text{[Equation 3.1]}$$

$$\log\left(FDI_{ih,t}\right) = \alpha + \beta_0 t + \beta_1 \log(Sovereign\ Risk_t) + \beta_2 G_{ih} + \beta_3 OC_{ih} + \beta_4 \log\left(Taxes_{h,t}\right) + \varepsilon_{ih,t} \qquad \text{[Equation 3.2]}$$

In the regression equations, *i* is the country of the foreign direct investor (or origin country), while *h* denotes the host country. Our main variables of analysis are $Banking\ Risk_t = \{Banking\ Risk_{i,t}, Banking\ Risk_{h,t}\}$ consisting of banking sector risk origin countries *i* and host countries *h*; and, $Sovereign\ Risk_t = \{Sovereign\ Risk_{i,t}, Sovereign\ Risk_{h,t}\}$ which represents sovereign yields of origin (*i*) and host countries (*h*). $G_{ih}$ includes our set of gravity variables, representing transaction (and information) costs and the cultural bonds connecting the host-origin country pairs. $OC_{ih}$ stands for other control variables (see subsection 3.4.3 Additional risk measure and main controls), accounting for other motives that could drive

[20] As in Beck et al. (2016), we consider all Euro Area (EA) countries with the exception of small countries with large financial sectors (i.e., Malta and Luxembourg) and Lithuania, as it joined the EA in 2015.
[21] As Lane & Milesi-Ferretti (2008), since several observations in the FDI dataset have value of zero. Before taking the *log*, we replaced those values of cross-country FDI with the value of 1 USD. This enable us to preserve the greatest possible amount of observations without affecting the reliability of our results.

direct investment in the EA. *Taxes*$_h$ represents host EA countries tax revenues over GDP, and proxies host countries' fiscal regimes. *t* is instead a time dummy included to account for time fixed-effects causing abnormal variations in FDI. Finally, $\varepsilon_{ih,t}$ represents the error term. We estimate (3.1) and (3.2) using a least squares approach with Huber-Eiker-White robust standard errors, clustered at the bilateral-country level[22].

## 3.4 Data

### 3.4.1 *Dependent variable*

The dependent variable used in our paper is the bilateral FDI holdings of 112 direct investor countries in the Euro Area (EA). In a similar vein to Beck et al. (2016), we compose our dataset using end-of-the-year bilateral FDI in the Euro Area, collected from the IMF Coordinated Foreign Direct Investment Survey (CDIS) between 2009 and 2016.

The CDIS is a dataset published by the IMF in 2010 and updated on an annual basis. It has been created to allow a global analysis of cross-country linkages. In the dataset, the IMF provides data on bilateral direct investment holdings of more than 100 countries, participating in the survey. Moreover, disaggregating countries' FDI positions using their immediate counterpart, the CDIS data allows for a cross-country and over time comparison of FDI positions (Damgaard & Elkjaer 2017). Consequently, we are in a position to observe bilateral direct investment, disentangling effects and drivers of origin and host countries. This allows for a better identification of effects as compared to standard approaches used in the literature which implicitly assumes that host characteristics are the main drivers.

To emphasise, the main advantage of this dataset is that it enables us to disentangle origin and destination of FDI. This is of course necessary in order to be able to test our

[22] Test for the error component structure have been performed using Wooldridge test for serial correlation (Wooldridge 2010) and Pesaran (2004) test for cross-sectional dependence.

hypothesis. Our hypothesis requires use information on the host and origin country simultaneously as determinants of the direct investment. As highlighted in Beck et al. (2016), the understanding of the causes and origins of these foreign investors' positions is of crucial importance for policy makers. For instance, with respect to central bank policy, while intra Euro Area flows can be easily managed by the ECB, significant variations of outside (non-EA) FDI – particularly 'sudden stops' in FDI – could potentially undermine central banks' goals and targets. As a matter of fact, as pointed out by the authors, intra-EA capital allocation can be more easily supervised and managed by the ECB through Target balances and variations in official flows. In the following sections, we exploit the bilateral properties of our data to compare bilateral inward FDI in "stressed" and "non-stressed" Euro Area countries[23] (cf. Table 3.2) from all countries with inward FDI.

Of course, there are some caveats to mention related to the use of this data which we try to minimise. Firstly, FDI data from the CDIS is unadjusted for valuation effects. Secondly, to increase the representativeness of the data, CDIS include data on both listed and unlisted firms, however, different valuation methods, especially for unlisted firms, can generate significant geographical asymmetries in the data (Damgaard & Elkjaer, 2017). Thirdly, data from the CDIS is not adjusted for exchange rate effects. Therefore, changes in stock positions could potentially reflect EUR/USD exchange rate movements. As Beck et al. (2016, p.452) notes, "purging these valuation effects from the stock positions would require detailed knowledge about the currency and maturity composition of the holdings, on which data do not exist." Finally, as the dataset discloses FDI by immediate counterpart economy, it also includes transactions performed by MNEs through Special Purpose Entities (SPEs), often for tax avoidance purposes or financial engineering (Dellis et al. 2017; Damgaard & Elkjaer, 2017;

[23] Defined according to their exposure to the European sovereign debt crisis (see Table 3.7 – Summary Statistics, for reference).

Damgaard et al., 2018; Haufler et al., 2018; Egger et al., 2018). This effect might be greater in smaller countries that have relatively large financial sectors.

Therefore, as remarked on by Beck et al. (2016) and Milesi-Ferretti et al. (2010), ideally we would use a panel dataset collecting consolidated bilateral flows, adjusted for exchange rate effects and recorded on a residence (locational) basis, where "the 'ultimate risk' basis implies that the borrower is the entity ultimately responsible for the liability" (Milesi-Ferretti et al., 2010: 21), but such data does not exist. Thus, to minimise the aforementioned biases and avoid data distortions, following Beck et al. (2016) we exclude countries considered major tax heavens and smaller countries with proportionately large financial sectors and we use stock data.[24] Finally, to mitigate the impact of the exchange rate channel, we build our baseline model 'in levels' and test the robustness of our results to economic growth, using GDP per capita in USD. Note that Table 3.7 presents summary statistics for our dependent variable and risk measures for GIIPS and non-GIIPS Euro Area countries.

For the sake of transparency and completeness, in Figure 3.1, we also present aggregated – non-bilateral – data on FDI flows collected from UNCTAD. Such flow data, unfortunately, does not suit our empirical study due to its opacity regarding the nationality of the foreign direct investor (origin country), limiting its use to a descriptive assessment of FDI behaviour during and after the crisis. Interestingly, looking at FDI inflows in the Euro Area, we observe a substantial drop during the GFC. Subsequently, it appears to stabilise (see Figure 3.1) and stagnate until early 2015, when it surges. Recent work on FDI has also observed this pattern and argued that direct investment appears to differ in its drivers from all other forms of international investments and has proved considerably more resilient than portfolio flows to domestic countries during crises (Milesi-Ferretti & Tille, 2010; Forster et al., 2011; Darvas et al., 2013; Pegkas, 2015; Sondermann & Vansteenkiste, 2019). Several authors observed this

[24] For a detailed overview see Appendix A.3.0.2.

intriguing response of FDI to the crisis. Habib and Venditti (2018) found that FDI is less sensitive to global risk and that it seems to “follow a cycle which is different from other asset classes” (Habib & Venditti, 2018:17). Sondermann and Vansteenkiste (2019) controlled for both the GFC and for the sovereign debt crisis found evidence of a low sensitivity of FDI in the EMU to their domestic crisis dummies. Recent work from Milesi-Ferretti and Tille (2010), considering just the period of the GFC, yielded also similar results. This *per se* seems to provide some validation for our hypotheses on the importance of other factors of risk, other than the domestic ones.

### 3.4.2 *Independent variables*

As said, we focus on specific risks for MNEs involved in FDI. Particularly, we look at financial stability, arising from concerns about a fragile banking sector and high sovereign indebtedness with implications for the overall economy and consequently on the expected investment return (Acharya et al., 2018).

Specifically, as proxy for bank risk taking, we opt for using the ratio of banks non-performing loans-over-total loans (NPL ratio), which measures the outstanding banks credit risk, by quantifying the vulnerable portion of banks’ assets. Hence, this constitutes a straightforward measure of banks’ risk. NPLs affect bank lending through at least three main channels: (i) eroding banks’ profitability, as NPLs generate less income for banks and require more provisions, reducing their net income; (ii) reducing banks available capital, since banks’ capital adequacy regulation require banks to allocate capital buffers proportionally to the risk of their assets; (iii) greater funding costs, arising from the worsening of banks credit profile, as a result of their impaired balance sheet (Aiyar & Monaghan, 2015). European Institutions significantly increased their focus on reducing the level of banks’ non-performing loans of EA banks after the GFC (see Deslandes et al., 2018, for a review of European institutions debate and initiatives on NPLs). Higher NPLs impact the private sector, particularly in countries relying heavily on bank financing such as within the Euro Area, making access to credit harder and more expensive, especially for SMEs (ibid.). Data on non-performing loans ratio is collected from the 'Financial Institutions: Stability' indicators of the World Bank Global Financial Development DataBank.

To measure sovereign risk we use instead 10-year government bond yields. This is a widely agreed proxy for sovereign risk (Arghyrou & Kontonikas, 2012; Bernoth & Erdogan, 2012; Afonso et al., 2014, 2018). Recent works, by e.g. Cai et al. (2018), have examined the relation between sovereign credit ratings and FDI. While using credit ratings is a reasonable measure, we believe that using sovereign bond yields for our purposes is a superior approach, as it reflects the market perspective and should react more quickly to changes in relevant information – see Barroso (2010) and De Vries & de Haan (2016). To maximise our sample coverage, we merge data from IMF International Financial Statistics (IMF IFS), OECD Financial Statistics, CEIC, Oesterreichische Nationalbank, and Bloomberg.

Figure 3.2 shows the evolution of our sovereign and banking risk measures. We observe a decline outside the EA zone and for non-GIIPS countries, whilst for GIIPS countries, sovereign risk increased dramatically until mid-2012. At the peak of the sovereign debt crisis, sovereign yields in GIIPS countries being more than 3 times higher than non-GIIPS ones, and still twice higher at the end of 2016. After the extraordinary commitment from the ECB to stabilise the EMU, spreads began to fall. They remain, however, at elevated levels by the end of our sample period. Non-performing loans-over-total loans also show a similar pattern. Therefore, even if in 2016 non-performing loans of EA banks were still at a much higher than in 2009, we can observe that in 2013, just after the announcement of the Outright Monetary Transactions (OMT) program and the creation of the Banking Union, they either stabilised (in non-GIIPS countries) or substantially reduced (in GIIPS). Moreover, the substantial variation that we detect in both our measures of risk is certainly something that we can exploit in our analysis.

As evident from Figure 3.2, however, neither financial stability risk nor the following recovery is homogeneous across the EA. In particular, sovereign yields and non-performing loans remain considerably higher in GIIPS countries than in non-GIIPS countries, leaving overall risk in the EA at high levels. In light of this, we question whether financial stability risk in EA might just be driven by risk in the former group, rather than in the latter, but then affecting the EA as a whole. To address this empirical question, in our empirical analysis, we test the impact of financial stability risk on inward FDI considering both the EA as a whole and separating it between GIIPS and non-GIIPS countries (see Tables 3.1 and 3.2).

Overall, the implication of these graphs are twofold: on the one hand, they highlights again the importance of the 'regulator' in improving sovereign and banks' safeness – as the ECB Outright Monetary Transactions (OMT) and Quantitative Easing (QE) programs have reduced both EA countries average yields and banks' exposure to NPLs; on the other hand, the graphs also supports the hypothesis of a strong fragmentation within the Euro Area, arising from significant differences in both measures of risk.

### 3.4.3 *Additional risk measure*

For robustness reasons, we re-estimate our models using a different bank risk measure. We select a popular measure that has been frequently used to measure the outstanding risk of banks: banks Regulatory Capital to Risk-Weighted Assets. This, we think that certainly is a focused measure of the stability of each country's banking system, particularly given its contemporary policy attention. Our idea is that if banks are asked to hold more regulatory capital, this will likely have a detrimental impact on the amount lent to firms (Fraisse et al. 2017; De Goede, 2004; Flinders and Buller, 2006; Dovis et al., 2016).

In more detail, Regulatory Capital to Risk-Weighted Assets measures the aggregate amount of core capital allocated by a country's banking sector as a buffer on their risky assets. This variable is commonly used in the banking literature to assess the stability of the banking sector (see De Bruyckere et al. (2013), Afonso et al. (2018), Delatte et al. (2017) and reflects policymakers attempts to address excessive bank risk taking through greater capital buffers. In order to maximise the country sample, we combined data from the IMF Financial Soundness Indicators and World Bank Global Financial Development DataBank.

In Figure 3.3 we observe that, after the GFC, greater worldwide regulation of the banking sector led banks globally to increase the amount of capital allocated as a buffer for their risky assets. The new regulatory frameworks have considerably shrunk the credit availability of banks, hence resulting in lower bank risk taking. Also, in the case of our latter variable, the enhancement of banks solvency appears as especially pronounced post-OMT and Banking Union announcements, which is sign of an improvement in banks safety. However, overall we observe a similar picture to that presented in Figure 3.2, disclosing a significantly higher banking risk in GIIPS countries as opposed to non-GIIPS, represented by much riskier positions of banks (supported by thinner capital buffers).

[Insert Figures 3.1, 3.2 and 3.3 about here]

### 3.4.4 *Main Controls*

Finally, we include in our baseline model several additional control variables. In particular, we include standard gravity model variables, controlling both for information frictions and transaction costs arising from the individual FDI bilateral transactions and for cultural links, arising from a shared historical background of origin and host countries. The inclusion of gravity model variables is a standard practice in the literature on bilateral cross-border investment, especially when studying FDI. Portes & Rey (2005) provide evidence that gravity variables proxying country size and transaction costs – arising from informational frictions differences in technology – might explain up to 83% of bilateral cross-country equity flows (Martin & Rey 2004, Portes & Rey 2005). Daude & Fratzscher (2008) confirm that FDI is much more dependent on informational frictions than portfolio flows. With respect to gravity variables, we follow Lane & Milesi-Ferretti (2008) amongst others and include several control variables, such as: (i) a dummy variable identifying whether the analysed countries share the same official language; (ii) a control for the physical distance between the countries; (iii) a dummy variable disclosing whether the considered countries share a geographical border; (iv) a dummy variable identifying countries with a common religion; (v) a control variable for the time difference between the analysed countries; and (vi) a dummy variable determining country pairs with a common legal origin.

In addition to the gravity variables, we also added supplementary control variables, identifying other potential drivers of FDI. Following Lane & Milesi-Ferretti (2008), we controlled for the trade link between origin and EA countries, using the average bilateral import of the EA from the considered origin countries between 2009 and 2016. While, as suggested by Davis et al. (2000), we included correlation between host and origin countries GDP growth and between host countries' stock market capitalisation and origin countries GDP growth. Specifically, the former variable accounts for diversification incentives (benefits) which could lead origin countries to FDI, while the latter to control for hedging incentives, arising from potential negative output shocks in the origin country. We also control for origin countries wealth and financial sector development, using respectively the second lag of origin countries GDP per capita and financial market capitalisation-over-GDP. This is motivated in the case of wealth by the idea that, as risk aversion is decreasing with wealth, we expect richer countries to be strongly driving FDI (Lane & Milesi-Ferretti, 2008). In the case of financial market development instead, this is based on the assumption that financial sophistication can facilitate foreign investment – see Lane & Milesi-Ferretti (2001). Lastly, since push factors from the home country may include the need to escape domestic taxes or high exchange rate fluctuations, we added a control for host countries fiscal policies, using host countries' government tax revenues-over-GDP, and for exchange rate movements, using the standard deviation of bilateral currencies (for more details on the computation of our control variables, see Appendix A.3.0.1).

## 3.5 Results

In this section, we present and discuss the estimation results of equations (3.1) and (3.2). Table 3.1 contains our main specification where we focus on the two core risk variables – Non-Performing Loans and 10-Year Sovereign Bond Yields. Given the bilateral nature of our data, we estimate for each risk proxy, two equations (3.1) and (3.2), for the origin and host country risk, respectively. Doing this, we can assess which one is the most relevant for FDI, i.e. whether risk in the origin country or in the host country matter the most, or whether they matter in a similar fashion. In Table 3.2, we split our sample into GIIPS and non-GIIPS countries. The separate consideration of our full sample of countries is a standard step performed by literature analysing the geographical pattern of capital flows – see Milesi-Ferretti et al. (2010), Beck et al. (2016) – and is especially crucial for our study. This is justified by the considerable difference that we observe in the levels of sovereign and banking risk within the Monetary Union (see Figure 3.2).

Considering Table 3.1 first of all, the included gravity variables are statistically significant and have the expected sign. In line with the previous literature (Beck et al., 2016; Daude & Fratzscher, 2008; Martin & Rey, 2004; Portes & Rey, 2005), both average import and standard gravity variables – proxying information and transaction costs – are important drivers of FDI. Sharing the same official language and high proximity, increase foreign direct investment. This is testified by *comm_lang* dummy with a coefficient of about 1.4 in both columns (1) and (2) and by the two variables of *log(distance)* and *contig*[25]. The latter variables have respectively coefficients of -0.95 in column (1) (and 0.6 in column (2)) – in the case of *log(distance)* – and 2.10 in column (1) (and 1.37 in column (2)) – for *contig*. All the coefficients are supporting our "story" and are significant at 1% level. Similarly, we found that cultural and institutional affinity also positively affect FDI in the EA. Specifically, having a shared religion or colonisation history positively influence FDI as well as sharing a legal origin. Apart from the common religion dummy, however, the other two variables are mostly found non-significant. Similarly, also not significant appear to be the correlation in host and origin countries GDP growth and government tax revenues-over-GDP, ruling out the diversification incentive as potential driver for FDI, and the tax evasion motif. As expected, we found exchange rate volatility as extremely significant, both economically and statistically, as 1 percent increase in volatility in the origin currencies-over-euro lead to an almost equivalent loss in foreign direct investment in EA countries (the coefficients are -1.17 in column(1) and -0.92 in column (2)).

### 3.5.1 *Country risk impact on FDI*

Considering next the effect of greater non-performing loans in banks' balance sheet on inward FDI – column (1), the origin country coefficient estimate in column (1) is statistically significant and has negative sign (-0.16), implying a reduction of FDI volume invested by MNEs. To the contrary, we observe that the coefficient estimate capturing the risk of host countries is not significant. These results do not confirm our hypothesis, highlighting that origin country risk hugely matters when dealing with FDI. As discussed in Section 3.1, increases in non-performing loans are likely to lead to less credit availability, particularly for firms wishing

[25] We tested our result also using the time difference between host and origin countries, the results are unaffected, and the coefficients are similar to those of the *log(distance)* variable. The two variables have not been included together because of the high correlation between them.

to invest overseas where imperfect knowledge considerations are greater. This matters much more in origin countries, where a closer institutional affinity and familiarity between banks and MNEs may well see more FDI financing take place than in host markets. In other words, our findings present an asymmetric effect across origin and host countries, resulting in FDI in the origin country being predominantly carried out via local banks, hence insensitive to host countries' risk.

Continuing to focus on Table 3.1 and examining 10-year Sovereign Bond Yields, we can observe that both coefficients in column (2) of Table 3.1 are statistically significant and present a negative sign. This implies that higher sovereign risk, both domestically as well as in the host country, results in lower FDI in the Euro Area and confirms the first hypotheses. An increase in either origin or host country sovereign risk, is likely to decrease the FDI of MNEs giving a higher motive for companies to engage in less risk-taking and accumulate more cash holdings. Analogously, recent work has identified higher cash holdings and less investment generally due to financial crises (Song & Lee, 2012). Notably when comparing the magnitude of the coefficient estimates in column (2), we observe that the coefficient of the origin country is bigger than the coefficient of the host country. In particular, our regression model predicts an increase of 1% in 10 years government bonds' yields in origin countries to result in a 1.4 percent decrease in FDI, while an equivalent increase in host countries bond yields to result in a much less strong impact – a 0.46 percent decrease (more than three times smaller). Hence, it appears that origin countries risk is considerably more relevant than that of the host country, also providing evidence of the key role held by banks in financing global FDI – via the so-called *lending channel* – discussed by the existent literature (Bridges et al., 2014; Bacchetta et al., 2014; Harford, 2005; Aiyar & Monaghan, 2015; Fraisse et al., 2017).

In Table 3.2, we have a closer look at the EA countries and split the sample into GIIPS (i.e., stressed) and non-GIIPS (i.e., non-stressed) Euro Area countries. Given the sharper increase of sovereign risk for GIIPS countries over our sample period, the effect of such risk should be more pronounced in GIIPS countries than in non-GIIPS countries. Table 3.2 contains the relevant estimation results. Again, our main hypotheses, are confirmed. We confirm that banking risk and sovereign risk are both relevant. Banking risk is relevant for the origin country only, with respect to non-GIIPS countries (see column (1)), while sovereign risk is important for both origin and host country in all specifications (see column (2)). Surprisingly, the coefficient estimates of our chosen risk variables become larger in absolute magnitude in the non-GIIPS country sub-sample. This might be attributed to foreign investors' awareness of GIIPS greater levels of non-performing loans, hence to a previous embodiment of this piece of information. Undoubtedly, FDI in GIIPS countries, whose banking sector has been severely disrupted by the crises, seem to be also sensitive to an increase in banking sector stability. For example, an increase in banks' capital buffers of 1 percent seem to increase FDI in GIIPS of 0.16 percent. Sovereign yield shocks, among other variables, have instead a much stronger impact on FDI in GIIPS. This is coherent with a much stronger impact that the sovereign debt crisis had on the EA periphery, and with the numerous sovereign rating downgrades that took place in the years of analysis.

This finding of an asymmetric behaviour of FDI in the EA, which came out contraposing direct investment in stressed as opposed to non-stressed EA countries, we believe has very important policy implications. This, as it increases the fragmentation within the European Monetary Union (EMU), both in terms of growth potential and in terms of availability of public finances, putting additional risk on GIIPS countries, hence enhancing political and financial market tensions in the European Union (Beck et al., 2016). Furthermore, this asymmetry between investor behaviour – mostly arising from origin countries – significantly limit ECB capital flow management policies, requiring a narrower and more specific scope.

Several alternative specifications have been estimated, where we added various controls and fixed effects (e.g. we tested all variables in one regression, we excluded intra-EA FDI, and so on). Results are qualitatively unaffected by these alterations and are available on request.

[Insert Tables 3.1 and 3.2 around here]

### 3.6 Robustness

In the paper, we present several robustness tests of our baseline model results.

In Table 3.3 below we include an additional proxy for banking risk discussed previously in Section 3.4.4. Overall, our results and conclusions remain unaffected with further support provided for our hypotheses. In particular, also Regulatory Capital-over-Risk-Weighted Assets confirms that the origin country's, as opposed to the host country's, banking risk situation matters for FDI decisions.

In Table 3.4, we test the possibility that a *hedging incentive* (see in columns (1) and (2)) or greater investors' *risk aversion* are driving FDI positions of origin countries (in columns (3) and (4)) in the Euro Area. Therefore, following Lane & Milesi-Ferretti (2008), Davis et al. (2000), in columns (1) and (2) we add to the baseline models the correlation between host countries financial market capitalisation and origin countries GDP per capita – proxy for a hedging incentives. In case of a hedging channel, we expect to observe the variable to have a negative coefficient, meaning that when domestic conditions in origin countries' financial markets are impaired MNEs have the incentive to invest abroad. This would further support our theory on FDI being driven considerably more by origin country conditions, rather than host country ones. In columns (3) and (4), we test instead the relevance of origin countries' economic wealth as driver for FDI. According to Lane & Milesi-Ferretti (2008), since FDI involves risk, and risk aversion is a decreasing function of economic wealth, greater economic wealth should have a positive impact on origin countries FDI (i.e. richer countries would display greater levels of FDI).

Overall, in Table 3.4, we find weak evidence of a hedging channel and strong support for the importance of origin countries' wealth. Looking at columns (1) and (2) of Table 3.4, we find that a 1 percent increase in the synchronisation host-origin countries' economic conditions implies a decrease in 0.44 percent in FDI. The result, however, is only significant at 10% level in column (1), it is not significant instead in the second regression. In accordance with the findings of Lane & Milesi-Ferretti (2008), we confirm the importance of countries' wealth, which we proxy using second lag of origin countries GDP per capita. Therefore, we find that 1 percent increase in GDP per capita (*t-2*) results in a 0.6 increase in FDI in column (3) – and a 0.5 increase in column (4). Moreover, in both regressions model our core signs and economic significance remain unaffected.

In Table 3.5 and 3.6, to further ensure that that our baseline regressions capture country specific risk – of origin and host countries – as opposed to global risk, we perform two additional tests. Firstly, we use two measures of global risk aversion (the VIX and the World Uncertainty Index[26]) capturing "push" (or common) risk factors, as opposed to "pull" (or country-specific) ones – already embedded in our baseline model. Secondly, to account for any cross-sectional variation arising at the host country level, we use host country and time fixed effects and we replace our core explanatory variables (banking and sovereign risk) with the corresponding differences between origin and host country risk. This is a standard practice of the gravity model literature (e.g. Beck et al. (2016); Carril-Caccia & Pavlova (2018)).

[26] In order to determine the components of banking and sovereign risk which are not determined by global "push" factors, we used a two-stage approach. Specifically, in the first stage we separately regressed non-performing loans ratio and 10-years government bond yields on the VIX. The residuals from the first stage are then used in the second stage regression as additional explanatory variables for respectively the component of global risk, not captured by either banking or sovereign risk.

Tables 3.5 and 3.6 again confirms the validity of our results, which remain qualitatively unaffected both after the inclusion of global risk variables and when we replace individual countries' banking and sovereign risk with the difference between origin and host countries' values of these variables[27]. Therefore, we still find that origin country characteristics outweigh those of the host when trying to explain inward FDI in the EMU.

Lastly, when estimating FDI movements within a monetary union, it might be relevant to distinguish Euro Area FDI inflow from non-Euro Area FDI inflow. Hence we estimate the regression from Table 3.2 with inward FDI from non-Euro Area countries only (see Table 3.12 – Appendix A.3.2). Our results suggest that even when excluding intra-EA FDI allocation, origin country banking and sovereign risk conditions remain the main causes of lower FDI in the EA.

[Insert Tables 3.3, 3.4, 3.5 and 3.6 around here]

### 3.7 Conclusions

In this paper we investigate how elevated sovereign and banking risk affect Euro Area countries' ability to attract foreign investment. In analysing this type of investment, the international finance and international business literature have examined several determinants of FDI, including those arising from political, social, geographical, technological, regulatory and/or firm specific spheres (Alam & Zulfiqar, 2013; Borin & Mancini, 2016; Dellis et al., 2017; Narula, 2014). However, financial sector risk has often been considered less important and consequently, the risks to FDI, emanating both from recent financial crises (e.g., the GFC and sovereign debt crisis) and any policy responses to these, have been underexplored. To remedy this, we inspect inward FDI stock in the Euro Area between 2009 and 2016 in relation

[27] In Table 3.6, instead of contraposing origin and host country risk factors, we include 'Diff_bank_risk' computed as the difference in 'NPL ratio_orig' and 'NPL ratio_host' as banking risk measure; and, 'Diff_sov_risk' computed as the difference in 'Sovereign yields_orig' and 'Sovereign yields_host' as sovereign risk measure. The results have been supplemented with both gravity and control variables previously explained, as well as time (*t*) and host country fixed effects (*i*).

to various measures of financial stability, including non-performing loans and sovereign yields. Most importantly, we newly discriminate between effects emanating from the host and origin country.

Interestingly, when we analyse the impact of non-performing loans across both origin and host country banks, we find that host country banking risk is never significant in any our regression models or robustness tests. By contrast, origin country banking risk appears as an important determinant of the volume of FDI received by Euro Area countries. We attribute this finding to a 'leverage channel', whereby firms borrow from banks to finance investment, including FDI. Drawing on the banking literature, we suggest that banks' lending in origin countries will be considerably tighter when banks in their home countries display high levels of NPL, or, more generally speaking, in moments of greater uncertainty.

When we analyse sovereign risk of origin and host countries and inspect how this affects FDI, our findings are mixed. As a matter of fact, greater sovereign risk in either origin countries or hosts (EMU countries) leads to lower FDI positions in the Euro Area. However, in absolute magnitude, sovereign risk of the origin country matters more than that of the host country; an interesting finding given the typical weight placed on the importance of the host country characteristics in attracting FDI. We think that our findings are consistent with the literature on uncertainty and precautionary motives, whereby an increase in domestic country risk encourages its own MNEs to engage in less risk-taking. On the other hand, an increase in host country yield arguably implies that other destinations appear more attractive.

When the Euro Area sample is separated into two subsamples representing non-stressed and stressed (i.e., Greece, Ireland, Italy, Portugal and Spain) countries, our findings remain qualitatively unaffected in our baseline regressions, as well as in all our robustness tests. Additionally, the reduction in FDI from origin countries with respect to sovereign risks, is clearly greater in the stressed case. The opposite is found with respect to banking risk, as an increase in such risks has a greater impact on non-GIIPS ability to attract FDI. However, origin country risk always appears to matter more than that of the host.

Overall, our theoretical arguments and empirical results show that financial stability, both in origin and host countries, matters for FDI. This study provides further illustration of the dynamics of such processes, focusing on the effects of variations in bank-related risk, a key systemic feature where the range of regulatory choices is somewhat circumscribed. We would encourage policymakers in countries that seek to attract FDI not only to be mindful of the domestic conditions that lead to lower sovereign risk, but also to be cognisant of the changing financing environment that MNEs may face in their home countries, and, indeed, in deciding which countries to target in seeking FDI. Additionally, we suggest the importance of addressing the asymmetric behaviour of FDI within the core and periphery of the Euro Area. Improving Euro Area convergence with respect to inward foreign investment, we believe could substantially reduce its fragmentation as well as curtail political and financial market tensions in the European Union.

## Tables

**Table 3.1 The impact of banking and sovereign risk on inward-FDI**

Estimation results on the impact of banking and sovereign risk on inward FDI in the EMU by OLS.

| | **Country Risk** | |
|---|---|---|
| | Banking Risk | Sovereign Risk |
| | (1) | (2) |
| | log (FDI) | log (FDI) |
| log (NPL ratio_orig) | -0.163*** (0.034) | |
| log (NPL ratio_host) | 0.055 (0.042) | |
| log (Sovereign yields_orig) | | -1.402*** (0.137) |
| log (Sovereign yields_host) | | -0.456*** (0.134) |
| avg (log(import)) | 0.381*** (0.063) | 0.470*** (0.085) |
| comm_lang | 1.331** (0.452) | 1.420** (0.489) |
| log(distance) | -0.954*** (0.090) | -0.591*** (0.103) |
| contig | 2.099*** (0.425) | 1.366*** (0.413) |
| comrelig | 1.014*** (0.271) | 0.723* (0.380) |
| colony | 0.491 (0.635) | 0.956 (0.695) |
| com_leg_orig | -0.188 (0.188) | 0.690* (0.348) |
| corr (GDP) | 0.155 (0.203) | 0.019 (0.254) |
| log (vol FX) | -1.173*** (0.070) | -0.920*** (0.077) |
| log(taxes) | 0.137 (0.341) | 0.205 (0.447) |
| Constant | 12.381*** (1.457) | 11.180*** (1.759) |
| N | 9,636 | 6,098 |
| Time FE | Yes | Yes |
| R-squared | 0.385 | 0.478 |

*Notes:* *, **, and *** imply statistical significance at the 10, 5, and 1 percent levels respectively. In the parentheses are reported robust standard errors clustered within country pairs. Yearly time fixed effects are included but unreported. See the ‘Data’ section for variable description.

**Table 3.2 The impact of banking and sovereign risk on inward-FDI (non-GIIPS vs GIIPS countries)**

Estimation results on the impact of banking and sovereign risk on inward FDI in GIIPS and non-GIIPS EMU countries by OLS.

| Country Risk | | | | |
|---|---|---|---|---|
| | Banking Risk measure | Sovereign Risk measure | Banking Risk measure | Sovereign Risk measure |
| | non-GIIPS | | GIIPS | |
| | (1) | (2) | (3) | (4) |
| | log (FDI) | log (FDI) | log (FDI) | log (FDI) |
| log (NPL ratio_orig) | -0.175*** (0.047) | | -0.160** (0.047) | |
| log (NPL ratio_host) | 0.058 (0.057) | | 0.201 (0.601) | |
| log (Sovereign yields_orig) | | -1.379*** (0.190) | | -1.433*** (0.203) |
| log (Sovereign yields_host) | | -0.413** (0.169) | | -0.957** (0.257) |
| avg (log(import)) | 0.395*** (0.076) | 0.494*** (0.115) | 0.388** (0.134) | 0.414** (0.115) |
| comm_lang | 0.927 (0.697) | 0.831 (0.748) | 1.542** (0.463) | 1.239 (0.971) |
| log(distance) | -0.923*** (0.109) | -0.513*** (0.112) | -1.120*** (0.223) | -0.876*** (0.188) |
| contig | 2.696*** (0.392) | 2.094*** (0.440) | 0.787 (1.091) | 0.187 (0.951) |
| comrelig | 0.581 (0.490) | -0.091 (0.557) | 1.372*** (0.294) | 1.060** (0.359) |
| colony | 0.290 (0.893) | 0.461 (0.978) | 0.596 (0.450) | 1.819* (0.712) |
| com_leg_orig | -0.308 (0.313) | 0.446 (0.494) | -0.039 (0.132) | 1.132*** (0.159) |
| corr (GDP) | 0.135 (0.202) | 0.263 (0.253) | 0.177 (0.342) | -0.265 (0.233) |
| log (vol FX) | -1.130*** (0.102) | -0.898*** (0.122) | -1.294*** (0.080) | -1.016*** (0.058) |
| log(taxes) | 0.384 (0.466) | 0.364 (0.623) | -0.490 (0.878) | 0.585 (0.281) |
| Constant | 11.459*** (1.716) | 10.023*** (2.280) | 15.322*** (3.680) | 13.255*** (1.709) |
| N | 6,944 | 3,993 | 3,220 | 2,105 |
| Time FE | Yes | Yes | Yes | Yes |
| R-squared | 0.398 | 0.476 | 0.372 | 0.510 |

*Notes*: *, **, and *** imply statistical significance at the 10, 5, and 1 percent levels respectively. In the parentheses are reported robust standard errors clustered within country pairs. Yearly time fixed effects are included but unreported. See the 'Data' section for variable description.

**Table 3.3 The impact of banking risk on inward-FDI (additional risk measure)**

Robustness check on the impact of banking risk (proxied by RC/RWA) on inward FDI in Euro Area by OLS.

| Additional banking Risk measure | |
|---|---|
| | log (FDI) |
| log (RC/RWA_orig) | -1.827*** (0.283) |
| log (RC/RWA_host) | 0.649 (0.387) |
| avg (log(import)) | 0.403*** (0.062) |
| comm_lang | 1.336*** (0.450) |
| log(distance) | -0.975*** (0.086) |
| contig | 1.987*** (0.404) |
| comrelig | 0.942*** (0.293) |
| colony | 0.495 (0.616) |
| com_leg_orig | -0.209 (0.190) |
| corr (GDP) | 0.039 (0.191) |
| log (vol FX) | -1.150*** (0.068) |
| log(taxes) | 0.175 (0.404) |
| Constant | 15.001*** (1.833) |
| N | 9,636 |
| Time FE | Yes |
| R-squared | 0.395 |

*Notes*: *, **, and *** imply statistical significance at the 10, 5, and 1 percent levels respectively. In the parentheses are reported robust standard errors clustered within country pairs. Yearly time fixed effects are included but unreported. See the ‘Data’ section for variable description.

**Table 3.4 The impact of sovereign and banking risk on inward-FDI (hedging incentives vs risk aversions aversion transmission channel)**

Estimation results on the impact of foreign investors' hedging incentives and wealth on inward FDI in EMU countries by OLS.

| | Country Risk | | | |
|---|---|---|---|---|
| | Banking Risk measure | Sovereign Risk measure | Banking Risk measure | Sovereign Risk measure |
| | *Test for Hedging incentives* | | *Test for Origin country Risk Aversion* | |
| | (1) | (2) | (3) | (4) |
| | log (FDI) | log (FDI) | log (FDI) | log (FDI) |
| log (NPL ratio_orig) | -0.172*** (0.037) | | -0.121*** (0.029) | |
| log (NPL ratio_host) | 0.137 (0.083) | | 0.044 (0.045) | |
| log (Sovereign yields_orig) | | -1.430*** (0.152) | | -1.099*** (0.124) |
| log (Sovereign yields_host) | | -0.533*** (0.162) | | -0.477*** (0.133) |
| avg(log(import)) | 0.458*** (0.067) | 0.501*** (0.098) | 0.385*** (0.063) | 0.480*** (0.085) |
| comm_lang | 1.350** (0.492) | 1.347** (0.548) | 1.340*** (0.447) | 1.411*** (0.459) |
| log (distance) | -0.928*** (0.097) | -0.588*** (0.121) | -0.845*** (0.085) | -0.536*** (0.104) |
| contig | 2.053*** (0.469) | 1.148** (0.450) | 1.989*** (0.383) | 1.359*** (0.392) |
| comrelig | 0.932*** (0.273) | 0.731* (0.384) | 1.040*** (0.266) | 0.672* (0.381) |
| colony | 0.191 (0.668) | 0.750 (0.749) | 0.547 (0.569) | 0.965 (0.641) |
| com_leg_orig | -0.133 (0.192) | 0.827** (0.356) | -0.099 (0.170) | 0.727** (0.327) |
| corr (GDP) | 0.079 (0.241) | -0.077 (0.277) | 0.087 (0.185) | -0.043 (0.240) |
| log (vol FX) | -1.219*** (0.070) | -0.952*** (0.085) | -0.799*** (0.044) | -0.768*** (0.072) |
| log(taxes) | 0.146 (0.338) | 0.224 (0.450) | 0.100 (0.341) | 0.208 (0.453) |
| corr (GDP, MKTCAP) | -0.444* (0.218) | -0.332 (0.204) | | |
| L2 (GDP per capita orig) | | | 0.634*** (0.070) | 0.504*** (0.054) |
| Constant | 11.627*** (1.795) | 11.162*** (1.976) | 4.315** (1.733) | 4.959** (2.015) |
| N | 8,026 | 5,308 | 9,617 | 6,080 |
| Time FE | Yes | Yes | Yes | Yes |
| R-squared | 0.375 | 0.477 | 0.426 | 0.497 |

*Notes:* *, **, and *** imply statistical significance at the 10, 5, and 1 percent levels respectively. In the parentheses are reported robust standard errors clustered within country pairs. Yearly time fixed effects are included but unreported. In columns (1) and (2) we proxy hedging incentives using the correlation between host country stock market capitalisation and origin country GDP growth. In columns (3) and (4), defined origin country wealth using the second lag of GDP per capita of origin countries and assuming that wealth is positively associated to risk-taking.

**Table 3.5 The impact of sovereign and banking risk on inward-FDI ('push' vs 'pull' risk factors)**

Results on the impact of 'push' and 'pull' risk factors on inward FDI in the EMU by two-stage OLS regression.

| | **Country Risk** | | | |
|---|---|---|---|---|
| | Banking Risk | Sovereign Risk | Banking Risk | Sovereign Risk |
| | *VIX* | | *WUI* | |
| | (1) | (2) | (3) | (4) |
| | log (FDI) | log (FDI) | log (FDI) | log (FDI) |
| log (NPL ratio_orig) | -0.162*** (0.043) | | -0.116*** (0.036) | |
| log (NPL ratio_host) | 0.057 (0.044) | | 0.056 (0.039) | |
| log (Sovereign yields_orig) | | -1.334*** (0.107) | | -0.701*** (0.102) |
| log (Sovereign yields_host) | | -0.300*** (0.112) | | -0.148* (0.086) |
| res_VIX | 0.065 (0.149) | 3.035*** (0.435) | | |
| res_WUI | | | 0.144 (0.112) | -1.395*** (0.332) |
| avg (log(import)) | 0.381*** (0.040) | 0.470*** (0.047) | 0.428*** (0.020) | 0.484*** (0.032) |
| comm_lang | 1.331*** (0.411) | 1.420*** (0.435) | 1.453*** (0.369) | 1.796*** (0.378) |
| log (distance) | -0.954*** (0.099) | -0.591*** (0.114) | -0.445*** (0.091) | -0.305*** (0.109) |
| contig | 2.099*** (0.411) | 1.366*** (0.415) | 1.504*** (0.374) | 0.732* (0.385) |
| comrelig | 1.014*** (0.293) | 0.723** (0.361) | 0.881*** (0.256) | 0.598* (0.333) |
| colony | 0.491 (0.524) | 0.956* (0.576) | -0.118 (0.474) | 0.186 (0.521) |
| com_leg_orig | -0.188 (0.180) | 0.690*** (0.231) | -0.404** (0.159) | 0.289 (0.224) |
| corr (GDP) | 0.155 (0.139) | 0.019 (0.178) | 0.254** (0.125) | 0.143 (0.167) |
| log (vol FX) | -1.173*** (0.078) | -0.920*** (0.097) | -0.804*** (0.067) | -0.691*** (0.091) |
| log (taxes) | 0.137 (0.370) | 0.205 (0.425) | 0.275 (0.318) | 0.197 (0.393) |
| Constant | 12.326*** (1.514) | 8.833*** (1.640) | 6.240*** (1.353) | 5.503*** (1.589) |
| N | 9,636 | 6,098 | 9,406 | 5,911 |
| Time FE | Yes | Yes | Yes | Yes |
| R-squared | 0.440 | 0.494 | 0.496 | 0.535 |

*Notes:* *, **, and *** imply statistical significance at the 10, 5, and 1 percent levels respectively. In the parentheses are reported robust standard errors clustered within country pairs. Yearly time fixed effects are included but unreported. In columns (1) and (2) we report the results of a two-stage OLS regression having the VIX as of 'push' risk factor. In columns (3) and (4) we report the results of a two-stage OLS regression using the World Uncertainty Index (WUI) as of 'push' risk factor. In Table 5, we disclose only the results of the second stage regression.

**Table 3.6 The impact of sovereign and banking risk growth rate on inward-FDI**

Estimation results on the impact of banking and sovereign risk on inward FDI in the EMU by OLS.

| | Banking Risk | Sovereign Risk | Both |
|---|---|---|---|
| | (1) | (2) | (3) |
| | log (FDI) | log (FDI) | log (FDI) |
| log (Δbank_risk) | -0.148*** (0.036) | | -0.088** (0.044) |
| log (Δsov_risk) | | -1.145*** (0.097) | -1.116*** (0.097) |
| avg (log(import)) | 0.697*** (0.236) | -0.203 (0.309) | -0.266 (0.308) |
| comm_lang | 1.255*** (0.428) | 1.238*** (0.461) | 1.209*** (0.463) |
| log (distance) | -0.947*** (0.098) | -0.579*** (0.113) | -0.622*** (0.114) |
| contig | 2.182*** (0.408) | 1.558*** (0.418) | 1.534*** (0.418) |
| comrelig | 0.980*** (0.307) | 0.597* (0.357) | 0.600* (0.358) |
| colony | 0.584 (0.520) | 1.042* (0.591) | 1.030* (0.597) |
| com_leg_orig | -0.205 (0.190) | 0.629*** (0.231) | 0.655*** (0.232) |
| corr (GDP) | 0.081 (0.157) | 0.062 (0.182) | 0.056 (0.182) |
| log (vol FX) | -1.180*** (0.078) | -1.025*** (0.094) | -1.024*** (0.094) |
| log (taxes) | 1.028** (0.497) | -0.773 (0.757) | -0.925 (0.754) |
| Constant | 7.772*** (2.475) | 14.964*** (3.530) | 16.124*** (3.524) |
| N | 9,636 | 6,098 | 6,098 |
| Time FE | Yes | Yes | Yes |
| Host FE | Yes | Yes | Yes |
| R-squared | 0.399 | 0.484 | 0.486 |

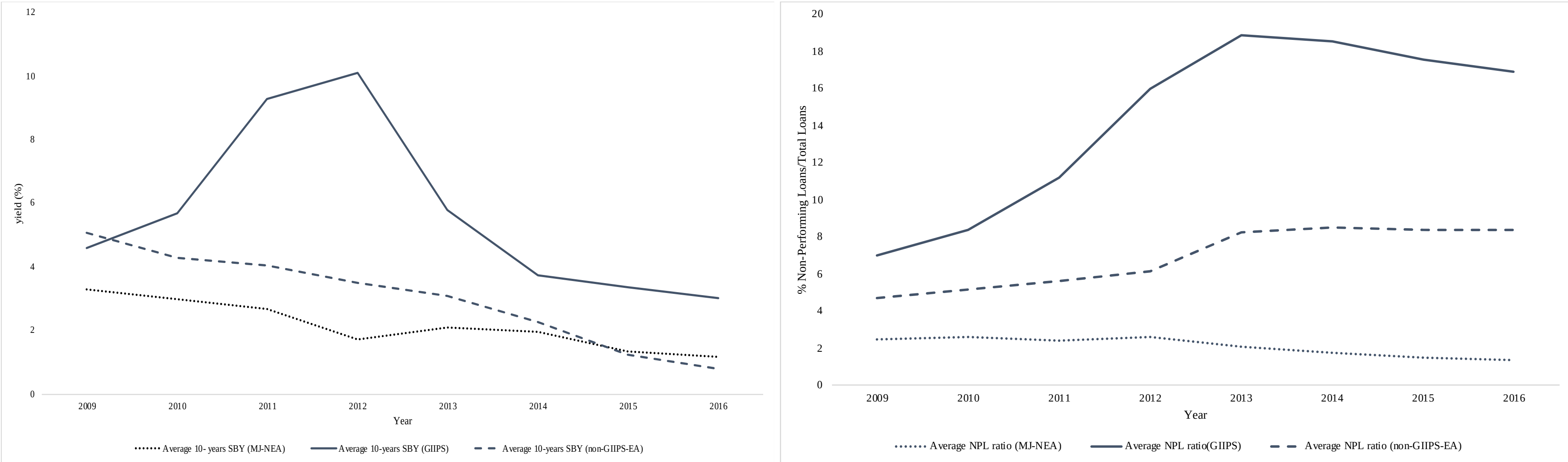
*Notes*: *, **, and *** imply statistical significance at the 10, 5, and 1 percent levels respectively. In the parentheses are reported robust standard errors clustered within country pairs. Yearly time fixed effects and host country fixed effects are included but unreported. See the 'Robustness' section for variable description.

## Figures

**Figure 3.1 FDI inflows in the EA (in all countries, in non-GIIPS and GIIPS countries)**

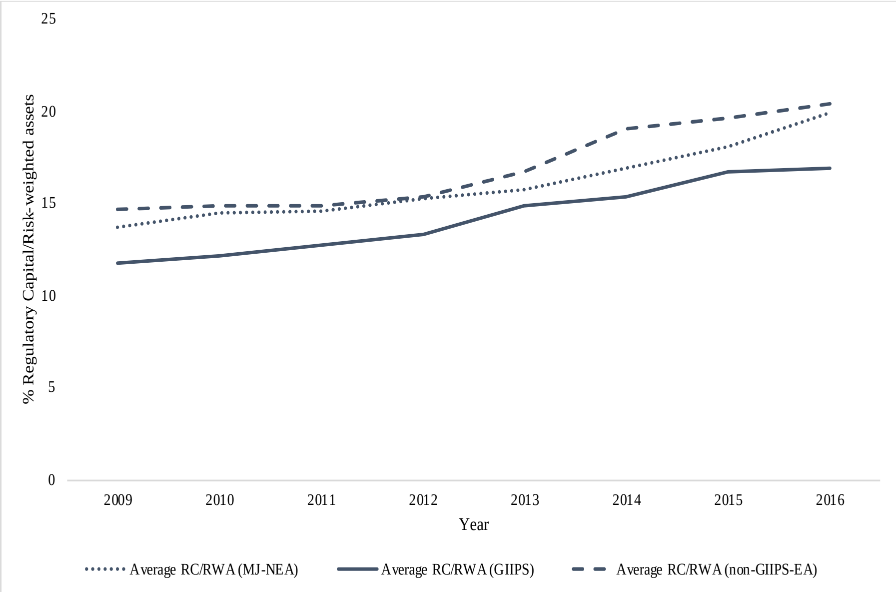

*Notes.* In this Figure, we display FDI inflows in the Euro Area (dotted line), as well as in GIIPS (solid line) and Non-GIIPS (dashed line) countries. FDI inflow data ranges from 2002 to 2016 and its reported at current prices in million USD.
*Source.* UNCAD

**Figure 3.2 Sovereign and Banking Risk measures (in all countries, in non-GIIPS and GIIPS countries)**




*Notes.* On the left-hand side, we present the average 10-year Sovereign Bond Yields. In our paper, we use this indicator to measure EA sovereign risk. On the right-hand side, we show instead Non-Performing Loans/Total Gross Loans. In our paper, we use this indicator to measure the risk of the EA banking sector. Both measures have been averaged across three main groups of countries: major non-EA countries {USA, UK, CAN, JPN} (MJ-NEA), Euro Area Periphery (GIIPS) and non-Periphery EA countries (non-GIIPS-EA). For a detailed list of the countries included in each of the aforementioned categories, see Table 7.
*Source.* IMF International Financial Statistics (IMF IFS), OECD Financial Statistics, CEIC, Oesterreichische Nationalbank, Bloomberg, World Bank Global Financial Development DataBank.

**Figure 3.3 Banks' Regulatory Capital-to-Risk-weighted Assets (in all countries, in non-GIIPS and GIIPS countries)**




*Notes*. Averages of Regulatory Capital/Risk-Weighted Assets of major non-EA countries {USA, UK, CAN, JPN} (MJ-NEA), Euro Area Periphery (GIIPS) and non-Periphery EA countries (non-GIIPS-EA). In our paper, we use this indicator to measure the risk of the EA banking sector. For a detailed list of the countries included in each of the aforementioned categories, see Table 7.
*Source.* WorldBank

# 4 Deal or No Deal? Modelling the Impact of Brexit Uncertainty on UK Private Equity Activity[28]

## 4.1 Introduction

*"…for management researchers, Brexit provides a natural experiment to explore the effects on PE of a major exogenous shock"* (Wright *et al*., 2016: p. 682)

The Brexit vote to leave the EU, recorded at the UK referendum of 23 June 2016, was a momentous event. Largely unexpected by most academics, practitioners and policymakers, the result led to a considerable rise in uncertainty for UK business in general.[29] Such Brexit-related uncertainty is different to prior uncertainty shocks due partially to its length, magnitude and political complexity (Bloom *et al*., 2018; 2019) and the ongoing and widespread impact is still being debated and evaluated. So far, the focus has been typically on the detrimental economic effects of Brexit (e.g., Van Reenen, 2016; Born *et al*., 2019; Bloom *et al*., 2019; Steinberg, 2019; McGrattan and Waddle, 2020; Hassan et al., 2020; Hill et al., 2019) and the related impact on banks and financial markets (e.g., Schiereck *et al*., 2016; Davies and Studnicka, 2018; Berg *et al*., 2019; Hudson et al., 2020).

Recent work from Wright *et al*. (2016) explores the impact of uncertainty from the Brexit referendum on the UK private equity (PE) market, noting that the UK PE market is the largest in Europe. In particular, they highlight that whilst in the years that followed the global

[28] The work of this Chapter is based on the article "Deal or No Deal? Modelling the Impact of Brexit Uncertainty on UK Private Equity Activity" published in the British Journal of Management by myself, Neil Kellard, Alexandros Kontonikas and Michael Lamla (DOI: https://doi.org/10.1111/1467-8551.12479).
[29] The referendum outcome was a largely unexpected event as the leaders of the three largest parties in the UK and the majority of MPs were pro-remain. We thank an anonymous reviewer for this point.

financial crisis (GFC) of 2007/8, the PE market recovered to pre-crisis activity levels, deal values fell precipitously in 2016 reflecting higher uncertainty. Moreover, the paper posits early in the Brexit debate that the referendum result produced an extraordinary shock, damaging market confidence and likely impairing PE funds' returns as well as their ability to fundraise and relatedly, their reliance on debt availability. On the other hand, the future activities of UK PE firms may be subject to less regulation, possibly generating a deregulation premium, and the EU will no longer necessarily be able to inhibit UK state aid. Hence, Wright *et al*. (2016) conclude by stressing that Brexit generates both threats and opportunities for PE activity in the UK and creates "an exciting new research agenda" (p. 685) for researchers in entrepreneurial finance.[30]

Building on the work of Wright, co-authors, and other existing literature on PE (e.g., Leslie and Oyer, 2009; Lerner *et al*., 2011; Kaplan and Strömberg, 2009; Hotchkiss *et al*., 2011; Cumming *et al*., 2020; for an excellent review see Gilligan and Wright, 2020), our paper investigates two associated research questions: firstly, what is the effect of uncertainty and, in particular, Brexit-related uncertainty, on PE activity in the UK? And secondly, what are the channels that operationalise the transmission of uncertainty to the PE market? In terms of measuring activity, we follow others (e.g., Wright *et al*., 2016)[31] in defining PE as the 'risk capital employed to finance the acquisition of mature businesses via a leveraged buyout (LBO).' Less straightforward is the identification an appropriate analytical framework given that the conceptualisation and measurement of uncertainty is a non-trivial task. To circumvent this, we employ a set of uncertainty measures including the Bloom *et al*. (2019) Brexit Uncertainty Index (BUI) and the Baker *et al*. (2016) Economic Policy Uncertainty Index (EPU).

[30] Policymakers, analysts, and PE practitioners have expressed concerns about the implications of Brexit. See, for example, Bank of England (2019), Deloitte (2016), British Private Equality and Venture Capital Association (2019).
[31] The same paper notes that LBOs represent about three-quarters of total UK merger and acquisition activity.

Our analysis is performed on a novel dataset that we construct by conflating several data sources. We collect data on buyout investors and targets from S&P Market Intelligence and Capital IQ, identifying UK targets acquired by PE buyout firms over the 2010-2019 period and following standard deal classification criteria from the existing literature (see Axelson *et al*., 2013; Faccio and Hsu, 2017). Subsequently, we employ Capital IQ, Compustat Global and Orbis databases to obtain data for the necessary accounting and financial fundamentals of our sample targets. After matching targets to available accounting data, we obtain a sample of 765 UK targets. Moreover, to provide a suitable control group to these targets, we consider all UK firms with analogous size characteristics, generating a final dataset of 290,022 firms.

To derive appropriate hypotheses, we follow Bonaime *et al*. (2018) and Adra et al. (2020) in drawing on related literature including: work positing that uncertainty will increase the real option to delay investment (cf. Quigg, 1993; Gulen & Ion, 2015); notions of an interim risk channel of uncertainty (see Bhagwat *et al*., 2016), where periods of high uncertainty widen the interim period occurring between announcement and completion of an acquisition (or buyout deal); and principal-agent theory, whereby greater uncertainty can lead to increased moral hazard if limited partners (principals) ability to control general partners (agents) is impaired. In doing so, our investigation sheds light on the impact of uncertainty for PE and entrepreneurial finance (e.g., Wright *et al*., 2016; Cumming and Zahra, 2016; Brown *et al*., 2019), the general economic and financial effects of uncertainty (e.g., Baker *et al*., 2016; Gulen and Ion, 2016; Drobetz *et al*., 2018; Bonaime *et al*., 2018), and related issues of effective policy for supporting investment during periods of higher uncertainty due to exogenous shocks.

We find that Brexit uncertainty negatively affects UK PE activity, primarily arises from policy, FX and CFOs (firm-level) uncertainty and transmits through real-options and interim risk channels. These results imply industries most deeply affected are those relying on fixed assets, durable goods, or heavily exposed to the EU because of their export/import activities.

We also find that the impact and transmission of uncertainty varies according to the different nature of uncertainty itself. Different types of uncertainty have different degrees of persistence or lead to longer deal interim periods, therefore "scaring off" potential PE investors. These considerations lead us to urge policy makers to address uncertainty arising from Brexit whilst encouraging a more holistic view of uncertainty 'types' and channels.

The rest of the paper is structured as follows. Section 4.2 considers the extant literature and theoretical underpinnings of our work, whilst Section 4.3 provides an overview of the data. Section 4.4 presents the empirical methodology and results on the effects of uncertainty on PE buyout activity, whilst Section 4.5 explores the channels of transmission. Section 4.6 concludes.

## 4.2 Literature and theoretical underpinnings

### 4.2.1 *Uncertainty*

As noted in the introduction, the conceptualisation and measurement of uncertainty, and in particular policy-related economic uncertainty, is not straightforward. Baker *et al*. (2016: p.1598) comment, 'We aim to capture uncertainty about *who* will make economic policy decisions, *what* economic policy actions will be undertaken and *when*, and the economic *effects* of policy actions (or inaction) – including uncertainties related to the economic ramifications of "noneconomic" policy matters, for example, military actions." Most likely, types of uncertainty (e.g., Policy, Brexit, pandemic, monetary and fiscal) will affect individual sectors of the economy differently and display varying degrees of persistence. For this reason, when analysing such uncertainty, it is crucially important to model the economic effect of various uncertainty measures and their related transmission mechanisms.

In this paper, we address this issue by collecting a set of measures, reflecting differing (but potentially overlapping) aspects of uncertainty. Firstly, the Baker *et al*. (2016) Economic

Policy Uncertainty (EPU) index, quantifies UK policy-related economic uncertainty by examining the frequency of the words ‘uncertain’ or ‘uncertainty’, ‘economic’ or ‘economy’, as well as other policy-relevant terms, such as ‘policy’, ‘tax’, ‘spending’, ‘regulation’, ‘Bank of England’, ‘budget’, and ‘deficit’ in the eleven most popular UK newspapers. Secondly, we include an index created by Bank of England on UK macroeconomic uncertainty which reflects the economic uncertainty of British households and companies. More specifically, this combines macroeconomic measures of economic and financial market uncertainty, with survey data collected by the Bank of England on households and firms’ short and medium-term expectations.

Our third and fourth measures capture financial market uncertainty: specifically, Sterling option-implied volatility (i.e. exchange rate uncertainty) and the FTSE All-Share option-implied volatility (i.e. stock market uncertainty). Both measures are likely to, at least partially, reflect Brexit-related expectations of investors. Our fifth and final measure attempts to explicitly identify uncertainty arising from the Brexit Referendum. In contrast to indices described beforehand, the Bloom *et al*. (2019) Brexit Uncertainty Index (BUI) is built using surveys to the CFOs of approximately 3,000 UK businesses, therefore capturing company level uncertainty.

### 4.2.2 *Uncertainty and the level, value and likelihood of LBOs*

Wright et al. (2016) remark that in the first half of 2016, UK PE deal values decreased significantly and suggest this reflected higher macroeconomic uncertainties, in part due to the uncertainties surrounding Brexit. They argue that in this environment, PE firms find it difficult to both raise investment and obtain debt (e.g., via banks or debt funds). This funding squeeze, when combined with potentially less buyout opportunities, can lead a reduction in the overall number as well as the value of deals. In any case, Ljungqvist *et al*. (2020) and Malenko and

Malenko (2015) find that buyouts significantly accelerate when credit market conditions ease. Extending this work, Axelson *et al*. (2013) examine capital structure theories using cross-sectional factors and showing that credit conditions are the main driver of PE acquisitions.

In a more general context of US merger and acquisitions (M&As), Bonaime *et al*. (2018) show empirically that policy-related economic uncertainty is negatively associated with M&A activity. Several theoretical rationales for the linkage are investigated including the real options channel (see Bloom, 2009), the interim risk channel (Bhagwat *et al*., 2016) and moral hazard framing (Duchin and Schmidt, 2013). We shall explore these potential transmission channels for uncertainty in more detail below but when combined with earlier arguments that relate uncertainty to worsening credit conditions, lead to our first hypothesis:

> **H1**: Greater uncertainty significantly reduces the level, value and likelihood of PE buyouts.

Of course, it could be that greater uncertainty causes PE firms to simply delay investment, rather than engage in an actual reduction. However, there is some *prima facie* evidence that the effects of policy-related economic uncertainty (including Brexit) can be long-lasting. For example, Bloom *et al*. (2019: p.2) suggests, 'Brexit is unusual in that it generated persistent uncertainty – three years after the original vote, the UK had not left the EU, there was still no clarity on the eventual outcome […].' Such persistence in uncertainty, can lead to persistent effects on variables of interest and this leads to our second hypothesis:

> **H2**: Greater policy uncertainty, including Brexit, presents persistent and negative effects on PE firms buyout likelihood.

### 4.2.3 *The real-options PE transmission channel*

In the next three subsections, we examine the transmission channels of uncertainty to the UK PE market. To begin, we note that when uncertainty is higher, the value of the real option to delay investment increases (cf. Quigg, 1993; Gulen & Ion, 2015). In a buyout context, this implies that when uncertainty is elevated, PE firms could have a greater incentive to postpone buyouts. As a result of this argument, PE firms performing buyouts during periods of elevated uncertainty are either those for which delaying investment is more costly or those that cannot delay the investment. This has important implications in terms of the bargaining power between buyer (PE firm) and seller (portfolio firm management/shareholders) since it potentially increases the bargaining power of the seller. Within this theoretical framework, the value of the option depends on three main factors. Firstly, the degree of investment irreversibility – clearly, the less reversible the investment, the higher the value of an option to delay. Secondly, the cost of postponing the buyout. For example, and as is suggested by Grenadier (2002), delaying investment is considerably more expensive when the target firms operate in a highly competitive industry, where a delay could lead to competitors' appropriation of part of the benefits (profitability) yielded by the investment project. Finally, the extent to which uncertainty affects the investment target (i.e., the PE portfolio target). Bloom *et al*. (2019: p.2) emphasises, 'The vote for Brexit was a largely unexpected event and we observe that it has had a heterogeneous impact on firms according to their pre-referendum exposure to Europe.' In this spirit, we argue that the incentive to delay investment when uncertainty arises is likely greater for industries that are more exposed to Brexit (e.g., those relying more on the external trade sector). Taken together, these arguments lead to our third hypothesis:

> **H3**: Greater uncertainty increases the real-option value for PE firms to delay investment.

### 4.2.4 *Interim risk channel of uncertainty*

Next, we explore the interim risk channel of uncertainty, proposed by Bhagwat *et al*. (2016). They posit that in periods of higher uncertainty, interim periods between the announcement and completion of an acquisition tend to be wider. Longer interim periods significantly discourage M&As – and of course LBOs and management buyout (MBOs) – since equity prices are highly volatile in the interim period. Indeed, target price volatility strongly enhances the risk for the acquirer in a public-to-private transactions (i.e. leading to less convenient buyout terms) and moreover, can increase the cost of bank financing and the risk of breaking debt covenants.

Considering the persistence of policy-related economic uncertainty and the related Brexit referendum, we suggest that PE investors could have decided to delay (or dismiss) buyout investment in the UK because of the greater interim risk imposed by the inherent complexities in the relationship between EU and UK (e.g., market access, labour market rules, regulatory changes, and so on), leading to our fourth hypothesis:

> **H4**: Greater uncertainty is transmitted to the PE buyout market via the interim risk channel.

At this point, it can be noted that several transmission channels can co-exist; therefore, any evidence of an interim risk channel would not contradict evidence for the real-option channel.

### 4.2.5 *Moral hazard channel*

Lastly, we consider the existence of a moral hazard channel of uncertainty, as suggested by Duchin and Schmidt (2013). According to this theoretical framing, greater uncertainty can lead to greater moral hazard incentives if limited partners (principals) ability to control general partners (agents) is impaired, creating "empire building incentives." Lower control can motivate general partners to invest in deals of lower quality and try to "rip off" target companies profit and cash holdings. The question of whether PE buyouts are optimal for portfolio target firms has been subject of extensive academic and policy makers debate,[32] with considerable evidence of greater "value-destroying" deals when moral hazard incentives are at play. Of course, it is perhaps likely that the moral hazard channel is not the primary transmission channel of (Brexit) uncertainty; however, some effects from this channel may still a play a role in buyout decisions. This leads to the fifth hypothesis:

**H5**: Greater uncertainty is transmitted to the PE buyout market via the moral hazard channel.

## 4.3 Data

### 4.3.1 *Data on Buyouts*

To identify UK PE targets from 2010 to 2019, we first use data from S&P Market Intelligence and Capital IQ and the methodology outlined in Axelson *et al.* (2013) and Faccio and Hsu (2017). This approach recognises PE buyouts based on the deal structure adopted in the acquisition of the portfolio firm, the target's country of incorporation, and the investment stages adopted by the PE investor[33] (see Appendix A.4.1 for more detail on dataset construction).

Second, we use Capital IQ, Compustat Global and Orbis to obtain several accounting measures that are potential drivers of PE buyouts in the UK. These include total assets, return on assets (ROA), leverage and cash-to-assets (see Appendix A.4.2). This information is

[32] Poul Rasmussen (former Danish Prime Minister and author of European Commission's Alternative Investment Fund Managers Directive) stated that "'leveraged buy-outs' leave the company saddled with debt and interest payments, its workers are laid off, and its assets are sold, ... benefiting neither workers nor the real economy" (Rasmussen, 2008, p. 130-132).
[33] There is no country restriction for PE firms.

available for 765 target firms – constituting our sample of UK target portfolio firms – and allowing for a rich set of firm specific control variables.

This study covers three main categories of buyouts: LBOs, going private transactions and MBOs. These constitute 25% of all PE activity in the UK, a significant portion, over the period of analysis (2010-2019)[34] and consisting of a total buyout volume of US $180 trillion.

[Insert Table 4.1 and Figure 4.1]

Among buyouts, LBOs constitute the large majority of PE transactions in the UK and reach a maximum of 92 percent in 2013 (see Table 4.1, Panel A). As evident from Figure 4.1a and 4.1b, after the Brexit referendum in 2016, we observe a slowdown in UK buyout activity with a substantial decrease in investment amounts; this coincides with a reduction in the absolute numbers of these types of deals (see Table 4.1, Panel B). Going private transactions reach their peak in 2019, when the percentage of funds invested almost equals that of LBOs (see Table 4.1, Panel A). Finally, in Figure 4.1a and 4.1b, we also juxtapose buyouts in the UK and the rest of the world (RoW). Noticeable differences between the two series appear to correspond with phases of elevated uncertainty, over both the whole sample period and those periods associated with Brexit.

To form an appropriate control group for UK PE targets, we obtained the universe of all UK (listed and unlisted) firms from Orbis and information on their financial statements, industry sector, age and so on. In a further refinement, we only consider UK firms with similar size characteristics to our PE targets (see Appendix A.4.3). We merged this refined dataset with our data on UK PE targets, generating a final annual frequency sample of 290,022 firms from 2010 to 2019

[34] Other deal structures include: acquisition financings, add-on, asset acquisitions, other corporate acquisitions/ divestitures, follow-on offerings, growth capital transactions, IPOs, mergers, Private Investment in Public Equity (PIPE), private placement transactions, recapitalizations and other unclassified activities.

### 4.3.2 *Measures of uncertainty*

As discussed earlier in Section 4.2.1, different types of uncertainty will have differing effects on separate sectors of the economy and are likely to display varying degrees of persistence. Therefore, we collect a set of uncertainty measures, which we explore in more detail below.

#### *4.3.2.1 Policy-related economic uncertainty*

Our first measure is the economic policy uncertainty index (EPU) of Baker *et al*. (2016). The index measures domestic uncertainty derived from British newspapers by examining the frequency of words identifying several dimensions of uncertainty related to government. To extract the monthly value of policy uncertainty, the index is then normalized to obtain a standard deviation of 1 and a mean 100 before 2011.

The index cleverly captures a dimension of uncertainty (sentiment) concerning government policies that were previously difficult to quantify. As reported in Baker *et al*. (2016), at a macro level, EPU displays a high correlation with popular uncertainty measures (e.g., implied stock market volatility) and a lack of bias towards newspapers' political orientation. Moreover, EPU seems to have some success in predicting variations in employment and investment. As a result, this measure of uncertainty is widely used in the extant economic and finance literature.

[Insert Figure 4.2]

As shown in Figure 4.2, EPU increased at the start of the Global Financial Crisis (GFC) and most strikingly, we can observe a sharp increase during 2016, at the time of the Brexit referendum. The 'Brexit Period' itself seems to be characterised by more volatility in EPU.

#### *4.3.2.2 Index of macroeconomic uncertainty*

Our second measure of uncertainty is an index of macroeconomic uncertainty produced by Bank of England (cf. Haddow et al., 2013). The index considers a wide range of dimensions of uncertainty, which are aggregated by the Bank using principal component analysis and subsequently, retrieving the first principal component. In more detail, the index includes the three-month option-implied volatility of the FTSE All-Share index, and the three-month option-implied volatility of sterling-euro and sterling-dollar export-weighted exchange rates, as generic proxies of overall corporate sector uncertainty. It also incorporates the dispersion of annual company earnings GDP growth forecasts, which provide a supply-side measure of private sector uncertainty. Lastly, as proxy of demand-side uncertainty, the measure uses several surveys assessing businesses' expectations and sentiment, such as the: (i) GfK unemployment expectations balance; (ii) CBI 'demand uncertainty limiting investment' score; and (iii) number of press articles citing 'economic uncertainty.' The former two surveys are used by the Bank to assess the impact of greater unemployment and households' precautionary savings on domestic demand; the latter is meant as a barometer of the 'public mood.'

#### *4.3.2.3 FTSE All-Share index and Sterling option-implied volatility*

We separately include the FTSE All-Share index and Sterling option-implied volatility (described above) in our regression models as indicators of financial (stock and FX) market uncertainty. Equity option-implied volatility is one of the most popular measures of financial market uncertainty. The underlying idea is that the higher the uncertainty about the future performance of the UK stock market, the higher the price that investors – including PE investors highly exposed to their target performance – would be prepared to pay for options hedging their risk. This measure, therefore, provides a forward-looking measure of investors' expectations after an uncertainty shock.

In the wake of the Brexit referendum, UK investors and businesses observed drastic variations in the value of Sterling. In October 2016, during the so-called 'Sterling flash crash', the dollar rate fell below $1.20 (as low as 1.15$), reaching the lowest value since 1985 and experienced an unprecedented level of volatility. Sharp variations in the exchange rate significantly affect UK businesses, by impacting their export prices – reducing their export-related revenues – and increasing the cost of imported production input. For PE firms, a significant decrease in operating financial performance reduces the incentive to invest in UK businesses. In Figure 4.3, we show the time-series pattern of uncertainty across all the previously described measures.

[Insert Figure 4.3]

#### *4.3.2.4 Brexit Uncertainty Index (BUI)*

In an attempt to isolate the effect of Brexit-specific uncertainty on UK firms, we employ the Bloom *et al*. (2019) Brexit Uncertainty Index (BUI). This index is built using survey data from the Decision Maker Panel (DMP), a monthly survey performed on a wide sample of UK firms across several industries. Through the survey, the authors estimate the extent to which Brexit has been affecting British firms, which industries have been more impacted and how?[35] The BUI crucially extends the scope of the DMP by estimating the portion of firms heavily affected by Brexit uncertainty – measured as the percentage of CFOs reporting Brexit in the top three sources of uncertainty in the DMP survey. BUI, therefore, provides a relatively clear-cut identification of the transmission of Brexit uncertainty to the UK corporate sector.

In the earlier Figure 4.2, we present a graphical representation of the BUI, alongside the EPU index. Compared to EPU and other indexes of uncertainty, uncertainty captured by BUI remains elevated and even increases following the referendum. Notably, the highest values

[35] This is accomplished by asking detailed questions to CFOs on their exposure to Brexit – e.g. by asking about their share of sales to the EU, their share of EU exports or the share of EU migrants in their workforce – and their expected percentage change in performance in comparison to the previous fiscal year (Bloom *et al*. 2019, 2020).

of Brexit uncertainty appear in 2018-2019, i.e., close to the original deadline for Brexit negotiations, where more than 50 percent of all CFOs surveyed in the DMP report Brexit as one of the top three sources of uncertainty for their firm.

#### 4.3.3 *Other macroeconomic and industry specific control variables*

In line with Valkama, Maula, Nikoskelainen and Wright (2013), we also include several macroeconomic and industry control variables. According to the authors, these are in fact important drivers of buyout returns in the UK – in particular target industry growth fundamentals, which explains most of the heterogeneity in PE investors' performance[36]. Our first macroeconomic control is a proxy for the UK economic activity (henceforth 'Investment Opportunity Index'). This is computed using several proxies of the future performance of the economy, such as the: (i) Agents' survey of investment intentions, Confederation of British Industry (CBI) survey on investment intentions, Bank of England's General economic situation expectations survey; (ii) Bank of England's Household personal financial situation expectations survey and unemployment projection (inverted); and (iii) Bank of England one year-ahead GDP growth forecast at market rates. To avoid multicollinearity issues, without losing information, we compute the first principal component of the series reported above. We also control for market liquidity using the UK TED spread, employing data collected from Bank of England.

As industry-specific controls, we use the industry median of proxies for equity valuation (i.e. 36-month cumulative stock return) and volatility (i.e. the standard deviation of the former variable), as indicators of industry performance. We include industry median Tobin's q as an additional forward-looking proxy of firms' valuation, where a high Tobin's q

[36] Valkama et al. (2013) find that in the UK economic performance, industry growth and stock market returns are the main predictors of PE buyout returns.

indicates high valuation periods. Lastly, to create proxies for industry-level economic shocks we combine CRSP and Compustat Global databases and follow Harford (2005) to construct each of the 48 Fama and French (1997) industries (see Appendix A.4.2).

## 4.4 Empirical methodology and results

### 4.4.1 *The response of PE buyouts to different measures of uncertainty*

In this section we examine investment dynamics at the firm-level. Specifically, using a logit model, we estimate the probability of a buyout – investing in an LBO, MBO and/or going private transaction – as a function of the mean level of uncertainty in the previous year, after controlling for numerous determinants of PE investment. In our logit regression model therefore $Y_j = 1$ if a given firm $j$ receives a buyout in year $t + 1$; $Y_j = 0$ if firm $j$ does not receive a buyout. Subsequently, we estimate the probability of $Y_j = 1$ given a set of firm-level, industry-level and macro-level independent variables in the following manner:

$$P(Y = 1|x_1, x_2, \dots, x_n) = f(x_1, x_2, \dots, x_n) \quad \text{[Equation 4.1]}$$

#### *4.4.1.1 Uncertainty and the likelihood of a buyout*

The results of our baseline logit estimations, presented in Table 4.2, support H1 since for several uncertainty measures, greater uncertainty significantly reduces the likelihood of PE buyouts the following year.

[Insert Table 4.2]

In particular, EPU, Sterling option-implied volatility and BUI (see Table 4.2 - columns 1, 3 and 5, respectively) are negatively signed and statistically significant, the first and latter measure at the one percent level. In other words, increases in these three measures significantly reduce the likelihood of UK PE buyouts in the upcoming year. Turning to the marginal effects of the considered logit models (at the mean), consider the case of BUI, the most explicit measure of Brexit uncertainty[37]. Here, a one percent increase in BUI leads to a mean marginal decrease in the likelihood of buyouts in the following year of about 0.016 percent, corresponding to approximately 79 percent of the unconditional probability of a buyout during the Brexit period.

By contrast in Table 4.2, both the Bank of England macroeconomic uncertainty index and FTSE All-Shares option-implied volatility are not significant at the 10 percent level (see columns 2 and 4). We gently attribute this finding to the different components and forecast horizons of the uncertainty measures; for example, the FTSE All-Shares option-implied volatility might be considered a short-term indicator. In any case, such a result sheds light on the importance of considering differences in indicators of uncertainty when assessing impact on domestic economic activity and investment.

Other control variables included in the regressions are portfolio targets' specific controls, such as: the natural logarithm of the firm assets, ROA, firms' leverage (computed as liabilities-over-equity), and cash and equivalents-over-assets. As standard, some control variables are omitted from the regression if they display high correlation with the core explanatory variable of the regression to avoid multicollinearity problems (see Appendix A.4.4). In each regression we use robust standard errors clustered at the level of the buyout target (portfolio firm). Moreover, we include industry and firm-level variables measured in the previous fiscal year (*t*).

#### *4.4.1.2 The persistence of uncertainty effect on buyouts*

Following our baseline results in Table 4.2, we assess the persistence of the effect of an uncertainty shock on buyout activity. If greater uncertainty leads PE investors to delay

[37] See Table A.6 in the Appendix for the marginal effects.

investment, rather than reduce it, we would expect a reversal in the logit coefficient sign. Therefore, in Table 4.3, we re-explore our baseline regression, this time considering the likelihood of a buyout up to five-years ahead (*t*+1, *t*+2, *t*+3, t+4, and t+5) given an uncertainty shock at time *t* (controlling for industry and macroeconomic shocks).

[Insert Table 4.3]

We start our analysis on the persistence of uncertainty by analysing economic policy uncertainty, or EPU. As reported in Panel A of Table 4.3, we do not observe a sign reversal in the response to greater policy uncertainty in the three following years – although after two years the level of significance reduces. The coefficient sign of the EPU index changes in year *t+4,* indicating that after an event increasing policy uncertainty on average it takes four years for PE investment to recover (the PE investment receives a 4-year delay). This provides evidence to both the economic significance and persistence of a policy uncertainty shock to PE investment, which is in line with our H2. Additionally, we observe in Panel B that Sterling uncertainty significantly reduces the likelihood of a buyout for years (*t*+1 and *t*+2), with no significant reversal in *t*+3. As for the EPU index, we observe a sign reversal in the likelihood of a buyout four years after sterling uncertainty arose, which lead us to conclude that sterling uncertainty causes an average four years delay of PE buyouts. Finally, Panel C presents the impact of Brexit uncertainty on the future likelihood of a buyout. In a strong confirmation of H2, one can observe that the response of three-year ahead buyout volume to BUI is negative and persistent. Eventually, it has no significant effect on the likelihood of a buyout in year *t+4*.

Overall, we observe that Brexit uncertainty leads to an average of four-year delay in PE buyout, after which investment is recovered. Following the second year ahead of the uncertainty event, the coefficient of year *t+3* is often not significant, while that of year *t+4* is instead positive and significant for the EPU and sterling uncertainty variables.

#### *4.4.1.3 Country Counterfactual using the US PE Market*

To further establish the findings, we re-run our analysis for a country that has not experienced Brexit and hence should not be negatively affected by the related uncertainty. Arguably one could even postulate that the US market could have even profited from Brexit by attracting PE capital. In such a context, the coefficient estimate on uncertainty measures associated with Brexit should be either insignificant or even positive.

For this purpose, we use the sample selection criteria adopted in Section 4.3.1 (for UK PE targets) and create a comparable sample of US private equity targets firms (exploiting the data from Capital IQ). As the Brexit uncertainty shock is specifically localised in Britain and the EU, testing our baseline models on this last sample may further validate our findings and support the lack of sampling bias in our results. Given the lack of the identical firm and industry specific variables in the new sample, we perform a panel fixed effect logistic regression using industry and time-fixed effects. We include in the regression our baseline models' variables of uncertainty – i.e. EPU, Sterling Option-Implied Volatility and the BUI.

[Insert Table 4.4]

Our results, reported in Table 4.4, show that Brexit dimensions of uncertainty adopted in our baseline model (with the exception of sterling option-implied volatility – which also accounts for USD uncertainty) have strikingly positive effect on the likelihood of a buyout in the US. This indicates that Brexit uncertainty had an important and UK-specific negative effect on PE activity, supporting the validity of our prior results and potentially pointing to cross-country spillovers effects arising from Brexit.

#### *4.4.1.4 Additional results*

In Appendix A.4.6 we present some additional results. First, we re-estimate the baseline regression during the 'Brexit period' (2016-2019) and find that uncertainty has a significantly negative impact on PE buyout activity (Appendix A.4.6.1). Second, we follow the merger waves literature to account for the counter-cyclicality of target firms' valuations. We show that the key result about the negative effect of uncertainty is robust.

## 4.5 The transmission channels of uncertainty to the PE market

We investigate the three postulated transmission channels of uncertainty characterised in our hypotheses H3-H5 and developed earlier in sections 4.2.3, 4.2.4 and 4.2.5. First, we consider predictions from theory predicting that uncertainty will increase the real option (general partner incentive) to delay investment (cf. Quigg, 1993; Gulen and Ion, 2015). Bloom *et al*. (2018) analysing the impact of Brexit on business investment found a significant decrease in business investment in the UK since the Brexit Referendum. Likewise, other authors such as Serwicka and Tamberi (2018), or McGrattan and Waddle (2020) found evidence of a significant shift of foreign direct investment (FDI) from the UK to other countries in the European Union. Second, we test the potential effect of a greater interim risk channel, known to significantly depress equity valuations (see Bhagwat *et al.*, 2016) in the interim period between announcement and completion of an acquisition. Finally, we test the existence of a greater moral hazard incentive, created by the high period of uncertainty and leading limited partners to have lower control and ability to assess the performance of general partners. According to this argument, when uncertainty is elevated if limited partners (principals) control over general partner (agent) actions are impaired, this could create greater empire-building incentives.

### 4.5.1 *Testing the real-options transmission channel*

As we noted earlier in section 4.2.3, the value of the option is conditional on three main factors: (i) the degree of investment irreversibility; (ii) the cost of postponing the investment (buyout); and (iii) the extent to which uncertainty affect the investment target (PE portfolio target). We explore these factors in more detail below.

#### *4.5.1.1 Investment irreversibility*

To assess the validity of the real option theory applied to the context of UK buyouts, we use three different proxies of investment irreversibility to assess whether the effect of uncertainty on leveraged-buyouts is stronger for irreversible investments. All measures of investment irreversibility are measured at the target level of a given buyout.

The first proxy of investment irreversibility is the PE target industry capital intensity ratio – computed as the industry mean net property, plant, and equipment (PPE) over total assets. The underlying assumption is that investment in firms with greater amounts of fixed assets (PPE) would be harder to reverse. Therefore, we create a dummy variable taking the value of one if a buyout target in a given year has a greater capital intensity ratio than the industry median.

Our second proxy of investment irreversibility is based on a given investment sunk costs. In a similar spirit to Kessides (1990) and Farinas and Ruano (2005), we argue that the greater is the rent and lease of firm tangible assets, the faster is its fixed capital depreciation i.e., the shorter is the life cycle of its assets, and the greater is the available secondary market for firm assets, the lower would be the sunk costs associated with an acquisition. Lower sunk costs should reduce the value of the option to delay a given buyout. Therefore, following Bonaime *et al*. (2016) and Gulen and Ion (2016), we compute the average industry level of: rent and lease expenditure; depreciation expense; and, yearly sales of PPE (all scaled by lagged

PPE). We then create a dummy variable to characterise an industry as having low investment sunk costs if all three measures are contemporaneously above the industry median in a given year.

We then follow Shleifer and Vishny (1992) and Almeida and Campello (2007) by suggesting that highly cyclical industries receive a considerably higher discount on asset liquidation values in periods of crisis. Therefore, in periods of high uncertainty, highly cyclical industries are significantly riskier than less cyclical ones, as firms in the same industry would be similarly affected by a given uncertainty shock. To identify cyclical industries, as standard practice in the relevant literature (cf. Sharpe, 1994), we use SIC industry codes identifying cyclical industries as those industries characterised by the greater amount of durable goods.

Lastly, if predictions from the real option theory hold, hence greater uncertainty creates the incentive for the general partner to postpone investment, this incentive should be lower when postponement is more costly. In particular, as suggested by Grenadier (2002), delaying investment is considerably more expensive when the target firms operate in a highly competitive industry, where a delay could lead to competitors' appropriation of part of the benefits (profitability) yielded by the investment project. Based on this assumption, the incentive to delay the (completion of the) investment until uncertainty is resolved is considerably higher in concentrated industries – i.e. less competitive – where it is actually relatively inexpensive to delay. To assess industry concentration, we adopt the methodology used for the creation of the Herfindahl sales-based index of industry concentration. Therefore, we use a dummy variable taking the value of one if the median industry sales in a given year exceed all industries sales median, and zero otherwise. Also with respect to this proxy of industry concentration, the results appear robust and all point to a greater impact of uncertainty on PE investment within industries that are more concentrated rather than vice versa, as predicted by the real option theory.

[Insert Tables 4.5, 4.6 and 4.7]

In Tables 4.5, 4.6 and 4.7, we show the results of our baseline model regressions including the aforementioned proxies of industry capital intensity, sunk costs, and cyclicality. All the results point to a uniformly strong effect of uncertainty (with the exception of Sterling option-implied volatility) on PE activity for buyouts characterised by high levels of investment irreversibility and analogous measures – in accordance with H3. This appears to be the case, with respect to both PE investment in the entire period of analysis and during the Brexit period, with statistical significance being generally higher for regressions estimated using the BUI. On the contrary, we document a much weaker real option channel with respect to the transmission of Sterling uncertainty.

#### *4.5.1.2 Industry-level transmission of Brexit uncertainty*

Next, we examine industry-level transmission of Brexit uncertainty. As pointed out in Bloom *et al*. (2019), "The vote for Brexit was a largely unexpected event and we observe that it has had a heterogeneous impact on firms according to their pre-referendum exposure to Europe" (Bloom *et al*., 2019: p. 2). In light of these findings, we argue that the incentive to delay investment when Brexit Uncertainty arises is greater for industries that are more exposed to Brexit uncertainty – i.e. more exposed to the external trade sector (as in Bloom *et al*., 2019; 2020). Of course, measuring exposure to uncertainty can be non-trivial. Hassan et al. (2020), using tools from computational linguistics, measured firm-level exposure to Brexit analysing the recurrence of discussions of benefits (and costs) associated to Brexit in listed firms' quarterly earning conference calls proceedings. They find a much stronger transmission of Brexit-related uncertainty (e.g., leading to outcomes such as: loss of investment, employment, productivity, etc) to firms that are highly exposed to Brexit. We measure external exposure using data on industry-level import and export from the UK Office for National Statistics

(ONS). In particular, we compute for each industry and year the difference between the industry median of import (IM), export (X), and total exposure (IM+X) and national median in a given year *t*. We then assess the impact of Brexit-related uncertainty on probably of a buyout in an industry with high exposure to Brexit (i.e. its exposure to the external sector).

[Insert Table 4.8]

In Table 4.8, we find that sectors more heavily exposed to the external sector have a lower likelihood of buyout as a result of greater Brexit uncertainty, in line with H3. We repeat the test using the EPU and sterling uncertainty from 2016 onward, instead of the BUI, and our results remain robust and unaffected (see columns 2, 5, and 7). In confirmation of the above argument, we do not find evidence of a greater transmission of uncertainty to industries heavily exposed to the external sector before the Brexit Referendum (see columns 3 and 6).

### 4.5.2 *Testing the interim risk channel*

In Table 4.9, we test whether across our whole sample period and in the Brexit period, uncertainty transmitted to the buyout market through this channel. In an interim risk channel (see section 4.2.4), uncertainty transmits to PE activity in the interim period, hence leading investors to postpone (or cancel) investment[38]. However, crucially, deals with a longer interim period are subject to much greater interim risk than deals with shorter interim periods.

[Insert Table 4.9]

Therefore, we measure the interim periods of all buyout deals considered in our analysis and assess the impact of policy uncertainty (in column 1), Sterling option-implied volatility (in column 2, and Brexit uncertainty (in column 3) on the likelihood of a buyout of a target with a longer than the industry median interim period. We find that neither policy uncertainty nor

[38] Test for this channel are exclusively performed on UK firms that at some point in the period of analysis were target of a buyout. These are indeed the only ones that can have an interim period – i.e. hence are exposed to this channel.

Sterling uncertainty significantly affect the likelihood of a buyout – based on the target interim period – hence, we find no evidence of an interim risk channel for the whole period of analysis (2010-2019). On the contrary, Brexit uncertainty significantly reduced the likelihood of buyout of a target with longer interim period than the industry median. This implies that during the years of elevated Brexit uncertainty, not only were buyouts were more unlikely, and investment lost (as we found in Tables 4.2 and 4.3) but the interim risk channel played a role, in agreement with H4.

### 4.5.3 *Testing the moral hazard channel*

We build our empirical setting to investigate the empire building incentive by focusing on the "value-destruction" implications of this channel (see section 4.2.5). We do so by assessing the change in our baseline model accounting variables (ROA, Operating Income, Total Assets, and Cash-to-Assets) around the time of the buyout (between *t*-1 and *t*+1) in moments of high (Brexit) uncertainty and low (Brexit) uncertainty[39], and we test the significance of the difference of the coefficients in the two time periods.

[Insert Table 4.10]

The results presented in Table 4.10 show deals realised in periods of high policy uncertainty are characterised by a higher short-term growth in ROA and by lower operating income than those in periods of low policy uncertainty (see Panel A). We find no sign of moral hazard when comparing periods of high and low sterling option volatility (see Panel B). Hence, the evidence does not support H5. In periods of high Brexit uncertainty, we observe that only deals with a greater change in ROA are significant – all other variables being not significant (see Panel C). We find this evidence as refuting the 'empire building channel'. Periods of high uncertainty

[39] We classify years of high uncertainty as such if in those years a given uncertainty measures have values above the median for the whole period of analysis. *Vice versa*, years with low uncertainty have a value below the entire period median.

are in fact characterised by a loss of buyout deals, as explained above, rather than an increase – as the moral hazard channel would predict. Moreover, deals realised in periods of uncertainty do not seem to compromise shareholder value, as hypothesised by Duchin and Schmidt (2013).

## 4.6 Conclusions

In this paper we explore the role of uncertainty on PE activity in the UK by developing new hypotheses and employing a novel dataset of PE targets and non-targets from 2010 to 2019. Our particular focus is to elicit the uncertainty stemming from the Brexit referendum and contrast it with other forms of uncertainty (e.g., macroeconomic, equity and currency). Uncertainty from Brexit is directly measured by employing the recent Bloom *et al*. (2019) Brexit Uncertainty Index (BUI) constructed from surveys to the CFOs of approximately 3,000 UK businesses. To complement this approach, we conduct a finer grained analysis of the relevance of potential uncertainty transmission channels that might affect buyouts.

Strikingly, we provide evidence that uncertainty affects PE activity negatively, even when controlling for economic activity. Strikingly, Brexit-related uncertainty has a significant negative effect which is distinctly different from other forms of uncertainty and consequently augments the other uncertainties PE companies are facing. Moreover, uncertainty not only reduces PE activity but also delays PE buyouts. In terms of transmission channels, we provide evidence that Brexit-related uncertainty operates via the real option channel and the interim channel but has no statistically measurable effect via the moral hazard channel. Notably, uncertainty particularly affects sectors where investments are relatively irreversible, sunk costs are high and good durable. Overall, our empirical analysis finds strong empirical support for the negative effects of uncertainty on PE activity in the UK as conjectured by Wright *et al*. (2016).

Of course, presently, Brexit uncertainty is ongoing. Our results suggest that this *particular* uncertainty will continue to result in less PE activity and as a corollary, reduced investment and economic activity in UK. To avoid the continued amplification of negative long run economic effects, we would urge UK policymakers to resolve such uncertainties as quickly as possible. This work and our conclusions are built on the foundations of some earlier work by Mike Wright and co-authors. We would like to note that Mike Wright's work was highly original, influential and vast, in both scope and scale. He was also a great friend to many. We very much hope that our work above, building on just a few of his many insights into private equity, can be seen as part of a fitting tribute.

# Tables

**Table 4.1 Investment in PE buyouts**

In this Table we present British PE Buyouts disaggregated in their individual deal structure: Going Private, LBO, MBO. In Panel A, we report the portion PE investment allocated to each of the three deal structures reported above in a given year. In Panel B, we report instead the total number of buyout deals in the UK in a considered year. Once again, we disclose both the aggregate number of deals in a given year and the individual amounts of deals as divided in: Going Private, LBO, MBO. The numbers of deals included in Panel B does include multiple purchases of a same target in a given year. In this case, each deal is considered as separate even if it involves the same target.

*Panel A. Percentage invested in each PE Buyouts structure*

| Date | Going Private | LBO | MBO | Total |
|---|---|---|---|---|
| 2010 | 10% | 74% | 16% | 100% |
| 2011 | 6% | 70% | 24% | 100% |
| 2012 | 12% | 78% | 10% | 100% |
| 2013 | 0% | 92% | 8% | 100% |
| 2014 | 8% | 80% | 12% | 100% |
| 2015 | 0% | 89% | 11% | 100% |
| 2016 | 14% | 81% | 5% | 100% |
| 2017 | 22% | 72% | 6% | 100% |
| 2018 | 31% | 66% | 3% | 100% |
| 2019 | 43% | 56% | 1% | 100% |

*Panel B. Total number of PE Buyout deals in the UK*

| Date | Going Private | LBO | MBO | Total |
|---|---|---|---|---|
| 2010 | 9 | 160 | 70 | 239 |
| 2011 | 12 | 188 | 86 | 286 |
| 2012 | 10 | 173 | 79 | 262 |
| 2013 | 1 | 178 | 67 | 246 |
| 2014 | 7 | 234 | 99 | 340 |
| 2015 | 1 | 193 | 70 | 264 |
| 2016 | 4 | 184 | 59 | 247 |
| 2017 | 6 | 178 | 65 | 249 |
| 2018 | 4 | 196 | 57 | 257 |
| 2019 | 7 | 166 | 48 | 221 |

**Table 4.2 Uncertainty and PE buyout activity**

The Table displays the results of our baseline logistic regression of the likelihood of a buyout ('Buyout t+1') on Economic Policy Uncertainty (EPU; column 1), Macro-economic Uncertainty (column 2), Sterling Option-implied Volatility index (column 3), FTSE All-Share Option-implied Volatility index (column 4), and Brexit Uncertainty Index (BUI; column 5). All regressions are supplemented with several controls for industry and target-specific economic fundamentals. In each regression, the dependent variable assumes a value of 1, if at time *t+1* a certain target firm is the object of a buyout, and zero otherwise. All independent variables are continuous and measured instead at time *t*. Further in-depth information on the variables included in this Table is reported in the Appendix A.4.2.1.

| | (1)<br>Buyout<br>t+1 | (2)<br>Buyout<br>t+1 | (3)<br>Buyout<br>t+1 | (4)<br>Buyout<br>t+1 | (5)<br>Buyout<br>t+1 |
|---|---|---|---|---|---|
| Policy Uncertainty (EPU) | -0.280*** | | | | |
| | (0.089) | | | | |
| Macro Uncertainty | | -0.032 | | | |
| | | (0.099) | | | |
| Sterling Opt-Impl. Volatility | | | -0.165** | | |
| | | | (0.071) | | |
| FTSE Opt-Impl. Volatility | | | | 0.062 | |
| | | | | (0.172) | |
| Brexit Uncertainty (BUI) | | | | | -0.108*** |
| | | | | | (0.026) |
| Investment Opportunity | -0.096* | | -0.073 | | -0.014 |
| | (0.057) | | (0.057) | | (0.034) |
| Industry Shock | 0.354*** | 0.356*** | 0.368*** | 0.354*** | 0.377*** |
| | (0.078) | (0.078) | (0.080) | (0.078) | (0.077) |
| TED Spread | -1.451 | -0.501 | -1.011 | -0.616 | |
| | (0.911) | (0.885) | (0.931) | (0.939) | |
| Industry Cumulative Returns | -0.771*** | -0.696*** | -0.808*** | -0.641** | -0.531** |
| | (0.222) | (0.249) | (0.237) | (0.251) | (0.234) |
| Industry Cumulative STD Returns | 0.237 | 0.418 | 0.501 | 0.325 | -0.399 |
| | (0.598) | (0.602) | (0.588) | (0.613) | (0.640) |
| Industry q | 0.443*** | 0.440*** | 0.412*** | 0.451*** | 0.499*** |
| | (0.094) | (0.094) | (0.098) | (0.095) | (0.090) |
| Total Assets | 0.004*** | 0.005*** | 0.004*** | 0.005*** | 0.005*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| ROA | 0.005*** | 0.005*** | 0.005*** | 0.005*** | 0.005*** |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| Leverage | -0.000 | -0.000 | -0.000 | -0.000 | -0.000* |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Cash-to-Asset | -1.593*** | -1.593*** | -1.593*** | -1.592*** | -1.590*** |
| | (0.254) | (0.255) | (0.255) | (0.255) | (0.253) |
| Constant | -6.640*** | -7.295*** | -7.159*** | -7.385*** | -7.243*** |
| | (0.328) | (0.254) | (0.265) | (0.321) | (0.196) |
| Observations | 412,622 | 412,622 | 412,622 | 412,622 | 412,622 |

*Notes:* ***, **, *, or ◎ mark regression coefficients significant 1, 5, 10 or 15 percent level. Standard Errors are reported in the parentheses underneath the regression coefficients.

**Table 4.3 The persistence of uncertainty effects**

The Table displays the results of a logistic regression of the likelihood of a buyout in the future ('Buyout t+1'; 'Buyout t+2'; 'Buyout t+3'; 'Buyout t+4'; 'Buyout t+5') on Economic Policy Uncertainty (EPU; Panel A), Sterling Option-Implied Volatility (Panel B), and Brexit Uncertainty Index (BUI; Panel C). All regressions are supplemented with several controls for industry and target-specific economic fundamentals, which for space reasons are not presented below. In each regression, the dependent variable assumes a value of 1, if at time *t+1, t+2, t+3, t+4, t+5* a certain target firm is the object of a buyout, and zero otherwise. All independent variables are continuous and measured instead at time *t*. Further in-depth information on the variables included in this Table is reported in the Appendix A.4.2.1.

*Panel A. Economic Policy Uncertainty*

| | (1) Buyout t+1 | (2) Buyout t+2 | (3) Buyout t+3 | (4) Buyout t+4 | (5) Buyout t+5 |
|---|---|---|---|---|---|
| Policy Uncertainty (EPU) | -0.280*** | -0.225*** | -0.095 | 0.793* | 0.462 |
| | (0.089) | (0.086) | (0.077) | (0.415) | (0.602) |
| Observations | 412,622 | 362,609 | 311,788 | 261,615 | 214,549 |
| Macroeconomic Controls | Yes | Yes | Yes | Yes | Yes |
| Industry-level Controls | Yes | Yes | Yes | Yes | Yes |
| Firm-level Controls | Yes | Yes | Yes | Yes | Yes |

*Panel B. Sterling Option-Implied Volatility*

| | (1) Buyout t+1 | (2) Buyout t+2 | (3) Buyout t+3 | (4) Buyout t+4 | (5) Buyout t+5 |
|---|---|---|---|---|---|
| Sterling Opt-Impl. Volatility | -0.165** | -0.181*** | -0.007 | 0.220** | 0.132 |
| | (0.071) | (0.069) | (0.065) | (0.089) | (0.122) |
| Observations | 412,622 | 362,609 | 311,788 | 261,615 | 214,549 |
| Macroeconomic Controls | Yes | Yes | Yes | Yes | Yes |
| Industry-level Controls | Yes | Yes | Yes | Yes | Yes |
| Firm-level Controls | Yes | Yes | Yes | Yes | Yes |

*Panel C. Brexit Uncertainty Index*

| | (1) Buyout t+1 | (2) Buyout t+2 | (3) Buyout t+3 | (4) Buyout t+4 | (5) Buyout t+5 |
|---|---|---|---|---|---|
| Brexit Uncertainty (BUI) | -0.108*** | -0.101*** | -0.077 | -0.189 | - |
| | (0.026) | (0.032) | (0.051) | (0.189) | - |
| Observations | 412,622 | 362,609 | 311,788 | 261,615 | - |
| Macroeconomic Controls | Yes | Yes | Yes | Yes | - |
| Industry-level Controls | Yes | Yes | Yes | Yes | - |
| Firm-level Controls | Yes | Yes | Yes | Yes | - |

*Notes:* ***, **, *, or ◎ mark regression coefficients significant 1, 5, 10 or 15 percent level. Standard Errors are reported in the parentheses underneath the regression coefficients. We cannot produce 5-years ahead predictions, since the BUI is different from zero between 2015 and 2019, i.e. the time window is too narrow.

**Table 4.4 Comparing the impact of uncertainty on buyouts in the UK vs. the US**

The Table displays in columns (1), (2) and (3), the results of a fixed effect logistic regression of the likelihood of a buyout in the United States in year t+1 on several UK measures of uncertainty: Economic Policy Uncertainty (EPU), Sterling Option-Implied Volatility, and Brexit Uncertainty Index (BUI). All regressions are supplemented with industry effects. In columns (4), (5), and (6), we repeat this model specification on our baseline UK buyouts sample to provide a clear comparison of the regression coefficients of our uncertainty measures. In both regression models, we do not include a control sample of firms that are never target of PE buyouts.

| | United States sample | | | UK sample | | |
|---|---|---|---|---|---|---|
| | (1) Buyout t+1 | (2) Buyout t+1 | (3) Buyout t+1 | (4) Buyout t+1 | (5) Buyout t+1 | (6) Buyout t+1 |
| Policy Uncertainty (EPU) | 0.090*** | | | -0.288*** | | |
| | (0.030) | | | (0.087) | | |
| Sterling Opt-Impl. Volatility | | -0.144*** | | | -0.251*** | |
| | | (0.019) | | | (0.052) | |
| Brexit Uncertainty (BUI) | | | -0.008 | | | -0.080*** |
| | | | (0.007) | | | (0.018) |
| Constant | -2.539*** | -2.345*** | -2.386*** | -1.958*** | -2.311*** | -2.295*** |
| | (0.397) | (0.398) | (0.395) | (0.131) | (0.015) | (0.021) |
| Observations | 60,024 | 60,024 | 60,024 | 10,008 | 10,008 | 10,008 |
| Industry-level FE | Yes | Yes | Yes | Yes | Yes | Yes |

Notes: ***, **, *, or ◎ mark regression coefficients significant 1, 5, 10 or 15 percent level. Standard Errors are reported in the parentheses underneath the regression coefficients.

**Table 4.5 Real-options channel – Economic policy uncertainty**

The Table displays the results of a logistic regression of the likelihood of a buyout on Economic Policy Uncertainty (EPU). All regressions are supplemented with several controls for industry and target-specific economic fundamentals. In column 1, the dependent variable assumes a value of 1, if at time *t+1* target firms with a degree of investment irreversibility with above the industry median are the object of a buyout, and zero otherwise. In column 2, the dependent variable assumes a value of 1, if at time *t+1* a target firm pertaining to an industry with higher sunk costs is the object of a buyout, and zero otherwise. In column 3, the dependent variable assumes a value of 1, if at time *t+1* a firm from an industry classified in Sharpe (1994) as a durable good industry is the target of a buyout, and zero otherwise. Eventually, in column 4, the dependent variable assumes a value of 1, if at time *t+1* a target firm from an industry with a high degree of concentration is the object of a buyout, and zero otherwise. All independent variables are continuous and measured instead at time *t*. Further in-depth information on the variables included in this Table is reported in the Appendix A.4.2.1.

| | (1)<br>Investment Irreversibility | (2)<br>Sunk Costs | (3)<br>Durable Goods Industry | (4)<br>Industry Concentration |
|---|---|---|---|---|
| Policy Uncertainty (EPU) | -0.319** | -0.281** | -0.433* | -0.539*** |
| | (0.130) | (0.117) | (0.236) | (0.156) |
| Investment Opportunity | -0.213*** | -0.199** | 0.032 | -0.228** |
| | (0.080) | (0.084) | (0.125) | (0.090) |
| Industry Shock | 0.350*** | 0.775*** | -0.038 | 1.801*** |
| | (0.103) | (0.106) | (0.170) | (0.151) |
| TED Spread | -1.202 | -2.432** | -1.700 | -0.862 |
| | (1.165) | (1.229) | (2.171) | (1.335) |
| Industry Cumulative Returns | -0.550* | -0.759** | -2.191*** | -0.332 |
| | (0.287) | (0.324) | (0.471) | (0.330) |
| Industry Cumulative STD Returns | 0.696 | 5.061*** | 4.540*** | -1.214 |
| | (0.697) | (0.736) | (0.866) | (0.976) |
| Industry q | 0.348*** | 0.421*** | 0.701*** | 0.655*** |
| | (0.132) | (0.133) | (0.192) | (0.171) |
| Total Assets | 0.006*** | 0.003* | -0.004 | 0.002 |
| | (0.002) | (0.002) | (0.004) | (0.002) |
| ROA | 0.010*** | 0.008*** | 0.001 | 0.006*** |
| | (0.002) | (0.002) | (0.005) | (0.002) |
| Leverage | -0.000 | -0.000 | -0.000 | -0.000** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Cash-to-Asset | -2.078*** | -1.454*** | -2.429*** | -1.871*** |
| | (0.305) | (0.325) | (0.665) | (0.373) |
| Constant | -7.098*** | -7.580*** | -8.503*** | -9.127*** |
| | (0.445) | (0.424) | (0.773) | (0.668) |
| Observations | 412,622 | 181,738 | 412,622 | 412,622 |

Notes: ***, **, *, or ◎ mark regression coefficients significant 1, 5, 10 or 15 percent level. Standard Errors are reported in the parentheses underneath the regression coefficients.

**Table 4.6 Real-options channel - Sterling option implied volatility**

The Table displays the results of a logistic regression of the likelihood of a buyout on BoE Sterling Option-Implied Volatility. All regressions are supplemented with several controls for industry and target-specific economic fundamentals. In column 1, the dependent variable assumes a value of 1, if at time *t+1* target firms with a degree of investment irreversibility with above the industry median are the object of a buyout, and zero otherwise. In column 2, the dependent variable assumes a value of 1, if at time *t+1* a target firm pertaining to an industry with higher sunk costs is the object of a buyout, and zero otherwise. In column 3, the dependent variable assumes a value of 1, if at time *t+1* a firm from an industry classified in Sharpe (1994) as a durable good industry is the target of a buyout, and zero otherwise. Eventually, in column 4, the dependent variable assumes a value of 1, if at time *t+1* a target firm from an industry with a high degree of concentration is the object of a buyout, and zero otherwise. All independent variables are continuous and measured instead at time *t*. Further in-depth information on the variables included in this Table is reported in the Appendix A.4.2.1.

| | (1) Investment Irreversibility | (2) Sunk Costs | (3) Durable Goods Industry | (4) Industry Concentration |
|---|---|---|---|---|
| Sterling Opt-Impl. Volatility | -0.045 ◎ | -0.198* | -0.258 | -0.423*** |
| | (0.097) | (0.104) | (0.178) | (0.123) |
| Investment Opportunity | -0.171** | -0.192** | 0.060 | -0.211** |
| | (0.081) | (0.087) | (0.124) | (0.087) |
| Industry Shock | 0.355*** | 0.785*** | -0.028 | 1.896*** |
| | (0.105) | (0.110) | (0.174) | (0.161) |
| TED Spread | -0.388 | -2.193* | -1.251 | -0.431 |
| | (1.149) | (1.294) | (2.301) | (1.435) |
| Industry Cumulative Returns | -0.463 | -0.795** | -2.306*** | -0.450 |
| | (0.311) | (0.358) | (0.539) | (0.368) |
| Industry Cumulative STD Returns | 0.822 | 5.318*** | 4.877*** | -0.650 |
| | (0.690) | (0.757) | (0.928) | (0.963) |
| Industry q | 0.341** | 0.373*** | 0.669*** | 0.527*** |
| | (0.135) | (0.143) | (0.206) | (0.188) |
| Total Assets | 0.006*** | 0.003* | -0.004 | 0.002 |
| | (0.002) | (0.002) | (0.004) | (0.002) |
| ROA | 0.010*** | 0.008*** | 0.001 | 0.006** |
| | (0.002) | (0.002) | (0.005) | (0.002) |
| Leverage | -0.000* | -0.000 | -0.000 | -0.000*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Cash-to-Asset | -2.079*** | -1.452*** | -2.433*** | -1.873*** |
| | (0.305) | (0.325) | (0.666) | (0.373) |
| Constant | -7.777*** | -8.016*** | -9.246*** | -10.019*** |
| | (0.338) | (0.382) | (0.590) | (0.586) |
| Observations | 412,622 | 181,738 | 412,622 | 412,622 |

*Notes:* ***, **, *, or ◎ mark regression coefficients significant 1, 5, 10 or 15 percent level. Standard Errors are reported in the parentheses underneath the regression coefficients.

**Table 4.7 Real-options channel - Brexit uncertainty index**

The Table displays the results of a logistic regression of the likelihood of a buyout on Bloom et al. (2019) Brexit Uncertainty Index (BUI). All regressions are supplemented with several controls for industry and target-specific economic fundamentals. In column 1, the dependent variable assumes a value of 1, if at time *t+1* target firms with a degree of investment irreversibility with above the industry median are the object of a buyout, and zero otherwise. In column 2, the dependent variable assumes a value of 1, if at time *t+1* a target firm pertaining to an industry with higher sunk costs is the object of a buyout, and zero otherwise. In column 3, the dependent variable assumes a value of 1, if at time *t+1* a firm from an industry classified in Sharpe (1994) as a durable good industry is the target of a buyout, and zero otherwise. Eventually, in column 4, the dependent variable assumes a value of 1, if at time *t+1* a target firm from an industry with a high degree of concentration is the object of a buyout, and zero otherwise. All independent variables are continuous and measured instead at time *t*. Further in-depth information on the variables included in this Table is reported in the Appendix A.4.2.1.

| | (1) Investment Irreversibility | (2) Sunk Costs | (3) Durable Goods Industry | (4) Industry Concentration |
|---|---|---|---|---|
| Brexit Uncertainty (BUI) | -0.216*** | -0.089*** | -0.097 | -0.144*** |
| | (0.036) | (0.033) | (0.064) | (0.037) |
| Investment Opportunity | -0.114*** | -0.046 | 0.132 | -0.150*** |
| | (0.043) | (0.045) | (0.081) | (0.051) |
| Industry Shock | 0.380*** | 0.769*** | -0.016 | 1.820*** |
| | (0.101) | (0.099) | (0.170) | (0.145) |
| TED Spread | | | | |
| Industry Cumulative Returns | -0.242 | -0.522 | -1.968*** | 0.036 |
| | (0.289) | (0.318) | (0.517) | (0.337) |
| Industry Cumulative STD Returns | -0.318 | 4.733*** | 4.129*** | -1.843* |
| | (0.764) | (0.710) | (0.904) | (1.076) |
| Industry q | 0.440*** | 0.538*** | 0.739*** | 0.755*** |
| | (0.128) | (0.116) | (0.180) | (0.160) |
| Total Assets | 0.006*** | 0.003** | -0.004 | 0.002 |
| | (0.002) | (0.002) | (0.004) | (0.002) |
| ROA | 0.010*** | 0.007*** | 0.001 | 0.006** |
| | (0.002) | (0.002) | (0.005) | (0.002) |
| Leverage | -0.000 | -0.000 | -0.000 | -0.000** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Cash-to-Asset | -2.071*** | -1.446*** | -2.427*** | -1.864*** |
| | (0.302) | (0.325) | (0.665) | (0.372) |
| Constant | -7.608*** | -8.545*** | -9.417*** | -10.037*** |
| | (0.256) | (0.235) | (0.354) | (0.487) |
| Observations | 412,622 | 181,738 | 412,622 | 412,622 |

*Notes:* ***, **, *, or ◎ mark regression coefficients significant 1, 5, 10 or 15 percent level. Standard Errors are reported in the parentheses underneath the regression coefficients.

**Table 4.8 Buyouts in industries highly exposed to Brexit**

The Table displays the results of a logistic regression of the likelihood of a buyout in a given industry on Economic Policy Uncertainty (EPU; columns 1, 2 and 3), Sterling Option-Implied Volatility (column 4, 5, and 6), and Brexit Uncertainty Index (BUI; column 7). The likelihood of an industry receiving PE investment is expressed as a function of the industry exposure to the external sector (IM+X). All regressions are supplemented with several controls for industry and target-specific economic fundamentals. In each year (*t*), the dependent variable assumes a value of 1, if at time *t+1* a firm belonging to an industry with external sector exposure higher than the median for all industries is the target of a buyout, and zero otherwise. In columns 1, 4, and 7, we consider the likelihood of PE buyouts in industries highly exposed to the external sector over the whole period (pre- and post-Brexit Referendum). In columns 2, and 5, we analyse the likelihood of PE buyouts in industries highly exposed to the external sector just in the year of the Brexit referendum and after. Instead, in columns 3 and 6, we re-perform the logistic model analysing the years before the Referendum. Overall, this analysis enables us to compare the coefficients' sign and significant before and after the Referendum, therefore, to assess potential differences in the transmission of uncertainty to the private equity industry. All independent variables are continuous and measured instead at time *t*. Further in-depth information on the variables included in this Table is reported in the Appendix A.4.2.1.

| | 2010-2019 Industry Exposure to the EU | 2016-2019 Industry Exposure to the EU | 2010-2015 Industry Exposure to the EU | 2010-2019 Industry Exposure to the EU | 2016-2019 Industry Exposure to the EU | 2010-2015 Industry Exposure to the EU | 2010-2019 Industry Exposure to the EU |
|---|---|---|---|---|---|---|---|
| Policy Uncertainty (EPU) | -0.262** | -0.248 ◎ | 0.899 | | | | |
| | (0.120) | (1.179) | (0.850) | | | | |
| Sterling Opt-Impl. Volatility | | | | -0.092 | 0.093 | 0.242 ◎ | |
| | | | | (0.100) | (0.442) | (0.168) | |
| Brexit Uncertainty (BUI) | | | | | | | -0.119*** |
| | | | | | | | (0.034) |
| Observations | 408,036 | 163,050 | 261,615 | 408,036 | 163,050 | 261,615 | 408,036 |
| Macroeconomic Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry-level Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm-level Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

*Notes:* ***, **, *, or ◎ mark regression coefficients significant 1, 5, 10 or 15 percent level. Standard Errors are reported in the parentheses underneath the regression coefficients.

**Table 4.9 Interim risk channel**

The Table displays the results of a logistic regression of the likelihood of a buyout of a target firm with interim period above the industry median on Economic Policy Uncertainty (EPU; column 1), Sterling Option-Implied Volatility (column 2) and Brexit Uncertainty Index (BUI; column 4). All regressions are supplemented with several controls for industry and target-specific economic fundamentals, which for space reasons are not presented below. In each regression, the dependent variable assumes a value of 1, if at time *t+1* a PE target firm has interim period greater than the industry median, and zero otherwise. All independent variables are continuous and measured instead at time *t*. Tests for this regression are performed exclusively on firms which at some point in time have been target of buyouts, as only those would have data on the buyout interim period. The considered period of analysis is 2010-2019. Further in-depth information on the variables included in this Table is reported in the Appendix A.4.2.1.

| | (1) | (2) | (3) |
|---|---|---|---|
| | Interim risk | Interim risk | Interim risk |
| Policy Uncertainty (EPU) | -0.107 | | |
| | (0.201) | | |
| Sterling Opt-Impl. Volatility | | 0.080 | |
| | | (0.161) | |
| Brexit Uncertainty (BUI) | | | -0.100** |
| | | | (0.050) |
| Investment Opportunity | 0.003 | 0.028 | 0.041 |
| | (0.078) | (0.077) | (0.059) |
| Industry Shock | -0.167 | -0.164 | -0.122 |
| | (0.186) | (0.184) | (0.168) |
| TED Spread | -0.500 | -0.437 | |
| | (0.440) | (0.395) | |
| Industry Cumulative Returns | -0.217 | -0.112 | -0.088 |
| | (0.471) | (0.474) | (0.490) |
| Industry Cumulative STD Returns | -3.493** | -3.406** | -4.068*** |
| | (1.445) | (1.472) | (1.530) |
| Industry q | 0.208 | 0.211 | 0.262 |
| | (0.156) | (0.155) | (0.166) |
| Total Assets | 0.154*** | 0.154*** | 0.150*** |
| | (0.023) | (0.023) | (0.022) |
| ROA | 0.017* | 0.017* | 0.015* |
| | (0.009) | (0.009) | (0.009) |
| Leverage | 0.011*** | 0.011*** | 0.011*** |
| | (0.002) | (0.002) | (0.002) |
| Cash-to-Asset | -0.168 | -0.142 | -0.346 |
| | (0.572) | (0.566) | (0.592) |
| Constant | -3.366*** | -3.613*** | -3.502*** |
| | (0.560) | (0.396) | (0.420) |
| Observations | 6,888 | 6,888 | 6,888 |

*Notes:* ***, **, *, or ◎ mark regression coefficients significant 1, 5, 10 or 15 percent level. Standard Errors are reported in the parentheses underneath the regression coefficients.

**Table 4.10 Moral hazard channel**

The Table displays the results of a logistic regression of the likelihood of year *t* displaying a level of Economic Policy Uncertainty (EPU) above (or below) the median (Panel A), Sterling Option-Implied Volatility above (or below) the median (Panel B), and Brexit Uncertainty Index (BUI) above (or below) the median (Panel C). All regressions use as independent variables target-level information on the change in return on assets (ROA), total assets, operating income, cash-to-assets in the two years around the buyout – i.e. in the period ranging from one year before to after the buyout. In column 1, the dependent variable takes value of 1 if in year *t* the level of uncertainty is above the median for the whole period. In column 2, the dependent variable takes value of 1 if in a given year, the level of uncertainty is above the median for the whole period. In column 3, we test the significance of the difference between the logistic regression coefficients. The considered period of analysis is 2010-2019. Further in-depth information on the variables included in this Table is reported in the Appendix A.4.2.1.

*Panel A. Economic Policy Uncertainty*

| | High EPU | Low EPU | High - Low |
|---|---|---|---|
| Delta ROA | 0.016*** | 0.002 | 0.014** |
| | (0.005) | (0.005) | |
| Delta Total Assets | 0.040 | -0.036 | 0.004 |
| | (0.026) | (0.046) | |
| Delta Oper. Income | -0.009*** | 0.002 | -0.011*** |
| | (0.004) | (0.003) | |
| Delta Cash-to-Asset | 0.049 | -0.071 | 0.11 |
| | (0.044) | (0.201) | |
| Constant | -2.257*** | -2.061*** | -0.196 |
| | (0.051) | (0.053) | |

*Panel B. Sterling Opt-Impl. Volatility*

| | High FX Uncertainty | Low FX Uncertainty | High - Low |
|---|---|---|---|
| Delta ROA | 0.008 | 0.010** | -0.002 |
| | (0.005) | (0.005) | |
| Delta Total Assets | 0.022 | 0.006 | 0.016 |
| | (0.037) | (0.033) | |
| Delta Oper. Income | -0.008* | -0.008 | 0.000 |
| | (0.003) | (0.004) | |
| Delta Cash-to-Asset | 0.026 | 0.136 | -0.011 |
| | (0.043) | (0.159) | |
| Constant | -2.219*** | -2.161*** | 0.058 |
| | (0.061) | (0.061) | |

*Panel C. Brexit Uncertainty Index*

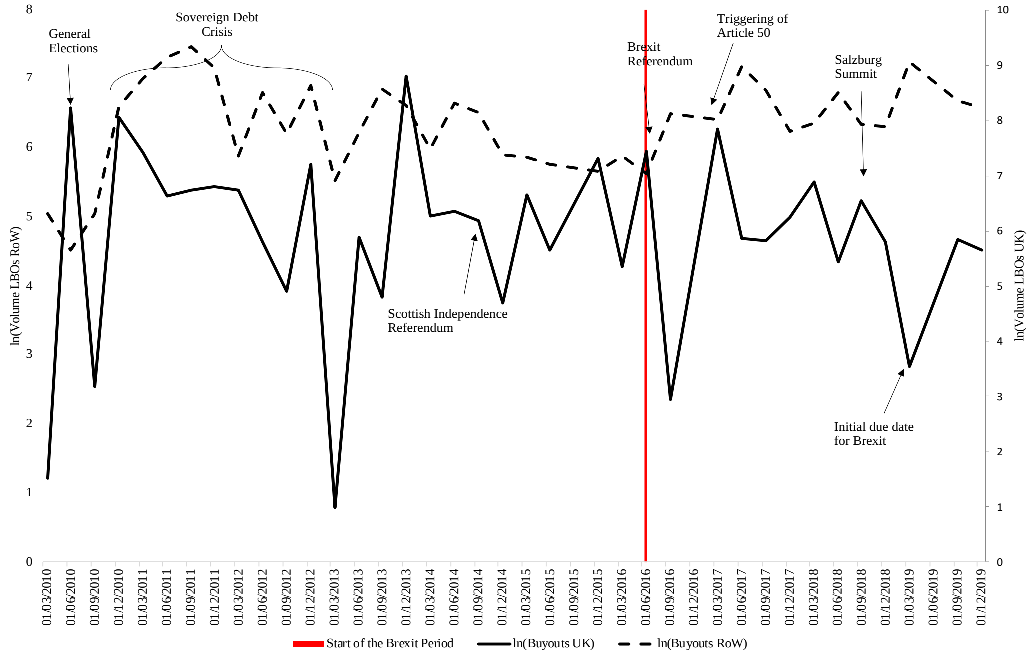
| | High BUI | Low BUI | High - Low |
|---|---|---|---|
| Delta ROA | 0.016*** | 0.003 | 0.013** |
| | (0.005) | (0.005) | |
| Delta Total Assets | 0.022 | 0.004 | 0.018 |
| | (0.030) | (0.036) | |
| Delta Oper. Income | -0.007* | -0.003 | -0.004 |
| | (0.004) | (0.005) | |
| Delta Cash-to-Asset | 0.043 | -0.060 | 0.103 |
| | (0.041) | (0.280) | |
| Constant | -2.185*** | -2.254*** | 0.069 |
| | (0.045) | (0.062) | |

*Notes:* ***, **, *, or ◎ mark regression coefficients significant 1, 5, 10 or 15 percent level. Standard Errors are reported in the parentheses underneath the regression coefficients.

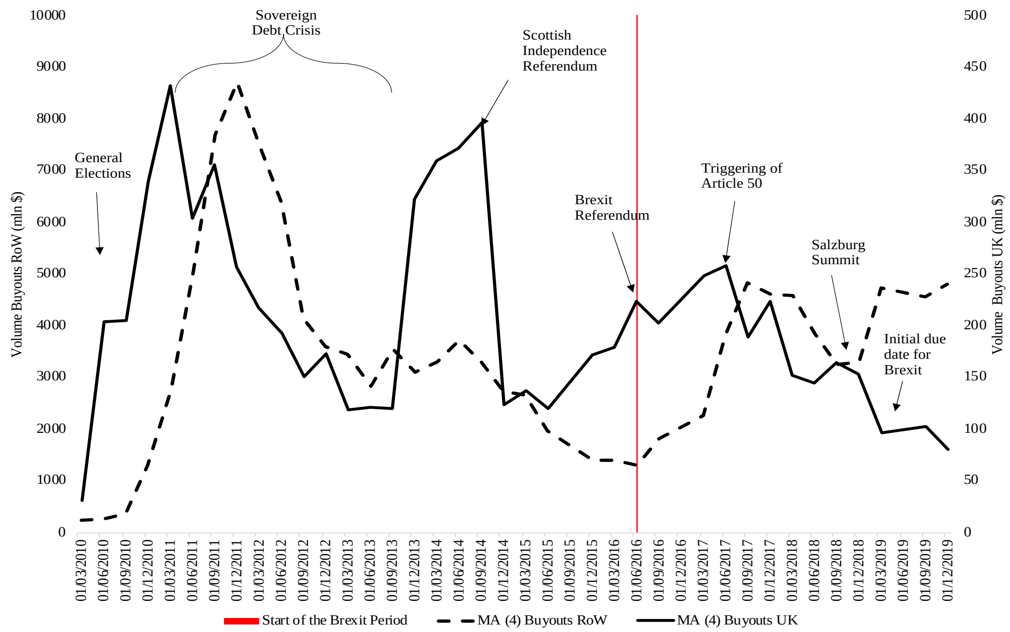
# Figures

**Figure 4.1 Buyout activity in the UK vs. rest of the world (RoW)**

(a) Natural logarithm of total buyout volume

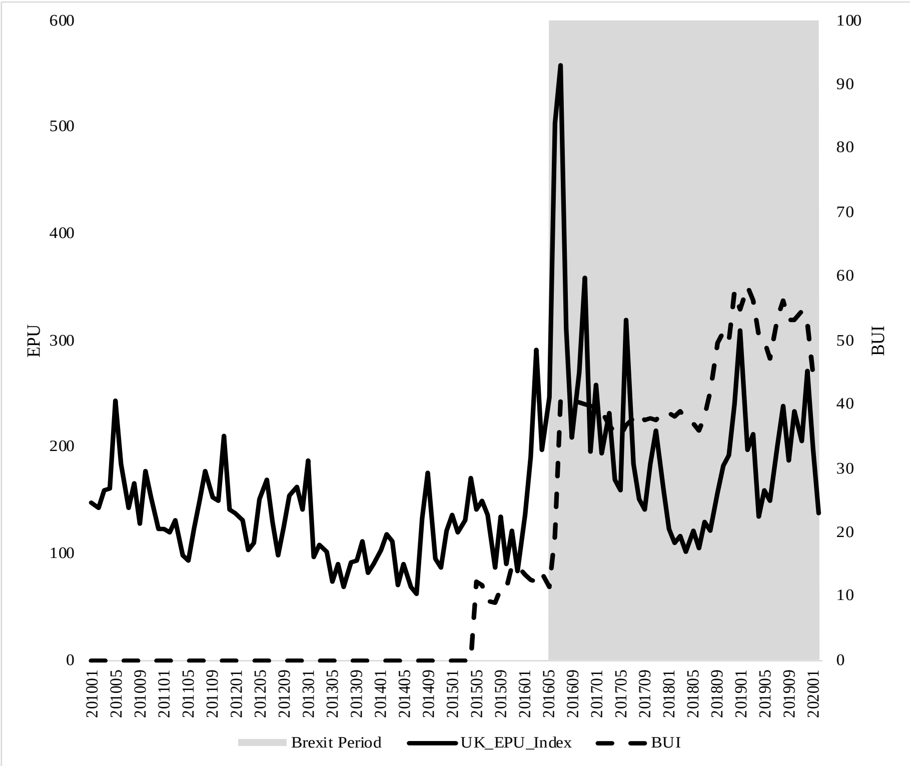



(b) Yearly moving average



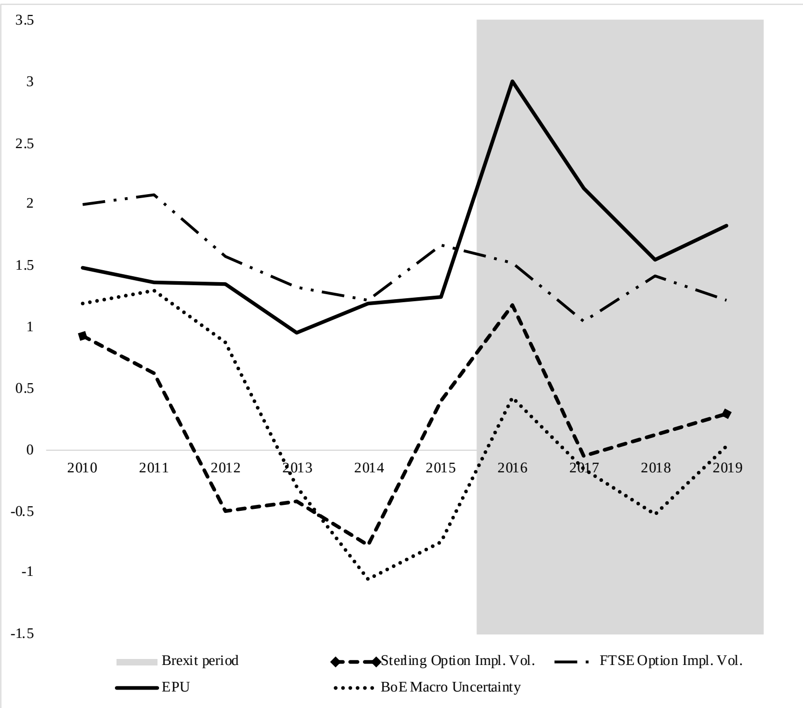

*Notes.* Figure 4.1 uses all deals with structure of leveraged-buyout, management buyout, and going private transactions. These are presented in Panel A as the natural logarithm of the total number of buyout deals and of the total buyout volume in mln of USD in the UK vs in the Rest of the World (RoW). In Panel B, we present instead the 12-months moving average of the total number of buyout deals and of the total buyout volume in mln of USD in the UK vs in the Rest of the World (RoW). Both Panels indicate a strong deviation of the two series after the Brexit Referendum. This is particularly elevated after the triggering of Article 50.

**Figure 4.2 Brexit uncertainty and UK economic policy uncertainty**




*Notes.* Monthly data is used for this Figure. EPU and BUI represent the indices of Economic Policy Uncertainty and Brexit Uncertainty, respectively. The shaded area corresponds the period onwards from the Brexit referendum.

**Figure 4.3 Other measures of uncertainty in the UK**




*Notes.* Annual data is used for this Figure.

# 5 Concluding Remarks

Uncertainty, its origin and spillovers, have been at the core of academic, practitioners and policy debates for quite some time. However, never before, as it is in recent years, this has been seen as a critical component of policy decisions of governments, central banks and policymakers in general as today. Recent uncertainty events like the Global Financial Crisis, the EMU Sovereign Debt Crisis, Brexit, and Covid-19 today made topics such as spillovers, spill backs and contagion become well-known concepts by most scholars. That is because most of the relevant literature recognised that financial markets worldwide have become more interconnected than ever. However, still, many government and central banks mandates are strictly defined in domestic terms. That brought significant uncertainty spillovers, causing the Chinese corporate debt crisis among many economic issues (that I examine in Chapter 2). On the bright side, it also led to the awareness that sound policies to reduce domestic countries' vulnerability and contain the transmission of financial imbalances have never been more crucial. Ultimately, this brought about a stronger and more widely adopted banking regulation and targeted macro-prudential policies to contain and mitigate the specificity of many vulnerabilities built up because of this greater globalisation.

Even though current research made progress in understanding the implications of global spillovers, much is still unknown about their transmission dynamics. The work of this thesis aims to contribute to that effort. In other words, by making a detailed analysis of recent important uncertainty events, this thesis brings forward the *status quo* to facilitate a better understanding of these phenomena and ultimately more straightforward incorporation of this knowledge into policy.

Chapter 2 considers the impact of uncertainty on cross-border investment in China and the resulting build-up of vulnerabilities arising from an expansion of banks' capital availability similar to that observed during domestic easing monetary policies. As I show in that chapter, the expansion caused greater risk-taking of banks and a resulting greater credit to firms with worse economic fundamentals. Banks' risk-taking appears as asymmetric across firms' industry and size and particularly affect firms operating in capital-intensive industries and smaller firms. Note that Chapter 4, analysing Brexit-related uncertainty reports similar findings and extend this work significantly by analysing the transmission channels of uncertainty to the private equity industry and the reasons for a stronger transmission to this category of firms.

These results suggest that spillovers from advanced economies caused significant credit growth and a less resilient corporate sector build-up. In the context of China, greater central government control over the banking sector significantly reduces concerns of corporate or banking sector defaults (because of the central government implicit bailout guarantee). However, the extensive use of implicit guarantees and the resulting increase in banks' risk-taking pose significant threats to the corporate sector's financial stability and, therefore, to the whole system's stability. Private companies not enjoying the state-ownership are growing as a proportion of SOE in China and government intervention in case of these entities' bankruptcy might be less straightforward. The greater reliance of both entities' categories (SOE and privately-owned enterprises) on foreign capital could lead China to drain its foreign reserves quickly. As it happened during the GFC, that may cause undesired consequences on the renminbi, among other adverse outcomes. Therefore, I recommend policymakers stricter supervision of banks during capital inflow surges and more targeted macroprudential policies to account for heterogeneities in leverage growth across firms with different sizes and industries.

Chapter 3 assesses both the effect of uncertainty on foreign investment and the sources at the origin of these effects by discriminating between domestic and foreign country risk. The analysis performed in that Chapter shows that risk in the country of origin (rest of the world) matters and matter more than the risk in the host country (EA). Similar to the findings of

Chapter 2, the banking sector’s capital constraint (or banks' capital availability) of the origin country is the main driver for international investment. Analysing sovereign risk of origin and host countries, it appears that they both matter despite the origin one has a significantly more substantial effect on FDI than that of the domestic country. That is an interesting finding considering that poor financial discipline by host governments has been widely blamed as the primary factor likely to frighten off overseas investors.

The main takeaway of this study is that, again, a domestic focus might not always be the most effective assessment mechanism when dealing with uncertainty resolution. Jaime Caruana, in 2015, at the Sixth Annual Conference on "Monetary and financial shifts: challenges and possible outcomes", suggested that the game we (policymakers) are playing is global. Still, the rules that we employ to play it are way too often local. That inevitably leads to policy ineffectiveness, such as biased policy targets and recommendations. In line with this argument, I encourage policymakers in countries that seek to attract FDI to consider not only domestic risks.

On the contrary, to be mindful of the changing financing environment that MNEs may face in their home countries when deciding which countries to target in seeking FDI. Additionally, I suggest the importance of addressing the asymmetric behaviour of FDI within the core and periphery of the Euro Area. I believe that improving Euro Area convergence with respect to inward foreign investment could be a first step towards reducing its fragmentation and curtailing political and financial market tensions in the European Union.

Chapter 4 studies instead how different uncertainties affect the investor behaviour, why and for how long. In the Chapter, I consider the uncertainty stemming from the Brexit referendum and contrast it with other forms of uncertainty (e.g., macroeconomic, equity and currency). Brexit-related uncertainty has a significant negative effect that is distinctly different from other forms of uncertainty and consequently augments the other uncertainties PE companies face. Moreover, uncertainty not only reduces PE activity but also delays PE buyouts. In terms of transmission channels, I provide evidence that Brexit-related uncertainty operates via a real-options and the interim risk channels but has no statistically measurable effect via the moral hazard channel. Notably, uncertainty particularly affects sectors where investments are relatively irreversible, sunk costs are high, and goods are durable.

These results suggest that this particular uncertainty will continue to result in less PE activity and, as a corollary, could reduce investment and economic activity in the UK. To avoid the continued amplification of adverse long-run economic effects, I would urge UK policymakers to resolve such uncertainties as quickly as possible.

This thesis presents multiple avenues for future research. On a broader level, we can ask ourselves whether these uncertain events and crises are "isolated tremors", arising from an unexpected build-up of idiosyncratic vulnerabilities or the result of a prolonged accumulation of risks arising from economic, financial, and socio-political spheres. And, most importantly, how can we measure these risks, assess their spillovers and include them in policy action? In this thesis, as in most of the relevant literature, I strongly support transmission channels that arise far beyond the domestic country of origin of uncertainty events and that are far from idiosyncratic.

Still, more research is needed on uncertainty spillovers to ensure a quicker resolution and policy better targeted to mitigate its dramatic effects on the real economy. Recent evidence of more robust business cycle synchronisation, zero-interest rate monetary policies in advanced economies (before the GFC and basically ever since), global evidence of small bubbles (such as current housing bubbles in most countries' largest metropolitan cities) are a wake-up call for researchers in international finance. Ultimately, the most basic question that should come to mind is: are we living in a different and more financially stable economic environment than before the GFC, or is this just the second season of the same TV series we were watching back then?

Within the context of China, presented in Chapter 2, I would argue that there is still a lot we do not know because of the vast opacity of Chinese data. Additionally, the entrenchment of the central government in the banking and corporate sectors and the not fully liberalised financial markets and balance of payments make research on financial spillovers in China very challenging. Better publicly available data on Chinese firms, banks' positions and state ownerships stakes in the corporate and banking sector are needed to understand better the vulnerabilities and their transmission channels in emerging markets. As the Chinese government owns most of China's corporate debt, I urge future research to explore risks arising from this exposure and the elevated debt in non-government owned firms (which have substantially grown in recent years). I also argue that the consequences of excessive interconnections between sovereign and banking sectors are well-known after the substantial distress experienced by many European countries during and after the Sovereign Debt Crisis. Therefore, this awareness creates viable avenues for future research on the systemic risks arising from such interconnection, as well as on the sovereign risk arising from the large exposure of the Chinese central government to the documented large banking sector-fuelled corporate debt. Once again, it is worth highlighting that China's systemic importance for the global economy makes risks in China risks everywhere else. As a result, I strongly encourage future research on capital outflows from China and the real effects of such flows. For researchers on moral hazard or vice versa chartered value of government bailout guarantees, I argue that the Chinese context offers a unique opportunity to identify the effect of implicit government guarantees on risk or value creation and derive important policy implications.

Despite the substantial contribution of Chapter 3 to the extant literature, its main limitation is to merely analyse the symptoms and causes of FDI loss (and potential government misguide over its reasons) rather than the effect of the phenomenon. I welcome future research on sovereign and banking contagion dynamics, potentially worsening banking and sovereign sector imbalances in the origin countries and affecting EA FDI loss. Still, today, most literature on international capital flows (particularly on FDI flows) assesses country-specific risks in isolation, without considering cross-country contagion dynamics that are well-known to have a prominent effect in crisis times (see, e.g., Beirne and Fratzscher, 2013) and the consequent results on such flows. Lastly, future research is also needed on the real effects of FDI losses on the host country's economic and MNEs ecosystem. Many authors pointed to the advantages of FDI flows taking a country-level perspective (Carril-Caccia & Pavlova, 2018; Neto & Veiga, 2013). However, to date, there is much less firm-level evidence on the real effects of an FDI increase or loss due to events such as a change in regulations, uncertainty and crises. A better understanding of firm-level changes in FDI and what determines such decisions can have important policy implications and help regulators find practical solutions to attract (or contain) this form of investment.

Concerning Brexit, Chapter 4, the main limitation of this study is that Brexit uncertainty still persists. However, the start of the Covid-19 pandemic brought a dramatic shift in press, academic and policymakers' attention away from Brexit. As a result, interestingly, Brexit uncertainty has dramatically decreased (since the publication of this chapter), and buyout activity in the UK has increased in the UK instead of being delayed (as predicted in this thesis). That, of course, might be due to undervalued UK assets and cheaper sources of alternative finance made available to PE investors. Baker et al. (2009) refer to this phenomenon as cross-border capital arbitrage. Topics of future research on the Brexit uncertainty could try to decompose uncertainty from Brexit from that arising from the Covid-19 pandemic and compare these two sources of uncertainty and their effects on PE investment. Since Brexit uncertainty persists and regulation in many sectors is undue, much more research is required on the Brexit topic. Potential avenues include: (i) the previously mentioned cross-border capital arbitrage, which could explain PE activity increase; (ii) Brexit spillovers on the UK economy and its more interconnected countries; (iii) Brexit effects on assets that are highly synchronised with the UK business cycle.

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# Appendix

### A.2.1. IMF definitions of cross-country financial transactions

In this Appendix, we report the explanation of international cross-country financial transactions reported in the International Financial Statistics of the IMF. All the definitions are reported in the Balance of Payment Manual published by the IMF in 1993.

1. **Portfolio investments** includes, in addition to equity securities and debt securities in the form of bonds and notes, money market instruments and financial derivatives such as options. […] Equity securities covers all instruments and records acknowledging, after the claims of all creditors have been met, claims to the residual values of incorporated enterprises. Shares, stocks, participation, or similar documents (such as American Depositary Receipts) usually denote ownership of equity. Preferred stock or shares, which also provide for participation in the distribution of the residual value on dissolution of an incorporated enterprise, are included. […] Debt securities cover (i) bonds, debentures, notes, etc.; (ii) money market or negotiable debt instruments; and (iii) financial derivatives or secondary instruments, such as options, that usually do not extend to actual delivery and are utilized for hedging of risks, investment, and trading purposes. […] Transactions in items classified as portfolio investment are entered at market prices.
2. **Direct investment** is the category of international investment that reflects the objective of a resident entity in one economy obtaining a lasting interest in an enterprise resident in another economy. (The resident entity is the direct investor and the enterprise is the direct investment enterprise.) The lasting interest implies the existence of a long-term relationship between the direct investor and the enterprise and a significant degree of influence by the investor on the management of the enterprise. Direct investment comprises not only the initial transaction establishing the relationship between the investor and the enterprise but also all subsequent transactions between them and among affiliated enterprises, both incorporated and unincorporated. […] Reflecting the difference noted previously, a direct investment enterprise is defined in this Manual as an incorporated or unincorporated enterprise in which a direct investor, who is resident in another economy, owns 10 percent or more of the ordinary shares or voting power (for an incorporated enterprise) or the equivalent (for an unincorporated enterprise). Direct investment enterprises comprise those entities that are subsidiaries (a

nonresident investor owns more than 50 percent), associates (an investor owns 50 percent or less) and branches (wholly or jointly owned unincorporated enterprises) either directly or indirectly owned by the direct investor.

3. **Other investment** is a residual category that includes all financial transactions not covered in direct investment, portfolio investment, or reserve assets […] the types reflect most of the financial instruments and channels utilized for the acquisition of assets and incurrence of liabilities—other than for direct investment, portfolio investment, and reserve assets. The instrument classification comprises trade credits, loans (including the use of Fund credit and loans from the Fund), currency and deposits (both transferable and other), and other assets and liabilities (for example, miscellaneous accounts receivable and payable).

### A.2.2. Chinese Industrial Classification

In this Appendix, we report the Chinese industrial classification adopted in the paper. This classification follows the 2008 Chinese industrial classification available at the United Nations (Department of Economic and Social Affairs).

| Code | Section | Division | Group | Class |
|---|---|---|---|---|
| A | Agriculture, Forestry, Animal husbandry and Fishing | 5 | 18 | 38 |
| B | Mining | 6 | 15 | 33 |
| C | Manufacture | 30 | 169 | 482 |
| D | Reduction and distribution of electricity, gas and water | 3 | 7 | 10 |
| E | Construction | 4 | 7 | 11 |
| F | Transport, Storage and Post | 9 | 24 | 37 |
| G | Information transmission, computer services and software | 3 | 10 | 14 |
| H | Whole sell and retail sell | 2 | 18 | 93 |
| I | Accommodation and Restaurants | 2 | 7 | 7 |
| J | Finance and Insurance | 4 | 16 | 16 |
| K | Real estate | 1 | 4 | 4 |
| L | Renting and lending, commercial service | 2 | 11 | 27 |
| M | Science research, technique service and geologic perambulation | 4 | 19 | 23 |

| | | | | |
|---|---|---|---|---|
| N | Water conservancy, Environment resource, Management of public infrastructure | 3 | 8 | 17 |
| O | Resident service and other service | 2 | 12 | 16 |
| P | Education | 1 | 5 | 13 |
| Q | Health, Social security and Welfare | 3 | 11 | 17 |
| R | Culture, Sports and Recreation | 5 | 22 | 29 |
| S | Commonality manage and social organizations | 5 | 12 | 24 |
| T | International organizations | 1 | 1 | 1 |
| Total | 20 | 95 | 396 | 912 |

**Source:** The Situation of China's Industrial Classification (United Nations, Department of Economic and Social Affairs, Statistical Division)

## Appendix A.2.3. Variable description

In this Appendix, we provide a detailed description of all the variables adopted in our regressions, the calculations that we performed to compute them and the source of our data on each of these variables.

| Variables names | Extended name | Calculation | Source |
|---|---|---|---|
| Lev. ratio | Firms-level change in leverage ratio | Δlog(Debt\L1.Assets) | Wind and own calculations |
| CIF | Capital inflows | L1.[log(CIF\GDP)] | IMF IFS and own calculations |
| CIF_CA | Capital inflows from the current account | L1.[log(CAB\GDP)] | IMF IFS and own calculations |
| Profitability | Firms accounting cash flows, used as indicator of firms' profitability | Cash Flows = Gross Profit - Interest Expenses - Corporate taxes | Wind and own calculations |
| Z (1) | Z-score, used as proxy for firms' solvency | $z = \frac{\overline{ROA}-\overline{E/A}}{\sigma(ROA)}$ | Wind and own calculations based on De Nicoló et al. (2006) |
| Z (2) | Z-score, used as proxy for firms' solvency | $z = \frac{\overline{ROA}-\overline{E/A}}{\sigma(ROA)}$ | Wind and own calculations based on Back and Leaven (2006) |
| Z (3) | Z-score, used as proxy for firms' solvency | $z = \frac{\overline{ROA}-\overline{MVE/A}}{\sigma(ROA)}$ | Wind and own calculations based on Leaven and Levine (2009) |
| Q | Tobin's Q | $Q = \frac{(A - BVE) + MVE}{A}$ | Wind and own calculations based on Huang and Mazouz (2018) |
| ROA | Return on Assets | | Wind |
| $\sigma$(ROA) | Return on Assets volatility | $\sigma$(ROA) | Wind and own calculations |
| Sharpe | Sharpe ratio | $\text{Sharpe} = \frac{\text{ROA}-\text{Rf}}{\sigma(\text{ROA})}$ | Wind and own calculations |
| MPI | Chinese Monetary Policy Index | Detailed explanation in Appendices A.2.4 and A.2.5 | CEIC and own calculations, based on Giardin et al. (2017) |

| | | | |
|---|---|---|---|
| MP | Residuals from Monetary Policy Index after controlling for banking sector credit and CIF | VAR approach, detailed explanation in Appendices A.2.4 and A.2.5 | CEIC and own calculations |
| Bank Loans | Chinese banks loans to the non-financial corporate sector | | BIS |
| Banks ROA | Banking sector Return on Assets | | CEIC |
| Sov. Yields | Chinese 10-year sovereign bond yields | log (Sov. Yields) | CEIC |
| Mkt Cap | Shanghai and Shenzhen aggregate market capitalisation | Shanghai Equity Mkt Cap + Shenzhen Equity Mkt Cap | CEIC and own calculation |
| mkt vol | Volatility in Shanghai and Shenzhen aggregate market capitalisation | $\sigma$(Mkt Cap) | CEIC and own calculation |
| GDP p.c. | Per capita Gross Domestic Product | | CEIC |

### A.2.4. Summary statistics

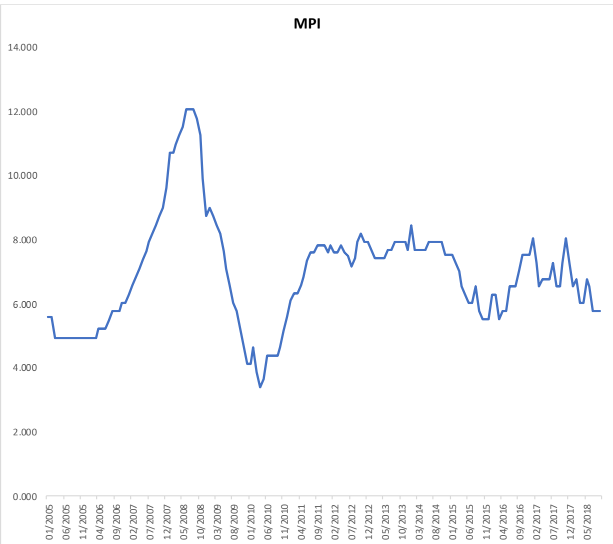
For a better characterisation of the variables adopted in our study (presented in Appendix A.2.3), we report below a standard summary statistics Table, including number of observations, mean, standard deviation, minimum and maximum values assumed by each variable our dataset.

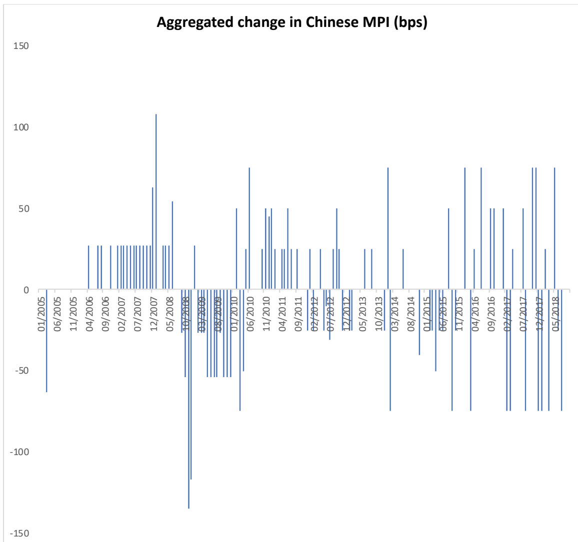
| | Obs | Mean | Std Dev. | Min | Max |
|---|---|---|---|---|---|
| *Dependent variable:* | | | | | |
| Lev. ratio | 93,419 | 0.010 | 0.635 | -10.817 | 15.296 |
| *Main explanatory variable:* | | | | | |
| CIF | 82,301 | -4.435 | 0.437 | -5.246 | -3.502 |
| *Core firm fundamentals:* | | | | | |
| Profitability | 97,284 | 1.12E+08 | 3.11E+09 | -1.09E+11 | 1.51E+11 |
| Tobin's Q | 97,325 | 3.046 | 20.413 | -0.397 | 3480.877 |
| Z-score | 94,099 | 117.941 | 1586.058 | 0.446 | 462209.900 |
| *Additional firm fundamentals:* | | | | | |
| ROA | 97,330 | 0.028 | 0.140 | -1.435 | 20.788 |
| $\sigma$(ROA) | 94,119 | 0.032 | 0.134 | 0.000 | 11.246 |
| Sharpe | 94,099 | 1.235 | 11.165 | -2600.032 | 1276.796 |
| Equity | 97,330 | 1.32E+10 | 7.04E+10 | 0 | 5.29E+12 |
| *Financial maket fundamentals:* | | | | | |
| MPI | 97,330 | 6.997 | 1.629 | 3.890 | 12.060 |
| log(Bank ROA) | 82,667 | 0.186 | 0.131 | -0.105 | 0.358 |
| log(Mkt Cap) | 97,330 | 16.933 | 0.702 | 14.966 | 17.884 |
| log(Mkt vol) | 97,330 | 13.866 | 1.003 | 10.639 | 15.380 |
| *Macroeconomic fundamentals:* | | | | | |
| log(Sov. Yields) | 92,115 | 1.260 | 0.136 | 1.015 | 1.508 |
| $\Delta$log(CPI) | 97,329 | 1.009 | 0.135 | 0.731 | 1.368 |

### A.2.5. Chinese Monetary Policy Index (MPI)

Following Giardin et al. (2017), we built our Chinese Monetary Policy Index (MPI) on four main steps. Firstly, we converted a change in any of the considered monetary policy instruments into a 27 basis point (bps) monthly change; this corresponds to the usual variation in regulated bank deposit and lending rates, paid or charged by PBoC. As the authors, we then assumed a conversion in multiples of 27 for variations in other monetary policy instruments. For instance, a 50 bps change in Required Reserves Ratio (RRR) corresponds to a 27 bps rate change. Regarding Open Market Operations (OMOs), we assumed a variation (withdrawal or injection) of CNY 200 billion as equivalent to 27bps, while a CNY 350 billion change as equivalent to 54bps and CNY 500 billion as 81 basis points. Secondly, we converted all the monthly changes into an aggregate change for all instruments. We perform the aggregation as follows: (i) using a simple arithmetic sum when at least one instrument variation has a different sign instead of the others; (ii) selecting the maximum monthly change, when all instruments changes have the same sign. Afterwards, we adjusted the aggregate change to account for the change in window guidance (a proxy for unobserved policy changes) for the Chinese New Year or one-off variations in PBoC monetary policy stance. Adjustments for the Chinese New Year are adopted as liquidity is often injected and withdrawn the following month. Eventually, we cumulated this into a monthly monetary policy index.

Since our firm-level and capital flow data is quarterly, once we created our monetary policy index, we built our MPI using end-of-the-quarter index values.



### A.2.6. Construction of our monetary policy indicator

To address potential endogeneity problems arising from the simultaneity of banks' lending (debt growth) and PBOC monetary policy. Using a reduced-form VAR model, we study the transformation of capital inflows into bank credit after PBOC monetary policy.

$$y_t = \alpha + \sum_1^p \phi_p y_{t-p} + \mathcal{E}_t \quad \text{[Equation 2.2]}$$

where: $E(\mathcal{E}_t) = 0$, $E(\mathcal{E}_t \mathcal{E}_t') = \Sigma$ and $E(\mathcal{E}_t \mathcal{E}_s') = 0$

In particular, in our VAR specification, $y_t$ is our variable of interest and is built as a *K x 1*, vector of variables; $\phi_p$ is our coefficient estimate matrix with *K x P* estimates – where *p* corresponds to the number of lags included in the VAR and *K* stands for the number of variables included in the VAR. Eventually, $\mathcal{E}_t$ is a *K x 1* vector containing *K* serially uncorrelated white-noise error terms. As specified in the statement underneath Equation 2.2 – $E(\mathcal{E}_t) = 0$, $E(\mathcal{E}_t \mathcal{E}_t') = \Sigma$ and $E(\mathcal{E}_t \mathcal{E}_s') = 0$, in our model the error structure has the following characteristics: (i) it has expected value of zero; (ii) as standard when observing macro variables, error terms are correlated across the *K* different equations; and, (iii) error terms have zero expected correlation across time.

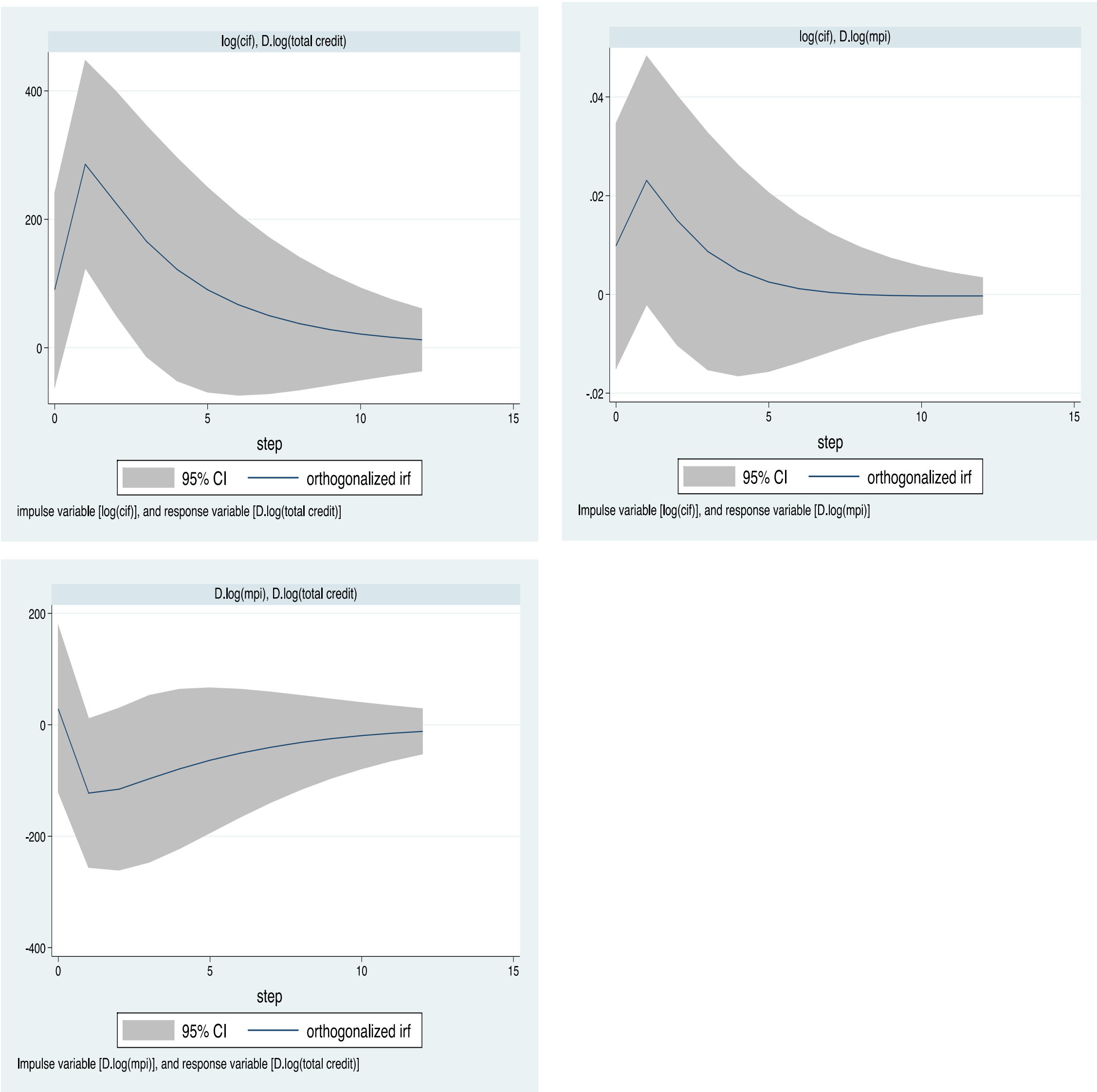
In more detail, the K variables included in the VAR are the natural logarithm of capital inflows in China ('CIF'), our monetary policy index ('mpi') and of total financial institutions credit in China (collected from CEIC).

As standard in reduced-form VAR models, the specification results depend on the selected hierarchical order of the variables. In our case, we specify the hierarchy by considering the theoretical transmission that we hypothesised in our paper (coherent with international capital flow literature). As shown in Figure 2.3, we assume that global factors are the primary determinant of capital inflows, potentially affecting Chinese monetary policy. Therefore, on the one hand, the order of the variables comes as a natural consequence of our theorised specification. On the other hand, despite being a good proxy for Chinese monetary policy, our monetary policy measure – as all indexes – does not constitute an actual monetary policy measure. Indeed, for its construction, we arbitrarily assembled multiple monetary policy indicators to make it as close as possible to the actual Chinese monetary policy. Therefore, we position capital inflows in China as the first variable in the VAR hierarchical specification for both these reasons. The order of the variables in the VAR is, therefore: [CIF MPI Credit]'.

As standard, before executing the reduced-form VAR, we tested the stationarity of our variables using the Augmented Dickey-Fuller test. Not surprisingly, the financial institution credit and monetary policy index are I(1) variables. Using the Johansen Cointegration test, we tested the cointegration of the variables in our model. Since we found that they are not cointegrated, we performed an unconstrained reduced-form VAR, replacing our' log (mpi)' and 'log (total Chinese credit)' variables with their first difference. Unfortunately, because of the lack of stationarity and of cointegration of the analysed, the variables in our model do not allow us to study the long-term effects of capital inflow shocks.

As pictured in the Figure below, a shock to international capital inflows significantly expands domestic banks' credit in the short term and leads PBOC to tighten its monetary policy. For instance, one standard deviation shock to the log of international capital flows leads to a significant increase (about 190 percent) of total bank credit growth, lasting for about 1 year, before the shock to credit growth dissipates. Similarly, one standard deviation growth in capital inflows also significantly affects the change in the monetary policy index (which increases by about 1 percent); however, the effect dyes out much faster and is not significant at 5 percent level since the second quarter following the shock.

After the VAR estimation, eventually, we store the residuals of our equation having the log-change of the Chinese monetary policy index ('mpi') as $y_t$. In this way, we obtain a variable that we will use as a regressor in our baseline model, which accounts for the impact of capital inflows on domestic monetary policy in China. That, we think that reduces to the minimum potential endogeneity arising in the model.




*Notes:* In this Figure, we present the orthogonalised impulse-response functions derived from our reduced-form VAR. In the graphs, we show the response of the first difference of log(total credit) ('D.log(total credit)') – on the left-hand side – and of the log of Chinese monetary policy index ('D.log(mpi)') – on the right-hand side – to one standard deviation shock to the log of capital inflows in China.

## A.3.0: Dataset Description

### *A.3.0.1 Data*

**Inward FDI:** Annual data on foreign countries' FDI holdings in EA countries is collected from the IMF Coordinated Direct Investment Survey (CDIS). From this dataset, we collected 'inward' FDI positions in EA countries, cross-classified by economy of the immediate investor (see IMF's Coordinated Direct Investment Survey Guide – 2015).

**Gravity Variables:** Gravity variables of 'Geographical Distance', 'Common Official Language', 'Contiguity', 'Common Religion', 'Colony', 'Time difference' and 'Common Legal Origin' are instead collected from the 'Comptes Harmonisés sur les Echanges et L'Economie Mondiale (CHELEM)' database, developed by the CEPII Research Center. The 'Gravity Dataset' is a dyadic dataset, disclosing many features for the reported country pairs, such as: geographical distance (in kilometres) between the capitals of most of the countries in the world, whether or not the countries share the same official language, whether the countries share a geographical border, whether the countries share the same official religion or colonization history, the time difference between the countries, their legal origin and more (see Meyer and Zignago, 2011).

**Country Risk Variables:** Country Risk variables have been gathered the World Bank Global Financial Development Database and from IMF Financial Soundness Indicators Database (with the exception of the 10-year Sovereign Bond Yields, for which we used IMF IFS, supplemented for a few missing observations with OECD Financial Statistics, Oesterreichische NationalBank, CEIC and Bloomberg). The World Bank Global Financial Development Database is an extensive dataset gathering information on the functioning of the financial system. Among the information presented in this database, it reports statistics on: financial depth, financial services access, efficiency and stability (resilience) of the financial system and of the institutions operating in it. Almost all our 'Country Risk' variables have been collected from the Financial Stability Section of this database. Additionally, the IMF Financial Soundness Indicators Database is also a comprehensive dataset providing statistics on financial system resilience. In particular, it contains granular information on: financial intermediaries' stability, as well as detailed statistics on other entities such as financial and non-financial corporations. From the latter database, we collected data on banks' regulatory capital to risk-weighted assets, that we then further supplemented using the World Bank Global Financial Development Database.

**GDP per capita and GDP Growth:** Annual data on GDP per capital has been obtained from World Bank Statistics. This database combines macro-economic data from the World Bank National Account database and from the OECD National Accounts data files.
Average host country imports: Annual bilateral import of Euro Area countries (host) from origin countries have been collected from the International Monetary Fund, Direction of Trade Statistics. This data has been then used to compute the average between 2009 and 2016.

**Foreign Exchange rate and Foreign Exchange volatility:** Bilateral exchange rate of all origin countries national currencies against the euro, have been collected from S&P Global Database. In the case of Euro Area countries, we reported the value of the Euro defined in terms of the SDR. The SDR is an international reserve asset, created by the IMF in 1969 to supplement its member countries' official reserves, whose value is determined in terms of a basket of five major currencies (U.S. dollar, the euro, the Chinese renminbi, the Japanese yen, and the British pound sterling). Data for the SDR have been collected from the IMF Exchange rate data.

**Taxes:** Annual data on domestic government tax revenues as a percentage of GDP are collected from World Bank Global Financial Development Database.

**A.3.0.2 – Countries**

In our analysis we included a broad range of countries (i.e., 112 countries). The countries that we considered are all those voluntarily participating in the IMF Coordinated Direct Investment Survey (CDIS), with the exception of tax heavens, small countries with large financial centres or war zones. Specifically, below we report the detailed composition of our dataset:

**Countries included in the dataset:** Within the Euro Area (EA), we considered all countries with the exception of Lithuania, as it joined the EA in 2015, Malta and Luxembourg. With respect to non-Euro Area countries, we consider: Albania, Algeria, Angola, Argentina, Armenia, Australia, Bangladesh, Belarus, Bolivia, Bosnia and Herzegovina, Botswana, Brazil, Brunei Darussalam, Bulgaria, Cabo Verde, Cameroon, Cambodia, Canada, Central African Republic, Chile, China, P.R. Mainland, Colombia, Congo, Republic of Cote d'Ivoire, Croatia, Czech Republic, Denmark, Dominica, Egypt, El Salvador, Gabon, Georgia, Ghana, Guatemala, Guinea, Guinea- Bissau, Guyana, Hungary, Iceland, India, Indonesia, Iran, Islamic Republic of, Israel, Japan, Jordan, Kazakhstan, Kenya, Korea, Republic of Kuwait, Kyrgyz Republic, Lao People's Democratic Republic, Liberia, Lithuania, Macedonia, FYR, Madagascar, Malawi, Malaysia, Mali, Mauritania, Mexico, Mongolia, Morocco, Mozambique, Namibia, New Zealand, Niger, Norway, Oman, Pakistan, Papua New Guinea, Paraguay, Peru, Philippines, Poland, Qatar, Russian Federation, Rwanda, Saudi Arabia, South Africa, Sri Lanka, Sudan, Swaziland, Sweden, Tanzania, Thailand, Turkey, Uganda, Ukraine, United Arab Emirates, United Kingdom, United States, Uruguay, Venezuela, Republica Bolivariana de, Vietnam, Yemen, Republic of Zambia, Zimbabwe.

### A.3.0.3 – Descriptive Statistics

**Table 3.7**
Summary statistics on foreign direct investment and key independent variables.

| Panel A: EA inward direct investment (mln $) | | | | | | |
|---|---|---|---|---|---|---|
| **GIIPS** | **Country Code** | **N** | **Mean** | **Std Dev** | **Min** | **Max** |
| Greece | GRC | 115 | 405.877 | 1,085.274 | -1,633.905 | 5,358.714 |
| Ireland | IRL | 120 | 10,968.990 | 36,481.940 | -23,034.350 | 154,667.400 |
| Italy | ITA | 120 | 17,134.910 | 27,606.310 | 7.640 | 124,198.700 |
| Portugal | PRT | 120 | 1,563.345 | 4,669.577 | -8,047.017 | 24,486.880 |
| Spain | ESP | 120 | 6,962.184 | 10,769.410 | -13,549.280 | 38,622.490 |
| **Non-GIIPS EA** | **Country Code** | **N** | **Mean** | **Std Dev** | **Min** | **Max** |
| Austria | AUT | 120 | 5,389.935 | 8,987.756 | -841.423 | 35,873.030 |
| Belgium | BEL | 120 | 20,817.410 | 46,705.070 | -3,770.425 | 225,544.700 |
| Cyprus | CYP | 119 | 2,095.746 | 5,230.197 | -5,192.275 | 27,625.580 |
| Estonia | EST | 120 | 85.241 | 281.451 | -76.971 | 1,962.515 |
| Finland | FIN | 120 | 3,085.604 | 6,469.908 | -1,011.345 | 31,934.490 |
| France | FRA | 120 | 34,176.300 | 50,160.460 | 45.023 | 178,235.400 |
| Germany | DEU | 120 | 27,228.140 | 47,179.820 | 87.096 | 242,784.100 |
| Latvia | LVA | 119 | 41.694 | 112.753 | -40.353 | 649.823 |
| Netherlands | NLD | 120 | 55,631.900 | 64,693.200 | 0.000 | 248,562.200 |
| Slovak Republic | SVK | 120 | 79.657 | 383.796 | -602.303 | 2,907.801 |
| Slovenia | SVN | 114 | 13.949 | 116.841 | -246.902 | 1,140.897 |
| Panel B: 10-years Sovereign Bonds Yields (%) | | | | | | |
| **GIIPS** | **Country Code** | **N** | **Mean** | **Std Dev** | **Min** | **Max** |
| Greece | GRC | 120 | 10.959 | 5.244 | 5.174 | 22.498 |
| Ireland | IRL | 120 | 4.352 | 2.771 | 0.736 | 9.602 |
| Italy | ITA | 120 | 3.710 | 1.444 | 1.488 | 5.493 |
| Portugal | PRT | 120 | 5.755 | 2.921 | 2.423 | 10.548 |
| Spain | ESP | 120 | 3.741 | 1.542 | 1.393 | 5.845 |
| **Non-GIIPS EA** | **Country Code** | **N** | **Mean** | **Std Dev** | **Min** | **Max** |
| Austria | AUT | 120 | 2.184 | 1.195 | 0.377 | 3.937 |
| Belgium | BEL | 120 | 2.505 | 1.311 | 0.476 | 4.233 |
| Cyprus | CYP | 120 | 5.350 | 1.061 | 3.773 | 7.000 |
| Estonia | EST | 30 | 6.873 | 0.920 | 5.968 | 7.778 |
| Finland | FIN | 120 | 2.005 | 1.106 | 0.363 | 3.739 |
| France | FRA | 120 | 2.226 | 1.090 | 0.467 | 3.649 |
| Germany | DEU | 120 | 1.673 | 1.042 | 0.090 | 3.223 |
| Latvia | LVA | 120 | 5.064 | 4.029 | 0.534 | 12.358 |
| Netherlands | NLD | 120 | 2.000 | 1.108 | 0.292 | 3.687 |
| Slovak Republic | SVK | 120 | 3.029 | 1.567 | 0.543 | 4.707 |
| Slovenia | SVN | 120 | 3.865 | 1.644 | 1.149 | 5.812 |
| Panel C: Non-Performing Loans/Total Gross Loans | | | | | | |
| **GIIPS** | **Country Code** | **N** | **Mean** | **Std Dev** | **Min** | **Max** |
| Greece | GRC | 120 | 24.055 | 11.623 | 7.000 | 36.647 |
| Ireland | IRL | 120 | 17.357 | 5.453 | 9.800 | 25.709 |

| | | | | | | |
|---|---|---|---|---|---|---|
| Italy | ITA | 120 | 14.334 | 3.371 | 9.400 | 18.064 |
| Portugal | PRT | 120 | 9.325 | 2.821 | 4.800 | 11.962 |
| Spain | ESP | 120 | 6.486 | 1.714 | 4.100 | 9.381 |
| **Non-GIIPS EA** | **Country Code** | **N** | **Mean** | **Std Dev** | **Min** | **Max** |
| Austria | AUT | 120 | 2.885 | 0.359 | 2.300 | 3.473 |
| Belgium | BEL | 120 | 3.578 | 0.476 | 2.799 | 4.245 |
| Cyprus | CYP | 120 | 27.329 | 18.361 | 4.500 | 48.676 |
| Estonia | EST | 120 | 2.745 | 1.766 | 0.870 | 5.375 |
| Finland | FIN | 60 | 0.550 | 0.050 | 0.500 | 0.600 |
| France | FRA | 120 | 4.112 | 0.227 | 3.759 | 4.495 |
| Germany | DEU | 105 | 2.773 | 0.442 | 1.980 | 3.300 |
| Latvia | LVA | 120 | 9.039 | 4.703 | 3.652 | 15.934 |
| Netherlands | NLD | 120 | 2.912 | 0.239 | 2.531 | 3.227 |
| Slovak Republic | SVK | 120 | 5.222 | 0.403 | 4.444 | 5.836 |
| Slovenia | SVN | 120 | 10.136 | 3.351 | 5.071 | 15.180 |
| Panel D: EA Regulatory Capital/Risk-Weighted Assets | | | | | | |
| **GIIPS** | **Country Code** | **N** | **Mean** | **Std Dev** | **Min** | **Max** |
| Greece | GRC | 120 | 13.108 | 2.527 | 9.569 | 16.947 |
| Ireland | IRL | 120 | 19.988 | 4.480 | 12.780 | 26.941 |
| Italy | ITA | 120 | 13.295 | 1.018 | 11.650 | 14.789 |
| Portugal | PRT | 120 | 11.807 | 1.308 | 9.780 | 13.327 |
| Spain | ESP | 120 | 13.031 | 1.198 | 11.586 | 14.849 |
| **Non-GIIPS EA** | **Country Code** | **N** | **Mean** | **Std Dev** | **Min** | **Max** |
| Austria | AUT | 120 | 16.500 | 1.027 | 15.026 | 17.976 |
| Belgium | BEL | 120 | 18.389 | 0.637 | 17.262 | 19.305 |
| Cyprus | CYP | 120 | 13.351 | 2.908 | 7.343 | 16.943 |
| Estonia | EST | 120 | 24.721 | 5.969 | 18.607 | 35.653 |
| Finland | FIN | 120 | 17.455 | 3.463 | 14.188 | 23.337 |
| France | FRA | 120 | 14.804 | 2.054 | 12.324 | 17.752 |
| Germany | DEU | 120 | 17.423 | 1.413 | 14.820 | 19.160 |
| Latvia | LVA | 120 | 17.578 | 2.736 | 13.724 | 21.823 |
| Netherlands | NLD | 120 | 16.481 | 3.091 | 13.478 | 22.375 |
| Slovak Republic | SVK | 120 | 15.501 | 2.142 | 12.571 | 17.982 |
| Slovenia | SVN | 120 | 14.458 | 3.294 | 11.320 | 19.155 |

*Notes:* Panel A discloses descriptive statistics on inward FDI stock received by EA countries between 2009 and 2016. Panel B contains descriptive statistics on 10-year sovereign bond yields of EA countries. In Panel C we report descriptive statistics EA banks NPL ratio. Panel D shows descriptive statistics on Regulatory Capital held by EA banks as a portion of their Risk-Weighted assets. For all the Panels, we report statistics on GIIPS and non-GIIPS EA countries separately.

## A.3.1 Additional analyses

### *A.3.1.2 Correlation matrix*

**Table 3.8. Correlation Matrix**

| | log(import)) | comm_lang | l_distance | contig | comrelig | colony | com_leg_orig | corr(GDP) | log(FX) | log(vol FX) |
|---|---|---|---|---|---|---|---|---|---|---|
| log(import)) | 1 | -0.003 | 0.000 | **0.040** | **0.153** | **0.030** | **-0.038** | **0.032** | 0.007 | 0.009 |
| comm_lang | | 1 | **-0.053** | **0.199** | **0.126** | **0.320** | **0.268** | **0.063** | **-0.056** | **-0.041** |
| log(distance) | | | 1 | **-0.468** | **-0.178** | **-0.109** | **-0.054** | **-0.354** | **0.267** | **0.480** |
| contig | | | | 1 | **0.194** | **0.264** | **0.175** | **0.223** | **-0.107** | **-0.142** |
| comrelig | | | | | 1 | **0.116** | **0.166** | **0.154** | **-0.238** | **-0.210** |
| colony | | | | | | 1 | **0.093** | 0.019 | -0.016 | **-0.037** |
| com_leg_orig | | | | | | | 1 | **0.050** | **-0.025** | **0.041** |
| corr(GDP) | | | | | | | | 1 | **-0.096** | **-0.279** |
| log(FX) | | | | | | | | | 1 | **0.554** |
| log(vol FX) | | | | | | | | | | 1 |

***Table 3.8 Continued. Transposed***

| | log(taxes) | log(10SBY)orig | log(10SBY)host | log(RCRWA)orig | log(RCRWA)host | log(NPL)orig |
|---|---|---|---|---|---|---|
| log(import)) | **-0.239** | 0.006 | **-0.273** | 0.014 | **-0.051** | -0.008 |
| comm_lang | **0.027** | -0.02 | -0.009 | 0.003 | **0.101** | -0.013 |
| log(distance) | 0.012 | **0.322** | **0.043** | **-0.045** | **-0.043** | **-0.22** |
| contig | -0.05 | **-0.137** | **-0.053** | -0.019 | **0.029** | **0.075** |
| comrelig | **-0.054** | **-0.078** | **-0.091** | -0.006 | 0.0181 | **0.046** |
| colony | **-0.045** | 0.008 | -0.012 | -0.021 | -0.022 | 0.004 |
| com_leg_orig | **0.058** | **0.062** | **0.082** | **-0.051** | **-0.043** | **0.076** |
| corr (GDP) | **-0.086** | **-0.168** | **-0.191** | -0.011 | **0.156** | **0.052** |
| log (FX) | 0.008 | **0.263** | **-0.036** | **0.221** | **0.027** | 0.009 |
| log (vol FX) | 0.007 | **0.501** | -0.013 | **0.123** | 0.013 | **-0.026** |
| log(taxes) | 1 | **-0.035** | **0.13** | **0.027** | **0.0627** | -0.018 |
| log (10SBY)_orig | | 1 | **0.195** | -0.007 | **-0.151** | **0.148** |
| log (10SBY)_host | | | 1 | **-0.164** | **-0.596** | **0.101** |
| log (RCRWA)_orig | | | | 1 | **0.111** | **-0.095** |
| log (RCRWA)_host | | | | | 1 | **-0.074** |
| log (NPL) orig | | | | | | 1 |

*Notes:* All the coefficients reported in bold are significant at 5% level.

### *A.3.1.3 Additional tests*

As additional tests, we performed: (i) Wooldridge test for serial correlation, (ii) Pesaran test for cross-sectional dependence and (iii) Fisher test on variable stationarity. As a result of evidence of serial correlation and cross-sectional dependence, we corrected our standard error structure using time fixed-effects and clustering of our standard errors at the host country level.

## A.3.2 Additional test results

In this section, we present the results of other tests that we perform to robustify the validity of our theory.

**Table 3.9**

Estimation results on the impact of banking and sovereign risk on inward FDI in the EMU, accounting for origin countries' economic growth. Regression results obtained by OLS.

| | **Country Risk** | |
|---|---|---|
| | Banking Risk measure | Sovereign Risk measure |
| | (1) | (2) |
| | log (FDI) | log (FDI) |
| log (NPL ratio_orig) | -0.178*** (0.038) | |
| log (NPL ratio_host) | 0.065 (0.047) | |
| log (Sovereign yields_orig) | | -1.449*** (0.157) |
| log (Sovereign yields_host) | | -0.443*** (0.149) |
| avg (log(import)) | 0.353*** (0.060) | 0.431*** (0.083) |
| comm_lang | 1.180** (0.425) | 1.133** (0.466) |
| log (distance) | -0.992*** (0.102) | -0.562*** (0.104) |
| contig | 2.411*** (0.341) | 1.669*** (0.368) |
| comrelig | 0.938*** (0.308) | 0.704 (0.427) |
| colony | 0.357 (0.683) | 0.595 (0.765) |
| com_leg_orig | -0.251 (0.231) | 0.623 (0.395) |
| corr (GDP) | -0.045 (0.218) | -0.079 (0.300) |
| log (vol FX) | -1.178*** (0.081) | -0.936*** (0.087) |
| log (taxes) | 0.176 (0.313) | 0.186 (0.426) |
| L1 (GDP Growth_orig) | 0.042 (0.043) | 0.064 (0.045) |
| Constant | 12.845*** (1.462) | 11.309*** (1.759) |
| N | 6,545 | 4,071 |
| Time FE | Yes | Yes |
| R-squared | 0.395 | 0.478 |

*Notes*: *, **, and *** imply statistical significance at the 10, 5, and 1 percent levels respectively. In the parentheses are reported robust standard errors clustered within country pairs. Yearly time fixed effects are included but unreported. As proxy for economic growth, in this Table we adopt the first lag of GDP growth of origin countries; other variables are described in the 'Data' section.

**Table 3.10**

Estimation results on the impact of banking and sovereign risk on inward FDI in the EMU, accounting for origin countries' financial sophistication[40]. Regression results obtained by OLS.

| **Country Risk** | | |
|---|---|---|
| | Banking Risk measure | Sovereign Risk measure |
| | (1) | (2) |
| | log (FDI) | log (FDI) |
| log (NPL ratio_orig) | -0.224*** (0.036) | |
| log (NPL ratio_host) | 0.040 (0.043) | |
| log (Sovereign yields_orig) | | -1.168*** (0.151) |
| log (Sovereign yields_host) | | -0.483** (0.174) |
| avg(log(import)) | 0.384*** (0.062) | 0.561*** (0.097) |
| comm_lang | 1.418*** (0.438) | 1.192* (0.617) |
| log(distance) | -1.118*** (0.087) | -1.085*** (0.106) |
| contig | 1.507*** (0.390) | 0.412 (0.447) |
| comrelig | 1.003*** (0.284) | 0.597 (0.450) |
| colony | 0.494 (0.619) | 0.740 (0.617) |
| com_leg_orig | -0.131 (0.171) | 0.504* (0.271) |
| corr (GDP) | 0.117 (0.176) | 0.044 (0.292) |
| log (vol FX) | -1.008*** (0.051) | -0.879*** (0.089) |
| log(taxes) | 0.120 (0.341) | 0.088 (0.510) |
| log (MKTCAP/GDP orig) | 0.346*** (0.042) | 0.927*** (0.125) |
| Constant | 12.659*** (1.411) | 11.436*** (1.850) |
| N | 9,636 | 6,098 |
| Time FE | Yes | Yes |
| R-squared | 0.440 | 0.494 |

*Notes*: *, **, and *** imply statistical significance at the 10, 5, and 1 percent levels respectively. In the parentheses are reported robust standard errors clustered within country pairs. Yearly time fixed effects are included but unreported. As proxy for financial market sophistication, in this Table we adopt the logarithm of the ratio of origin countries' equity market capitalisation-over-GDP; other variables are described in the 'Data' section.

[40] Note that, according to Davis et al. (2000) argument, origin countries financial sophistication should favour their FDI, once foreign countries' conditions prove as preferable to those of their home country. On the contrary, countries with less developed financial markets could face higher costs (barriers to entry) in investing abroad. This would bias them towards investing in their home market.

**Table 3.11**
Estimation results on the impact of banking and sovereign risk on inward FDI in the EMU, controlling for origin countries' Business Cycle (BC). Regression results obtained by OLS.

| | **Country Risk** | |
|---|---|---|
| | Banking Risk | Sovereign Risk |
| | (1) | (2) |
| | log (FDI) | log (FDI) |
| log (NPL ratio_orig) | -0.113*** (0.037) | |
| log (NPL ratio_host) | 0.061 (0.040) | |
| log (Sovereign yields_orig) | | -0.765*** (0.107) |
| log (Sovereign yields_host) | | -0.360*** (0.125) |
| BC | 0.103 (0.077) | -0.012 (0.134) |
| avg (log(import)) | 0.428*** (0.020) | 0.484*** (0.032) |
| comm_lang | 1.453*** (0.369) | 1.796*** (0.378) |
| log (distance) | -0.446*** (0.091) | -0.305*** (0.109) |
| contig | 1.503*** (0.374) | 0.732* (0.385) |
| comrelig | 0.881*** (0.256) | 0.598* (0.333) |
| colony | -0.118 (0.474) | 0.186 (0.521) |
| com_leg_orig | -0.405** (0.159) | 0.290 (0.224) |
| corr (GDP) | 0.254** (0.125) | 0.143 (0.167) |
| log (vol FX) | -0.804*** (0.067) | -0.691*** (0.091) |
| log (taxes) | 0.275 (0.318) | 0.196 (0.393) |
| Constant | 6.166*** (1.350) | 6.377*** (1.579) |
| N | 9,406 | 5,911 |
| Time FE | Yes | Yes |
| R-squared | 0.496 | 0.535 |

*Notes*: *, **, and *** imply statistical significance at the 10, 5, and 1 percent levels respectively. In the parentheses are reported robust standard errors clustered within country pairs. Yearly time fixed effects are included but unreported. Origin countries' BC has been computed as the cyclical component of these countries' GDP, obtained using a Hodrick-Prescott filtering process with smoothing factor of 100; other variables are described in the 'Data' section.

**Table 3.12**
Estimation results on the impact of banking and sovereign risk on inward FDI from non-EA countries in the EMU (GIIPS and non-GIIPS countries) by OLS.

| | **Country Risk** | | | |
|---|---|---|---|---|
| | Banking Risk measure | Sovereign Risk measure | Banking Risk measure | Sovereign Risk measure |
| | non-GIIPS | | GIIPS | |
| | (1) | (2) | (3) | (4) |
| | log (FDI) | log (FDI) | log (FDI) | log (FDI) |
| log (NPL ratio_orig) | -0.201*** (0.063) | | -0.207*** (0.078) | |
| log (NPL ratio_host) | 0.086 (0.054) | | 0.085 (0.294) | |
| log (Sovereign yields_orig) | | -1.471*** (0.172) | | -1.302*** (0.206) |
| log (Sovereign yields_host) | | -0.428* (0.221) | | -1.061*** (0.297) |
| avg (log(import)) | 0.400*** (0.051) | 0.521*** (0.068) | 0.460*** (0.100) | 0.465*** (0.117) |
| comm_lang | -0.244 (0.808) | 0.223 (1.355) | 1.968*** (0.687) | 2.083** (0.821) |
| log(distance) | -0.806*** (0.134) | -0.442*** (0.156) | -0.593*** (0.207) | -0.514** (0.208) |
| contig | 2.816*** (0.564) | 2.260*** (0.627) | -0.522 (1.329) | -1.733 (1.074) |
| comrelig | 0.036 (0.444) | -0.688 (0.580) | -0.006 (0.453) | 0.044 (0.646) |
| colony | 1.180 (0.736) | 0.817 (0.888) | 1.605 (1.071) | 3.167** (1.246) |
| com_leg_orig | -0.186 (0.258) | 0.598* (0.337) | -0.700*** (0.249) | -0.131 (0.406) |
| corr (GDP) | 0.096 (0.188) | 0.411 (0.273) | 0.179 (0.243) | -0.094 (0.302) |
| log (vol FX) | -0.997*** (0.105) | -0.806*** (0.143) | -1.116*** (0.156) | -1.013*** (0.176) |
| log(taxes) | 0.448 (0.504) | 0.537 (0.599) | 0.033 (0.821) | 1.014 (0.889) |
| Constant | 9.810*** (2.088) | 8.634*** (2.320) | 9.138*** (3.220) | 8.823*** (3.284) |
| N | 5,215 | 2,930 | 2,660 | 1,575 |
| Time FE | Yes | Yes | Yes | Yes |
| R-squared | 0.293 | 0.427 | 0.295 | 0.478 |

*Notes*: *, **, and *** imply statistical significance at the 10, 5, and 1 percent levels respectively. In the parentheses are reported robust standard errors clustered within country pairs. Yearly time fixed effects are included but unreported. See the 'Data' section for variable description.

**Table 3.13**
Estimation results on the impact of banking and sovereign risk on inward FDI in the EMU, controlling for the size and capital intensity of origin and host countries. Regression results obtained by OLS.

| | **Country Risk** | |
|---|---|---|
| | Banking Risk | Sovereign Risk |
| | (1) | (2) |
| | log (FDI) | log (FDI) |
| log (NPL ratio_orig) | -0.080** (0.040) | |
| log (NPL ratio_host) | -0.014 (0.042) | |
| log (Sovereign yields_orig) | | -1.107*** (0.118) |
| log (Sovereign yields_host) | | -0.684*** (0.124) |
| ln_sumGDPg | -0.038 (0.040) | -0.147*** (0.049) |
| L1_log (diffGDPpc) | 0.112*** (0.009) | 0.077*** (0.010) |
| avg (log(import)) | 0.461*** (0.038) | 0.507*** (0.046) |
| comm_lang | 1.438*** (0.407) | 1.560*** (0.442) |
| log (distance) | -0.882*** (0.094) | -0.579*** (0.112) |
| contig | 2.052*** (0.387) | 1.353*** (0.401) |
| comrelig | 1.224*** (0.275) | 0.847** (0.353) |
| colony | 0.451 (0.475) | 0.914* (0.534) |
| com_leg_orig | -0.109 (0.173) | 0.749*** (0.226) |
| corr (GDP) | 0.128 (0.132) | -0.052 (0.175) |
| log (vol FX) | -0.808*** (0.082) | -0.740*** (0.101) |
| log (taxes) | 0.384 (0.344) | 0.467 (0.410) |
| Constant | 9.788*** (1.430) | 9.410*** (1.573) |
| N | 9,626 | 6,088 |
| Time FE | Yes | Yes |
| R-squared | 0.432 | 0.499 |

Notes: *, **, and *** imply statistical significance at the 10, 5, and 1 percent levels respectively. In the parentheses are reported robust standard errors clustered within country pairs. Yearly time fixed effects are included but unreported. In this Table, we use the natural logarithm of the sum of GDP growth of origin and host country as proxy for size of the economies involved in the bilateral transaction. We exploit the first lag of the natural logarithm of the difference in origin and host countries GDP per capita to control instead for the economies' capital intensity.

### A.4.1. Construction of the dataset on PE buyouts

We create our dataset exploiting several data sources. First, we identify 2,050 targets acquired by PE buyout firms over the period 2008 to 2019 in the UK from S&P Market Intelligence.

Second, using S&P Capital IQ and Market Intelligence, we classify PE transactions (deals) as buyouts. Deals considered in our paper are those that satisfy the following criteria: (i) the target firm is incorporated in the UK; (ii) the transaction is announced and completed between 2008 and 2019; (iii) the deal structure of the transaction – as reported on S&P Capital IQ and Market Intelligence – is reported as: "leveraged buyout", "LBO", "management buyout", "MBO", or "going private transaction"; (iv) the PE investor has reported interest in at least one of the following stages: bridge, buyout, early venture, emerging growth, growth capital, incubation, industry consolidation, late venture, mature, mezzanine/sub-debt, middle market, mid-venture, pipes, seed/start-up, or turnaround. This identification strategy is widely popular in the buyout literature and is consistent with widely known work such as Axelson *et al*. (2013) and Faccio and Hsu (2017). This next step produces a result of 1,869 buyouts targets.

Finally, we match this data with accounting databases such as: Capital IQ, Compustat and Orbis, to obtain firm-level accounting controls for the previously defined PE targets. This reduces the useable sample to 833 UK target firms. When we match this with the available data on non-target UK firms from Orbis (data only available from 2010) this results in a final sample of UK PE targets of 765 firms over the period 2010 to 2019.

### A.4.2. Variables: Definition and construction

*A.4.2.1.1. Macro-economic and industry-level control variables*

1. Investment Opportunity Index: To compute this variable, we used a Principal Component Analysis (PCA) and selected the first principal component of the following variables (all available at quarterly frequency):
   a) Agents survey on investment intentions: Survey of Bank of England's Agents, performed for service and non-service sector.
   b) CBI survey on investment intentions: Survey of Confederation of British Industry, performed for manufacturing, financial services, business/consumer/professional services and distributive trade.
   c) General economic situation expectations (Survey of Bank of England)
   d) Personal financial situation expectations (Survey of Bank of England)
   e) Unemployment expectations (inverted) (Survey of Bank of England)
   f) One year-ahead GDP growth forecast at market rates (Statistic of Bank of England)

2. Industry Shock: To build this variable, we follow Harford (2005). We use the first principal component of economic shocks to targets' industries operating performance. We calculate industry shocks to operating performance as the median of the absolute yearly change in: (i) net income-to-sales turnover; (ii) R&D expenditure-to-assets; (iii) capital expenditure-to-assets; (iv) ROA; (v) growth in sales turnover. As industries, we use Fama and French (1997) 48-industry classification.
3. TED Spread: Standard measure of market liquidity (or funding cost). For the UK, it is measured as the difference between the 3-month UK LIBOR and 3-month UK Treasury Bill yields.
4. Industry Cumulative Returns: This variable is calculated as the industry annual median of monthly firm-level 36-months log-cumulative returns. In the transformation of the return variable into *ln*, i.e. to compute log-cumulative returns, the following approximation has been used: $ln\ (ret_1) = ln\ (1+ ret_1)$ to avoid losing information on periods with returns having a negative sign. Data on equity prices has been collected from CRSP and industries have been defined following Fama and French (1997) 48-industry definition.
5. Industry Cumulative Standard Deviation (STD) of Returns: After calculating 'Industry Cumulative Returns', for each year, we compute the standard deviation of 36-months log-cumulative returns.
6. Industry Tobin's q: This variable is calculated as the industry annual median Tobin's q, for each of Fama and French (1997) 48 industries. We calculate yearly firms' Tobin's q as (Total Assets + Book-Value of Equity – Market Value of Equity)-over-Total Assets.

*A.4.2.1.2. Firm-specific control variables*

1. Total Assets: It represents the Book Value of Assets of target portfolio firms, measured in million US dollars and scaled by 100. When constructing this variable, we exclude all firms having Book Value of Assets lower than 0. Data on this variable has been collected from Compustat, Orbis, and S&P Capital IQ.
2. ROA: The Return on Asset have been collected from Compustat, Orbis, and S&P Capital IQ. In case of missing values, this variable has also been computed as Net Income-to-Total Assets. Eventually, we winsorize this variable at the 1st and 99th percentiles.

3. Leverage: This variable is computed as Total Liabilities-to-Book-Value of Equity. Data on equity and liabilities have been collected from Compustat, Orbis, and S&P Capital IQ.
4. Cash-to-Assets: This variable is computed as Cash and Equivalents-to-Total Assets. Data on these two variables have been collected from Compustat, Orbis, and S&P Capital IQ.

Below, we report the total number of observations for each firm-level control variable:

**Table A1. Accounting variables yearly observations**

In this Table, we display the total number of firm-year observation reached after merging the original sample of private equity buyouts with our asset-based control group. All the variables included in this Table are target-specific balance sheet and income statement variables adopted in our baseline regression models.

| Date | Total Assets | ROA | Operating Revenues | Total Liabilities (Curr & Non-curr) | Leverage | Cash-to-Assets |
|---|---|---|---|---|---|---|
| 2010 | 182,795 | 64,910 | 40,497 | 180,760 | 155,849 | 134,989 |
| 2011 | 190,219 | 66,348 | 55,902 | 176,663 | 176,652 | 146,319 |
| 2012 | 198,794 | 67,368 | 56,803 | 184,741 | 184,727 | 154,604 |
| 2013 | 204,769 | 68,684 | 58,428 | 193,313 | 193,295 | 162,971 |
| 2014 | 210,145 | 70,186 | 59,866 | 198,989 | 198,976 | 169,258 |
| 2015 | 219,319 | 73,167 | 61,306 | 203,405 | 203,392 | 173,807 |
| 2016 | 228,830 | 77,233 | 63,394 | 213,341 | 213,324 | 180,959 |
| 2017 | 237,107 | 78,454 | 65,931 | 222,800 | 222,782 | 184,832 |
| 2018 | 240,522 | 78,189 | 66,638 | 228,555 | 228,537 | 187,099 |
| 2019 | 72,922 | 17,290 | 15,147 | 72,034 | 72,032 | 61,156 |

*A.4.2.1.3. Proxies for investment irreversibility, sunk costs, industry cyclicality, and concentration*

1. Capital Intensity: This variable is computed as the ratio of Net Property, Plant and Equipment (PPE)-to-Total Assets. Data on this variable has been collected from Compustat, Orbis, and S&P Capital IQ. Our proxy of high capital intensity is built using an indicator variable that, for each year, takes value of one if the target firm capital intensity ratio is greater than the industry median; zero otherwise.
2. High Investment Sunk Costs: Following Bonaime et al. (2018), we first compute the following three ratios: Rent Expense-to-first lag of PPE; Depreciation Expense-to-first lag of PPE; and, Annual Sales of PPE-to-first lag of PPE. Our proxy for 'high investment sunk cost' takes value of one, if the industry average of all three ratios is

contemporaneously greater than the industry median (in a given year); zero otherwise. We define industries following Fama and French (1997) 48-industry definition.

3. Industry Cyclicality: To define this variable, we follow the definition of cyclical industries given by Sharpe (1994), which found durable goods industries to be much more cyclical than non-durable goods ones. Therefore, as in Sharpe (1994), we classify durable goods industries based on their SIC code. We then use an indicator variable that takes value of one, if the industry is classified as durable goods industry in Sharpe (1994), zero otherwise.
4. Industry Concentration: We follow a similar approach to that employed for the construction of the Herfindahl index. We assume that if markets are efficient and competitive sales should be similar across industries and not deviate from a certain optimum. Therefore, our indicator variable 'Industry Concentration' takes value of one if, in a given year, median sales of one industry exceed the median sales from all industries, and zero otherwise.
5. Industry Exposure to the EU: In a similar spirit to Bloom et al. (2019), we measure exposure based on industries exposure to the external sector (IM + X) of the Balance of Payment. Industry Import (IM), and Export (X) are available from the UK Office of National Statistics (ONS). Industry with high exposure to the EU are those that in a given year have Total External Sector (IM + X) higher than the UK median.

### A.4.3. Construction of the control group

As comparing PE firms with all British firms might create a bias as many firms have not the characteristics of ever being a PE target, we need create a control group which best represent our sample of private equity targets. To create a control group which is representative of our sample of private equity targets, we select just those firms whose total assets lies in a +/- one standard deviation range around the mean assets of our initial sample of our UK portfolio targets. This leads us to the section of a total of 290,022 British control firms, whose size we describe below.

**Table A2. Asset distribution of estimation sample**

In this Table, we show the asset characteristics of all firms considered in our study. This is inclusive of both PE portfolio targets and firms which are not target of buyout – constituting our control sample.

| Date | Quartiles of firms' total assets | | | |
|---|---|---|---|---|
| | [0 - 0.25] | [0.25 - 0.50] | [0.50 - 0.75] | [0.75 - 1] |
| 2010 | 55,085 | 44,963 | 40,340 | 42,407 |
| 2011 | 55,571 | 46,907 | 43,186 | 44,555 |
| 2012 | 57,759 | 49,343 | 45,219 | 46,473 |
| 2013 | 54,717 | 49,955 | 49,150 | 50,947 |
| 2014 | 52,149 | 52,108 | 52,159 | 53,729 |
| 2015 | 53,276 | 54,993 | 55,188 | 55,862 |
| 2016 | 56,391 | 61,820 | 55,783 | 54,836 |
| 2017 | 50,442 | 58,969 | 64,191 | 63,505 |
| 2018 | 45,694 | 57,971 | 69,392 | 67,465 |
| 2019 | 15,272 | 19,326 | 21,748 | 16,576 |

### A.4.4. Descriptive statistics and correlation analysis

**Table A3. Descriptive statistics**

The Table presents the main descriptive statistics for all the independent variables of our baseline logistic regression. In Panel A, we present statistics on the adopted uncertainty measures. In Panel B, we display macro-economic and industry level controls. Eventually, Panel C and D show statistics on firm-level variables computed on a sample of just target portfolio firms (Panel C) and a sample including both target and non-target firms (Panel D). We winsorized data on firm-level variables presented in Panel D at the 1st and 99th percentiles. In-depth information on the variables included in this Table is reported in Appendix A.4.2.1.

| | Obs | Mean | Standard Deviation | Min | Max |
|---|---|---|---|---|---|
| *Panel A. Uncertainty measures* | | | | | |
| Policy Uncertainty (EPU) | 2,900,219 | 1.6 | 0.5 | 1.0 | 2.9 |
| Macro Uncertainty | 2,900,219 | 0.1 | 0.8 | -1.1 | 1.3 |
| Sterling Opt-Impl. Volatility | 2,900,219 | 0.2 | 0.6 | -0.8 | 1.2 |
| FTSE Opt-Impl. Volatility | 2,900,219 | 1.5 | 0.3 | 1.1 | 2.1 |
| Brexit Uncertainty Index (BUI) | 2,900,219 | 1.7 | 2.0 | 0.0 | 5.3 |
| *Panel B. Macro-economic and industry-level controls* | | | | | |
| Investment Opportunity | 2,900,219 | 0.5 | 1.1 | -1.1 | 2.4 |
| TED Spread | 2,900,219 | 0.2 | 0.1 | 0.0 | 0.3 |
| Industry Shock | 2,555,630 | 1.1 | 0.6 | 0.0 | 2.5 |
| Industry Cumulative Returns | 2,447,711 | 0.1 | 0.2 | -0.7 | 1.4 |
| Industry Cumulative STD Returns | 2,447,711 | 0.2 | 0.1 | 0.0 | 0.6 |
| Industry q | 2,440,248 | 1.3 | 0.5 | 0.0 | 5.8 |
| *Panel C. Firm-level controls for buyout targets only* | | | | | |
| Total Assets | 10,842 | 0.4 | 1.4 | 0.0 | 24.2 |
| ROA | 10,842 | 3.3 | 10.1 | -59.9 | 52.1 |
| Leverage | 10,842 | 0.4 | 3.7 | 0.0 | 189.8 |
| Cash-to-Asset | 10,842 | 0.1 | 0.5 | -0.02 | 31.8 |
| *Panel D. Firm-level controls for all British firms (both PE targets and control)* | | | | | |
| Total Assets | 1,985,422 | 9.6 | 20.3 | 0.0 | 137.4 |
| ROA | 661,832 | 5.1 | 17.9 | -62.2 | 95.0 |
| Leverage | 1,849,684 | 18.2 | 3,276.7 | 0.0 | 35.4 |
| Cash-to-Asset | 1,556,282 | 3.5 | 99.3 | 0.0 | 3,213.8 |

## Table A4. Correlation matrix

The Table presents the correlation between all independent variables of our baseline logistic regression. In the Table below, 'EPU' is Economic Policy Uncertainty; 'macro unc' is BoE Macro-economic Uncertainty; 'sterl vol' is Sterling Option-Implied Volatility; 'FTSE vol' is FTSE All-Share index option-implied volatility; 'inv opp' is our investment opportunity index; 'ind shock' corresponds to industry shocks; 'TED' is TED spread; 'Ind cum_ret' is FTSE All-Share index 36-months cumulative returns; 'Ind cum_ret' is the standard deviation of FTSE All-Share index 36-months cumulative returns; 'q' is Tobin's q; 'Assets' is target-level firms' book value of assets; 'ROA' represents target's return on assets; 'Lev' is targets' leverage; and, 'Cash_asset' is targets' ratio of cash and equivalents-to-total assets. In-depth information on the variables included in this Table is reported in Appendix A.4.2.1.

| | EPU | macro unc | sterl vol | FTSE vol | inv opp | ind shock | TED | Ind cum_ret | Ind cum_STD | q | Assets | ROA | Lev | Cash_asset |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| EPU | 1 | | | | | | | | | | | | | |
| macro unc | 0.121$^{***}$ | 1 | | | | | | | | | | | | |
| sterl vol | 0.399$^{***}$ | 0.721$^{***}$ | 1 | | | | | | | | | | | |
| FTSE vol | -0.194$^{***}$ | 0.813$^{***}$ | 0.734$^{***}$ | 1 | | | | | | | | | | |
| inv opp | 0.016 | -0.935$^{***}$ | -0.593$^{***}$ | -0.732$^{***}$ | 1 | | | | | | | | | |
| ind shock | -0.007 | -0.029$^{*}$ | -0.001 | -0.087$^{***}$ | 0.037$^{**}$ | 1 | | | | | | | | |
| TED | -0.186$^{***}$ | 0.649$^{***}$ | 0.429$^{***}$ | 0.807$^{***}$ | -0.648$^{***}$ | -0.220$^{***}$ | 1 | | | | | | | |
| Ind cum_ret | -0.098$^{***}$ | -0.298$^{***}$ | -0.359$^{***}$ | -0.319$^{***}$ | 0.255$^{***}$ | -0.040$^{***}$ | -0.209$^{***}$ | 1 | | | | | | |
| Ind cum_STD | -0.152$^{***}$ | 0.335$^{***}$ | 0.140$^{***}$ | 0.286$^{***}$ | -0.347$^{***}$ | 0.048$^{***}$ | 0.205$^{***}$ | 0.233$^{***}$ | 1 | | | | | |
| q | 0.031$^{*}$ | -0.159$^{***}$ | -0.166$^{***}$ | -0.225$^{***}$ | 0.139$^{***}$ | 0.173$^{***}$ | -0.181$^{***}$ | 0.123$^{***}$ | -0.007 | 1 | | | | |
| Assets | -0.017 | 0.033$^{**}$ | 0.017 | 0.039$^{**}$ | -0.030$^{*}$ | -0.002 | 0.044$^{***}$ | -0.001 | -0.027$^{*}$ | -0.023 | 1 | | | |
| ROA | -0.081$^{***}$ | 0.048$^{***}$ | -0.018 | 0.060$^{***}$ | -0.031$^{*}$ | 0.046$^{***}$ | 0.051$^{***}$ | 0.025$^{*}$ | 0.066$^{***}$ | -0.006 | -0.004 | 1 | | |
| Lev | -0.024$^{*}$ | 0.044$^{***}$ | 0.017 | 0.040$^{***}$ | -0.039$^{**}$ | 0.024$^{*}$ | 0.028$^{*}$ | -0.0063 | 0.011 | -0.009 | 0.089$^{***}$ | 0.079$^{***}$ | 1 | |
| Cash_asset | -0.113$^{***}$ | 0.166$^{***}$ | 0.055$^{***}$ | 0.166$^{***}$ | -0.145$^{***}$ | 0.039$^{**}$ | 0.123$^{***}$ | 0.008 | 0.082$^{***}$ | -0.037$^{**}$ | -0.0253$^{*}$ | 0.216$^{***}$ | 0.018 | 1 |

*Notes:* ***, **, or * mark correlation coefficients significant 1, 5, or 10 percent level.

**Table A5. VIF analysis**

The Table presents the VIF analysis for all independent variables of our baseline logistic regression.

*Panel A. Economic Policy Uncertainty*

| *Independent variables* | *VIF* | *1/VIF* |
|---|---|---|
| Policy Uncertainty (EPU) | 5.94 | 0.17 |
| Investment Opportunity | 1.92 | 0.52 |
| Industry Shock | 5.8 | 0.17 |
| TED Spread | 7.75 | 0.13 |
| Industry Cumulative Returns | 8.45 | 0.12 |
| Industry Cumulative STD Returns | 1.65 | 0.60 |
| Industry q | 10.6 | 0.09 |
| Total Assets | 1.48 | 0.67 |
| ROA | 1.09 | 0.91 |
| Leverage | 1 | 1.00 |
| Cash-to-Asset | 1 | 1.00 |
| Mean VIF | 4.25 | |

*Panel B. Sterling Option-Implied Volatility*

| | | |
|---|---|---|
| Sterling Opt-Impl. Volatility | 1.16 | 0.86 |
| Investment Opportunity | 1.87 | 0.54 |
| Industry Shock | 5.78 | 0.17 |
| TED Spread | 7.55 | 0.13 |
| Industry Cumulative Returns | 8.41 | 0.12 |
| Industry Cumulative STD Returns | 1.73 | 0.58 |
| Industry q | 9.56 | 0.10 |
| Total Assets | 1.47 | 0.68 |
| ROA | 1.09 | 0.91 |
| Leverage | 1 | 1.00 |
| Cash-to-Asset | 1 | 1.00 |
| Mean VIF | 3.69 | |

*Panel C. Brexit Uncertainty Index*

| | | |
|---|---|---|
| Brexit Uncertainty (BUI) | 1.75 | 0.57 |
| Investment Opportunity | 1.49 | 0.67 |
| Industry Shock | 5.81 | 0.17 |
| Industry Cumulative Returns | 5.94 | 0.17 |
| Industry Cumulative STD Returns | 1.47 | 0.68 |
| Industry q | 8.75 | 0.11 |
| Total Assets | 1.45 | 0.69 |
| ROA | 1.09 | 0.91 |
| Leverage | 1 | 1.00 |
| Cash-to-Asset | 1 | 1.00 |
| Mean VIF | 2.98 | |

### A.4.5. Marginal Effects

When using a logit model, it is useful and common practice to report marginal effects to interpret the magnitude of the regression coefficients that in a logistic distribution are scale dependent. The marginal effects reflect the change in probability of our categorical dependent variable assuming value of 1 (‘a buyout the following year’), given a unit change in our independent variables.

Since logit model coefficients depend on the scale of each independent variable, it is standard practice to measure marginal effects at a specific value of the independent variables: the mean. Of course, in this framework, to assess the magnitude of marginal effects coefficients, it becomes crucial also reporting the unconditional probability of our event of interest (‘a buyout at *t+1*’), which we report in the ‘Frequency Tables’ below the marginal effects’ Table.

## Table A6. Marginal effects: Baseline regressions

| | Delta-method: at means (%) | | | | |
|---|---|---|---|---|---|
| | *dy/dx* | *dy/dx* | *dy/dx* | *dy/dx* | *dy/dx* |
| Policy Uncertainty (EPU) | -0.0318** | | | | |
| Macro Uncertainty | | 0.00250 | | | |
| Sterling Impl. Volatility | | | -0.0203** | | |
| FTSE Impl. Volatility | | | | 0.00808 | |
| Brexit Uncertainty (BUI) | | | | | -0.0132*** |
| Investment Opportunity | 0.00253 | | -0.00898 | | -0.00169 |
| Industry Shock | 0.0434*** | 0.0442*** | 0.0453*** | 0.0440*** | 0.0460*** |
| TED Spread | -0.1777 | -0.0196 | -0.124 | -0.0186 | |
| Industry Cumulative Returns | -0.0944*** | -0.0817** | -0.0994*** | -0.0804** | -0.0648* |
| Industry Cumulative STD Returns | 0.0290 | 0.0497 | 0.0617 | 0.0472 | -0.0486 |
| Industry q | 0.0543*** | 0.0553*** | 0.0507*** | 0.0559*** | 0.0609*** |
| Total Assets | 0.000544*** | 0.000563*** | 0.000548*** | 0.000563*** | 0.000572*** |
| ROA | 0.000613** | 0.000624** | 0.000614** | 0.000624** | 0.000590** |
| Leverage | -1.47E-07 | -1.30E-07 | -1.22E-07 | -1.30E-07 | -1.48E-07 |
| Cash-to-Asset | -0.195*** | -0.197*** | -0.196*** | -0.197*** | -0.194*** |
| Observations | 412,622 | 412,622 | 412,622 | 412,622 | 412,622 |

*Notes:* ***, **, or * mark regression coefficients significant 1, 5, or 10 percent level.

| **Frequency Table (2010-2019)** | Likelihood L(M)BOs | Freq. | Percent (%) |
|---|---|---|---|
| No Buyout at t+1 | 0 | 2,609,421 | 99.97 |
| Buyout at t+1 | 1 | 776 | 0.03 |
| Total Obs | | 2,610,197 | 100 |

### A.4.6. Additional results

*A.4.6.1. Baseline Regressions for Brexit period (2016 to 2019)*

To further explore the impact of the referendum, in this Appendix, we re-estimate the baseline model contraposing the impact of uncertainty before the Brexit referendum (2010-2015) and after (2016-2019).

In Table A7, reported below, we observe that as for the whole period, in the years following the referendum results greater policy uncertainty and FX uncertainty had a negative effect on PE buyout activity. We find similar, albeit less significant results, using the Bank of England index of macroeconomic uncertainty and the FTSE Option Implied Volatility index. From Table A7 we can observe that, after the Brexit referendum, uncertainty (e.g. EPU) has a stronger impact on reducing the likelihood future buyouts than what we found in our baseline regression models (see Table 4.2).

Examining results for the period before the Brexit referendum (2010-2015), we observe that the coefficients of our core uncertainty variables are larger in both absolute magnitude and significance in the period following the referendum (2016-2019). Of course, newspaper coverage of Brexit and arguably, its related uncertainty started well before the referendum. This also implies that Brexit uncertainty (and although our BUI commences mid-2015; see Figure 2) may have manifested much earlier than the referendum date. Therefore, in columns 5-8 of Table A7, we also disclose the results of our baseline regressions performed on an earlier 'pre-Brexit period' that excludes 2015 (i.e., from 2010-2014). Overall, we observe that the magnitude of the coefficients has again reduced. Moreover, none of our applicable measures of uncertainty has a significant impact on the likelihood of PE buyouts in the UK between 2010 and 2014. This is in line with the previously identified enhanced transmission of Brexit uncertainty to the PE industry.

## Table A7. Uncertainty and PE buyout activity during Brexit period

The Table displays the results of our baseline logistic regression of the likelihood of a buyout ('Buyout t+1') on Economic Policy Uncertainty (EPU; column 1, 5 and 9), Macro-economic Uncertainty (column 2, 6 and 10), Sterling Option-implied Volatility index (column 3, 7 and 11), and FTSE All-Share Option-implied Volatility index (column 4, 8 and 12) during the pre-Brexit (2010-2015) vs Brexit (2016-2019) periods. All regressions are supplemented with several controls for industry and target-specific economic fundamentals. In each regression, the dependent variable assumes a value of 1, if at time *t+1* a certain target firm is the object of a buyout, and zero otherwise. All independent variables are continuous and measured instead at time *t*. Further in-depth information on the variables included in this Table is reported in Appendix A.4.2.1.

| | Pre-Brexit period (2010-2015) | | | | Pre-Brexit period (2010-2014) | | | | Brexit Period (2016-2019) | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Buyout t+1 | Buyout t+1 | Buyout t+1 | Buyout t+1 | Buyout t+1 | Buyout t+1 | Buyout t+1 | Buyout t+1 | Buyout t+1 | Buyout t+1 | Buyout t+1 | Buyout t+1 |
| Policy Uncertainty (EPU) | -1.017** | | | | -0.434 | | | | -1.314*** | | | |
| | (0.436) | | | | (0.607) | | | | (0.220) | | | |
| Macro Uncertainty | | 0.052 | | | | -0.068 | | | | -0.075 ◎ | | |
| | | (0.061) | | | | (0.244) | | | | (0.194) | | |
| Sterling Opt-Impl. Volatility | | | -0.147◎ | | | | 0.026 | | | | -3.307*** | |
| | | | (0.093) | | | | (0.123) | | | | (0.590) | |
| FTSE Opt-Impl. Volatility | | | | -0.178 | | | | 0.018 | | | | -0.982 ** |
| | | | | (0.193) | | | | (0.310) | | | | (0.470) |
| Observations | 261,615 | 261,615 | 261,615 | 261,615 | 214,549 | 214,549 | 214,549 | 214,549 | 151,007 | 151,007 | 151,007 | 151,007 |
| Macroeconomic Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry-level Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm-level Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

*Notes:* ***, **, *, or ◎ mark regression coefficients significant 1, 5, 10 or 15 percent level. Standard Errors are reported in the parentheses underneath the regression coefficient

## Table A8. PE waves and uncertainty

The Table displays the results of an industry-level logistic regression of the likelihood of a PE buyout wave ('Wave t+1') on Economic Policy Uncertainty (EPU; column 1), Sterling Option-Implied Volatility (column 2), and Brexit Uncertainty Index (BUI; column 3). All regressions are supplemented with several controls for industry-specific economic fundamentals. In each regression, the dependent variable assumes a value of 1, if at time *t+1* a certain industry experiences buyout wave, and zero otherwise. We identify industry-level waves similarly to Harford (2005). For each year and industry, we count the number of buyout deals and then divide time *t* industry deals by the total volume of deals within that industry (in the whole period of analysis). Eventually, for each year, we scale the above ratio by the median of all industries' deals. We consider the industry as experiencing a 'wave' if, after considering each industry-year 'deal ratios', the ratio assumes a value lying in the top 5 percentile over the 10 years of analysis. All independent variables are continuous and measured instead at time *t*. Further in-depth information on the variables included in this Table is reported in Appendix A.4.2.1.

| | (1)<br>Wave t+1 | (2)<br>Wave t+1 | (3)<br>Wave t+1 |
|---|---|---|---|
| Policy Uncertainty (EPU) | -3.732*** | | |
| | (1.155) | | |
| Sterling Opt-Impl. Volatility | | -1.112*** | |
| | | (0.126) | |
| Brexit Uncertainty (BUI) | | | -0.292 |
| | | | (0.236) |
| Investment Opportunity | -0.158 | 1.208*** | 0.153 |
| | (0.296) | (0.055) | (0.282) |
| Industry Shock | -1.434* | 0.180 | -1.394* |
| | (0.757) | (0.204) | (0.720) |
| TED Spread | -3.870** | -37.862*** | -2.177* |
| | (1.973) | (0.907) | (1.228) |
| Industry Cumulative Returns | -3.512** | -0.597 | -3.337* |
| | (1.461) | (0.798) | (1.714) |
| Industry Cumulative STD Returns | -1.759 | -4.534 | -0.748 |
| | (3.863) | (2.878) | (3.212) |
| Industry q | 0.528** | -0.150* | 0.508** |
| | (0.265) | (0.089) | (0.231) |
| Constant | 3.199 | 4.629*** | -2.126* |
| | (2.220) | (0.386) | (1.279) |
| Observations | 361 | 361 | 361 |

*Notes:* ***, **, *, or ◎ mark regression coefficients significant 1, 5, 10 or 15 percent level. Standard Errors are reported in the parentheses underneath the regression coefficients.