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Essays on Financial Stability and Macroprudential Regulation

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Doctoral Thesis

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Abstract

The Global Financial Crisis (GFC) of 2008–2009 brought to light the importance of taking a macroprudential approach to financial stability in order to ensure that the financial system is resilient to periods of severe stress which would result in a lower incidence of financial crises. The lessons learned from this exceptional event fostered international efforts to develop a comprehensive macroprudential framework promoting financial stability and the resilience of the financial system. As countries worldwide have been adopting policy instruments from this continuously expanding macroprudential toolkit over the last decade, this dissertation revolves around the assessment of the macroprudential framework. In particular, we focus on i) its effectiveness in delivering on its intended goals; ii) potential unintended consequences of macroprudential policy reforms; and iii) developing new monitoring approaches for macroprudential risks to anticipate and build resilience against the next source of shock to financial stability. Chapter 1 proposes a novel empirical setup that accounts for the simultaneous effects of macroprudential policies on the probability of financial crises and economic growth and also allows for an assessment of their net effect on the probability of a crisis. Our empirical setup is designed to account for the potential direct and indirect effects that macroprudential policies can have on banking crises. We document the empirical relevance of both effects. Chapter 2 provides an analysis of the transmission of macroprudential regulation across both financial and non-financial sectors through the lens of its impact on short- and long-term probabilities of default at the sector level. Tighter macroprudential regulations lower default risk in both financial and non-financial sectors. Higher capital requirements improve the long-run resilience of the financial sector while raising long-term default risk in non-financial sectors. A strengthening in the resolution framework for failing banks has beneficial long-run effects on financial and non-financial sectors. Chapter 3 proposes to broaden the scope of systemic risk monitoring, which is centered around the financial sector, to encompass systemic risk originating in the non-financial sector and potential systemic risk spillovers across sectors. We model time-varying systemic risk of US financial and non-financial firms by fitting a flexible dynamic factor copula model to their CDS spread data.

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Introduction

Macroprudential regulation: looking back, taking stock and the way forward

The Global Financial Crisis (GFC) of 2008–2009 brought to light the importance of taking a macroprudential approach to financial stability in order to ensure that the financial system is resilient to periods of acute stress and can continue to provide essential services to the real economy, such as the provision of credit. The lessons learned from this exceptional event fostered international efforts to develop a comprehensive macroprudential framework to prevent the build-up of financial vulnerabilities in the financial system; strengthen its resilience to various types of shocks; and weaken the key amplification channels of shocks to the real economy by the financial system.[1]

As countries worldwide have been adopting policy instruments from this continuously expanding macroprudential toolkit over the last decade, the question of the effectiveness of these tools in achieving their intended goals naturally arises. This assessment is complicated by the breadth of the policy instruments available in the macroprudential toolkit and the fact that they are targeted at multiple parts of the financial system. Furthermore, evaluating the success of macroprudential regulation on the basis of its ultimate goal of improving the resilience of the financial system raises additional challenges in terms of

[1]In particular, the Basel Committee on Banking Supervision (BCBS) published a series of revisions to its international standards for bank regulation — also known as the Basel Accords — to address the existing shortcomings brought to light by the GFC. The interested reader is referred to the Appendix section of this chapter for a brief summary of the different phases of the Basel Accords.

measurement. Indeed, a more resilient financial system would result in a lower incidence of financial crises.

The assessment of the effectiveness of macroprudential regulation in achieving its intended goals has a counterpart that also requires a careful quantitative assessment, namely, the unintended consequences of macroprudential policy reforms. Indeed, reforms targeted at a specific part of the financial system can have leakages or spillovers to other part of the financial system and real economy. This is true for policies focused on improving resilience; but also for measures aimed at addressing key vulnerabilities or amplification channels to the real economy. The growth of Market-Based Finance (MBF) and Non-Bank Financial Intermediaries (NBFIs) in the post-GFC period is a good example of these unintended consequences as increased regulation of the banking sector led to a shift of activities towards this less regulated segment of the financial system. This is also a relevant concern for financial stability as vulnerabilities in NBFIs have been a source of financial market stress amplification — e.g. during the financial market "dash for cash" at the onset of the Covid-19 pandemic in March 2020.

Looking forward, the macroprudential toolkit will need to continue evolving to keep pace with a constantly changing environment. This includes finalising the reforms of banking regulation started after the GFC — particularly in light of the lessons from the pandemic — but also addressing key vulnerabilities and amplification channels in MBF and NBFIs. However, macroprudential regulation also needs to keep a forward-looking approach as an overemphasis on historical drivers of financial instability creates a risk of missing early warning signals of the next relevant shock. This is particularly relevant as macro-financial and geopolitical developments — including the aftermath of the pandemic, global inflationary pressures and the war between Russia and Ukraine — subject the financial system to multiple forms of stress which can reveal unsuspected fault lines. It is therefore crucial to maintain and keep developing a flexible monitoring framework for macroprudential risks in order to anticipate and build resilience against the next source of shock to the financial system.

Outline of the thesis

The developments in the macroprudential framework outlined above open interesting avenues of research. First, the question of the effectiveness of macroprudential tools in achieving their intended goals highlights that our understanding of the extent to which they are successful in enhancing financial stability and lowering the incidence of financial crises — their ultimate goal — is far from being complete. On the one hand, macroprudential policies can smooth financial cycles by mitigating growth in credit and housing markets. There is however limited empirical analysis documenting whether such mitigation of credit and housing market cycles eventually reduces the occurrence of financial crises. On the other hand, the effectiveness of macroprudential policies in fostering financial stability cannot be fully assessed by restricting the analysis to their credit and housing markets effects as these policies can have possibly harmful effects on economic activity — in particular through their negative impact on credit supply and investment. This is particularly relevant as weak economic growth can itself be a trigger of financial instability.

In Chapter 1, Belkhir et al. (2022b) propose a novel empirical setup that accounts for the simultaneous effects of macroprudential policies on the probability of financial crises and economic growth and also allows for an assessment of their net effect on the probability of a crisis. Using a sample covering emerging market and advanced economies, our empirical setup is designed to account for the potential direct and indirect effects that macroprudential policies can have on banking crises. We find that while macroprudential policies exert a direct stabilizing effect, they also have an indirect destabilizing effect, which works through the depressing of economic growth. It turns out that mitigating effects of macroprudential policies on the likelihood of banking crises are more pronounced in emerging market economies relative to advanced economies.

Second, the assessment of potential unintended consequences of macroprudential policy reforms is also a crucial component of the evaluation of the macroprudential framework. Indeed, the analysis in Chapter 1 focuses on aggregate effects of macroprudential regulation but little is known about the transmission of macroprudential policies to the non-financial sectors of the economy or whether some of them are more sensitive to short-term contractions in credit supply and economic activity resulting from tighter regulation. Chapter 2, which is based on Belkhir et al. (2022a), provides a comprehensive analysis of the transmission of macroprudential regulation across both financial and non-financial sectors of the economy through the lens of its impact on short- and long-term probabilities of default at the sector level. By analysing how macroprudential regulation impacts probabilities of default of non-financial sectors of the economy, we contribute to a better understanding of the potential unintended consequences from macroprudential regulation on areas of the economy not directly targeted by the policies.

To this end, we combine a detailed database on macroprudential policies in European countries with data on short-term and long-term probabilities of default for financial and non-financial sectors. We first document that tighter macroprudential regulations implemented in Europe over the period 2008-2017 lowered default risk not only in the financial sector, but also in non-financial sectors on average for both short- and long-term default risks. The economic and statistical significance of this decrease in default risk is comparable to the results for the financial sector. Second, we analyse how two reforms in the macroprudential framework taking place at the European level dynamically impact default risk in the financial and non-financial sectors. Higher capital requirements improve the long-run resilience of the financial sector but at the cost of raising long-term default risk in non-financial sectors. Strengthening the resolution framework for failing banks has beneficial long-run effects on short- and long-term default risks of the financial and non-financial sectors. Our results concur with the literature documenting how banks adjust their balance sheet composition and credit supply in reaction to changes in their regulatory environment.

Finally, macroprudential regulation also needs to keep a forward-looking approach — leveraging a flexible monitoring framework for macroprudential risks — in order to anticipate and build resilience against the next source of shock. Based on this insight, we propose to broaden the scope of systemic risk monitoring, which is centered around the financial sector, to encompass systemic risk originating in the non-financial sector and potential systemic risk spillovers across sectors. In Chapter 3, based on Wijnandts (2022), we model time-varying systemic risk of US financial and non-financial firms by fitting a flexible dynamic factor copula model to their CDS spread data. In addition, using a long sample for the period from 2007 to 2022 allows us to investigate the impact of different types of systemic stress — including a global financial crisis and a pandemic. We document that dependence across firms has been increasing steadily from 2007 to end-2013 and from 2018 until the end of the sample — mainly driven by lower-frequency factors. Using two measures of systemic risk capturing the dependence in failure across firms in the system, we document low levels of systemic risk in the period before the GFC. They then rise materially during the crisis and remain higher than pre-crisis afterwards. The 2018-2022 period is associated with higher levels of systemic risk on average, with peaks reaching levels broadly comparable to the GFC period. Finally, systemic spillover risks from the non-financial to the financial sector are higher than the respective spillover risks from the financial to non-financial sector over the majority of the sample. We observe two notable exceptions where systemic spillovers from the financial to the non-financial sector peak at higher levels around end-2008 and at the beginning of the Covid-19 pandemic in March 2020.

The three main chapters of this dissertation are self-contained research articles that can be read independently from each other.

Appendix: the different phases of the Basel Accords

The Basel Committee on Banking Supervision (BCBS) introduced in 1988 the Basel Accord on the "*International convergence of capital measurement and capital standards*", commonly referred to as Basel I (BCBS, 1988). Basel I set out a system for the measurement of capital and introduced a minimum capital requirement of 8% of risk-weighted assets, with a limit for implementation by end-1992.[2] While the initial text was solely focused on credit risk, the "*Market Risk Amendment*" was issued in 1996, with binding effects in 1997, to incorporate a requirement capitalizing banks against the risks associated with their market exposures (BCBS, 1996a). This amendment also introduced the standardised and internal model approaches to calculate the capital requirements associated with market risk.

The BCBS issued in 1999 a proposal for a revised capital adequacy framework that would supersede the 1988 Accord. The final revised framework, known as Basel II, was eventually released in 2004 (BCBS, 2004) and consisted of three pillars.[3] The first pillar focused on expanding the standardised rules for minimum capital requirements introduced in Basel I.[4] The second pillar emphasized the role of supervision in monitoring both banks' capital adequacy and their internal risk assessment process. Lastly, the third pillar emphasized the role of market discipline in promoting sound banking practices through the use of disclosure requirements.

The Basel III revised standards were introduced in the aftermath of the GFC to strengthen the Basel II framework as banks entered the crisis with high levels of leverage and inadequate liquidity buffers (BCBS, 2010a; BCBS, 2010b). The revised framework

[2] The initial text was subsequently amended to clarify capital adequacy calculations (BCBS, 1991); to recognise bilateral netting for off-balance-sheet credit exposures on derivative products (BCBS, 1995); and to recognise the multilateral netting of forward value foreign exchange transactions (BCBS, 1996b).

[3] While the 2004 framework focused primarily on the banking book, a separate document focusing on the treatment of trading activities under the new framework was issued in 2005 (BCBS, 2005).

[4] Note that banks still had to meet a minimum capital requirement of 8% of risk-weighted assets, of which at least 4% had to be met in Tier 1 capital (including at least 2% of Common Equity Tier 1 capital).

enhanced the three pillars established in Basel II and augmented them along several dimensions. First, they focused on improving the quality of the capital used to meet requirements, with a more central role for common equity (CET1 capital), and on increasing the level of banks' regulatory capital.[5] Second, the revised standards introduced a minimum leverage ratio requirement of 3% (to be met in Tier 1 capital) for internationally active banks, computed on both on- and off-balance sheet exposures, whose aim is to serve as a backstop for the risk-weighted capital framework. Third, a framework to mitigate excessive liquidity risk was introduced with to key components: the Liquidity Coverage Ratio (LCR) and the Net stable funding ratio (NSFR). The LCR is intended to ensure that banks have sufficient high quality liquid assets (HQLA) to withstand 30-day stressed funding scenario. A minimum requirement of 100% of total net cash flows in a stressed scenario has to be met. The aim of the NSFR is to reduce liquidity mismatches at a longer horizon (1 year) and to incentivize banks to use stable sources of funding. A minimum ratio of available stable funding (ASF) to total required stable funding (RSF) of 100% should be maintained.[6]

The Basel III post-crisis reforms were completed in 2017 with the publication of revised standards to calculate the capital requirements associated with credit, credit valuation adjustment (CVA), and operational risks (BCBS, 2017).[7] An overarching goal of this

[5]Minimum Tier 1 capital requirements increased from 4% to 6% of risk-weighted assets, of which at least 4.5% has to be met with CET1 capital (compared to 2% in Basel II). Moreover, Basel III introduced macroprudential capital buffers in the form of a Capital Conservation Buffer (CCoB) of 2.5% of risk-weighted assets; a Countercyclical Capital Buffer (CCyB) which would be set dynamically in the range from 0% to 2.5% in line with the buildup of systemic risk over the financial cycle; and additional capital surcharges for Globally or Domestically Systemically Important Banks (G-SIB and D-SIB) ranging from 0% to 2%. All macroprudential capital buffers have to be met with CET1 capital.

[6]The ASF is defined as the share of capital and liabilities that the bank is expected to be able to rely on over a 1-year horizon. The RSF of a bank will depend on the characteristics of its balance sheet in terms of liquidity and asset residual maturities as well as on its off-balance sheet exposures. See BCBS (2014) for more details on the definition and calculation of the NSFR.

[7]This second wave of Basel III reforms is sometimes referred to as Basel IV, or Basel 3.5 to reflect the smaller scope of the proposed reforms. I follow the BCBS terminology and group the 2010 and 2017 reforms under Basel III.

second wave of Basel III reforms was to reduce the excessive variability of risk-weighted assets. This was achieved through an improvement in the robustness of capital requirement calculations for credit and operational risks under the standardized approaches and by introducing a limit on the extent to which banks could reduce their capital requirements under the internal model approach with the introduction of the output floor (based on the revised standardized approach). Moreover, the package introduced a G-SIB leverage ratio buffer — set at 50% of the corresponding G-SIB buffer under the risk-weighted framework — whose goal was to continue ensuring that the leverage ratio capital requirements act as a backstop to risk-weighted capital requirements for the G-SIBs. Note that, while the reforms introduced in the first wave of Basel III were progressively phased in over the period from 2013 to 2019, the current phase-in period for the second wave is planned to end in 2028 (finalization of the output floor).[8]

In terms of next steps, the future phases of the Basel policy-making cycle will face several challenges, which I illustrate with two examples. First, the BCBS will have to continue carrying out rigorous Quantitative Impact Studies (QIS) to identify potential shortcomings in the existing framework and design prompt corrective measures. Particularly, the impediments to the usability of capital and liquidity buffers identified at the onset of the Covid-19 pandemic warrant additional policy responses (BCBS, 2021). Second, the complexity of the overall regulatory framework has substantially increased over the successive phases of Basel reforms. This has led to an increased cost of compliance and potential economies of scale in meeting this cost as each bank faces a material fixed cost associated with building sufficient in-house resources to navigate the legal aspects of the regulatory environment. However, this can introduce barriers to entry in the banking sector and lead to reduced competition and an increased concentration of financial intermediation services among a few larger financial institutions. Financial stability would also be affected by this trend as the associated increase in uniformity makes the financial system less resilient to systemic shocks. Therefore, a coordinated policy initiative

[8] Delays in the finalization of the first wave of reforms have occurred in some jurisdictions, which in some cases were compounded by the impact of the Covid-19 crisis.

focusing on designing a simplified regulatory regime for smaller domestically-active financial institutions would be beneficial to both consumers — through the reduction in costs associated with improved competition — and financial stability.[9]

[9]Note that some national authorities have already made progress on this policy agenda.

Chapter 1

Macroprudential Policies, Economic Growth and Banking Crises[1]

1.1 Introduction

The Global Financial Crisis (GFC) provided a stark reminder of the dangers and costs of systemic financial crises, leading public authorities to increasingly rely on macroprudential policies to contain the risk of incidence of such crises. These policies, used to prevent the build-up of financial vulnerabilities and strengthen the resilience of the financial system to various types of shocks, have been in use for many years before the GFC, especially by emerging market economies (Cerutti et al., 2017a). Their use has, however, been stepped up after the GFC by both emerging market and advanced economies (Akinci and Olmstead-Rumsey, 2018).

Yet, our understanding of the extent to which macroprudential policies are effective in enhancing financial stability and lowering the incidence of financial crises, which is their ultimate goal, is far from being complete. In fact, to the best of our knowledge, apart from Choi et al. (2018), no previous studies have undertaken the task of systematically

[1]This chapter corresponds to Belkhir, M., S. B. Naceur, B. Candelon, and J.-C. Wijnandts (2022): "Macroprudential Policies, Economic Growth and Banking Crises". *Emerging Markets Review, p.*100936, *doi: https://doi.org/10.1016/j.ememar.2022.100936.*

investigating the impact of macroprudential policies on the likelihood of financial crises. As we detail in the next section, the growing body of empirical research on macroprudential policies tends to emphasize the role that can be played by these policies in smoothing financial cycles by mitigating growth in credit and housing markets (e.g., Lim et al., 2011; Dell'Ariccia et al., 2012; IMF, 2012; Crowe et al., 2013; Claessens, 2015; Cerutti et al., 2017a). However, whether such mitigation of credit and housing market cycles eventually reduces the occurrence of financial crises remains an open question. In this paper, we depart from this approach and focus on the ultimate goal for which macroprudential policies are designed, which is making financial crises less likely. Specifically, we examine the impact of macroprudential policies on the likelihood of systemic banking crises.

Additionally, the effectiveness of macroprudential policies in fostering financial stability cannot be fully assessed by restricting the analysis to their credit and housing markets effects. Indeed, while there is increasing evidence pointing to the benefits of macroprudential policies with respect to smooth financial cycles, there are also growing concerns about their possible harmful effects on economic activity. In particular, by having a negative impact on credit supply and investment, macroprudential policies might depress economic growth. Using a panel of mostly OECD countries, Sanchez and Rohn (2016) report results suggesting that the use of macroprudential policies is costly as they are conducive to lower average economic growth. Kim and Mehrotra (2017) use a VAR framework and a sample of four countries from the Asia-Pacific region to analyze the responses of credit, output and inflation to changes in macroprudential and monetary policies. Their findings point to the existence of a negative impact of changes in macroprudential policies on economic output and inflation. Richter et al. (2019) quantify the effects of changes in maximum loan-to-value (LTV) ratios on output and "*find that over a four year horizon, a 10 percentage point decrease in the maximum LTV ratio leads to a 1.1 percent reduction in output*" (p.263). Any assessment of macroprudential policies should thus consider their potential damaging effect on the real economy. This is all the more important that weak economic growth can itself be a trigger of financial instability. Specifically, a slowdown in economic activity typically increases the amount of non performing loans and causes losses to the banking sector, which in the presence of vulnerabilities (excessive leverage, low liquidity buffers, etc.) can evolve into a full-blown crisis. Macroprudential policies whose aim is to ensure financial stability can thus end up being counterproductive by putting a drag on economic activity, which can in turn threaten financial stability. Despite the growing body of research pointing to the potential harmful effect of macroprudential policies on economic activity, no previous study has explored the implications of such an effect with respect to the ultimate goal of financial stability. In other words, we have no evidence on the net effect of macroprudential policies on the likelihood of financial crises.

This paper adds to the literature on the effectiveness of macroprudential policies by using a novel empirical setup that accounts for the simultaneous effects of these policies on the probability of financial crises and economic growth and also allows for an assessment of their net effect on the probability of a crisis. We specify an empirical framework wherein macroprudential policies exert both a direct and an indirect effect on the probability of a financial crisis through growth. In a first step, we investigate the impact of macroprudential policies on the likelihood of banking crises, specifying a dynamic logit model à la Candelon et al. (2014), where a lagged crisis index is included as regressor together with other predictors. In a second instance, we consider a bivariate vector autoregressive (VAR) model which also comprises this crisis index and output growth. This second equation (growth regression equation) is consistent with the one used in Cerutti et al. (2017a), with the exception that regressors are lagged and not contemporaneous.[2] Once the parameter estimates of this dynamic system have been obtained via the equation-by-equation MLE approach described above, a Generalized Impulse Response Function (hereafter GIRF) analysis is conducted in order to evaluate the impact of a macroprudential policy tighten-

[2] Cerutti et al. (2017a) use the Arellano and Bond (1991) GMM estimator to mitigate the endogeneity bias problem. Nevertheless, GMM based estimators suffer from a weak instrument problem in finite samples with persistent series, see e.g. Bun and Windmeijer (2010) who showed the impact of this issue in settings relevant for country-level panel data modelling. We thus adopt an MLE approach where the explanatory variables are lagged to mitigate concerns about endogeneity bias. Note that the Nickell (1981) bias affecting the fixed-effect estimates is unlikely to be a concern in our analysis given our relatively long time series dimension of 17 years.

ing[3] on the probability of a systemic banking crisis occurring. Indeed, the GIRFs for the crisis probability and output growth measure how this bi-variate dynamic system reacts over time to an initial tightening in the macroprudential policy stance while accounting for both the direct and indirect effects of this tightening — with the former having a positive stabilizing effect which reduces the probability of occurrence of a systemic banking crisis and the latter increasing the likelihood of a future crisis occurring through its negative impact on economic growth. This setup thus allows us to quantify the net effect of macroprudential policies on financial stability by disentangling the relative contributions from the direct and indirect channels over time and by determining which effect eventually dominates.

Using a sample comprising 121 countries over the 2000-2017 period, the macroprudential policies database assembled by Cerutti et al. (2017a) and the banking crisis database of Laeven and Valencia (2018), we find that the use of macroprudential policies reduces the probability of financial crises, but that it also drags down economic growth. The negative effects of macroprudential policies on both the probability of banking crises and economic growth are economically meaningful. Our baseline estimations suggest that a one unit increase in the macroprudential policy index (MPI) lowers the conditional probability of a systemic banking crisis by 7.29 percentage points on average when we use a sample that includes both advanced and emerging market economies. A one unit rise in the MPI also lowers economic growth by 23.7 basis points. Splitting the sample into advanced and emerging market economies, we find that the effects of macroprudential policies on both growth and banking crises are most significant in emerging market economies. Turning to the net effect of macroprudential policies on the probability of financial crises, a Generalized Impulse Response Function analysis (GIRF) of a dynamic system composed of output growth and the probability of crisis reveals that the direct stabilizing effect of macroprudential policies dominates the indirect destabilizing effect.

By examining the simultaneous impact of macroprudential policies on the probability of systemic banking crises and economic growth, this paper contributes to two strands

[3] Which is modelled in our framework as a positive shock on the macroprudential policy index.

of literature. First, we add to the existing evidence documenting the benefits of macroprudential policies to financial stability. Much of the empirical literature concerned with the effectiveness of macroprudential policy has focused on assessing the impact of macroprudential tools on intermediate target financial variables, such as credit growth, credit-to-GDP, non-performing loans, and real estate asset prices (Lim et al., 2011; Cerutti et al., 2017a; Cerutti et al., 2017b; Jiménez et al., 2017; Akinci and Olmstead-Rumsey, 2018). The direct effect of macroprudential policies on the incidence of financial crises has been rarely investigated. While instructive, the effect of macroprudential policies on the behavior of intermediate financial variables is not necessarily a good indicator of their effectiveness in taming financial crises. In particular, if taken one by one, the behavior of financial variables is not necessarily an adequate indicator of the degree of financial stability or the likelihood of a crisis. In this paper, we take a different approach and contribute to the literature on macroprudential policy effectiveness by examining the direct link between the use of macroprudential tools and the incidence of financial crises. To our knowledge, this is the first paper that attempts to empirically assess the effect of various macroprudential tools on the probability of financial crisis.

Second, our study contributes to a growing body of literature that examines the real economy effects of macroprudential policy. In particular, several recent studies investigate the potential of macroprudential policies to weaken economic growth (Sanchez and Rohn, 2016; Kim and Mehrotra, 2017; Boar et al., 2017; Richter et al., 2019). Their results point to a damaging effect of macroprudential policies on economic growth. However, this literature stops short of exploring the potential effect of weaker economic performance on financial stability. We take this literature a step forward by assessing not only the impact of macroprudential policies on economic growth in a novel empirical setting, but also by considering the feedback from weaker economic growth to the probability of banking crises.

Finally, the empirical methodology is novel, borrowing to the recent literature on mixed-measurement dynamic models (Creal et al., 2014) as the dynamic system under investigation simultaneously includes a dichotomous (crisis probability) and a continuous (growth) equation. Such an approach is therefore unique and well tailored to evaluate the direct/indirect impacts of macroprudential policies on economic growth and financial stability.

The remainder of the paper is organized as follows. Section 2 provides a literature review. Section 3 presents the methodology. Results are presented in Section 4. Section 5 provides robustness analyses. Finally, Section 6 concludes.

1.2 Literature review

The global financial crisis (GFC) has demonstrated the importance of adopting regulatory frameworks aimed at addressing systemic financial risks. Besides traditional microprudential regulation aimed at ensuring the safety and soundness of individual institutions, such frameworks ought to encompass macroprudential policies whose goal is to enhance the resilience of the financial system as a whole. In fact, there is now a widespread recognition that, while necessary, the microprudential approach to regulation is insufficient in ensuring financial stability and preventing the incidence of costly financial crises. Increasingly more emphasis is thus put, in both academic and policy-making circles, on the use of macroprudential regulation to reduce vulnerabilities and risks in the financial system (e.g. England, 2009; Claessens et al., 2011; Hanson et al., 2011; IMF, 2013a; IMF, 2013b; IMF, 2014; ESRB, 2014; FSB, 2014; Claessens and Kodres, 2014; Freixas et al., 2015).

A distinctive feature of macroprudential instruments is their focus on moderating excessive procyclicality in credit growth and leverage, and on dampening increases in interlinkages and common exposures across banks. The rationale for this focus is that these factors can lead to a build up of systemic risks in the financial system which can result in costly financial crises severely impacting the real economy (Jordà et al., 2013; Jordà et al., 2015; Mian et al., 2017; Giglio et al., 2016; and Brownlees and Engle, 2017). This emphasis sets macroprudential regulation apart from its microprudential counterpart which is focused on limiting banks' risks at the institution level and, therefore, attempts to build resilience in the financial system from the bottom up (see Borio, 2003). Jordà et al.

(2021) provide empirical support to the potential of macroprudential tools to complement and enhance existing microprudential regulation in promoting financial stability. Using an annual dataset for 17 advanced economies over the period from 1870 to 2015, they document that lower levels of capitalization in the financial system do not predict higher incidence of systemic banking crises. Moreover, they show that even highly capitalized banking sectors can experience crisis episodes — although better capitalized banks are more resilient to the fallout from financial crises, which reduces the subsequent impact for the real economy and the associated costs.

Despite the fact that many macroprudential tools have been in use for a long time, especially in emerging market economies (see Borio and Shim, 2007; McCauley, 2009; Lim et al., 2011), the use of such tools has intensified in the wake of the GFC in both emerging market economies (EMEs) and advanced economies (AEs). For instance, Cerutti et al. (2017a) document that macroprudential policies are used more frequently in EMEs whereas Akinci and Olmstead-Rumsey (2018) report that macroprudential policies have been used more actively after the GFC in both AEs and EMEs. Focusing on European Union countries over the period 1995-2014, Budnik and Kleibl (2018) document a widespread use of macroprudential regulations in this region and that "*the use of countercyclical policy tools has already been relatively common prior to the financial crisis*" (p.21).

Although countries across the globe have increased their use of macroprudential policies in recent years, there is no clear-cut evidence on the effectiveness of such policies in guaranteeing financial stability. Various countries, regions, periods and empirical designs have been used in studies seeking to gauge the extent to which macroprudential policy tools are successful in mitigating systemic financial risks. For instance, using IMF survey data, Lim et al. (2011) examine the effect of several macroprudential instruments on the procyclicality of credit growth.[4] Their findings suggest that these tools are effective in

[4]The instruments considered include caps on loan-to-value ratios, debt-to-income ratios, ceilings on credit growth, reserve requirements, time-varying/dynamic provisioning, countercyclical/time-varying capital requirements, and caps on foreign currency lending,

reducing the procyclicality of credit growth by lowering the correlation between credit growth and GDP growth. More recently, Cerutti et al. (2017a) examine the effectiveness of 12 macroprudential instruments in a sample of 119 countries over the 2000-2013 period. Their results point to the effectiveness of several macroprudential instruments in curbing the growth of real credit and house prices. Bruno et al. (2017) investigate the effectiveness of macroprudential and capital flow management policies in a sample of 12 Asia-Pacific countries. Their findings suggest that macroprudential policies are more successful in taming credit growth when they complement monetary policy by reinforcing monetary tightening, than when they act in opposite directions. Fendoğlu (2017) assesses the effectiveness of six macroprudential policy tools in eighteen EMEs and finds that borrower-based measures are particularly successful in lowering credit growth. Akinci and Olmstead-Rumsey (2018) focus on the use of seven categories of macroprudential tools in a sample of 57 AEs and EMEs covering the period from 2000:Q1 to 2013:Q4, with episodes of tightening and loosening recorded separately. Their empirical analysis suggests that the tightening of macroprudential policies has a significant negative effect on both bank credit and house price growth. Furthermore, their results indicate that policies targeted at credit growth in certain sectors are more effective.

Another set of cross-country studies focuses on the potential role of macroprudential policy instruments in limiting house credit and the ensuing house price bubbles. In their review of country experiences with various policy options intended to contain boom-bust cycles in real estate asset markets, Crowe et al. (2013) suggest that loan-to-value (LTV) and debt-to-income (DTI) caps can be effective in reducing house price appreciation rates. Analyzing real estate booms in a sample of more than fifty countries, Cerutti et al. (2017b) find that higher LTV ratios are associated with excessively rapid house-price and credit growth during booms and suggest that LTV limits can be a well-targeted tool for limiting real-estate price fluctuations. Zhang and Zoli (2016) investigate the use of macroprudential policy instruments in 13 Asian economies and 33 economies in other regions for the period 2000-2013 and find that housing-related macroprudential measures, especially LTV caps, have been used quite extensively in Asian countries. Their analysis also suggests that housing-related macroprudential instruments — particularly LTV caps and housing tax measures — have contributed to the curbing of housing price growth, credit growth, and bank leverage in Asia. Using a sample of 57 countries, Kuttner and Shim (2016) find that housing credit growth is significantly affected by changes in the maximum DSTI ratio, the maximum LTV ratio, limits on banks' exposure to the housing sector and housing-related taxes.

Besides studies using aggregate country-level data, macroprudential policy effectiveness has also been the subject of several studies using bank- and firm-level data. Analyzing the Korean experience with macroprudential policy, Igan and Kang (2011) find that LTV and DTI limits are associated with a decline in house price appreciation and transaction activity. Claessens et al. (2013)'s analysis based on bank balance sheet data in 48 countries over 2000-2010 suggests that macroprudential policy measures aimed at borrowers — DTI and LTV caps and limits on credit growth and foreign currency lending — are effective in reducing growth in leverage, asset and noncore to core liabilities during boom times. Aiyar et al. (2014a) examine micro-level evidence on the effectiveness of time-varying, bank-specific, minimum capital requirements in smoothing the credit cycle in the U.K. Their results indicate that regulated banks reduce lending in response to tighter capital requirements. Jiménez et al. (2017) use bank- and firm-level data to assess the impact of one macroprudential policy tool introduced in Spain in 2000 — dynamic provisioning — on the supply of credit during boom and bust periods. They document evidence that dynamic provisioning mitigates credit supply in good times while limiting credit crunches in bad times, which helps in smoothing downturns.

1.3 Methodology

To estimate the impact of macroprudential policies on the probability of financial crises, we begin with the univariate Early Warning System (EWS) model. Specifically, we use a dynamic panel logit model with fixed effects.

$$\begin{aligned}
&\Pr_{t-1}(y_{i,t}=1)=F(\pi_{i,t}),\\
&\qquad \pi_{i,t}=g_{i,t-1}\beta_1+x_{i,t-1}^{\top}\beta_2+MPI_{i,t-1}\beta_3+\delta\pi_{i,t-1}+\eta_i,
\end{aligned}\tag{1.1}$$

where i is the country index and $\Pr_{t-1}(y_{i,t}=1)$ is the conditional probability of observing a systemic banking crisis at time t in country i given the information at one's disposal at time $t-1$. This conditional probability relates to the crisis index, $\pi_{i,t}$, through the logistic mapping $F(\cdot)$. The dynamics of the crisis index depend on the lagged real GDP growth ($g_{i,t-1}$), the lagged macroprudential policy index ($MPI_{i,t-1}$), the lagged crisis index, a set of control variables (financial development, ratio of public debt to GPD, capital and trade openness) denoted by $x_{i,t-1}$ and a country fixed effect η_i capturing unobserved heterogeneity across countries.[5] Note that other approaches could be entertained for the modeling of the crisis probabilities such as the Linear Probability Model (LPM) or a dynamic panel probit model. The LPM would have the added benefits of being simple to implement; providing the best linear approximation to the data; and potentially delivering accurate estimates of average partial effects (Wooldridge, 2010). However, the LPM does not restrict the predicted probabilities to be in the [0;1] interval, which could potentially impact the results of the GIRF analysis in Section 1.4.4 as our approach crucially relies on the assessment of the conditional predicted path for the crisis probability at a given time horizon. We also prefer the dynamic panel logit approach over the probit alternative as the fatter-tailed profile of the logistic distribution is better suited to the frequency of systemic banking crisis episodes (Kumar et al., 2003; van den Berg et al., 2008; Betz et al., 2014).

The univariate panel logit model can be extended to take into account economic growth (the second dimension considered by Cerutti et al., 2017a), i.e. the growth regression. We thus extend our model to include the following equation:

[5] Appendix 1.B presents a more general formulation of the model in Equation (1.1) which, in the spirit of Kauppi and Saikkonen (2008), accommodates multiple lags of the latent index $\pi_{i,t}$ and of the systemic banking crisis dummy variable $y_{i,t}$. The section also provides a model specification analysis based on the Akaike and Bayesian Information Criteria (AIC and BIC).

$$g_{i,t} = g_{i,t-1}\Phi_1 + x_{i,t-1}^{\top}\Phi_2 + MPI_{i,t-1}\Phi_3 + \Psi\pi_{i,t-1} + c_i + \nu_{i,t}, \tag{1.2}$$

where c_i is a country fixed effect capturing unobserved heterogeneity across countries and $\nu_{i,t}$ is an error term. The system composed of equations (1.1) and (1.2) is estimated using the Maximum Likelihood Estimator (MLE). Our second equation resembles the model proposed by Cerutti et al. (2017a). However, there are two fundamental differences: (i) the probability of crisis as well as growth are weakly exogenous rather than strictly exogenous and (ii) the crisis variable does not enter as a binary variable as in Cerutti et al. (2017a), but instead as a continuous variable indicating the probability of occurrence of a crisis. This approach allows us to analyse the dynamic interactions between financial crises probability and output growth within the GIRF framework without being subject to the nonlinear "jump-like" effects that would arise from using a crisis binary variable instead.

We expect the activation of macroprudential instruments to reduce the probability of a financial crisis occurring. The MPI is thus expected to load negatively and be statistically significant in equation (1.1). Additionally, by constraining credit growth, the activation of macroprudential instruments should have a contractionary effect on economic activity, causing a slowdown in economic growth. In other words, we expect the MPI to have a negative and significant coefficient estimate in the growth equation (eq. 1.2). We subsequently use a GIRF analysis to measure the overall net effect of these two opposing effects of macroprudential policies on the probability of crises.

1.4 Empirical results

1.4.1 Data

The data we use covers the period 2000–2017 at a yearly frequency. For the banking crisis dummy, we use the Laeven and Valencia (2018) database, which records systemic financial crises across a large sample of countries. We obtain data on year-on-year growth in real GDP from the IMF World Economic Outlook (WEO) database. To extract the MPI variable, we use Cerutti et al. (2017a)'s database covering 134 countries (33 of which are advanced economies, 63 emerging and 38 developing ones). This database relies on the IMF survey on Global Macroprudential Policy Instruments (GMPI), which provided responses to more than 100 detailed questions on the use of 17 key macroprudential policy tools. To build their composite index, Cerutti et al. (2017a) use 12 macroprudential instruments, namely General Countercyclical Capital Buffer/Requirement (CTC); Leverage Ratio for banks (LEV); Time-Varying/Dynamic Loan-Loss Provisioning (DP); Loan-to-Value Ratio (LTV); Debt-to-Income Ratio (DTI); Limits on Domestic Currency Loans (CG); Limits on Foreign Currency Loans (FC); Reserve Requirement Ratios (RR); Levy/Tax on Financial Institutions (TAX); Capital Surcharges on SIFIs (SIFI); Limits on Interbank Exposures (INTER); and Concentration Limits (CONC). Cerutti et al. (2017a) also define LTV CAP as the subset of LTV measures used as a strict cap on new loans, as opposed to a loose guideline or merely an announcement of risk weights; and RRREV as the subset of RR measures that impose a specific wedge on foreign currency deposits or are adjusted countercyclically. Similar to Cerutti et al. (2017a) we also consider subsets of macroprudential instruments, separating those affecting borrowers' leverage and financial positions (LTV CAP and DTI) and those aimed at financial institutions' assets or liabilities (DP, CTC, LEV, SIFI, INTER, CONC, FC, RR REV, CG, and TAX).

We also include an indicator of financial development, which we extract from Svirydzenka and Brooks (2016). Ben Naceur et al. (2019) show that excessive financial development can lead to banking crises. They also show that taken individually, the various dimensions of financial development (access, depth and efficiency) are more informative than credit growth (Cerutti et al., 2017a). Following Richter et al. (2019), and to account for external factors, we also include a country's volume of trade (in percentage of GDP) and the Chinn-Ito capital account index. Finally, data on public debt to GDP ratios is obtained from Mbaye et al. (2018) global debt database.

Table 1.2 reports descriptive statistics for all the variables used in the empirical analysis. Panel A presents these statistics for the full sample while Panels B, C and D present

Table 1.1: Variable definitions and sources

Variable	Definition	Source
Dependent variables		
GDP growth ($g_{i,t}$)	Year on year real GDP growth (%)	IMF World Economic Outlook (WEO) database. We use GDP at constant prices.
Crisis ($y_{i,t}$)	Systemic banking crisis dummy	Laeven and Valencia (2018) crises database.
Independent variables		
FD	Financial development index	Svirydzenka (2016) aggregate index of financial development (access, depth and efficiency).
Debt-to-GDP	Public debt to GDP (%)	Mbaye et al. (2018) global debt database. We use general government debt when available and central government debt otherwise.
MPI	Macroprudential policy index (from 0 to 12)	Cerutti et al. (2017a) database. We also consider the borrower sub-index (LTV cap and DTI) and the financial sub-index (see text for details).
KA	Capital account openness index	Chinn and Ito (2006) normalized (from 0 to 1) index of capital account openness.
Trade-to-GDP	Sum of imports and exports to GDP (%)	World Bank World Development Indicators (WDI) database.

Table 1.2: Descriptive statistics of the data.

	Mean	Min	1st quartile	Median	3rd quartile	Max	Std. dev.	Obs.
Panel A: All countries								
GDP growth	4.06	−20.49	2.02	3.99	6.18	34.47	3.81	2178
Crisis	0.06	0.00	0.00	0.00	0.00	1.00	0.24	2178
FD	0.35	0.00	0.16	0.29	0.51	1.00	0.24	2178
Debt-to-GDP	54.33	3.09	30.08	45.07	69.59	260.96	36.13	2178
MPI	2.00	0.00	1.00	2.00	3.00	10.00	1.77	2178
MPI-Bor	0.33	0.00	0.00	0.00	0.00	2.00	0.63	2178
MPI-Fin	1.66	0.00	1.00	1.00	3.00	8.00	1.45	2178
KA	0.59	0.00	0.17	0.70	1.00	1.00	0.36	2178
Trade-to-GDP	83.36	0.17	54.98	75.09	103.41	437.33	44.66	2178
Panel B: Advanced Economies								
GDP growth	2.41	−14.81	1.14	2.45	3.93	25.01	3.33	576
Crisis	0.14	0.00	0.00	0.00	0.00	1.00	0.35	576
FD	0.66	0.20	0.56	0.70	0.81	1.00	0.19	576
Debt-to-GDP	63.65	3.66	36.31	53.86	85.29	237.65	40.68	576
MPI	1.86	0.00	1.00	2.00	3.00	6.00	1.53	576
MPI-Bor	0.45	0.00	0.00	0.00	1.00	2.00	0.68	576
MPI-Fin	1.41	0.00	0.00	1.00	2.00	6.00	1.25	576
KA	0.92	0.17	1.00	1.00	1.00	1.00	0.18	576
Trade-to-GDP	98.60	19.80	60.22	83.03	122.23	437.33	63.24	576
Panel C: Emerging Market Economies								
GDP growth	4.33	−15.10	2.39	4.23	6.26	34.47	3.80	1044
Crisis	0.04	0.00	0.00	0.00	0.00	1.00	0.19	1044
FD	0.31	0.06	0.21	0.29	0.39	0.73	0.13	1044
Debt-to-GDP	47.00	3.09	24.66	40.00	62.28	183.07	31.00	1044
MPI	2.46	0.00	1.00	2.00	3.00	10.00	1.89	1044
MPI-Bor	0.39	0.00	0.00	0.00	1.00	2.00	0.69	1044
MPI-Fin	2.06	0.00	1.00	2.00	3.00	8.00	1.51	1044
KA	0.52	0.00	0.17	0.45	0.76	1.00	0.33	1044
Trade-to-GDP	80.03	20.72	54.77	75.92	100.33	220.41	33.92	1044
Panel D:Low-Income Developing Countries								
GDP growth	5.26	−20.49	3.46	5.61	7.13	26.42	3.71	558
Crisis	0.02	0.00	0.00	0.00	0.00	1.00	0.13	558
FD	0.13	0.00	0.09	0.12	0.16	0.32	0.05	558
Debt-to-GDP	58.45	11.81	33.34	47.27	72.23	260.96	37.25	558
MPI	1.27	0.00	0.00	1.00	2.00	7.00	1.45	558
MPI-Bor	0.10	0.00	0.00	0.00	0.00	2.00	0.34	558
MPI-Fin	1.17	0.00	0.00	1.00	2.00	6.00	1.30	558
KA	0.38	0.00	0.17	0.17	0.70	1.00	0.35	558
Trade-to-GDP	73.85	0.17	48.65	67.52	95.08	206.77	34.02	558

Note: The table presents summary statistics for all observations over the period 2000-2017. Panel A presents the aggregate statistics for the 121 countries in our dataset. Panels B to D present the same summary statistics for the different country categories (respectively advanced economies, emerging market economies and low-income developing countries).

summary statistics for the subsamples of advanced economies, emerging market economies and low-income developing countries respectively. Table 1.2 suggests that systemic banking crises are most frequent in advanced economies (mean Crisis: 0.14, panel B) compared to emerging market economies (mean Crisis: 0.04) and low-income developing countries (mean Crisis: 0.02). Consistent with the findings of prior literature, on average, the use of macroprudential policy instruments is more prevalent in emerging market economies (mean MPI: 2.46) relative to both advanced economies (mean MPI: 1.86) and low-income countries (mean MPI: 1.27). We also find that borrower-based instruments are on average more used in advanced economies (mean MPI-Bor: 0.45) than in emerging market economies (mean MPI-Bor: 0.39).[6] By contrast, the use of lender-based instruments is on average more prevalent in emerging market economies (mean MPI-Fin: 2.06) than in advanced economies (mean MPI-Fin: 1.41). Economic growth rates are higher in emerging market economies and low-income developing countries compared to advanced economies. To get more insights on the time series properties of the data, Figure 1.5 in Appendix 1.A reports in Panel (a) the evolution over time of the total number of countries for which the systemic banking crisis dummy variable is equal to 1, with a breakdown for each subsample of countries, and Panels (b)-(g) report the time series of the median value across countries for the other variables considered in our empirical analysis.

1.4.2 Macroprudential policies and banking crises

Firstly, the probability of a banking crisis is estimated in a dynamic framework following Kauppi and Saikkonen (2008) and Candelon et al. (2012). Our specification captures the persistent nature of banking crises through the inclusion of the lagged crisis index.[7]

[6] Note that the MPI-Bor measure is composed of only two policy instruments which results in a distribution of the policy index exhibiting a large probability mass at zero for both AEs and EMEs. This is confirmed by the reported median value of the MPI-Bor which is zero in both cases. Therefore, comparisons between the two subsamples based on the mean of the MPI-Bor might be misleading.

[7] Other types of specifications, along the lines of the more general formulation in Kauppi and Saikkonen (2008), have been tested. Appendix 1.B summarises the model selection analysis supporting the choice of our model specification for the empirical analysis.

The estimation of the dynamic panel logit model specified in equation (1.1) is carried out by Maximum Likelihood. This estimator is inconsistent in settings where the cross-sectional dimension increases while holding constant the time series dimension — an issue known as the incidental parameter problem (Neyman and Scott, 1948). Bias-correction methods can be used to mitigate the resulting bias in estimated parameters and Candelon et al. (2014) adopt the Modified Maximum Likelihood Estimator (MMLE) of Carro (2007) which reduces the order of the bias without increasing the asymptotic variance. We opt instead for the estimation approach of Stammann et al. (2019) based on an iterative pseudo-demeaning algorithm, combined with the analytical bias correction of Hahn and Kuersteiner (2011) for general dynamic nonlinear models with fixed effects. Stammann et al. (2019) document through simulations the desirable finite sample properties of their bias-corrected estimator for parameter and average partial effect estimation. Moreover, their approach is particularly attractive for computationally demanding application such as the bootstrapped GIRF analysis we develop in Section 1.4.4.

Table 1.3 reports the estimates obtained for all the countries as well as for the sub-samples of advanced and emerging market economies.[8] Note that countries who did not experience at least one systemic banking crisis over our sample period do not contribute to the likelihood and are thus discarded prior to estimation. The results in Table 1.3 show that our main variables of interest load statistically significant and with the expected sign. Specifically, the coefficient estimate on the MPI is negative and significant, suggesting that the activation of macroprudential policies is conducive to a significant decrease in the probability of a banking crisis occurring. To assess the economic relevance of macroprudential regulation in mitigating the probability of occurrence of a systemic banking crisis, we calculate the Average Partial Effect (APE) of a one unit change in the MPI on the probability of observing a systemic banking crisis conditional on the observed values of the covariates and on the estimated parameters reported in Table 1.3.[9]

Based on this approach, we observe that macroprudential policies also have an eco-

[8]As the number of countries having experienced banking crises in low income countries is very small (N = 3), the maximization algorithm does not converge and the results are thus not reported.

[9]Note that, in the case of a continuous variable $\boldsymbol{x}_k$, the Average Partial Effect (APE) is calculated as

Table 1.3: Macroprudential Policies and Banking Crises

	All	AE	EME
MPI	-0.606^{***}	-0.411	-0.899^{***}
	(0.175)	(0.292)	(0.286)
GDP Growth	-0.192^{***}	-0.283^{***}	-0.18^{***}
	(0.039)	(0.065)	(0.059)
Crisis Index	0.56^{***}	0.534^{***}	0.2
	(0.113)	(0.143)	(0.185)
FD	12.574^{***}	11.884^{***}	18.289^{**}
	(3.308)	(4.06)	(7.205)
Debt-to-GDP	-0.009	-0.026^{**}	0.013
	(0.007)	(0.012)	(0.015)
KA	-1.439	-2.058	-0.779
	(1.109)	(1.595)	(1.725)
Trade-to-GDP	0.013	0.024	0.045
	(0.012)	(0.021)	(0.028)
AIC	532.396	321.042	170.112
BIC	727.937	429.619	238.075
Pseudo R^2	0.28	0.29	0.328
# Effect. Obs.	629	357	221
# Observations	2057	544	986
Country FE	Y	Y	Y
Year FE	N	N	N

Note: ML estimation is carried out using the iterative pseudo-demeaning algorithm of Stammann et al. (2016). The dependent variable is the systemic banking crisis binary. All regressors are considered as lagged values. We report bias-corrected estimates using the analytical bias correction of Hahn & Kuersteiner (2011). Standard errors clustered at the country level are reported between brackets. ***, **, and * indicate significance at the 1-, 5-, and 10-percent significance levels, respectively. We report the Akaike (AIC) and Bayesian (BIC) information criteria together with the McFadden pseudo R squared for each specification. The estimation period is 2001-2017 and we consider one-way country fixed effects. The total and effective number of observations considered in the estimation are also reported.

nomically meaningful impact as a one unit change in the MPI lowers the conditional probability of a systemic banking crisis by 7.29 percentage points on average for the case in which all the countries are pooled together. The average reductions in the banking crisis probability for advanced economies and emerging market economies are respectively of 5.21 and 8.83 percentage points. Likewise, the coefficient estimate on GDP Growth is negative and significant, implying that countries with higher economic growth rates face a lower probability of banking crises. The economic effect of real economic growth on the conditional probability of a systemic banking crisis occurring, measured by the APE, is also sizeable. A one percentage point increase in real GDP growth rate leads to a decline of the crisis probability by 2.31 percentage points when all the countries are pooled together and by respectively 3.58 percentage points and 1.78 percentage points for AEs and EMEs. In sum, better economic performance and active macroprudential policies are important ingredients for a more stable banking sector — i.e. one that is less prone to crises. A closer look at the results reveals however that the coefficient estimate on the MPI is negative and statistically significant only in the EME subsample; while it is negative, it is not statistically significant in the AE subsample. This result is consistent with Cerutti et al. (2017a) (p.211) who "*find that the statistically significant negative relation of MPI with credit growth is strongest for developing and emerging markets, and much less so for advanced economies*". The authors advance two possible reasons behind such finding: (i) the greater historical reliance of emerging markets on macroprudential policies relative to advanced countries and (ii) the fact that advanced economies tend to have more developed financial systems that offer alternative sources of finance and make regulation circumvention easier. Combined with those of Cerutti et al. (2017a), our findings can be interpreted as evidence that macroprudential policies have been used effectively by emerging market countries to tame credit growth, which eventually led to a lower incidence of banking crises. The upshot of this analysis is that macroprudential policies have

follows:

$$APE_k = \hat{\beta}_k (NT)^{-1} \sum_{t=1}^{T} \sum_{n=1}^{N} f(\hat{\pi}_{n,t}),$$

where $f(\cdot)$ is the logistic density function.

a meaningful positive impact on financial stability in emerging market economies while their role in fostering financial stability in advanced economies is less certain. Economic growth is however fundamental for financial stability in both groups of countries. Also, and as expected, the coefficient on the autoregressive index (Crisis Index) is lower than 1, meaning that there is no absorbing state of crisis. This coefficient is significantly different from 0 indicating that a static model would be misspecified. Consistent with the results reported by Ben Naceur et al. (2019), we find that greater financial development is conducive to a higher probability of a banking crisis; the coefficient estimate on the FD index is positive and significant in the full sample as well as across the two subsamples of AEs and EMEs. The other macroeconomic variables (Debt-to-GDP, KA and Trade openness) do not seem to matter for the likelihood of banking crises. Out of our set of explanatory variables, macroprudential policies, economic growth and financial development appear to be good predictors of banking crises.

Our two-step estimation approach for the system composed of Equations (1.1) and (1.2) means that the uncertainty in the first-stage estimate of the latent index $\hat{\pi}_{i,t}$ will also increase estimation uncertainty in the second-stage. While the main results presented in Section 1.4.3 implicitly assume that the latent index is observed, we also report in Appendix 1.C the confidence intervals obtained with a Moving-Block Bootstrap (MBB) procedure — which is outlined in Appendix 1.F. This approach takes into account the time series dependence in the data, the cross-sectional dimension of the panel, and the additional uncertainty in second-stage estimates introduced by the first-stage estimation of the latent index $\pi_{i,t}$.

Moreover, the results from Table 1.11 in Appendix 1.C also allow us to investigate the impact on inference from taking into account the dependence in the data and the relatively short length of our data set along the time series dimension. The reported 68% confidence intervals based on the MBB procedure confirm our main results. First, tighter macroprudential regulation significantly reduces the probability of a banking crisis occurring — with the effect being statistically significant at the 10-percent level in the subsample of EMEs. Second, countries experiencing better economic growth prospects have also a lower incidence of systemic banking crises. Third, higher financial development increases the probability of a financial crisis occurring. The effect is particularly significant for the full sample and the susbsample of EMEs (at the 10-percent level) but not for AEs.

1.4.3 Macroprudential policies, economic growth and banking crises

Secondly, we estimate the growth regression equation including the same explanatory variables as in the banking crisis equation estimated previously. It is worth clarifying that the probability of crisis can be introduced via the latent index estimated in the first equation; Crisis Index is thus a continuous variable taking values on the real line. Such an approach differs from Cerutti et al. (2017a) who include information about past crises as a binary variable. Results of the estimation are reported in Table 1.4.

Consistent with our expectations, the coefficient estimate on the MPI turns out to be negative and statistically significant, suggesting that the activation of macroprudential policies depresses economic growth. The effect of the MPI on economic growth is also economically meaningful; in the full sample, a one unit increase in the MPI lowers economic growth by 23.7 basis points. In the EME subsample, a one unit increase in the MPI depresses economic growth by 31.8 basis points. This result is consistent with Richter et al. (2019)'s findings that macroprudential measures, specifically changes in the maximum loan-to-value ratio, have a significant negative effect on output. It should, however, be noticed that this result is mainly driven by emerging market countries as the MPI does not load statistically significant in the AE subsample. For this latter group of countries, the activation of macroprudential policies does not seem to bear a cost in terms of economic growth. We can thus conclude from these preliminary evidence that the indirect channel of transmission of macroprudential policies to the likelihood of occurrence of a systemic banking crisis, through their impact on economic growth, is operative in emerging market economies but rather muted in advanced economies.

The coefficient estimate for the banking crisis index is negative and significant in both

Table 1.4: Macroprudential Policies and Real GDP growth

	All	AE	EM
MPI	-0.237^{***}	-0.037	-0.318^{***}
	(0.079)	(0.132)	(0.122)
GDP Growth	0.306^{***}	0.368^{***}	0.372^{***}
	(0.022)	(0.044)	(0.031)
Crisis Index	-0.204^{**}	-0.202^{*}	-0.147
	(0.092)	(0.117)	(0.150)
FD	-6.320^{***}	-6.863^{**}	-5.510^{**}
	(1.792)	(2.977)	(2.446)
Debt-to-GDP	0.011^{***}	0.023^{***}	0.028^{***}
	(0.004)	(0.009)	(0.008)
KA	-0.541	0.969	-0.766
	(0.627)	(1.379)	(0.778)
Trade-to-GDP	0.002	-0.031^{***}	0.021^{**}
	(0.005)	(0.011)	(0.009)
Country FE	Y	Y	Y
Year FE	N	N	N
Observations	2,057	544	986
R^2	0.361	0.299	0.347
Adjusted R^2	0.319	0.247	0.301

Note: Estimation is carried out by OLS with one-way country fixed effect dummies. The estimation period is 2001-2017. The dependent variable is the year-on-year real GDP growth rate. All regressors are considered as lagged values. We report estimates with Standard errors clustered at the country level between brackets. ***, **, and * indicate significance at the 1-, 5-, and 10-percent significance levels, respectively. We report both the R-squared and adjusted R-squared for each specification.

the full sample and the AE subsample. This indicates that banking crises, especially in advanced economies, put a drag on economic growth. This result is in line with the evidence documented by Candelon and Tokpavi (2016) and Ben Naceur et al. (2019) that advanced economies' economic performance is adversely affected by banking crises whereas low income and emerging market economies' economic performance mainly suffers from currency crises.

Contrary to the banking crisis equation results, some macroeconomic control variables turn out to be statistically significant. Debt-to-GDP loads positively indicating that countries with higher public debt relative to GDP enjoy higher economic growth. Trade openness seems to bear contradicting effects on economic growth depending on whether the economy is an advanced one or an emerging one. More trade openness spurs economic growth in emerging markets while it drags it down in advanced economies. While the sign on the coefficient estimates for Debt-to-GDP and for Trade-to-GDP in AEs might appear counter intuitive, this is likely due to the presence of lagged GDP growth in the specification which also enters in the denominator of these variables. Removing lagged GDP growth from the model leads to coefficient estimates for both Debt-to-GDP and Trade-to-GDP in AEs being not statistically different from 0.

We also carried out the estimation of Equation (1.2) using the GMM estimator proposed in Arellano and Bond (1991) to investigate the sensitivity of our main conclusions to endogeneity issues.[10] The results are reported in Table 1.13 of 1.D together with a short summary of the main findings. The analysis indicates that our main conclusions on the significance of the indirect channel of transmission of macroprudential policies are robust to the estimation approach adopted. The analysis in Section 1.4.4 on the direct and indirect effects of macroprudential regulation based on the MLE estimates might understate the indirect channel of transmission. This could result in more conservative estimates of the response in economic activity to a tightening in the macroprudential stance. However, our results would remain qualitatively robust to different estimates on

[10]This analysis is nevertheless subject to the caveat mentioned in the introduction about the weak instrument problem of GMM estimators in finite samples. See footnote 1 for more details.

the strength of the indirect channel of transmission for macroprudential policies.

Finally, the analysis reported so far in this section implicitly assumed that the lagged latent index for the probability of a systemic banking crisis, $\pi_{i,t-1}$, is observed without error in the estimation of Equation (1.2). Table 1.12 in Appendix 1.C reports the estimated 68% confidence intervals based on the Moving Block Bootstrap approach (Appendix 1.F). We observe that the confidence intervals for the coefficient estimates of the banking crisis index are markedly skewed towards negative values for the full sample and the subsample of AEs — consistent with the documented adverse impact of banking crises on economic growth. However, the estimates are no longer significant based on conventional statistical levels, which reflects the higher uncertainty in the estimates resulting from properly accounting for the first-stage estimation of the latent index and for the dependence in the data. Lastly, the results confirm that tighter macroprudential regulation depresses economic growth in EMEs, therefore corroborating that the indirect channel of macroprudential transmission is operative for these countries.

1.4.4 Direct versus indirect effects: a multivariate analysis

Our empirical analyses in the two previous subsections suggest that macroprudential policies can have an ambiguous impact on the incidence of banking crises. On the one hand, by mitigating vulnerabilities and risks in the banking sector, macroprudential policies decrease the probability of occurrence of a crisis. We call this the direct effect of macroprudential policies on banking crises (equation 1.1 effect). On the other hand, our estimation results for equation (1.2) reveal that macroprudential policies tend to depress economic growth, which according to the parameter estimates in equation (1.1) would raise the probability of financial crises occurring; i.e. the lower the economic growth and the higher is the probability of a banking crisis. We call this effect of macroprudential policies on the probability of crises, which works through economic growth, the indirect effect. It is thus interesting to further investigate this issue to uncover the net effect of macroprudential policies on financial stability. In particular, it is of interest to understand whether the stabilizing direct effect of macroprudential policies dominates or whether it is the destabilizing indirect effect that dominates. If the direct effect dominates, one should observe a positive net effect of macroprudential policies on financial stability — a lower probability of crisis. Inversely, if the indirect effect dominates, one should see a negative net effect of macroprudential policies on financial stability — a higher probability of crisis. To this end, we propose a Generalized Impulse Response Function (GIRF) analysis that disentangles these two effects and uncovers the time horizon within which the domination of one effect over the other takes place.[11]

We report the impact of a macroprudential policy tightening, measured by a positive variation in the MPI, on the conditional probability of a systemic banking crisis and on real GDP growth. In particular, a variation by one unit of the MPI corresponds to the activation of an additional macroprudential policy instrument. Examples of such activations include the introduction of a cap on loan-to-value ratios or the introduction of a capital surcharge for SIFIs. In this respect, our definition of a macroprudential policy tightening (i.e. of a positive shock) involves a substantial change in policy stance and has to be differentiated from other milder types of policy interventions such as further recalibrations/adjustments of existing policy instruments.[12] In order to give further insights on the magnitude of the macroprudential policy tightenings, we refer to the descriptive statistics of the macroprudential policy index reported in Table 1.2. We see that in the case of advanced economies, the MPI can take values ranging from 0 to 6 with a mean of 1.86 and a standard deviation of 1.53. For emerging economies, we observe that the distribution of MPI is skewed towards higher values. Indeed, the MPI values range from 0 to 10 with a mean of 2.46 and a standard deviation of 1.89. Given these summary statistics, we will refer to the three cases corresponding to a variation of the MPI by 1, 2

[11] 1.E describes in details the method used to obtain it at an horizon h.

[12] To illustrate, let us consider two examples of LTV policy actions conducted in South Korea: the introduction on September 9, 2002 of a maximum LTV ratio of 60% on real estate loans would be considered as a macroprudential tightening (MPI increasing by 1). On the contrary, the increase in the LTV ratio from 60 to 70% for long maturity loans introduced on March 24, 2004 would not be considered as a tightening (MPI does not change). Further information about the construction of the MPI index can be found in Cerutti et al. (2017a), pages 205–206.

and 3 (designated by *delta* in the columns of Figures 1.1 and 1.2) as respectively *small*, *moderate*, and *large* macroprudential policy tightenings. To summarize, our GIRF analysis quantifies how imposing an increase in the MPI at time $h = 0$ would conditionally impact the evolution of the crisis probability and output growth at times $h = 0, \dots, H$ — obtained from the dynamic system defined by Equations (1.1) and (1.2) — compared to a baseline scenario where no initial tightening in the MPI took place. In addition, we quantify the uncertainty around these estimates through a Moving-Block Bootstrap (MBB) procedure which takes into account both the time series dependence in the data and the cross-sectional dimension.[13]

The results of our analysis are presented respectively in Figures 1.1 and 1.2 for advanced economies and emerging market economies. For advanced economies, we see in the upper panel of Figure 1.1 that the impact of a macroprudential policy tightening on the conditional probability of a systemic banking crisis is always negative. The crisis probability decreases just after the implementation of a MPI tightening by respectively 3.93 percentage points for a small policy tightening, by 6.74 percentage points for a moderate tightening, and by 8.7 percentage points for a large policy tightening. Furthermore, these results are rather imprecisely estimated as the 68% Confidence Interval (CI) is consistent with an effect of a macroprudential policy tightening on the conditional probability of systemic banking crisis ranging from -1.31 to -23.9 percentage points in the small tightening case, from -2.24 to -36.21 percentage points in the moderate tightening case, and from -2.84 to -41.48 percentage points in the large tightening case. After the initial introduction of the macroprudential policy tightening, we do not find any statistically significant effect of macroprudential regulation on the probability of crisis at horizons ranging from 1 to 8 years. Moving on to the lower panel of Figure 1.1, we observe that there is no evidence of a significant effect of a macroprudential policy tightening on real GDP growth if we consider a 68% confidence interval for inference.

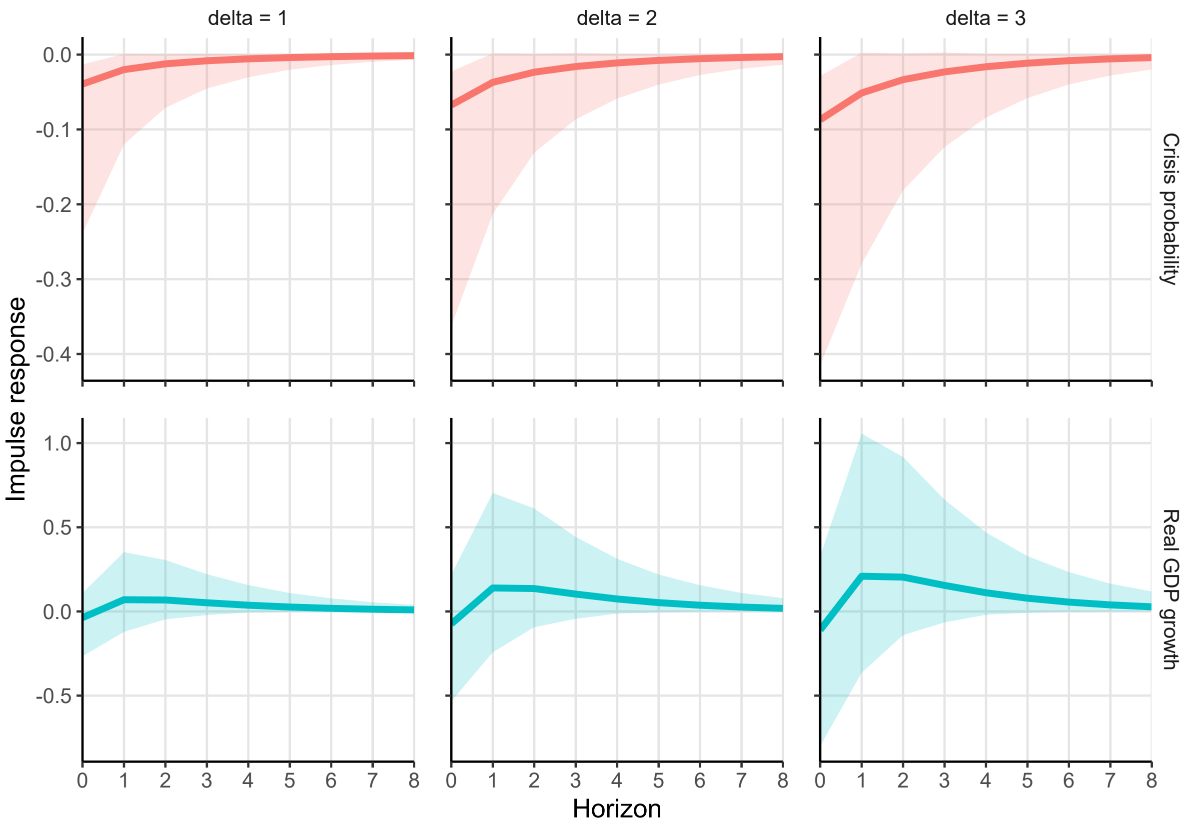
Taken together, these results for the impact of a MPI tightening on the conditional probability of a systemic banking crisis and on real GDP growth lead us to conclude that,

[13]The procedure for the Moving-Block Bootstrap is detailed in 1.F.

in the case of advanced economies, the stabilizing direct effect of macroprudential policies tend to dominate as we observe a statistically significant reduction in the probability of crisis following a macroprudential policy tightening.

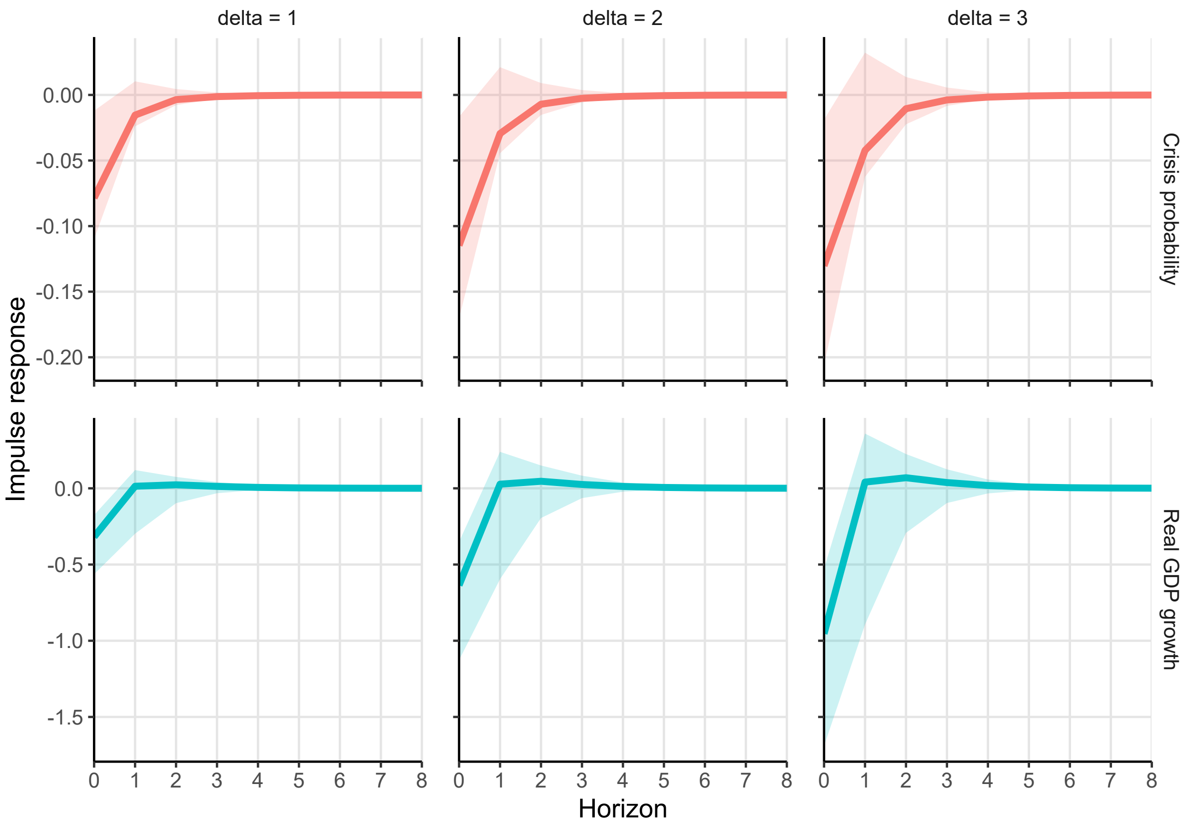
We now move to the analysis of the impact of a macroprudential policy tightening in the case of emerging market economies. The results are displayed in Figure 1.2. We see in the upper panel that the conditional probability of a systemic banking crisis decreases significantly after the introduction of a macroprudential policy tightening. The initial estimated decrease in crisis probability is 7.85 percentage points for a small policy tightening, 11.47 percentage points for a moderate tightening, and 13.02 percentage points for a large policy tightening. We thus observe that the estimated effect of a MPI tightening is larger for emerging market economies than for advanced economies. In addition, these results are more precisely estimated than in the case of advanced economies, as indicated by the narrower 68% confidence intervals. The 68% CI is consistent with an effect of a macroprudential policy tightening on the conditional probability of systemic banking crisis ranging from -1.21 to -11 percentage points in the small tightening case, from -1.67 to -17.06 percentage points in the moderate tightening case, and from -1.88 to -20.6 percentage points in the large tightening case. Similar to our results for advanced economies, we do not find any statistically significant effect of macroprudential regulation on the probability of crisis after the initial introduction of the macroprudential policy tightening.

Figure 1.1: GIRF analysis of a macroprudential tightening: advanced economies



Note: Comparison of the impulse responses of the probability of a systemic banking crisis (top-panel in red) and of real GDP growth (bottom-panel in green) to different levels of macroprudential tightenings (positive MPI shocks denoted by delta). The horizon of the responses displayed ranges up to eight years after the policy tightening. The Generalized Impulse Response Functions are computed following the procedure outlined in 1.E. The shaded areas around the response functions correspond to the 68% confidence intervals from the Moving-Block Bootstrap procedure detailed in 1.F with 5000 bootstrap replications and a block size of 5 years.

Figure 1.2: GIRF analysis of a macroprudential tightening: emerging market economies



Note: Comparison of the impulse responses of the probability of a systemic banking crisis (top-panel in red) and of real GDP growth (bottom-panel in green) to different levels of macroprudential tightenings (positive MPI shocks denoted by delta). The horizon of the responses displayed ranges up to eight years after the policy tightening. The Generalized Impulse Response Functions are computed following the procedure outlined in 1.E. The shaded areas around the response functions correspond to the 68% confidence intervals from the Moving-Block Bootstrap procedure detailed in 1.F with 5000 bootstrap replications and a block size of 5 years.

Turning to the impact of macroprudential regulation on real economic activity, we see in the lower panel of Figure 1.2 that real GDP growth experiences a contraction after the introduction of a macroprudential policy tightening. The initial decrease in real GDP growth is estimated to be 31.8 basis points for a small policy tightening, 63.6 basis points for a moderate tightening and 95.4 basis points for a large policy tightening. This initial drop in economic activity is also statistically significant as indicated by the 68% CIs which support an effect of a macroprudential tightening on real GDP growth ranging from -17.5 to -56.4 basis points in the small tightening case, from -35.1 to -112.7 basis points in the moderate tightening case, and from -52.6 to -169.1 basis points in the large tightening case. We do not find any statistically significant effect of macroprudential regulation on real economic activity for the periods following the initial introduction of the policy tightening.

We conclude that tighter macroprudential regulation in emerging market economies is improving financial stability at the cost of harming substantially economic growth at the time of the introduction of the stricter regulation. Nevertheless, the stabilizing direct effect of macroprudential policies seems also to dominate the indirect harmful effect on economic activity for emerging market economies.

In summary, our analysis suggest that despite the negative impact on growth, macroprudential policies are overall beneficial with respect to financial stability. In particular, there is a net positive effect of macroprudential policies on financial stability — reflected by a lower probability of systemic banking crises — in both advanced and emerging market economies. This positive effect on financial stability is also observed regardless of the size of the shock to macroprudential policy. Be it in advanced or in emerging market economies, a macroprudential policy tightening is thus likely to decrease the future occurrence of a banking crisis.

1.5 Robustness analysis

In this section, we conduct two robustness checks on the results obtained in the previous sections. First, we investigate whether the results we obtained for the impact of macroprudential policies on real GDP growth and on the probability of a systemic banking crisis change when we consider only a specific subset of macroprudential instruments. We focus on policies specifically aimed at borrowers' leverage and financial positions and on policies aimed at financial institutions' assets or liabilities. Second, we want to assess whether the Global Financial Crisis had an impact on the transmission of macroprudential regulation to systemic banking crises and real economic growth. We present the results of these two robustness checks in the following subsections.

1.5.1 Targeting borrowers vs. financial institutions

Following Cerutti et al. (2017a), we further divide the MPI into a subset of macroprudential instruments targeted at borrowers' leverage and financial positions,[14] which we label MPI-Bor and a subset of macroprudential instruments targeted at financial institutions' assets or liabilities,[15] which we label MPI-Fin.

We estimate again the dynamic panel logit specification reported in equation (1.1) on our full sample of countries and on the subgroups of advanced and emerging market economies. The estimation method, data filtering, and bias-correction are as described in Section 1.3 and we refer the reader to section 1.4.2 for details. The results are reported in Table 1.5 below. They confirm our main result that macroprudential policy tools lead to a significant decrease in the probability of systemic banking crisis. We also find that our result for the aggregate MPI is mostly driven by the effect of macroprudential instruments targeted at financial institutions' assets or liabilities — MPI-Fin. Indeed, the MPI-Bor does not contribute significantly to the conditional probability of a systemic banking crisis

[14] This subgroup includes loan-to-value caps and debt-to-income ratios.

[15] This subgroup contains dynamic loan-loss provisioning, countercyclical capital buffers, leverage ratios for banks, capital surcharges on SIFIs, limits on interbank exposures, concentration limits, limits on domestic and foreign currency loans, reserve requirements, and tax on financial institutions.

in advanced economies. MPI-Fin, on the other hand, significantly reduces the probability of a banking crisis for both advanced and emerging economies. These findings help thus in refining our analysis based on the overall MPI and improve our understanding of the particular types of macroprudential tools that lower the probability of the incidence of banking crises. While in aggregate the positive impact of macroprudential policies on financial stability is unambiguous for emerging market economies, this positive impact is mostly driven by policies directed towards financial institutions' assets or liabilities in the case of advanced economies. Our results thus complement and extend the analysis in Cerutti et al. (2017a) who document that the measures associated with the MPI-Bor and MPI-Fin significantly contribute to dampening credit growth in the full sample of countries and the subsample of EMEs but not in the subsample of AEs. We document that the measures associated with the MPI-Fin are also effective in promoting financial stability for AEs by significantly reducing the incidence of systemic banking crises.

Additionally, We observe that the economic significance of borrower- and financial-oriented macroprudential policies is even stronger than in our baseline case with the aggregate MPI. On average, a one unit change in the MPI-Bor lowers the probability of crisis by 8.91 percentage points when all countries are pooled together and by 16.21 percentage points when only EMEs are included in the sample. Likewise, a one unit change in MPI-Fin reduces the conditional probability of a banking crisis respectively by 9.38 percentage points when the sample includes all the countries, by 7.43 percentage points for the AEs subsample and by 8.91 percentage points for the EMEs subsample.

The results for the statistically significant negative effect of real GDP growth on the conditional probability of a systemic banking crisis are confirmed for both the MPI-Fin and the MPI-Bor indices. Furthermore, the economic effect of real economic growth on the conditional probability of a systemic banking crisis is comparable to our baseline results with the aggregate macroprudential policy index. We thus confirm our result that sound economic growth is fundamental for the stability of the financial sector.

We also re-estimate equation (1.2) for real GDP growth by considering borrower- and financial-based macroprudential policies instead of the aggregate MPI. The results are

Table 1.5: Macroprudential Policies and Banking Crises: borrower and financial indices

	All	AE	EME	All	AE	EME
MPI-Bor	-0.705^{*}	0.368	-1.556^{**}			
	(0.428)	(0.719)	(0.651)			
MPI-Fin				-0.78^{***}	-0.59^{*}	-1.094^{***}
				(0.219)	(0.343)	(0.356)
GDP Growth	-0.179^{***}	-0.282^{***}	-0.174^{***}	-0.188^{***}	-0.28^{***}	-0.176^{***}
	(0.038)	(0.065)	(0.057)	(0.04)	(0.066)	(0.06)
Crisis Index	0.532^{***}	0.492^{***}	0.04	0.553^{***}	0.532^{***}	0.2
	(0.124)	(0.139)	(0.214)	(0.114)	(0.144)	(0.194)
FD	11.061^{***}	13.465^{***}	15.464^{**}	12.406^{***}	11.929^{***}	15.602^{**}
	(3.156)	(4.174)	(6.852)	(3.243)	(4.069)	(6.422)
Debt-to-GDP	-0.009	-0.025^{**}	0.021	-0.009	-0.027^{**}	0.008
	(0.006)	(0.011)	(0.016)	(0.007)	(0.012)	(0.015)
KA	-1.212	-3.037^{*}	-1.351	-1.882^{*}	-2.341	-1.364
	(1.102)	(1.645)	(1.699)	(1.086)	(1.545)	(1.734)
Trade-to-GDP	0.01	0.009	0.066^{**}	0.013	0.029	0.043
	(0.012)	(0.017)	(0.028)	(0.012)	(0.021)	(0.028)
AIC	560.732	326.489	180.955	531.424	317.975	172.158
BIC	756.273	435.065	248.919	0.282	0.298	0.318
Pseudo R^2	0.234	0.275	0.271	0.282	0.298	0.318
# Effect. Obs.	629	357	221	629	357	221
# Observations	2057	544	986	2057	544	986
Country FE	Y	Y	Y	Y	Y	Y
Year FE	N	N	N	N	N	N

Note: ML estimation is carried out using the iterative pseudo-demeaning algorithm of Stammann et al. (2016). The dependent variable is the systemic banking crisis binary. All regressors are considered as lagged values. We report bias-corrected estimates using the analytical bias correction of Hahn & Kuersteiner (2011). Standard errors clustered at the country level are reported between brackets. ***, **, and * indicate significance at the 1-, 5-, and 10-percent significance levels, respectively. We report the Akaike (AIC) and Bayesian (BIC) information criteria together with the McFadden pseudo R squared for each specification. The estimation period is 2001-2017 and we consider one-way country fixed effects. The total and effective number of observations considered in the estimation are also reported.

reported in Table 1.6. Consistent with our baseline result using a sample that includes all the countries, both borrower- and financial-based macroprudential policies have a significantly negative impact on real economic growth. A closer look at Table 1.6 also reveals that the MPI-Fin results are driven by emerging market countries. The economic significance of the macroprudential policies targeting borrowers and financial institutions is also stronger than in the case of the aggregate MPI. A one unit change in the MPI-Bor leads to a contraction of real GDP growth by 36.6 basis points for the sample including all countries. In the case of the MPI-Fin, a one unit increase translates in a contraction of real economic activity by respectively 28.8 basis points when all the countries are pooled together and 36.8 basis points for emerging market economies.

Finally, the statistical significance of other macroeconomic control variables such as Debt-to-GDP (positive sign) and Trade-to-GDP (negative sign for AEs and positive sign for EMEs) is consistent with our baseline estimations reported previously.

We now turn to the assessment of the impact of financial- and borrower-based macroprudential policies considered separately on the trade-offs between the direct and indirect effects of macroprudential regulation outlined in section 1.4.4. First, the descriptive statistics reported in Table 1.2 provide additional information on the distribution of the MPI-Bor and MPI-Fin variables. The MPI-Fin in advanced economies takes values ranging from 0 to 6 with a mean of 1.41 and a standard deviation of 1.25. In EMEs, its values are comprised between 0 and and 8 with a mean of 2.06 and a standard deviation of 1.51. The MPI-Bor, which is only composed of two categories of macroprudential instruments, has de facto a much narrower range of variations with a large amount of country-year observations taking a value of zero. Given that the aggregate MPI is composed of ten instruments targeted at the financial sector out of a total of twelve and that the distribution of the MPI-Fin in advanced economies and emerging market economies is comparable to the aggregate MPI, we will keep our terminology of *small*, *moderate*, and *large* policy tightenings to refer to variations of the MPI-Fin by respectively 1, 2, and 3. In the interest of space, we will focus on the analysis of the results for the MPI-Fin in the rest of this section.[16] The results for advanced and emerging market economies are presented respectively in Figures 1.3 and 1.4 below.

For advanced economies, we see in the upper panel of Figure 1.3 that the introduction of a macroprudential policy tightening targeted at the financial sector produces a reduction in the conditional probability of a systemic banking crisis which is quantitatively similar to the one obtained with the aggregate macroprudential policy index. The crisis probability decreases just after the implementation of a MPI-Fin tightening by respectively 5.50 percentage points for a small policy tightening, by 8.87 percentage points for a moderate tightening, and by 10.84 percentage points for a large policy tightening. Similar to our results with the aggregate MPI, these impulse responses are rather imprecisely estimated as shown by the width of the reported 68% confidence intervals. A major difference in the results for the MPI-Fin compared to the aggregate MPI is that the reduction in the conditional probability of a conditional systemic banking crisis is still statistically significant at horizons of up to two years. The crisis probability two years after the introduction of the MPI-Fin tightening is lower than the value in the case of no policy change respectively by 2.1 percentage points for a small policy tightening, by 3.83 percentage points for a moderate tightening, and by 5.31 percentage points for a large policy tightening. We do not find any evidence of a significant effect of a macroprudential policy tightening targeted at the financial sector on real GDP growth. This result is consistent with our analysis for the aggregate macroprudential policy index. Furthermore, the width of the 68% confidence intervals reported for the real GDP growth impulse responses in the lower panel of Figure 1.3 indicate that the results are subject to more estimation uncertainty than in the aggregate MPI case.

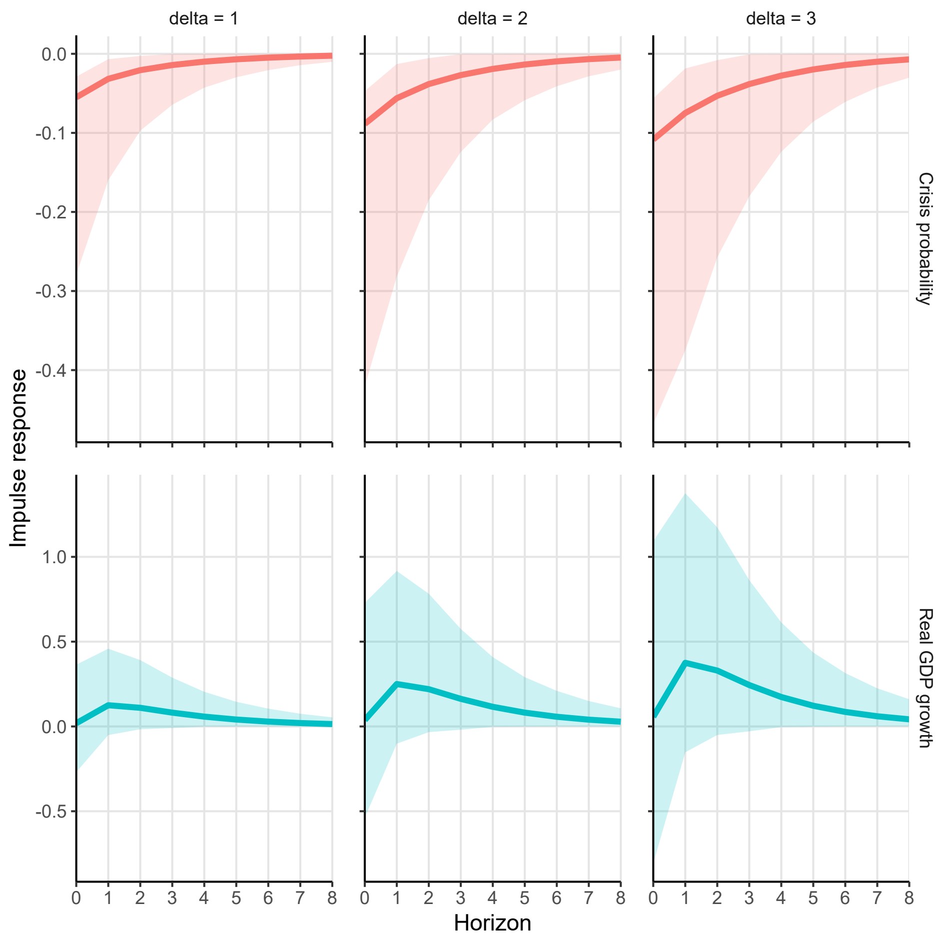
[16] We also computed the GIRFs for the MPI-Bor. Although we didn't find any statistically significant effect of a MPI-Bor tightening on crisis probability or on real economic activity, the results are provided in 1.G for completeness.

Table 1.6: Macroprudential Policies and Real GDP growth: borrower and financial indices

	All	AE	EM	All	AE	EM
MPI-Bor	-0.366^{**}	-0.191	-0.439			
	(0.186)	(0.268)	(0.282)			
MPI-Fin				-0.288^{***}	0.019	-0.368^{**}
				(0.103)	(0.183)	(0.156)
GDP Growth	0.307^{***}	0.361^{***}	0.379^{***}	0.306^{***}	0.367^{***}	0.374^{***}
	(0.022)	(0.044)	(0.031)	(0.022)	(0.044)	(0.031)
Crisis Index	-0.274^{**}	-0.231^{**}	-0.032	-0.194^{**}	-0.200^{*}	-0.106
	(0.114)	(0.115)	(0.183)	(0.091)	(0.115)	(0.159)
FD	-6.827^{***}	-6.632^{**}	-7.316^{***}	-6.512^{***}	-6.787^{**}	-5.887^{**}
	(1.765)	(2.972)	(2.297)	(1.785)	(2.974)	(2.427)
Debt-to-GDP	0.011^{***}	0.024^{***}	0.028^{***}	0.011^{***}	0.023^{**}	0.028^{***}
	(0.004)	(0.009)	(0.008)	(0.004)	(0.009)	(0.008)
KA	-0.593	0.893	-0.786	-0.545	0.886	-0.765
	(0.628)	(1.373)	(0.780)	(0.628)	(1.377)	(0.781)
Trade-to-GDP	0.001	-0.030^{***}	0.020^{**}	0.002	-0.032^{***}	0.020^{**}
	(0.005)	(0.010)	(0.009)	(0.005)	(0.011)	(0.009)
Country FE	Y	Y	Y	Y	Y	Y
Year FE	N	N	N	N	N	N
Observations	2,057	544	986	2,057	544	986
R^2	0.361	0.301	0.344	0.361	0.300	0.346
Adjusted R^2	0.319	0.249	0.298	0.319	0.247	0.300

Note: Estimation is carried out by OLS with one-way country fixed effect dummies. The estimation period is 2001-2017. The dependent variable is the year-on-year real GDP growth rate. All regressors are considered as lagged values. We report estimates with Standard errors clustered at the country level between brackets. ***, **, and * indicate significance at the 1-, 5-, and 10-percent significance levels, respectively. We report both the R-squared and adjusted R-squared for each specification.

Figure 1.3: GIRF analysis of a financial macroprudential tightening: advanced economies

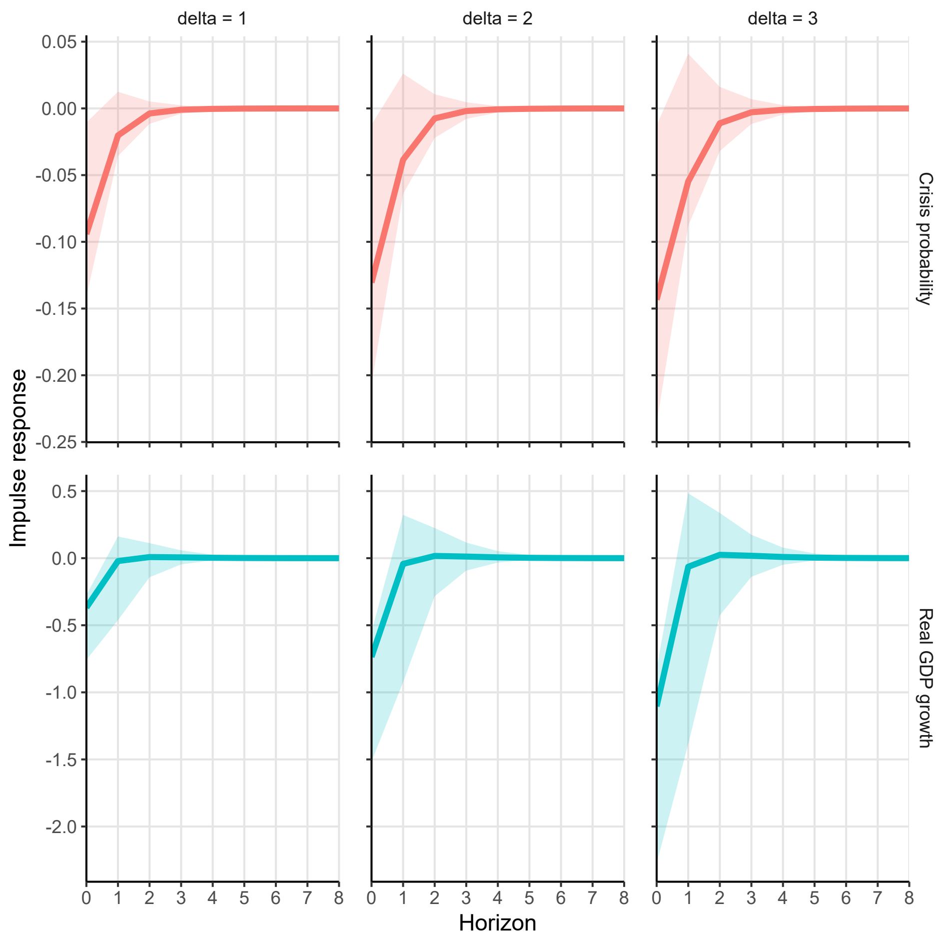


Note: Comparison of the impulse responses of the probability of a systemic banking crisis (top-panel in red) and of real GDP growth (bottom-panel in green) to different levels of financial macroprudential tightenings (positive MPI-Fin shocks denoted by delta). The horizon of the responses displayed ranges up to eight years after the policy tightening. The Generalized Impulse Response Functions are computed following the procedure outlined in 1.E. The shaded areas around the response functions correspond to the 68% confidence intervals from the Moving-Block Bootstrap procedure detailed in 1.F with 5000 bootstrap replications and a block size of 5 years.

We now shift our focus to the results obtained for EMEs and reported in Figure 1.4 below. We observe in the upper panel that the decrease in the systemic banking crisis probability after the introduction of a macroprudential policy tightening targeted at the financial sector is statistically significant and its magnitude is comparable to the results obtained in section 1.4.4 for the aggregate macroprudential policy index. We do not find any statistically significant effect of macroprudential regulation on the probability of crisis after the initial introduction of the policy tightening. The results for real GDP growth reported in the lower panel, on the other hand, highlight that the decrease in real economic activity induced by the introduction of a tightening in the financial macroprudential index is more pronounced than in the case of the aggregate MPI. The initial decrease in real GDP growth is estimated to be 36.8 basis points for a small policy tightening, 73.62 basis points for a moderate tightening and 110.43 basis points for a large policy tightening. This initial drop in economic activity is concentrated around more negative values as indicated by the 68% CIs which support an effect of a MPI-Fin tightening on real GDP growth ranging from -27.42 to -75.8 basis points in the small tightening case, from -54.83 to -151.59 basis points in the moderate tightening case, and from -82.25 to -227.39 basis points in the large tightening case. No further statistically significant effect is found at horizons longer than the initial introduction of the policy tightening.

In conclusion of this first robustness check, we confirm that there is a net positive effect of macroprudential policies targeted at the financial sector on financial stability in both advanced and emerging market economies. A macroprudential policy tightening targeting the financial sector decreases the future occurrence of a banking crisis, even after taking into account its indirect harmful effect on real economic activity. In the case of advanced economies, this reduction in the conditional probability of a systemic banking crisis persists at horizons of up to two years after the introduction of the policy tightening.

Figure 1.4: GIRF analysis of a financial macroprudential tightening: emerging market economies



Note: Comparison of the impulse responses of the probability of a systemic banking crisis (top-panel in red) and of real GDP growth (bottom-panel in green) to different levels of financial macroprudential tightenings (positive MPI-Fin shocks denoted by delta). The horizon of the responses displayed ranges up to eight years after the policy tightening. The Generalized Impulse Response Functions are computed following the procedure outlined in 1.E. The shaded areas around the response functions correspond to the 68% confidence intervals from the Moving-Block Bootstrap procedure detailed in 1.F with 5000 bootstrap replications and a block size of 5 years.

1.5.2 The impact of the Global Financial Crisis

As highlighted in the introduction, the Global Financial Crisis (GFC) prompted public authorities around the world to reassess their existing toolbox of macroprudential instruments and to implement new measures to reduce the future occurrence of systemic banking crises (see Claessens and Kodres (2014) for the regulatory responses to the GFC).

In this second robustness check, our aim is to test whether the changes in both the scale and composition of the macroprudential policy landscape in response to the GFC had a significant impact on the transmission of macroprudential regulation to the conditional probability of systemic banking crisis and to real economic activity. To this end, we modify equations (1.1) and (1.2) to account for a potential change after 2008 in the sensitivity of the conditional probability of systemic banking crisis and of real GDP growth to changes in the macroprudential policy index, MPI. The specification of the linear systemic banking crisis index, $\pi_{i,t}$, outlined in equation (1.1) is modified as follows

$$\begin{aligned}\pi_{i,t} &= g_{i,t-1}\beta_1 + x_{i,t-1}^{\top}\beta_2 + MPI_{i,t-1}\beta_3 \\ &\quad + \delta\pi_{i,t-1} + \mathbb{1}_{\{t-1\ \geq\ 2008\}}\ MPI_{i,t-1}.\beta_4 + \eta_i,\end{aligned} \tag{1.3}$$

where we added an interaction variable between the MPI variable and an indicator variable, $\mathbb{1}_{\{t-1\ \geq\ 2008\}}$, taking a value of 0 before 2008 and of 1 after 2008 to capture the potential change in the transmission of macroprudential policies after the GFC. Similarly, an interaction variable between the MPI and a post-GFC indicator function is added to the growth regression specified in equation (1.2):

$$\begin{aligned}g_{i,t} &= g_{i,t-1}\Phi_1 + x_{i,t-1}^{\top}\Phi_2 + MPI_{i,t-1}\Phi_3 \\ &\quad + \Psi\pi_{i,t-1} + \mathbb{1}_{\{t-1\ \geq\ 2008\}}\ MPI_{i,t-1}\Phi_4 + c_i + \nu_{i,t}.\end{aligned} \tag{1.4}$$

We estimate the dynamic panel logit model with the modified specification that we introduced in equation (1.3) on our full sample of countries and on the subgroups of advanced and emerging market economies. The results are reported in the right panel of

Table 1.7 below. We also report the results of our baseline specification (equation 1.1) in the left panel for ease of comparison.

Our estimations reveal that the impact of the GFC on the transmission of macroprudential policy to financial stability, as measured by the conditional probability of a systemic banking crisis, differs across advanced economies and EMEs. For advanced economies, the GFC did not significantly impact the ability of macroprudential policies to reduce the conditional probability of a systemic banking crisis. For EMEs, we notice that the effectiveness of macroprudential policies to lower the risk of a systemic banking crisis has significantly improved after the GFC; the coefficient estimate on the GFC-dummy variable is negative and significant at the 10 percent level in the EME sample in Table 1.7. This finding can be explained by a change in the type of macroprudential policies implemented in emerging market economies, by a change in the effectiveness of existing policies, or by a combination of both factors.

We confirm the statistically significant negative effect of real GDP growth on the conditional probability of a systemic banking crisis in all three cases. The economic significance of the positive effect of real economic activity on the crisis probability is quantitatively comparable to the results obtained in our baseline specification. For the linear crisis index, the results for the full sample of countries and for the sub-sample of advanced economies are also comparable to the baseline results. We note that, in the case of emerging market economies, the persistence of the linear crisis index increases and becomes statistically significant.

To summarize, accounting for potential changes after the GFC in the transmission of macroprudential policy to the conditional probability of a systemic banking crisis seems justified in the case of emerging market economies. This conclusion is also motivated by the better fit of this alternative model specification for the sub-sample of emerging market economies, both in terms of lower information criteria (AIC and BIC) and in terms of higher pseudo R^2 compared to the baseline specification.

We now turn our attention to the evaluation of the impact of the Global Financial Crisis on the trade-off between macroprudential regulation and real economic activity.

Table 1.7: Macroprudential Policies and Banking Crises: the impact of the Global Financial Crisis

	All	AE	EME	All	AE	EME
MPI	-0.606^{***}	-0.411	-0.899^{***}	-0.535^{**}	-0.66^{*}	-0.506
	(0.175)	(0.292)	(0.286)	(0.252)	(0.383)	(0.377)
MPI $\times\ \mathbb{1}_{\{t-1\ \geq\ 2008\}}$				-0.061	0.239	-0.43^{*}
				(0.15)	(0.253)	(0.256)
GDP Growth	-0.192^{***}	-0.283^{***}	-0.18^{***}	-0.195^{***}	-0.264^{***}	-0.228^{***}
	(0.039)	(0.065)	(0.059)	(0.04)	(0.066)	(0.068)
Crisis Index	0.56^{***}	0.534^{***}	0.2	0.581^{***}	0.476^{***}	0.289^{*}
	(0.113)	(0.143)	(0.185)	(0.112)	(0.149)	(0.169)
FD	12.574^{***}	11.884^{***}	18.289^{**}	12.727^{***}	12.341^{***}	21.31^{***}
	(3.308)	(4.06)	(7.205)	(3.334)	(4.063)	(7.873)
Debt-to-GDP	-0.009	-0.026^{**}	0.013	-0.008	-0.03^{**}	0.005
	(0.007)	(0.012)	(0.015)	(0.007)	(0.012)	(0.016)
KA	-1.439	-2.058	-0.779	-1.572	-1.842	-1.867
	(1.109)	(1.595)	(1.725)	(1.135)	(1.64)	(1.954)
Trade-to-GDP	0.013	0.024	0.045	0.012	0.028	0.05
	(0.012)	(0.021)	(0.028)	(0.012)	(0.021)	(0.032)
AIC	532.396	321.042	170.112	531.382	325.101	165.986
BIC	727.937	429.619	238.075	731.368	437.556	237.347
Pseudo R^2	0.28	0.29	0.328	0.285	0.284	0.36
# Effect. Obs.	629	357	221	629	357	221
# Observations	2057	544	986	2057	544	986
Country FE	Y	Y	Y	Y	Y	Y
Year FE	N	N	N	N	N	N

Note: ML estimation is carried out using the iterative pseudo-demeaning algorithm of Stammann et al. (2016). The dependent variable is the systemic banking crisis binary. All regressors are considered as lagged values. We report bias-corrected estimates using the analytical bias correction of Hahn & Kuersteiner (2011). Standard errors clustered at the country level are reported between brackets. ***, **, and * indicate significance at the 1-, 5-, and 10-percent significance levels, respectively. We report the Akaike (AIC) and Bayesian (BIC) information criteria together with the McFadden pseudo R squared for each specification. The estimation period is 2001-2017 and we consider one-way country fixed effects. The total and effective number of observations considered in the estimation are also reported.

The results of the estimation of the linear panel model specified in equation (1.4) are reported in the right panel of Table 1.8 below. Again, We report the results of our baseline specification (equation 1.2) in the left panel for ease of comparison.

A first interesting result is that the effect of macroprudential regulation on real economic activity appears to have changed substantially after the GFC. Indeed, the MPI coefficient has a statistically significant positive sign when considering all the countries pooled together and the sub-sample of advanced economies. If we consider, on the other hand, the interaction variable between the MPI variable and a post-crisis indicator variable, the coefficient estimates are negative and statistically significant in all the cases considered. We thus confirm our baseline result that macroprudential policies depress real economic activity for the post-GFC period when considering all the countries pooled together and emerging market economies.

Our alternative model specification does not alter the persistence or statistical significance of real GDP growth. Interestingly, the pervasiveness of the adverse impact of systemic banking crisis on real economic activity, measured by the coefficient estimate for the linear crisis index, becomes statistically significant in the case of EMEs while the opposite is true for AEs. The statistically significant negative impact of financial development on real economic activity is confirmed in all cases but emerging market economies. The statistical significance of Debt-to-GDP (positive sign) and Trade-to-GDP (negative sign for AEs and positive sign for EMEs) is also confirmed.

To conclude this section, our alternative specification seems also relevant in the case of the modeling of real GDP growth for two reasons. First, the sensitivity of real economic activity to macroprudential regulation seems to have experienced an important change in the period following the Global Financial Crisis. This is documented by the opposite signs of the coefficient for MPI and for the interaction variable between the MPI variable and a post-crisis indicator variable. Second, this alternative specification seems supported by the data, as indicated by the higher values of the adjusted R^2 in all three cases.

Table 1.8: Macroprudential Policies and real GDP growth: the impact of the Global Financial Crisis

	All	AE	EME	All	AE	EME
MPI	-0.237^{***}	-0.037	-0.318^{***}	0.297^{**}	0.712^{***}	0.161
	(0.079)	(0.132)	(0.122)	(0.121)	(0.267)	(0.163)
MPI $\times$ $\mathbb{1}_{\{t-1\,\geq\,2008\}}$				-0.434^{***}	-0.644^{***}	-0.419^{***}
				(0.075)	(0.199)	(0.092)
GDP Growth	0.306^{***}	0.368^{***}	0.372^{***}	0.282^{***}	0.352^{***}	0.336^{***}
	(0.022)	(0.044)	(0.031)	(0.022)	(0.044)	(0.032)
Crisis Index	-0.204^{**}	-0.202^{*}	-0.147	-0.179^{**}	-0.152	-0.203^{*}
	(0.092)	(0.117)	(0.150)	(0.089)	(0.123)	(0.119)
FD	-6.320^{***}	-6.863^{**}	-5.510^{**}	-4.541^{**}	-6.569^{**}	-2.885
	(1.792)	(2.977)	(2.446)	(1.802)	(2.954)	(2.476)
Debt-to-GDP	0.011^{***}	0.023^{***}	0.028^{***}	0.010^{***}	0.034^{***}	0.023^{***}
	(0.004)	(0.009)	(0.008)	(0.004)	(0.009)	(0.008)
KA	-0.541	0.969	-0.766	-0.846	0.688	-1.135
	(0.627)	(1.379)	(0.778)	(0.624)	(1.367)	(0.773)
Trade-to-GDP	0.002	-0.031^{***}	0.021^{**}	0.002	-0.034^{***}	0.021^{**}
	(0.005)	(0.011)	(0.009)	(0.005)	(0.011)	(0.009)
Country FE	Y	Y	Y	Y	Y	Y
Year FE	N	N	N	N	N	N
Observations	2,057	544	986	2,057	544	986
R^2	0.361	0.299	0.347	0.372	0.315	0.362
Adjusted R^2	0.319	0.247	0.301	0.331	0.262	0.317

Note: Estimation is carried out by OLS with one-way country fixed effect dummies. The estimation period is 2001-2017. The dependent variable is the year-on-year real GDP growth rate. All regressors are considered as lagged values. We report estimates with Standard errors clustered at the country level between brackets. ***, **, and * indicate significance at the 1-, 5-, and 10-percent significance levels, respectively. We report both the R-squared and adjusted R-squared for each specification.

1.6 Conclusion

This paper uses a novel empirical setup to assess the effectiveness of macroprudential policies in achieving their ultimate goal of reducing the incidence of financial crises. Our empirical specification allows us to quantify the effect of these policies on the probability of financial crises and on economic growth. Our main objective is to understand the channels through which macroprudential policies can have an influence on financial stability. In particular, we identify two possible channels. First, macroprudential policies can have a direct effect on the probability of banking crises if they happen to smooth financial cycles. Second, macroprudential policies can exert an indirect effect on the probability of banking crises by weakening economic growth. To this end, we use an empirical method that allows us to disentangle the direct and indirect effects of macroprudential policies as well as their net effect on the probability of systemic banking crises.

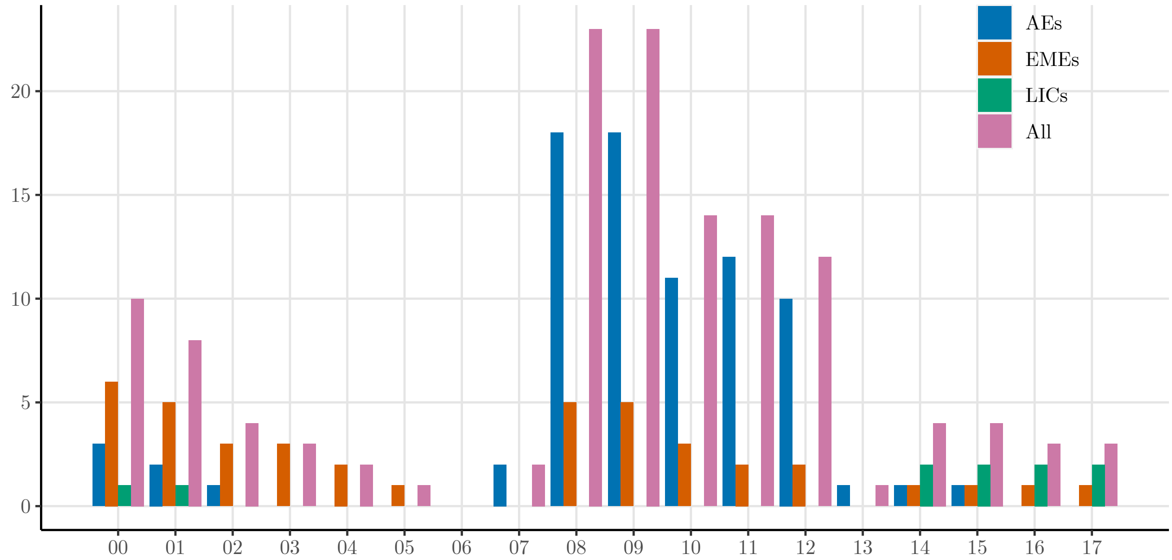
Our results indicate that macroprudential policies have a statistically and economically direct negative effect on the probability of banking crises. Moreover, we find that macroprudential policies depress economic growth. However, when we account for these two effects together, we find that macroprudential policies have a positive net effect on financial stability; even though, MPPs lower economic growth, they still lead to a lower incidence of systemic banking crises. Furthermore, our results suggest that the mitigating effect of MPPs on the likelihood of banking crises is more pronounced in emerging market economies relative to advanced economies. Our estimations also suggest that borrower-based macroprudential tools seem to be more effective in emerging market economies while financial-based macroprudential tools are more useful in taming the incidence of banking crises in advanced economies.

1.A Additional information on data

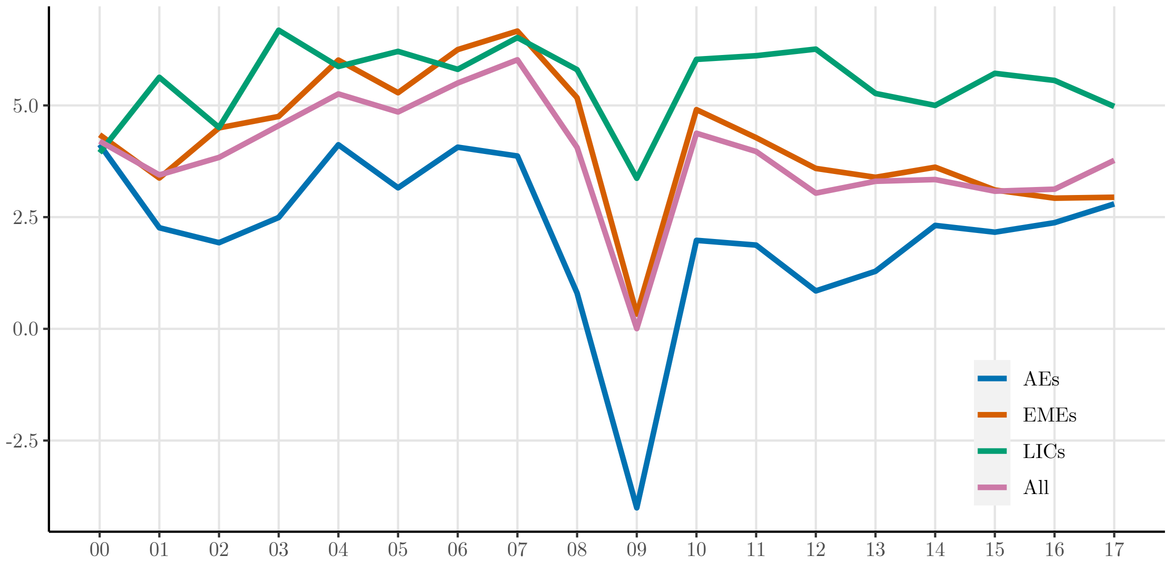
Table 1.9: List of countries used in the empirical analysis and group classification

Advanced Economies (AE)	Emerging Market Economies (EME)	Low-Income Developing Countries (LIDC)
Australia	Albania, Lebanon	Bangladesh
Austria	Algeria, Malaysia	Bhutan
Belgium	Angola, Mauritius	Burkina Faso
Canada	Argentina, Mexico	Cabo Verde
Cyprus	Armenia, Mongolia	Cambodia
Czech Republic	Azerbaijan, Morocco	Côte d'Ivoire
Denmark	Belarus, Namibia	Ghana
Estonia	Belize, Nigeria	Guinea-Bissau
Finland	Bolivia, North Macedonia	Guyana
France	Bosnia and Herzegovina	Haiti
Germany	Botswana, Pakistan	Honduras
Greece	Brazil, Panama	Kenya
Iceland	Bulgaria, Paraguay	Kyrgyz Republic
Ireland	Chile, Peru	Lao P.D.R.
Israel	China, Philippines	Madagascar
Italy	Colombia, Poland	Mali
Japan	Costa Rica, Russia	Moldova
Korea	Croatia, South Africa	Mozambique
Latvia	Dominican Republic	Myanmar
Lithuania	Ecuador, Sri Lanka	Nepal
Netherlands	Egypt, St. Kitts & Nevis	Nicaragua
New Zealand	El Salvador, Thailand	Niger
Norway	Georgia, Tunisia	Rwanda
Portugal	Guatemala, Turkey	Senegal
Singapore	Hungary, Ukraine	Sierra Leone
Slovak Republic	India, Uruguay	Tajikistan
Slovenia	Indonesia, Vietnam	Tanzania
Spain	Islamic Republic of Iran	The Gambia
Sweden	Jamaica	Togo
Switzerland	Jordan	Uganda
United States	Kazakhstan	Zambia
United Kingdom	Kuwait	

Figure 1.5: Variables used in the analysis

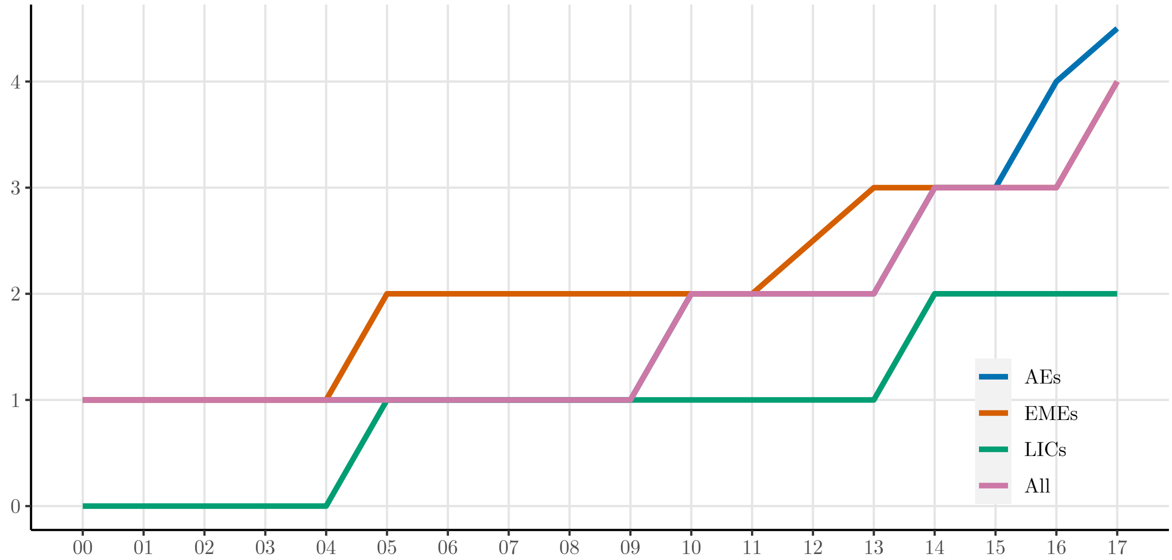


(a) Systemic banking crises (count)

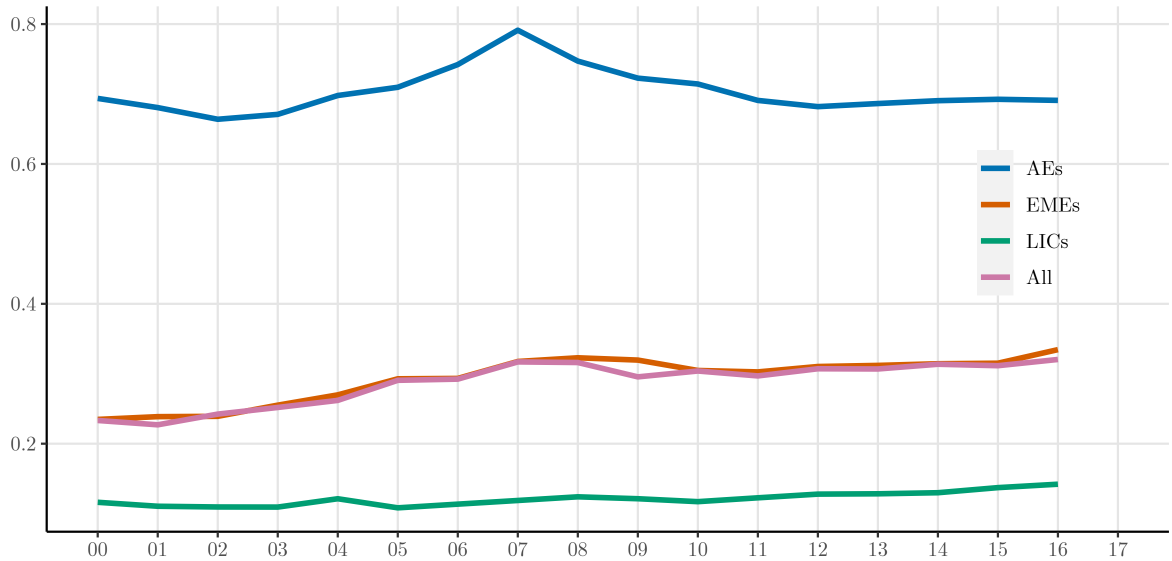


(b) Real GDP growth (in %)

Figure 1.5 (Continued)

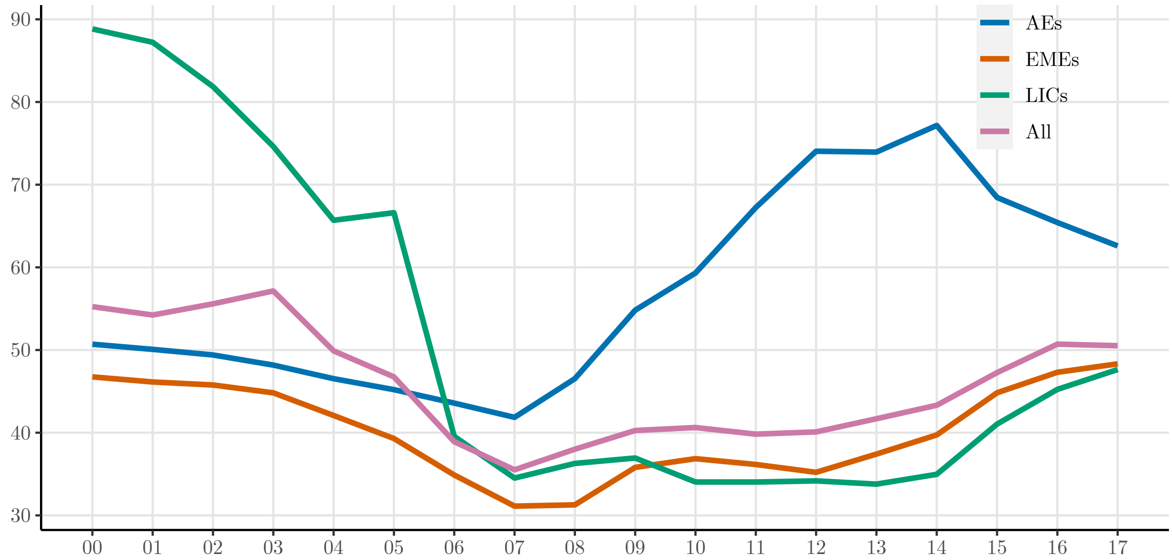


(c) Macroprudential policy index

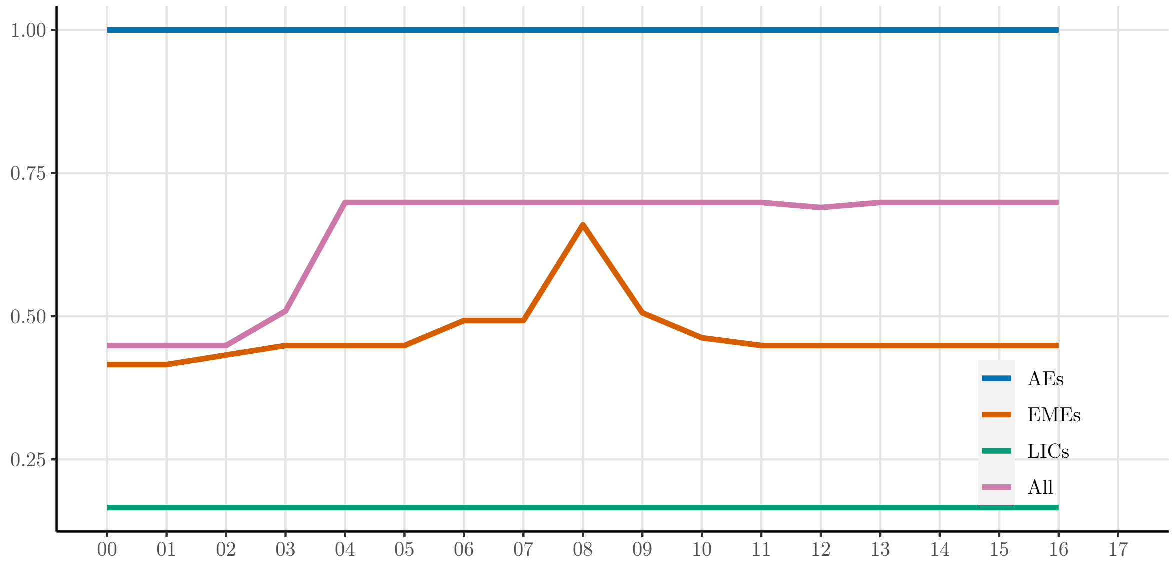


(d) Financial development index

Figure 1.5 (Continued)

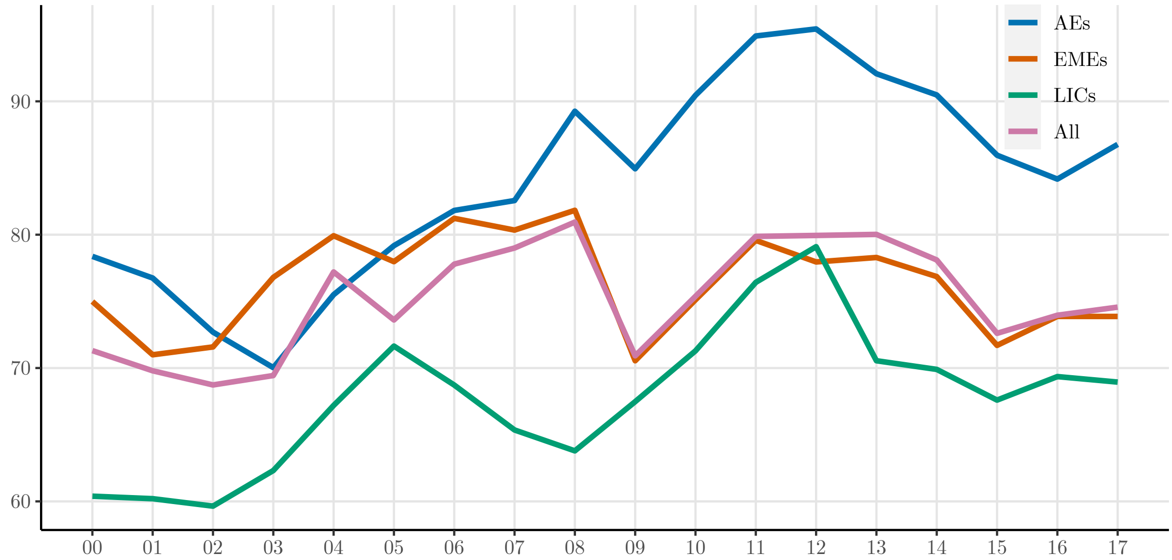


(e) Public debt to GDP (in %)



(f) Capital account openness index

Figure 1.5 (Continued)



(g) Trade to GDP (in %)

Note: The figure plots all the variables used in the empirical analysis. Panel (a) reports the total number of countries for which the systemic banking crisis dummy variable is equal to 1 in a given year (pink bar); together with a breakdown by subsamples (advanced economies in blue, emerging market economies in orange, and low income countries in green). Panels (b)-(g) report the median value of the variable for each year across the countries in the corresponding subsamples.

1.B Dynamic panel logit: general formulation and model selection

Following Kauppi and Saikkonen (2008), Equation (1.1) can be formulated more generally to accommodate multiple lags of the latent index $\pi_{i,t}$ and of the systemic banking crisis dummy variable $y_{i,t}$:

$$\pi_{i,t} = \sum_{j=1}^{p} \delta_j \pi_{i,t-j} + \sum_{j=1}^{q} \alpha_j y_{i,t-j} + x_{i,t-1}^{\top} \beta + \eta_i, \tag{1.5}$$

where we have grouped real GDP and the MPI index with the rest of the explanatory variables in $x_{i,t-1}^{\top}$ for ease of notation. In what follows, we explore how different lag orders for the latent index and the crisis dummy variable can help providing a better description of the data compared to the static version of the model (spec. 1, with $\delta_j = \alpha_j = 0$ for all j). We compare specifications with only lags of the latent variable or of the crisis dummy variable (respectively spec. 2 and 3) and with both of them included (spec. 4). For the latter, we assume for simplicity that the same lag order is applied to both variables.

Table 1.10 reports the Akaike and Bayesian information criteria (AIC and BIC) for these different specifications. We consider lag orders ranging from 1 to 3 and all the models are estimated on the full sample of countries over the period 2004-2017 for comparability reasons. We first observe that all the dynamic specifications (spec. 2 to 4) provide a better description of the data compared to the static one. This confirms previous results in the literature pointing to the added benefits of considering the crisis dynamics in the modelling of financial crises (Candelon et al., 2014). For specification 2, which is akin to an autoregressive panel logit model with additional explanatory variables, one lag seems to be sufficient to provide an adequate description of the dynamics. Higher lag orders result in increased values for the information criteria. Finally, incorporating lags of the systemic banking crisis dummy variable delivers the best performance in terms of model fit, with both information criteria minimized in the 2-lag version of specification 3.

Our final choice for the model specification adopted in the empirical analysis is the dynamic panel logit with 1 lag of the latent index (spec. 2). This choice is motivated by two main reasons. First, the specification preferred by the information criteria (spec. 3 with 2 lags) only features the crisis dummy variable. However, a specification with lags of the latent variable is better suited to the Generalized Impulse Function (GIRF) analysis that we carry out in the second part of the analysis. Indeed, the crisis binary variable would in practice take a value of 1 when the underlying continuous latent index rises above a predetermined fixed threshold. This would imply a loss of information when moving from the continuous index to the binary variable as variations in the latent index which are not associated with an increase above the fixed threshold would not result in changes in the crisis binary variable. Second, combining both the latent and crisis dummy variables as in specification 4 would result in slightly more involved derivations for multi-step iterative forecasts used in the GIRF analysis (see section IV in Kauppi and Saikkonen, 2008). We thus opt for specification 2 in the interest of simplicity and transparency of our proposed empirical strategy. However, future work could consider the other specifications outlined in this section — particularly to further investigate potential state dependence in the profile of the estimated impulse responses.[17]

[17] Note that this kind of analysis would likely require data with a longer time series dimension than currently available for our analysis.

Table 1.10: Model selection based on information criteria

	Spec. 1	Spec. 2	Spec. 3	Spec. 4
Lag order = 1				
AIC	595.6	562.0	479.0	481.3
BIC	1285.8	1257.7	1174.7	1182.3
Lag order = 2				
AIC	595.6	565.9	472.8	473.6
BIC	1285.8	1267.0	1173.9	1185.6
Lag order = 3				
AIC	595.6	568.6	474.7	477.0
BIC	1285.8	1275.1	1181.2	1199.8

Note: The table reports the Akaike and Bayesian information criteria (AIC and BIC) in the rows for the different model specifications considered (columns). Specification 1 is the static version of the model ($\delta_j = \alpha_j = 0$ for all j); specification 2 considers only lags of the latent variable $\pi_{i,t}$; specification 3 considers only lags of the crisis dummy variable $y_{i,t}$; and specification 4 considers lags of both the latent and crisis dummy variables. Each panel corresponds to a different lag order, ranging from 1 to 3, and all the models are estimated on the full sample of countries with data from 2004 to 2017.

1.C Estimation results with confidence intervals based on Moving Block Bootstrap

Table 1.11: Macroprudential Policies and Banking Crises

	All	AE	EME
MPI	−0.606	−0.411	−0.899*
	[−0.982; −0.252]	[−1.622; −0.177]	[−1.288; −0.445]
GDP Growth	−0.192*	−0.283	−0.18
	[−0.193; −0.06]	[−0.319; −0.098]	[−0.193; −0.012]
Crisis Index	0.56*	0.534	0.2
	[0.225; 0.584]	[0.171; 0.588]	[−0.023; 0.364]
FD	12.574**	11.884	18.289**
	[9.537; 24.152]	[8.352; 26.948]	[16.649; 34.393]
Debt-to-GDP	−0.009	−0.026	0.013
	[−0.027; 0.009]	[−0.053; 0.012]	[−0.021; 0.049]
KA	−1.439**	−2.058	−0.779*
	[−9.042; −1.853]	[−10.818; −1.328]	[−10.453; −1.237]
Trade-to-GDP	0.013	0.024	0.045
	[0.001; 0.075]	[0.013; 0.142]	[0.011; 0.125]

Note: ML estimation is carried out using the iterative pseudo-demeaning algorithm of Stammann et al. (2016). The dependent variable is the systemic banking crisis binary. All regressors are considered as lagged values. We report bias-corrected estimates using the analytical bias correction of Hahn & Kuersteiner (2011) and 68% confidence intervals between square brackets based on the Moving-Block Bootstrap procedure detailed in Appendix 1.F with 5000 bootstrap replications and a block size of 5 years. ***, **, and * indicate significance at the 1-, 5-, and 10-percent significance levels, respectively. The estimation period is 2001-2017 and we consider one-way country fixed effects.

Table 1.12: Macroprudential Policies and Real GDP growth

	All	AE	EM
MPI	-0.237	-0.037	-0.318
	$[-0.517; -0.16]$	$[-0.281; 0.107]$	$[-0.561; -0.166]$
GDP Growth	0.306^{**}	0.368^{***}	0.372^{**}
	$[0.144; 0.334]$	$[0.228; 0.452]$	$[0.159; 0.409]$
Crisis Index	-0.204	-0.202	-0.147
	$[-0.376; 0.0662]$	$[-0.318; 0.053]$	$[-0.268; 0.19]$
FD	-6.320^{*}	-6.863	-5.510
	$[-8.406; -3.883]$	$[-10.209; -2.173]$	$[-8.678; -2.557]$
Debt-to-GDP	0.011^{*}	0.023	0.028^{**}
	$[0.005; 0.023]$	$[0.011; 0.061]$	$[0.019; 0.054]$
KA	-0.541	0.969	-0.766^{**}
	$[-2.346; -0.262]$	$[0.803; 5.013]$	$[-2.9; -0.872]$
Trade-to-GDP	0.002	-0.031^{*}	0.021
	$[-0.014; 0.011]$	$[-0.081; -0.017]$	$[-0.003; 0.033]$

Note: Estimation is carried out by OLS with one-way country fixed effect dummies. The estimation period is 2001-2017. The dependent variable is the year-on-year real GDP growth rate. All regressors are considered as lagged values. We report estimates with 68% confidence intervals between square brackets based on the Moving-Block Bootstrap procedure detailed in Appendix 1.F with 5000 bootstrap replications and a block size of 5 years. ***, **, and * indicate significance at the 1-, 5-, and 10-percent significance levels, respectively.

1.D GMM estimation for macroprudential policies and real GDP growth

Table 1.13 below provides the estimates for the model specified in Equation (1.2) using the GMM estimator introduced in Arellano and Bond (1991). The OLS estimates from Table 1.4 are also reproduced for ease of comparison.

The reported p-values for a Sargan test on the joint validity of the instruments do not provide evidence supporting a rejection of the null hypothesis on the adequacy of the selected instruments.[18] We confirm our main result that tighter macroprudential regulation depresses economic growth. The estimated impact of the MPI on real economic activity is larger with the GMM estimator than with the OLS approach. For instance, a one unit increase in the MPI index lowers economic growth by 79.8 basis points in the full sample when considering the GMM results and 23.7 basis points for the OLS results. In addition, the estimated coefficient for the subsample of AEs is now statistically significant and its magnitude is comparable to the one for EMEs. We also confirm our results for the negative and significant impact of the banking crisis index in the full sample and in the subsample of AEs. We observe that the magnitude of the estimated coefficients is approximately doubled when comparing the GMM estimates to the OLS ones. Concerning the macroprudential controls, we confirm that countries with higher public debt relative to GDP enjoy higher economic growth and trade openness depresses economic activity in both AEs and EMEs.

[18] Note that it only holds at a 1% significance level in the subsample of EMEs.

Table 1.13: Macroprudential Policies and Real GDP growth (GMM results)

	All		AE		EM	
	OLS	GMM	OLS	GMM	OLS	GMM
MPI	−0.237***	−0.798***	−0.037	−0.614**	−0.318***	−0.550*
	(0.079)	(0.199)	(0.132)	(0.297)	(0.122)	(0.286)
GDP Growth	0.306***	0.294***	0.368***	0.641***	0.372***	0.414***
	(0.022)	(0.051)	(0.044)	(0.120)	(0.031)	(0.080)
Crisis Index	−0.204**	−0.464**	−0.202*	−0.567**	−0.147	−0.199
	(0.092)	(0.236)	(0.117)	(0.281)	(0.150)	(0.490)
FD	−6.320***	−1.208	−6.863**	6.093	−5.510**	6.635
	(1.792)	(5.062)	(2.977)	(5.623)	(2.446)	(6.267)
Debt-to-GDP	0.011***	0.06***	0.023***	0.188***	0.028***	0.141***
	(0.004)	(0.016)	(0.009)	(0.037)	(0.008)	(0.023)
KA	−0.541	−5.044*	0.969	5.208	−0.766	−2.763
	(0.627)	(2.956)	(1.379)	(3.528)	(0.778)	(1.899)
Trade-to-GDP	0.002	−0.031**	−0.031***	−0.181***	0.021**	−0.053**
	(0.005)	(0.014)	(0.011)	(0.049)	(0.009)	(0.022)
Country FE	Y	Y	Y	Y	Y	Y
Year FE	N	N	N	N	N	N
Observations	2,057	1815	544	480	986	870
Sargan Test	–	0.109	–	0.275	–	0.021

Note: The model estimated is specified in Equation (1.2). The estimation period is 2001-2017. The dependent variable is the year-on-year real GDP growth rate. All regressors are considered as lagged values. The OLS columns reproduce the estimates reported in Table 1.4. The GMM columns report the estimates from the Arellano and Bond (1991) GMM estimator. In the sample with all countries, we treat all the right-hand side variables as endogenous in the estimation. For the subsamples of AEs and EMEs, we treat GDP growth and the crisis index as endogenous and the remaining variables as additional instruments to avoid the issues arising from the use of numerous instruments in dynamic panel GMM estimation with a small cross-sectional dimension. We report estimates with Standard errors clustered at the country level between brackets. ***, **, and * indicate significance at the 1-, 5-, and 10-percent significance levels, respectively. We also report the p-values for the Sargan test of joint validity of the instruments.

1.E Generalized Impulse Response Function (GIRF) of a tightening shock to macroprudential supervision

We detail the procedure used to compute the response of the crisis probability and of real GDP growth to a (exogenous) shock to the macroprudential index. In the spirit of the Generalized Impulse Response Function (GIRF) approach, we do the following steps for $h = 0, \ldots, H$:

- For $h = 0$: we initialize all the explanatory variables to their unconditional means.[19] The country fixed effect parameters from equations (1.1) and (1.2) are set to the mean of the estimated parameters in each case.

- We compute 2 paths of the bivariate system consisting of the conditional probability of crisis and real GDP growth: the baseline case where variables are initialized as explained above and the second where we add a one-period shock, $\delta > 0$, to the initial value of the macroprudential index (MPI).

- For $h > 0$: the exogenous variables are set to their initial (unconditional mean) value. The endogenous variables (real GDP growth and the latent crisis index) are updated recursively using their lagged values according to our two-equation system (see equations (1.1) and (1.2)).

- The GIRF for the crisis probability and real GDP growth are obtained as the difference between the path with the one-period macroprudential tightening (i.e., positive shock) and the baseline path.

[19] We first compute country-specific averages and then take a cross-sectional average.

1.F Moving-block bootstrap procedure for GIRFs

We repeat, for clarity, the equation for the dynamic panel logit with fixed effect:

$$\begin{aligned} y_{1,it} &= \mathbb{1}_{\{y^*_{1,it} \geq 0\}} \\ y^*_{1,it} &= \alpha_{1,i} + \mathbf{x}_{it-1}^\top \, \boldsymbol{\beta}_1 + \mathbf{y}_{it-1}^\top \, \boldsymbol{\rho}_1 + u_{1,it} \end{aligned} \tag{1.6}$$

Where we made a distinction between exogenous ($\mathbf{x}_{it}$) and endogenous variables ($\mathbf{y}_{it}$) of our dynamic system. The second equation for real GDP growth ($y_{2,it}$) takes the form of a dynamic linear panel with fixed effects:

$$y_{2,it} = \alpha_{2,i} + \mathbf{x}_{it-1}^\top \, \boldsymbol{\beta}_2 + \mathbf{y}_{it-1}^\top \, \boldsymbol{\rho}_2 + u_{2,it} \tag{1.7}$$

Given parameter estimates $\hat{\boldsymbol{\theta}}_1 \equiv \begin{bmatrix} \hat{\boldsymbol{\alpha}}_1^\top, & \hat{\boldsymbol{\beta}}_1^\top, & \hat{\boldsymbol{\rho}}_1^\top \end{bmatrix}^\top$ for the dynamic panel logit model in equation (1.6) and $\hat{\boldsymbol{\theta}}_2 \equiv \begin{bmatrix} \hat{\boldsymbol{\alpha}}_2^\top, & \hat{\boldsymbol{\beta}}_2^\top, & \hat{\boldsymbol{\rho}}_2^\top \end{bmatrix}^\top$ for the dynamic linear panel model in equation (1.7), we define a new matrix $\boldsymbol{Z}_t \equiv \begin{bmatrix} \hat{\boldsymbol{u}}_{1t}, & \hat{\boldsymbol{u}}_{2t}, & \boldsymbol{X}_{t-1} \end{bmatrix}$ which maintain the cross-sectional dependence between the I countries for the fitted residuals ($\hat{u}_{1,it}$ and $\hat{u}_{2,it}$) and for the K exogenous variables indexed by $\mathrm{x}_{k,it-1}$:

$$\boldsymbol{Z}_t \equiv \begin{bmatrix} \hat{u}_{1,1t} & \hat{u}_{2,1t} & \mathrm{x}_{1,1t-1} & \mathrm{x}_{2,1t-1} & \dots & \mathrm{x}_{K,1t-1} \\ \hat{u}_{1,2t} & \hat{u}_{2,2t} & \mathrm{x}_{1,2t-1} & \mathrm{x}_{2,2t-1} & \dots & \mathrm{x}_{K,2t-1} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \hat{u}_{1,It} & \hat{u}_{2,It} & \mathrm{x}_{1,It-1} & \mathrm{x}_{2,It-1} & \dots & \mathrm{x}_{K,It-1} \end{bmatrix}$$

Note that in the case of countries which did not experience any systemic banking crisis over the period under consideration, and are therefore not taken into account in the estimation of model (1.6), we replace the fitted residuals of the model by a missing value.

We can now introduce the approach for the moving-block bootstrap (MBB). Given a block length b and a time-series dimension T for the panel, we can generate $T - b + 1$ overlapping blocks as follows:

$$\underbrace{\boldsymbol{Z}_1, \ \dots \ , \boldsymbol{Z}_b}_{\text{1 block of length } b} ; \ \boldsymbol{Z}_2, \ \dots \ , \boldsymbol{Z}_{b+1}; \ \dots \ ; \ \boldsymbol{Z}_{T-b+1}, \ \dots \ , \boldsymbol{Z}_T$$

The algorithm to compute the bootstrapped confidence intervals for the GIRFs of our dynamic system consists in applying the following steps:

1) Draw (with replacement) $(T_{\text{burn}} + T)/b$ blocks from the $T - b + 1$ overlapping blocks where T_{burn} is a burn in period. Call the resulting sample replicate $\boldsymbol{Z}^{(r)}$

2) Compute recursively the model implied endogenous variables $y_{1,it}^{(r)}$ and $y_{2,it}^{(r)}$ using equations (1.6)-(1.7) with the respective estimated parameters $\hat{\boldsymbol{\theta}}_1$ and $\hat{\boldsymbol{\theta}}_2$. Keep only the last T observations to avoid that the bootstrapped samples have dependence on the initial conditions.

3) Re-estimate models (1.6)-(1.7) and store $\hat{\boldsymbol{\theta}}_1^{(r)}$ and $\hat{\boldsymbol{\theta}}_2^{(r)}$.

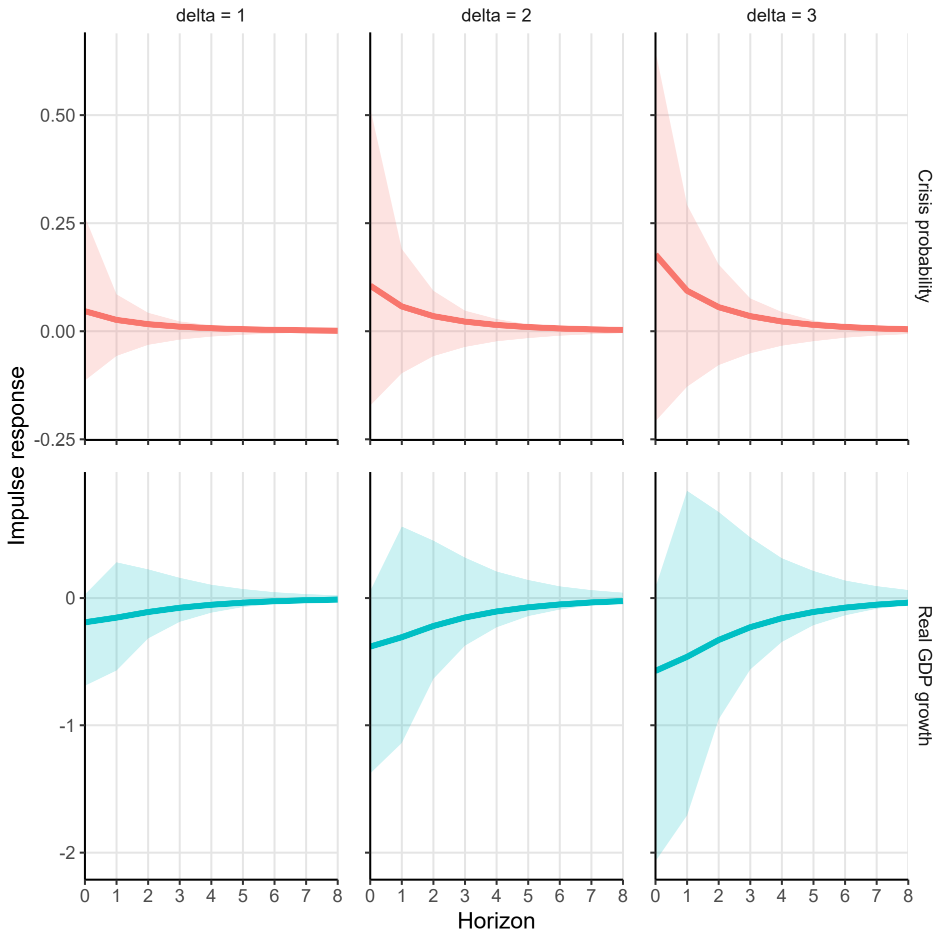
4) Compute and store the implied GIRFs using the approach outlined in 1.E, $\mathcal{I}_{\mathrm{Y}}(H, \delta, \Omega_{t-1})^{(r)}$.

5) Repeat points 1-4 for $r = 1, \ \dots \ , R$ where R is the total number of bootstrap replications.

6) For $h = 0, 1, \ \dots \ , H$, construct a 68% confidence interval around the GIRF for horizon h by taking the $16-$ and $84-$percentile of the distribution of the R replicas of $\mathcal{I}_{\mathrm{Y}}(h, \delta, \Omega_{t-1})^{(r)}$.

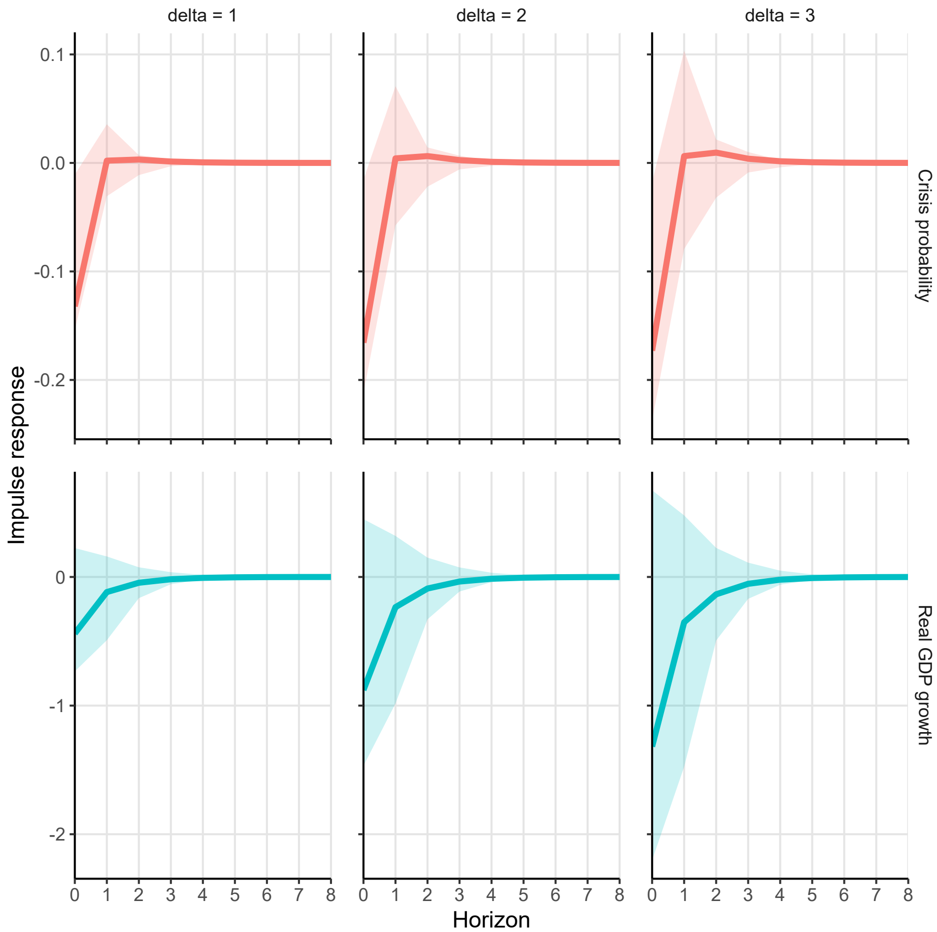
1.G Targeting borrowers vs. financial institutions: GIRFs for MPI-Borrower

Figure 1.9: GIRF analysis of a borrower macroprudential tightening: advanced economies



Note: Comparison of the impulse responses of the probability of a systemic banking crisis (top-panel in red) and of real GDP growth (bottom-panel in green) to different levels of borrower macroprudential tightenings (positive MPI-Bor shocks denoted by delta). The horizon of the responses displayed ranges up to eight years after the policy tightening. The Generalized Impulse Response Functions are computed following the procedure outlined in 1.E. The shaded areas around the response functions correspond to the 68% confidence intervals from the Moving-Block Bootstrap procedure detailed in 1.F with 5000 bootstrap replications and a block size of 5 years.

Figure 1.10: GIRF analysis of a borrower macroprudential tightening: emerging market economies



Note: Comparison of the impulse responses of the probability of a systemic banking crisis (top-panel in red) and of real GDP growth (bottom-panel in green) to different levels of borrower macroprudential tightenings (positive MPI-Bor shocks denoted by delta). The horizon of the responses displayed ranges up to eight years after the policy tightening. The Generalized Impulse Response Functions are computed following the procedure outlined in 1.E. The shaded areas around the response functions correspond to the 68% confidence intervals from the Moving-Block Bootstrap procedure detailed in 1.F with 5000 bootstrap replications and a block size of 5 years.

Chapter 2

Macroprudential Regulation and Sector-Specific Default Risk [1]

2.1 Introduction

The Global Financial Crisis (GFC) of 2008–2009 brought to light the importance of taking a macroprudential approach to financial stability. The lessons learned from this exceptional event fostered international efforts to develop a comprehensive macroprudential framework which could mitigate the risk of an amplification of shocks to the real economy by the financial system. A large literature, summarised in Forbes (2021), has focused on assessing the effectiveness of macroprudential regulation. However, far less progress has been made in the understanding of the calibration of macroprudential tools to achieve a balance between their benefits for financial stability and their costs for economic growth (Forbes, 2019). On the one hand, macroprudential tools can moderate excessive procyclicality in credit growth and leverage, which mitigates the build up of systemic risk in the financial system and reduces the likelihood of costly financial crises resulting in deeper economic downturns (Jordà et al., 2013; Jordà et al., 2015; Mian et al., 2017; Giglio

[1]This chapter corresponds to Belkhir, M., S. Ben Naceur, B. Candelon, and J.-C. Wijnandts (2022): "Macroprudential Regulation and Sector-Specific Default Risk". *IMF Working Papers, 22 (141), doi:https://doi.org/10.5089/9798400215421.001.*

et al., 2016; and Brownlees and Engle, 2017). On the other hand, the slower pace of credit growth resulting from a successful implementation of macroprudential regulation could impact economic activity given the key roles played by access to credit and financial development in economic growth (Jayaratne and Strahan, 1996; and Aghion et al., 2005). Belkhir et al. (2022b) study the joint impact of macroprudential regulation on financial stability and the real economy and find that tighter regulation improves the resilience of the financial system to shocks, although at the cost of depressing economic activity in the short run. Gadea et al. (2020) document that economic expansions tend to be longer when macroprudential regulation is in place and intermediate levels of credit growth strike a balance between longer expansions and deeper recessions. However, these studies only provide an aggregate assessment of the effects of macroprudential regulation and little is known about the transmission of macroprudential policies to the non-financial sectors of the economy or whether some of them are more sensitive to contractions in credit supply and economic activity resulting from tighter regulation.

In this paper, we provide a comprehensive analysis of the transmission of macroprudential regulation across both financial and non-financial sectors of the economy through the lens of its impact on short- and long-term probabilities of default (PDs) at the sector level. To this end, we combine a detailed database on macroprudential policies in European countries compiled by the European Central Bank (ECB) with data on short- and long-term PDs for financial and non-financial sectors (basic materials, consumer (non-)cyclical, industrial, and technology) in European countries over the period 2008–2017.

This paper has two main contributions. First, we investigate whether tighter macroprudential regulation also transmits to non-financial sectors of the economy and whether its impact is beneficial — i.e. reduces non-financial sector's risk of default — or detrimental. We construct an intensity-adjusted macroprudential policy index (MPI), which summarises the overall policy stance of each country, and study its interactions with sector-specific default risk in a dynamic panel setting which is particularly appropriate to capture the progressive transmission of macroprudential policies. For the financial sector, we document that a one unit increase in the MPI — corresponding to a new activation of a macroprudential policy instrument — significantly reduces long-term default risk at both short and long horizons — by respectively 0.425 and 4.20 basis points (bps). This impact at a long horizon corresponds to a 3.5% reduction in long-term default risk compared to its median level. For non-financial sectors, we find that a one unit change in the MPI significantly decreases both short- and long-term default risks. The reduction in long-term default risk at a long horizon ranges from 1.79 for the consumer cyclical sector to 4.7 bps for the industrial sector; corresponding to a reduction in long-term default risk ranging from 1 to 3% when compared to the respective median levels. Our analysis thus highlights that tighter macroprudential regulation also benefits non-financial sectors of the economy on average and that the economic and statistical significance of the reduction in default risk is comparable to the results for the financial sector.

Second, we analyse on a more granular level how specific reforms in the macroprudential framework dynamically impact default risk in the financial and non-financial sectors. Indeed, the analysis based on the MPI aggregates numerous macroprudential policy instruments which can differ in their aims and targets — e.g. instruments aimed at borrowers' level of indebtedness vs. those aimed at financial institutions' balance sheet resilience — and, therefore, can ultimately conceal the relevant channels of transmission involved. We study in a panel event-study framework two important macroprudential reforms taking place at the European level: i) the phasing in of the Basel III standards on capital requirements through the Capital Requirements Regulation and Directive (CRR/CRD IV) in June 2013; and ii) the introduction of a resolution framework for failing banks through the Bank Recovery and Resolution Directive (BRRD) in May 2014.

Concerning the impact of higher capital requirements, we find for the financial sector that the policy reform initially increased both short- and long-term default risks but eventually led to a significant decrease in default probabilities at a horizon of 5 quarters after its introduction and beyond; in particular, short-term default risk is 1.88 bps lower than before the reform — a 38% decrease compared to the median level. Non-financial sectors, on the other hand, appear to have suffered from a continued increase in default risk. This is especially the case for long-term default risk with increases at a horizon of 5 quarters after the policy reform ranging from 4.19 bps for the industrial sector to 12.05 bps for the basic material sector, respectively 2.5 to 7.6% higher than corresponding median levels. We also document a marked long-run increase in short-term PDs for the consumer non-cyclical and technology sectors of respectively 1.18 and 1.27 bps compared to before the reform, a 24% increase above median levels. Moving to the impact of the introduction of a European framework for bank resolution, we document that this policy reform led to a substantial decrease in both short- and long-term PDs for the financial and non-financial sectors at a horizon of 5 quarters after its introduction and beyond. Specifically, we observe decreases in short-term PDs ranging from 2.09 to 4.78 bps and from 9.3 to 20.44 bps for long-term PDs compared to before the reform — translating to a 47 (technology sector) to 76% (financial sector) decrease below median levels for short-term default risk and a corresponding 6.7 to 17.3% reduction for long-term default risk. We conclude from our analysis that the detrimental effect of the CRR/CRD IV package on the risk of default of non-financial sectors is likely a consequence of banks' reacting to increased capital requirements, expressed as a fraction of their risk-weighted assets, by shrinking their assets rather than increasing their capital levels and the resulting contraction in credit supply (Gropp et al. (2018)). This is however not the case for the impact of the BRRD as a strengthening in the resolution framework, fostering a transition away from government bailouts and towards a bail-in regime, increases risk-monitoring incentives for banks' shareholders and creditors which in turn reduces banks' risk-taking (Cutura (2021)) and increases their ability to supply credit (Altunbas et al. (2010); and Gambacorta and Mistrulli (2014)), thus reducing default risk in the non-financial sectors.

Our work contributes to multiple branches of the literature on macroprudential regulation. The first part of the paper complements and extends the literature documenting how macroprudential regulation contributes to improving the resilience of the financial system (Belkhir et al. (2022b); Meuleman and Vander Vennet (2020)) by providing evidence of its beneficial effects on short- and long-term average default risk in non-financial sectors. In this respect, it also relates to the literature documenting how a buildup of systemic risk in the financial system can increase downside risks to the real economy (Allen et al.

(2012); Giglio et al. (2016); Brownlees and Engle (2017)). Our analysis of the CRR/CRD IV package in the second part of the paper contributes to the literature studying the impact of higher capital requirements on the resilience of the financial system (Jordà et al. (2021)) and on the real economy (Gropp et al. (2018); Fraisse et al. (2020)). Our results also extend the literature studying how short-term transitional costs, due to a reduction in credit supply and aggregate demand, can partially offset longer-term benefits of increased capital requirements (Mendicino et al. (2020)). We document that the impact of reduced access to credit on default risk of non-financial sectors might have long-lasting effects. By studying the impact of the strengthening in the resolution framework associated with the introduction of BRRD, we complement the findings of Cutura (2021) about the perceived credibility of the newly introduced bail-in framework and provide evidence of the beneficial effects of transitioning away from a bailout regime where (expected) government recapitalizations increase banks' risk taking and default risk (Dam and Koetter (2012); Duchin and Sosyura (2014)) which can in turn increase default risk in non-financial sectors (Bersch et al. (2020)). Our contribution also relates to papers analysing the real effects of banks' bail-ins (Beck et al. (2020)). Finally, by analysing how macroprudential regulation impact probabilities of default of non-financial sectors of the economy, we also contribute to the literature studying the unintended consequences from macroprudential regulation on areas of the economy not directly targeted by the policies (Ahnert et al. (2021)).

The rest of the paper is structured as follows. Section 3.2 describes the data on sector-specific probabilities of default and macroprudential policies. Section 2.3 analyses the average impact of macroprudential regulation on sector-level default risk in a dynamic panel setting. Section 2.4 studies the implications of two important policy reforms, an increase in banks' capital requirements and a strengthening in the resolution framework for failing banks, using a panel event-study approach. Finally, Section 3.5 concludes.

2.2 Data

2.2.1 Sector-specific probabilities of default

Data on default probabilities are various. Still, if one wants to obtain sufficient granularity and a wide coverage for a large numbers of countries for a long sample size, the offer is rather limited. Nevertheless, the Credit Research Initiative (CRI) at the National University of Singapore tackles this limitation and provides daily updated probabilities of default (PDs) for $34,000$ actively-listed firms in 128 economies based on historical defaults and industry exits of listed firms.[2] Their methodology is based on the forward intensity model of Duan et al. (2012) which offers a parsimonious setting to predict corporate defaults at multiple horizons using both economy- and sector-wide variables; and firm-specific variables.[3] Following the extensions introduced in Duan and Fulop (2013), the current implementation of the model also accounts for correlations of individual forward intensities through common risk factors and apply Nelson-Siegel functional restrictions on model parameters across the different default horizons forecast to ensure consistency in the resulting predictions. The CRI approach thus delivers a comprehensive and accurate overview of the credit risk profile of corporate firms at both short- and long-term horizons. It is also worthwile mentioning that several recent papers have used it as Asis et al., 2020 inter alii.

We retrieve daily PDs, with default horizons of 6 months and 5 years, from the CRI database for 6 corporate sectors — namely basic materials, consumer cyclical, consumer non-cyclical, financial, industrial, and technology — and 28 European countries.[4] For each pair of country-sector, we have daily observations on the median of individual firms' PDs which we then aggregate to a monthly frequency by taking the average over the

[2]The interested reader can consult their website for more information: https://nuscri.org/en/.

[3]The economy/sector-wide variables considered are stock index return, short-term interest rate, and average distance-to-default of the financial and non-financial sector. The Firm-specific variables include volatility-adjusted leverage, liquidity, profitability, relative size, market misvaluation, and idiosyncratic volatility.

[4]The list of countries includes the 27 countries for the European Union (EU) and the United Kingdom.

observations within a given month. Our sample covers the period from 2008 to 2017 as data availability issues for some country-industry pairs restrict our ability to work with a fully-balanced panel for each sector. Our choice of 2008 as a starting point for the analysis thus attempts to strikes a balance between maximizing the country coverage for each sector and including relevant periods — i.e. the post Global Financial Crisis period — for macroprudential policy making. Note that our decision to end the sample in 2017 is conditioned by restrictions on data availability for our dataset of macroprudential policy decisions; see Section 2.2.2 for more details.

Table 2.1 provides summary statistics, expressed in basis points (bps), for the monthly median PDs across the 6 sectors considered in our analysis. Panel A presents these statistics for the full sample of 28 European countries and Panels B, C present summary statistics for the subsamples of euro area (EA) and non euro area (non-EA) countries. When considering long-term default risk, measured by the probability of default at a horizon of 5 years, we observe that the financial sector's default risk is materially lower than default risk in non-financial sectors of the economy.[5] This is however not the case when considering short-term default, measured by the probability of default at a horizon of 6 months, as the default risk of the financial sector is comparable to the ones in the consumer non-cyclical and technology sectors. A potential explanation for this difference lies in our choice of sample coverage for the analysis which includes the episodes of the GFC and the euro area sovereign debt crisis — both of which exerted considerable pressure on the resilience of the financial sector. This explanation is consistent with the higher short-term mean default risk and larger variability, measured by the standard deviation, observed in the subsample of EA countries which were directly impacted by the sovereign debt crisis. To get more insights on the time series properties of the probabilities of default, Figures 2.5 and 2.6 in Appendix 2.A plot for each sector (Panels (a)-(f)) the monthly median PDs across all countries, and across the subsamples of EA and non-EA

[5] The difference between the 5-year PDs of the consumer non-cyclical and financial sectors ranges from 15 to 30 bps, depending on the subsample considered and whether the mean or median is used in the calculations.

countries.

2.2.2 The Macroprudential Policies Evaluation Database

We use the recent dataset on macroprudential policies in the banking sectors for 28 European countries between 1995 and 2017. The Macroprudential Policies Evaluation Database (MaPPED) developed by Budnik and Kleibl (2018) offers a detailed overview of the "life-cycle" of policy instruments including their activation dates, ensuing changes in the scope or the level of the instruments, and finally their deactivation dates when applicable. As the legal framework organizing macroprudential supervision has been developed concurrently with its implementation, as exemplified by the 2013 European regulation on the Single Supervisory Mechanism (SSM) which confers macroprudential competencies to the ECB and national authorities, Budnik and Kleibl (2018) operationalize their definition of a macroprudential instrument as a prudential tool which satisfies at least one of the following conditions: i) it has been identified as macroprudential by the competent authority or in the relevant legislation; ii) its implementation is motivated by macroprudential objectives (e.g. preserving financial stability); iii) the prudential tool is comparable in its design or work through the same transmission channels as subsequently introduced macroprudential instruments and is likely to broadly impact the banking-sector.[6] Based on this definition, the authors created a closed list of 53 macroprudential policy instruments classified in 11 categories.[7]

The literature studying the impact and transmission of macroprudential regulation has adopted different approaches to track the evolution of the macropudential policy stance. A first approach focuses on the (de-)activation of policy tools by creating a policy index

[6]Relevant examples include the similarities between minimum capital requirements and macroprudential capital buffers (Aiyar et al. (2014b)), and between dynamic provisioning and the countercyclical capital buffer (Jiménez et al. (2017))

[7]The 11 categories are: minimum capital requirements, capital buffers, risk weights, leverage ratios, loan-loss provisioning, lending standards restrictions, limits on credit growth and volumes, limits on large exposures and concentration, liquidity requirement and limits to currency mismatches, and other measures which contains mainly crisis-related measures and resolution tools.

Table 2.1: Descriptive statistics for the sector-specific median probabilities of default.

Sector	Horizon	Mean	Min	1^{st} quartile	Median	3^{rd} quartile	Max	Std Dev
				Panel A: All countries				
Fin	6-M	9.61	0.03	1.95	4.96	10.38	623.83	21.56
	5-Y	124.57	15.93	74.16	118.32	155.96	1408.63	75.63
Cons cyc	6-M	13.66	0.03	3.10	7.12	17.34	171.53	17.76
	5-Y	173.02	13.86	116.58	159.05	217.85	687.75	83.47
Cons non-cyc	6-M	9.02	0.18	2.29	4.87	11.45	181.68	11.95
	5-Y	149.25	32.88	104.75	134.38	183.52	610.32	61.63
Indus	6-M	14.35	0.00	3.86	8.20	17.80	231.58	19.44
	5-Y	184.36	1.80	128.94	169.30	229.16	837.25	86.82
Bas mat	6-M	11.69	0.02	3.45	6.92	12.97	441.64	19.58
	5-Y	172.22	24.12	119.74	163.15	206.53	1726.56	89.59
Techno	6-M	8.51	0.00	2.59	5.27	11.18	71.40	9.10
	5-Y	151.06	11.44	113.45	145.60	187.62	541.57	60.20
				Panel B: EA countries				
Fin	6-M	9.98	0.03	1.49	4.16	10.37	623.83	25.36
	5-Y	118.85	15.93	63.88	105.72	152.11	1408.63	84.36
Cons cyc	6-M	13.07	0.03	2.14	5.41	16.56	171.53	18.73
	5-Y	158.26	13.86	98.22	142.15	195.59	687.75	86.89
Cons non-cyc	6-M	8.71	0.18	2.08	4.17	9.70	181.68	13.38
	5-Y	139.75	32.88	100.57	123.06	162.96	610.32	59.32
Indus	6-M	14.20	0.00	3.16	7.00	17.19	231.58	21.35
	5-Y	175.78	1.80	118.80	153.68	220.54	837.25	94.90
Bas mat	6-M	9.05	0.20	2.82	5.02	10.72	194.33	12.15
	5-Y	153.02	39.29	107.37	143.94	187.00	828.68	66.73
Techno	6-M	8.43	0.00	2.21	4.79	11.31	53.21	9.22
	5-Y	142.13	11.44	106.43	135.64	174.43	347.13	52.92
				Panel B: Non-EA countries				
Fin	6-M	8.92	0.44	3.21	5.76	10.40	140.53	11.30
	5-Y	135.37	49.43	100.91	128.83	161.08	556.70	53.93
Cons cyc	6-M	14.65	0.34	4.93	9.74	17.92	155.16	15.97
	5-Y	197.62	45.89	143.67	187.75	235.66	526.55	70.95
Cons non-cyc	6-M	9.53	0.43	3.06	6.53	13.29	62.08	9.05
	5-Y	165.08	51.56	117.44	158.93	201.79	486.13	62.19
Indus	6-M	14.72	0.67	5.67	10.17	19.89	113.75	13.77
	5-Y	205.20	68.06	160.84	200.99	242.19	436.62	58.01
Bas mat	6-M	16.21	0.02	6.19	9.85	15.80	441.64	27.48
	5-Y	205.13	24.12	159.90	192.36	227.72	1726.56	111.56
Techno	6-M	8.69	0.15	3.45	6.21	11.13	71.40	8.86
	5-Y	168.93	21.25	138.02	162.01	207.44	541.57	69.26

Note: The table presents summary statistics for the sector-specific median probabilities of default (in bps) at horizons of 6 months and 5 years over the period 2008-2017. Panel A considers all the countries in our sample and Panels B and C consider respectively the subsamples of EA and Non-EA countries.

summarising with dummy variables whether each of the policy instruments in a given reference category is active at a given point in time (Lim et al. (2011), Claessens et al. (2013)). A second approach also considers the recalibrations and changes in scope of the policy instruments occurring over their life-cycle — i.e. between their activation and potential phasing-out — together with an asymmetric treatment of policy decisions resulting in a tightening vs. easing of the regulatory stance; e.g. by assigning a positive sign to the dummy variables associated with tightening events and a negative sign to the ones associated with loosening events. This approach enables an investigation of the impact of macroprudential tightenings/easings (Kuttner and Shim (2016), Bruno et al. (2017)) and, at the same time, to create a Macroprudential Policy Index (MPI) summarizing the overall macroprudential policy stance at one point in time — or for a subset of policy instruments — by taking the difference between the cumulative index of tightenings and easings; see e.g. Cerutti et al. (2017a), Akinci and Olmstead-Rumsey (2018). A potential limitation of this last approach is that it only captures the direction of the variations in the macroprudential policy stance but provide limited information about the intensity of these variations. Further to this point, the equal treatment given to (de-)activations of policy instruments compared to changes in either the level or scope of these instruments can lead to a situation where large variations in the MPI do not reflect large variations in the underlying instruments and the policy stance. An example of the later is the case of an instrument which would be frequently recalibrated/reevaluated but only with small incremental variations.[8]

To address this limitation and use all the richness of the information contained in the MaPPED, we construct an intensity-adjusted macroprudential policy index which assigns different weights to the respective phases of the life-cycle of a given policy instrument; see e.g. Vandenbussche et al. (2015), Richter et al. (2019), and Meuleman and Vander Vennet (2020) for other examples of empirical analyses using an intensity-adjusted MPI. First, events associated with the introduction or phasing out of the policy instrument (first acti-

[8]Policy tools with a time-varying component, such as the countercyclical capital buffer or supervisory capital add-ons, are good examples of instruments whose level is reassessed periodically.

vation or deactivation) receive the highest weight of 1.00. Second, events affecting the level of the policy instrument receive a higher weight than events affecting the definition/scope of the instrument (respectively 0.25 and 0.10). Finally, events resulting in maintaining the level and scope of a tool receive a weight of 0.05. To complete the description of the intensity-adjusted MPI, we multiply weights associated with events reported as a policy tightening/loosening by +1/-1 to reflect their contribution to the overall macroprudential policy stance. Events whose impact on the policy stance are reported as ambiguous are not taken into account in our analysis.

Table 2.2 provides summary statistics for the intensity-adjusted MPI over the period ranging from 2008 to 2017 — our reference period in the empirical analysis. Panel A presents these statistics for the full sample of 28 European countries and Panels B, C present summary statistics for the subsamples of euro area (EA) and non euro area (non-EA) countries. The use of macroprudential policies appears to be more prevalent in non-EA countries (mean MPI: 18.13) than in EA ones (mean MPI: 15.49). In addition, the MPI has higher variability in the subsample of non-EA countries — with a standard deviation of 7.92 compared to 5.98 for EA countries — which potentially reflects the higher heterogeneity in the composition of the subsample. Panel (a) of Figure 2.3 in Appendix 2.A plots the time series of the monthly median MPI across all countries, and across the subsamples of EA and non-EA countries. We observe that macroprudential regulation is increasing progressively over our sample period, with a pick up in pace following the GFC which is particularly pronounced for non-EA countries. We also note that the MPI for the sample with all countries tracks quite closely the evolution of the MPI for the subsample of EA countries. This can be explained by the relatively larger share of EA countries in our sample (18 vs. 10 non-EA countries), and could lead to overemphasizing the role of EA countries in the results for the panel including all the countries. Therefore, we will also carry out our analysis on the two subsamples of countries to identify potential differences in the impact and transmission of macroprudential regulation.

2.3 Macroprudential regulation and default risk in a dynamic panel setting

This section sets out our empirical approach to analyze the impact of macroprudential policies on both short (6-month) and long-horizon (5-year) default probabilities of financial and non-financial sectors of the economy. We opt for a dynamic panel setting which has been favoured in the literature assessing the transmission of macroprudential policy decisions; see e.g. Kuttner and Shim (2016), Cerutti et al. (2017a), Akinci and Olmstead-Rumsey (2018) and Meuleman and Vander Vennet (2020). Section 2.3.1 details the model specification and Section 2.3.2 summarises the results.

2.3.1 Model specification and relevant predictors of corporate defaults

We propose to analyze the transmission of macroprudential policy decisions to default risk at the sector level by estimating the following dynamic panel regression model for each sector:

$$PD_{c,t}^{(h)} = \eta_c + \sum_{l=1}^{L} \rho_l PD_{c,t-l}^{(h)} + \delta MPI_{c,t-1} + \sum_{k=1}^{K} \beta_k X_{k,c,t-1} + \varepsilon_{c,t}, \tag{2.1}$$

where $PD_{c,t}^{(h)}$ is the sector-specific default probability at a horizon $h \in \{6\text{M}; 5\text{Y}\}$ in country c at time t and η_c is a country-specific fixed effect capturing cross-country differences in the average default probability.[9] First, we include lags of the dependent variable, PD, to control for any unmodeled sources of persistence in default probabilities and mitigate any potential concerns of serial correlation in the error term, $\varepsilon_{c,t}$.[10] Second, we include the

[9] As the estimation is carried out for each sector separately, η_c is *de facto* a country- and sector-specific fixed effect.

[10] We opted for a specification with 3 lags of the dependent variable. Our main results remain robust to alternative lag length choices. Appendix 2.C provides a comprehensive analysis of the model specification of our dynamic linear panel model and robustness checks of our key results to different model specifications.

lagged macroprudential policy index (MPI) introduced in Section 2.2.2. We follow the existing literature (Cerutti et al. (2017a), Akinci and Olmstead-Rumsey (2018), Meuleman and Vander Vennet (2020)) and consider a cumulative measure of the macroprudential policy stance to capture the fact that announced policy changes can affect our variable of interest both at the time of announcement and in subsequent months. Potential reasons for this delayed or progressive transmission of announced changes in the macroprudential policy stance are i) the implementation lag usually separating the announcement of a new policy action from its actual enforcement date; and ii) the use of transitional regimes by supervisory authorities.[11] Our dynamic panel setting is particularly appropriate to capture this aspect of macroprudential policy decisions as we capture both the announcement impact, via the parameter δ, and the long-run effect of a one unit change in the macroprudential policy stance which is given by $\delta/(1-\sum_{l=1}^{L}\rho_l)$. The dynamic specification also allows us to interpret the significance of the parameter estimates as indicative evidence for the presence of (Granger-) causality.

Third, we control for variations in default risk related to the evolution of the macro-financial environment by borrowing relevant explanatory variables from the literature on predictors of corporate default risk.[12] Macroeconomic conditions are a strong determinant of corporate default risks due to, e.g., their pro-cyclical impact on both corporate earnings (Longstaff and Piazzesi (2004)) and debt and equity issuance (Covas and Den Haan (2011)); and the emergence of flight-to-liquidity episodes in corporate bond markets during stressed economic conditions (Acharya et al. (2013)). Therefore, we include the

[11]To illustrate the first point, increases in the level of financial institutions' countercyclical capital buffer (CCyB) announced by the relevant supervisory authority should lead the effective date of implementation by up to 12 months (see Section 6 of BCBS (2015)). A relevant example on the second point is the transitional provision on the implementation of the capital conservation buffer (CCoB) provided in the Capital Requirements Directive (See CRD IV: 2013/36/EU Article 160) which permits a gradual phasing-in of the CCoB from 0.625% of risk-weighted assets (RWA) in 2016 to 2.5% of RWA in 2019.

[12]Note that we do not consider time fixed effects in our analysis as the lagged PDs and the lagged macro-financial explanatory variables are already capturing relevant time variations in sector-specific default risk. This approach is consistent with the existing literature; see e.g. Kuttner and Shim (2016), Cerutti et al. (2017a), Akinci and Olmstead-Rumsey (2018).

year-on-year percentage change in country-specific industrial production excluding construction (IP) to reflect that a contraction in economic activity tends to be associated with heightened corporate default risk (Lando and Nielsen (2010), Giesecke et al. (2011)). We also include the year-on-year percentage change in the country-specific harmonised index of consumer prices (HICP) as our measure of inflation (Inf) to capture the contribution of low (expected) inflation to corporate default risk through a corresponding increase in real debt liabilities (Bhamra et al. (2011), Fiore et al. (2011), Gomes et al. (2016)). In addition, we incorporate the trailing one-year inflation volatility (InfVol) as Kang and Pflueger (2015) showed that it contributes significantly to explaining credit spread variations for a panel of G7 countries over the period 1970–2010. We also consider a set of financial predictors, starting with the stock market return (StockRet) which we compute as the one-year trailing return for each country's major stock market index and the corresponding stock market volatility (StockVol). Giesecke et al. (2011) document that stock market downturns and increased stock market volatility correlates with higher corporate default probabilities. Finally, we include proxies for changes in short-term interest rates (Δ ShortRate) and for the slope of the government bond yield curve given their documented ability to forecast future real economic activity and variations in corporate default risk; see e.g. Estrella and Hardouvelis (1991) and Hamilton and Kim (2002) for an empirical analysis of predictive ability and Duffie et al. (2009) and Lando and Nielsen (2010) for an application to default risk modelling.[13] Note that we refrain from including firm or industry-specific risk factors such as measures of distance-to-default (Duffie et al. (2007), Lando and Nielsen (2010)) and accounting ratios as Azizpour et al. (2018) show that macroeconomic predictors of corporate default risk account for the majority of cross-sectional variations in firm-specific default risk factors.[14] Table 2.2 below provides

[13] Depending on data availability, we use a 3-month benchmark government bond yield or the interbank rate to proxy for short-term interest rate and the difference between the 10-year benchmark government bond yield and the corresponding 1- or 2-year yield to proxy for the slope of the yield curve.

[14] We have also considered in preliminary analysis variables capturing factors common across countries and sectors such as the Economic Policy Uncertainty (EPU) index of Baker et al. (2016). We decided not to include it in the final analysis as it was not a significant driver of PDs' variations.

descriptive statistics for our set of explanatory variables, and Panels (b)-(h) of Figure 2.3 in Appendix 2.A plot the monthly median of each explanatory variable across all countries, and across the subsamples of EA and non-EA countries.

Before moving to the analysis of the results, we consider potential challenges associated with the study of the transmission of macroprudential policies to sector-specific default risk within a reduced-form dynamic panel with country fixed effects as specified in Equation (2.1). Concerns about potential endogeneity issues with the macroprudential policy index could arise if the macroprudential policy authorities introduced new measures in reaction to changes in the macro-financial environment which also affect the probability of default in some sectors of the economy. This might induce a bias in the estimate of the coefficient measuring the impact of macroprudential policy decisions on default risk. However, we posit that endogeneity and reverse causality issues should not materially impact the interpretation of our results for two reasons. First, we carry out our analysis at the monthly frequency by aggregating daily data on probabilities of default at the sector level for each month in our sample. On the other hand, macroprudential monitoring is conducted at a lower frequency, usually quarterly, using a myriad of macro-financial variables which, in addition to being sampled at low frequency in the majority of cases, are often subject to publication delays and data cutoff dates applied prior to policy meetings.[15] This potential delay between changes in the macro-financial risk environment and the associated policy reaction, created by a lack of timeliness in data availability, is further complicated by the fact that the processes associated with the design and implementation of macroprudential policy measures are inherently time-intensive. Therefore, it appears unlikely that macroprudential authorities would be able to adjust, within the same month, the stance of their policy in reaction to shocks in the risk environment also driving the variations in sector-specific probabilities of default. The fact that the macroprudential policy index and the control variables enter Equation (2.1) with a lag further

[15]Relevant examples include measures of indebtedness levels and debt servicing costs for the assessment of corporates and households vulnerabilities and capital levels for the resilience assessment of the financial system.

Table 2.2: Descriptive statistics for explanatory variables

	Mean	Min	1^{st} quartile	Median	3^{rd} quartile	Max	Std Dev
			Panel A: All countries				
MPI	16.34	1.50	10.80	15.50	21.40	34.35	6.78
Inf	1.84	-4.30	0.40	1.5	2.90	17.70	2.23
IP	0.71	-31.70	-2.70	1.30	4.90	56.70	8.18
InfVol	0.74	0.08	0.36	0.57	0.91	4.49	0.58
StockRet	-3.32	-165.01	-15.95	3.49	15.54	96.33	30.48
StockRetVol	20.97	5.56	14.02	19.06	25.10	64.27	9.85
Δ ShortRate	-0.04	-8.20	-0.06	-0.01	0.02	4.14	0.36
Slope	1.86	-8.50	1.14	1.68	2.55	11.96	1.41
			Panel B: EA countries				
MPI	15.49	4.1	10.95	15.20	18.60	31.75	5.98
Inf	1.70	-4.30	0.30	1.40	2.80	17.70	2.18
IP	0.56	-31.70	-3.00	1.00	4.80	56.70	8.79
InfVol	0.74	0.08	0.37	0.56	0.91	4.49	0.60
StockRet	-4.48	-164.43	-17.68	3.45	15.40	75.97	30.82
StockRetVol	21.61	5.56	14.50	19.88	26.20	64.27	10.04
Δ ShortRate	-0.04	-8.20	-0.07	-0.01	0.02	4.14	0.40
Slope	2.02	-8.50	1.19	1.82	2.67	11.96	1.57
			Panel C: Non-EA countries				
MPI	18.13	1.50	10.55	19.20	23.80	34.35	7.92
Inf	2.13	-2.50	0.50	1.80	3.40	14.70	2.32
IP	1.04	-26.00	-1.90	1.85	5.10	17.20	6.71
InfVol	0.73	0.11	0.35	0.59	0.92	4.16	0.55
StockRet	-0.89	-165.01	-12.28	3.54	16.10	96.33	29.61
StockRetVol	19.63	6.85	13.37	16.82	22.73	51.67	9.28
Δ ShortRate	-0.04	-2.74	-0.06	-0.01	0.02	3.01	0.23
Slope	1.55	-2.27	1.02	1.44	2.23	3.51	0.91

Note: The table presents summary statistics for the explanatory variables over the period 2008-2017. Panel A considers all the countries in our sample and Panels B and C consider respectively the subsamples of EA and Non-EA countries.

mitigates such concerns. Second, by including explanatory variables capturing variations in default risk related to the evolution of macro-financial conditions, we also explicitly control for some of the changes in the risk environment that could endogenously drive variations in the macroprudential policy stance. Finally, we note that the Nickell (1981) bias is not a source of concerns in our analysis given that the bias vanishes in samples with longer time series dimension and we carry out our analysis on a sample with 10 years of monthly data.[16] This is confirmed by simulation results in Appendix 2.B, which consider different data generating processes (DGPs) for a dynamic linear panel model with fixed effects. The simulations compare the performance of the OLS estimator with the efficient one-step difference GMM estimator of Arellano and Bond (1991) in terms of bias, mean squared errors (MSE), and distributional variance. The results indicate that the OLS estimator results in lower bias, MSE, and variance compared to its GMM counterpart in settings relevant for our empirical application; namely a panel with a long time series dimension and a relatively small cross-sectional dimension.

2.3.2 Empirical results

We can now estimate the model specified in Equation (2.1) to assess the average impact of macroprudential policies on both short- and long-term default risks of the studied sectors. Table 2.3 reports the estimates obtained for each of the sectors in Panels A to F. Each panel is further divided in three parts to contrast the results obtained for the full set of countries ("All") with the results for two subsamples of countries — euro are countries ("EA") and other non-EA countries ("Non-EA").

The introduction of tighter macroprudential regulation, captured by our MPI variable, significantly decreases the 5-year default probability (DP) of the financial sector. A unit increase in the MPI, corresponding to the first-time activation of a policy instrument, decreases the 5-year DP by 0.425 bps in the short-run and 4.20 bps in the long-run. This result is robust across the two subsamples of EA and Non-EA countries and consistent with

[16] The Nickell (1981) bias refers to the bias affecting parameter estimates of panel models with fixed effects in small samples when lags of the dependent variable are used as regressors.

Meuleman and Vander Vennet (2020)'s result, using bank level data, that macroprudential policy actions decrease bank systemic risk on average.[17] The lack of statistical evidence supporting an impact of macroprudential regulation on the 6-month DP suggests that macroprudential policies tend to improve financial stability by addressing longer-term aspects of default risk.

Unexpectedly, we also find strong statistical evidence that tighter macroprudential regulation contributes to reducing default risks in non-financial sectors of the economy. The impact of a unit change in the MPI on the 5-year DP ranges from -0.24 bps (consumer cyclical sector) to -0.39 bps (industrial sector) in the short-run and, respectively, from -1.79 bps to -4.7 bps in the long-run.[18] We also obtain a statistically significant impact of tighter macroprudential regulation for the 6-month DPs with coefficient estimates whose magnitude is commensurate with the estimates for the financial sector. A subsample analysis of the robustness of these results indicates that they are mainly driven by the euro area countries. These results highlights that macroprudential regulation impacts also non-financial sectors mainly indirectly via the credit capacity of the financial sectors.

Looking at the estimation results in Table 2.3 for the control variables, we see that controlling for the persistence in default probabilities is important in our specification to avoid serial correlation in the residuals as the first two PD lags are significant in almost all cases and a third lag is necessary for the financial and basic materials sectors. Increased economic activity, measured by IP, significantly decreases short- and long-term default risk in the financial and consumer cyclical sectors (Lando and Nielsen (2010), Giesecke et al. (2011)).[19] The coefficient estimates for the slope of the yield curve are also significant and

[17]As mentioned in Section 2.3.1, the estimated long-run effect (Est LR effect) of a one unit change in the macroprudential policy stance is obtained by plugging the coefficient estimates of Equation (2.1) in $\delta/(1-\sum_{l=1}^{3}\rho_l)$. The results are reported at the bottom of each panel in Table 2.3.

[18]We note that the results for the basic materials sector point to an even stronger impact of macroprudential regulation on default risk at the 5-year horizon. However, our subsample analysis reveals that the coefficient estimate is driven upward by non-EA countries whose coefficient estimate is not statistically significant.

[19]Interestingly, we do not find a significant impact of higher yearly growth in industrial production on default risk in the industrial sector — although the coefficient estimates have the expected negative

with a negative sign, consistent with the literature documenting the predictive power of a steepening in the yield curve on future real economic activity (Estrella and Hardouvelis (1991), Estrella and Mishkin (1998), Hamilton and Kim (2002)). The results for short-term default risk confirm the negative relationship between stock market performance and default risk documented in Giesecke et al. (2011). However, the results for long-term default risk are consistent with the literature documenting a positive relationship between default risk and stock returns (Duffie et al. (2007), Chava and Purnanandam (2010), Friewald et al. (2014)).

The estimates for the consumer non-cyclical, industrial, and technology sectors in the non-EA subsample confirm the results in Duffie et al. (2007) on the negative relationship between changes in short-term risk-free interest rates and default risk; consistent with Jiménez et al. (2014) who document how less well-capitalized banks react to a loosening in monetary policy by increasing their credit supply to riskier firms with higher default likelihood ex-post and with Heider et al. (2019) who show that high-deposit European banks increased their risk taking after the introduction of negative policy rates. Inflation also contributes significantly to explaining variations in default risks across all sectors and horizons. While the positive sign of the coefficient estimates appears to be at odds with empirical evidence on low expected inflation predicting corporate defaults through its impact on real debt liabilities (Bhamra et al. (2011), Fiore et al. (2011), Gomes et al. (2016)), we conjecture that inflation — and its downward trend over the studied sample — contributes to explaining variations in default probabilities at the sector level by proxying for their trend component. Higher inflation volatility is associated with a significant decrease in default risk; consistent with the expectation that, in a low inflation environment, higher volatility would likely reduce the probability that firm will default due to higher real liabilities.[20]

sign. This can be partly explained by the fact that relevant information about the sector performance is already embedded in the dynamics of the lagged DPs and by observing that the yield curve slope, a well-documented predictor of economic activity, is significant for non-EA countries.

[20] Kang and Pflueger (2015) document a positive relationship between inflation volatility and corporate bond spreads using a panel of 6 countries over the period 1969 Q4 – 2010 Q4. Their analysis do not

The main conclusions from our analysis might be sensitive to some of the modelling choices we made. First, our results might be sensitive to potential model misspecifications arising from modelling probabilities of default with an i.i.d. Gaussian dynamic linear model. Indeed, the distribution of default probabilities displays high positive skewness given that they take values in $[0;1]$ with a mass of observations concentrated on the left-hand side of the support and periods of heightened default risk introducing a right tail in the distribution. We address this concern in Appendix 2.D by re-estimating the model in Equation (2.1) on the log-transformed probabilities of default. Our main conclusion that tighter macroprudential regulation decreases short- and long-term default risk appears to be robust to this potential source of model misspecification. Moreover, the results obtained for the default predictors are also broadly consistent with the key results set out above.

A second concern relates to the potential implications for our results of overlooking the impact of unconventional monetary policies during the period analyzed. We address this potential shortcoming in Appendix 2.E by introducing the shadow rate in our set of default predictors instead of the short-term interest rate.[21] This approach allows us to incorporate in our modelling both conventional and unconventional monetary policy tools in a tractable way. See e.g. Mouabbi and Sahuc (2019) and Wu and Zhang (2019) who adopt a similar approach in a Dynamic Stochastic General Equilibrium (DSGE) setting. The results of our analysis in Appendix 2.E confirm our main result that tighter macroprudential regulation decreases default risk on average in both financial and non-financial sectors. Our other key conclusions regarding the sign and significance of the coefficient estimates for the default predictors are unaffected by the introduction of the shadow rate. It is worth noting that the shadow rate significantly contributes to explaining variations in default risk for the consumer non-cyclical sector.[22] This, combined with the

include the recent low inflation period on which we focus our analysis but our results are consistent with their debt deflation channel.

[21]The shadow rate can be defined as the estimated short-term interest rate that would prevail in the absence of an effective lower bound (ELB) constraining short-term nominal rates.

[22]The sign of the parameter estimates is in line with the results obtained for the short rate above.

absence of significance for the MPI coefficient estimates, could be indicative of monetary policy — rather than macroprudential policy — being the main driver of variations in default risk for this sector. We observe the opposite result for the financial sector and other non-financial sectors, namely macroprudential regulation being the main driver of variations in default risk rather than (unconventional) monetary policy.[23]

[23]Alternatively, we could interpret this result as tighter macroprudential regulation offsetting the contribution of accommodative (unconventional) monetary policy to default risk.

Table 2.3: Macroprudential Policies and sector-specific median default risk

	Panel A: Financial						Panel B: Consumer cyclical					
	All		EA		Non-EA		All		EA		Non-EA	
	6-M	5-Y	6-M	5-Y	6-M	5-Y	6-M	5-Y	6-M	5-Y	6-M	5-Y
PD L1	1.31***	1.28***	1.31***	1.28***	1.18***	1.20***	1.04***	1.02***	1.11***	1.06***	0.944***	0.964***
	(0.146)	(0.108)	(0.165)	(0.128)	(0.104)	(0.054)	(0.071)	(0.046)	(0.080)	(0.062)	(0.120)	(0.064)
PD L2	-0.819***	-0.644***	-0.839***	-0.677***	-0.477***	-0.448***	-0.171**	-0.140**	-0.240***	-0.170**	-0.087	-0.102
	(0.210)	(0.203)	(0.236)	(0.231)	(0.117)	(0.085)	(0.075)	(0.058)	(0.089)	(0.084)	(0.118)	(0.076)
PD L3	0.356***	0.263**	0.371***	0.284**	0.098	0.124**	-0.011	0.015	-0.013	0.004	0.028	0.034
	(0.112)	(0.111)	(0.123)	(0.121)	(0.061)	(0.054)	(0.043)	(0.036)	(0.054)	(0.049)	(0.067)	(0.054)
MPI	-0.072	-0.425**	-0.112	-0.535*	-0.056	-0.429**	-0.101***	-0.242*	-0.114**	-0.330*	-0.075	-0.127
	(0.068)	(0.177)	(0.125)	(0.286)	(0.040)	(0.169)	(0.035)	(0.145)	(0.052)	(0.196)	(0.059)	(0.225)
Inf	0.609**	1.68***	0.973**	2.71***	0.234***	0.692**	0.395***	1.20***	0.354***	1.23***	0.504***	1.19**
	(0.247)	(0.505)	(0.455)	(0.887)	(0.075)	(0.299)	(0.099)	(0.315)	(0.129)	(0.464)	(0.161)	(0.486)
IP	-0.035**	-0.202***	-0.037*	-0.216***	-0.050*	-0.188*	-0.018	-0.104*	-0.023*	-0.071	-0.008	-0.215
	(0.017)	(0.054)	(0.021)	(0.064)	(0.030)	(0.112)	(0.014)	(0.060)	(0.013)	(0.061)	(0.042)	(0.169)
InfVol	-0.903**	-2.29**	-0.941	-1.74	-0.878**	-3.26**	-0.338	-0.014	-0.142	0.738	-1.06*	-1.51
	(0.425)	(1.08)	(0.679)	(1.53)	(0.401)	(1.43)	(0.347)	(1.14)	(0.447)	(1.55)	(0.603)	(1.66)
StockRet	-0.021*	0.009	-0.010	0.036*	-0.026***	-0.004	-0.013**	0.033*	-0.009	0.018	-0.018	0.065**
	(0.012)	(0.017)	(0.012)	(0.022)	(0.010)	(0.025)	(0.006)	(0.018)	(0.007)	(0.023)	(0.016)	(0.033)
StockRetVol	0.004	0.056	0.054	0.186	0.005	0.055	-0.025	0.043	-0.021	0.021	-0.044	0.084
	(0.031)	(0.075)	(0.061)	(0.127)	(0.024)	(0.093)	(0.018)	(0.068)	(0.021)	(0.085)	(0.031)	(0.112)
Δ ShortRate	-0.0006	-0.167	0.136	0.325	-1.56	-6.01	-0.132	-0.948	-0.181	-1.05	0.015	-0.519
	(0.431)	(1.44)	(0.491)	(1.64)	(1.22)	(3.96)	(0.302)	(0.970)	(0.300)	(0.952)	(1.32)	(3.98)
Slope	-0.662**	-1.29*	-0.763*	-1.52*	-0.423**	-0.650	-0.262	-0.678	-0.211	-0.616	-0.662**	-1.11
	(0.325)	(0.736)	(0.422)	(0.911)	(0.215)	(0.854)	(0.174)	(0.566)	(0.205)	(0.666)	(0.328)	(1.07)
Est LR effect	-0.471	-4.20	-0.709	-4.73	-0.281	-3.46	-0.711	-1.79	-0.797	-3.11	-0.652	-1.22
Adj. R^2	0.837	0.920	0.835	0.921	0.875	0.918	0.904	0.939	0.921	0.948	0.867	0.906
With Adj. R^2	0.822	0.885	0.820	0.886	0.866	0.889	0.852	0.857	0.855	0.868	0.851	0.839
Obs	3,120		2,040		1,080		2,880		1,800		1,080	
Countries	26		17		9		24		15		9	

Table 2.3 (Continued)

	Panel C: Consumer non-cyclical						Panel D: Industrial					
	All		EA		Non-EA		All		EA		Non-EA	
	6-M	5-Y	6-M	5-Y	6-M	5-Y	6-M	5-Y	6-M	5-Y	6-M	5-Y
PD L1	1.18***	1.14***	1.18***	1.13***	1.14***	1.14***	1.06***	1.07***	1.03***	1.06***	1.20***	1.11***
	(0.073)	(0.044)	(0.095)	(0.063)	(0.075)	(0.060)	(0.102)	(0.037)	(0.111)	(0.043)	(0.071)	(0.060)
PD L2	-0.343***	-0.255***	-0.357***	-0.268***	-0.273***	-0.228***	-0.247**	-0.194***	-0.223**	-0.183***	-0.433***	-0.246***
	(0.099)	(0.056)	(0.120)	(0.080)	(0.064)	(0.070)	(0.097)	(0.051)	(0.104)	(0.059)	(0.097)	(0.071)
PD L3	0.046	0.041	0.045	0.038	0.057	0.034	0.079	0.042	0.091	0.045	0.066	0.042
	(0.080)	(0.042)	(0.098)	(0.060)	(0.052)	(0.056)	(0.053)	(0.043)	(0.063)	(0.051)	(0.057)	(0.045)
MPI	-0.030	-0.081	-0.095**	-0.376**	-0.005	-0.034	-0.134***	-0.385***	-0.179**	-0.492**	-0.082**	-0.247*
	(0.026)	(0.110)	(0.048)	(0.173)	(0.019)	(0.133)	(0.048)	(0.140)	(0.076)	(0.221)	(0.034)	(0.145)
Inf	0.289***	0.680***	0.408***	1.17***	0.159***	0.149	0.468***	1.09***	0.538***	1.35***	0.445***	0.813**
	(0.080)	(0.250)	(0.144)	(0.372)	(0.061)	(0.297)	(0.104)	(0.276)	(0.146)	(0.389)	(0.102)	(0.315)
IP	0.004	0.022	-0.0001	0.016	0.022	0.069	-0.012	-0.075	-0.021	-0.080	-0.036	-0.077
	(0.011)	(0.049)	(0.013)	(0.051)	(0.019)	(0.131)	(0.018)	(0.060)	(0.020)	(0.068)	(0.022)	(0.105)
InfVol	-0.325*	-0.671	-0.372	-0.868	-0.300	0.342	-1.09**	-2.45**	-1.23**	-2.38	-1.02**	-3.26**
	(0.193)	(0.865)	(0.296)	(1.05)	(0.269)	(1.43)	(0.474)	(1.21)	(0.614)	(1.57)	(0.478)	(1.50)
StockRet	-0.004	0.029*	-0.001	0.035*	-0.0005	0.030	-0.011	0.032*	-0.003	0.037	-0.022*	0.056
	(0.005)	(0.015)	(0.006)	(0.019)	(0.006)	(0.027)	(0.008)	(0.019)	(0.009)	(0.023)	(0.012)	(0.038)
StockRetVol	-0.002	0.049	0.014	0.127	-0.015	-0.027	-0.023	0.034	-0.010	0.074	-0.046	-0.018
	(0.013)	(0.058)	(0.021)	(0.081)	(0.016)	(0.104)	(0.022)	(0.069)	(0.029)	(0.093)	(0.029)	(0.109)
Δ ShortRate	-0.282	-0.821	-0.165	-0.265	-1.32**	-6.14**	-0.459	-1.66	-0.337	-1.21	-1.90	-8.67**
	(0.231)	(0.903)	(0.263)	(0.972)	(0.534)	(2.56)	(0.347)	(1.03)	(0.349)	(1.08)	(1.40)	(4.32)
Slope	-0.219*	-0.549	-0.225	-0.710	-0.344**	-0.298	-0.280	-0.786	-0.222	-0.672	-0.578**	-1.61*
	(0.122)	(0.471)	(0.145)	(0.541)	(0.144)	(0.728)	(0.207)	(0.587)	(0.243)	(0.680)	(0.290)	(0.969)
Est. LR effect	-0.256	-1.09	-0.72	-3.76	-0.066	-0.63	-1.24	-4.7	-1.75	-6.31	-0.491	-2.63
Adj. R^2	0.903	0.927	0.903	0.929	0.906	0.919	0.903	0.947	0.901	0.948	0.921	0.932
With Adj. R^2	0.873	0.888	0.874	0.883	0.876	0.897	0.861	0.881	0.857	0.882	0.894	0.874
Obs	2,880		1,800		1,080		2,880		2,040		840	
Countries	24		15		9		24		17		7	

Table 2.3 (Continued)

	Panel E: Basic materials						Panel F: Technology					
	All		EA		Non-EA		All		EA		Non-EA	
	6-M	5-Y	6-M	5-Y	6-M	5-Y	6-M	5-Y	6-M	5-Y	6-M	5-Y
PD L1	1.21***	1.19***	1.05***	1.11***	1.24***	1.20***	1.07***	1.05***	1.06***	1.00***	1.03***	1.06***
	(0.118)	(0.136)	(0.098)	(0.067)	(0.141)	(0.183)	(0.044)	(0.042)	(0.053)	(0.042)	(0.063)	(0.074)
PD L2	-0.725***	-0.553**	-0.397***	-0.321***	-0.796***	-0.612**	-0.242***	-0.172***	-0.262***	-0.123**	-0.177*	-0.216**
	(0.214)	(0.230)	(0.117)	(0.115)	(0.240)	(0.287)	(0.066)	(0.050)	(0.081)	(0.054)	(0.099)	(0.087)
PD L3	0.351***	0.240*	0.206**	0.102	0.388***	0.274*	0.030	0.034	0.098	0.026	-0.099	0.003
	(0.122)	(0.123)	(0.083)	(0.076)	(0.143)	(0.156)	(0.052)	(0.027)	(0.061)	(0.035)	(0.074)	(0.048)
MPI	-0.123*	-0.720*	-0.116**	-0.388*	-0.102	-0.723	-0.100***	-0.322**	-0.132***	-0.678***	-0.104***	-0.192
	(0.064)	(0.368)	(0.054)	(0.215)	(0.107)	(0.611)	(0.027)	(0.152)	(0.039)	(0.236)	(0.037)	(0.214)
Inf	0.481***	0.772*	0.500***	2.03***	0.610**	0.552	0.196***	0.572*	0.259***	1.03***	0.146	0.266
	(0.184)	(0.433)	(0.142)	(0.540)	(0.290)	(0.698)	(0.054)	(0.307)	(0.080)	(0.386)	(0.092)	(0.606)
IP	0.0002	-0.025	0.020	0.065	-0.042	-0.215	-0.005	-0.011	-0.0007	-0.007	-0.026	0.024
	(0.025)	(0.110)	(0.021)	(0.082)	(0.071)	(0.320)	(0.009)	(0.054)	(0.009)	(0.056)	(0.025)	(0.132)
InfVol	-1.16**	-3.75**	-0.954	-2.18	-1.67**	-4.32**	-0.251	0.659	-0.506*	0.218	-0.212	-0.684
	(0.530)	(1.63)	(0.686)	(2.23)	(0.775)	(2.11)	(0.214)	(1.17)	(0.292)	(1.55)	(0.352)	(1.96)
StockRet	-0.026**	-0.003	-0.020	0.028	-0.011	0.066	-0.015**	0.024	-0.002	0.057**	-0.031***	-0.0001
	(0.012)	(0.034)	(0.012)	(0.034)	(0.018)	(0.058)	(0.006)	(0.019)	(0.007)	(0.025)	(0.011)	(0.033)
StockRetVol	-0.048	-0.090	-0.028	0.185	-0.087	-0.301	-0.052***	-0.080	-0.030	0.051	-0.074***	-0.205*
	(0.030)	(0.138)	(0.030)	(0.127)	(0.063)	(0.315)	(0.014)	(0.067)	(0.019)	(0.091)	(0.022)	(0.108)
Δ ShortRate	-0.022	-0.471	0.344	0.845	-4.17	-17.2	0.091	0.445	0.295	1.36	-1.53*	-7.84**
	(0.649)	(2.24)	(0.575)	(2.01)	(3.21)	(12.6)	(0.422)	(1.55)	(0.421)	(1.49)	(0.894)	(3.17)
Slope	-0.566***	-1.52**	-0.320	-0.854	-1.64***	-4.38***	-0.208**	-0.179	-0.276***	-0.614	0.018	1.36
	(0.203)	(0.663)	(0.196)	(0.629)	(0.493)	(1.68)	(0.085)	(0.384)	(0.093)	(0.401)	(0.233)	(1.24)
Est. LR effect	-0.75	-5.85	-0.823	-3.56	-0.607	-5.24	-0.704	-3.66	-1.27	-6.99	-0.423	-1.25
Adj. R^2	0.785	0.843	0.833	0.908	0.764	0.784	0.882	0.921	0.897	0.913	0.859	0.927
With Adj. R^2	0.766	0.800	0.809	0.858	0.757	0.778	0.844	0.858	0.867	0.888	0.804	0.789
Obs	2,280		1,440		840		2,160		1,440		720	
Countries	19		12		7		18		12		6	

Note: Estimation is carried out by OLS with one-way country fixed effect dummies. The estimation period is 2008-2017. The dependent variable is the median probability of default for the sector. All regressors are considered as lagged values. We report estimates with Driscoll Kraay standard errors between brackets which are robust to general forms of cross-sectional and temporal dependence (clustered at the country level). ***, **, and * indicate significance at the 1-, 5-, and 10-percent significance levels, respectively.

Taken together, our results for the financial and non-financial sectors indicate that the beneficial effects of tighter macroprudential regulation on financial sector's default risk also transmit to the real economy by lowering both short- and long-term default risks on average. Our results thus complement and extend the analysis of Meuleman and Vander Vennet (2020) by confirming the main result of their bank-level analysis using aggregate data and by documenting the positive contribution of macroprudential regulation to improving the resilience of non-financial sectors of the economy. We conjecture that the beneficial impact of macroprudential regulation on the default risk of non-financial sectors likely result from a combination of direct and indirect effects. First, studies have documented that more resilient banks, as measured e.g. by their expected default frequency, are able to supply larger volumes of credit and can better insulate their credit supply from variations in the monetary policy stance and the macroeconomic environment (Altunbas et al., 2010; and Gambacorta and Mistrulli, 2014). Second, the implementation of macroprudential policies tend to be associated with longer phases of economic expansions (Gadea et al., 2020), which indirectly benefit all sectors given that contractions in economic activity tend to be associated with heightened corporate default risk (Lando and Nielsen, 2010; and Giesecke et al., 2011). Lastly, improved resilience in the financial sector could spillover to non-financial sector through the reduction in downside risks to the economy resulting from a decrease in systemic risk (Allen et al., 2012; Giglio et al., 2016; and Brownlees and Engle, 2017) and through a reduction in the cross-sectoral contagion channel (Azizpour et al., 2018).

Our results are also consistent with Belkhir et al. (2022b) who model the joint impact of macroprudential regulation on the probability of financial crises and economic growth. They show that the beneficial effects of a tighter macroprudential policy stance on financial stability are not offset by its costs in terms of reduced economic activity — resulting in an overall beneficial effect of improved resilience in the financial system.[24] While, the

[24]Note that their results for Advanced Economies (AEs) show a muted impact of macroprudential regulation on real GDP growth (Table 1.4). This is even clearer for the subset of policies aimed at financial institutions for which the impact in AEs is overall net beneficial in terms of financial stability and real GDP growth — although the impulse response functions are imprecisely estimated due to the

results set out above capture the overall association between probabilities of default at the sector level and macroprudential regulation over the sample period, they do not allow us to shed lights on the potential short-term costs of a tighter macroprudential stance. This aspect is addressed in the next section.

2.4 Panel event-study on the transmission of macroprudential policy reforms

Having established that macroprudential regulation has a beneficial impact on average default risk in the financial and non-financial sectors of the economy, we now want to refine our analysis by investigating the impact of specific changes in the macroprudential framework on sector-specific probabilities of default. To this end, we focus on two major policy reforms which — due to their magnitude and scope of application at the EU level — provide us with an ideal setting to investigate the transmission of macroprudential policy to default risk at the sector level. The first one is the implementation of the Basel III standards into European law and the second one is the introduction of a European framework for the resolution of failing financial institutions.

We structure the exposition as follows: Section 2.4.1 details our empirical approach to analyse the dynamic effects of each policy event on sector-specific probabilities of default; Section 2.4.2 analyses the impact of the higher capital requirements introduced with Basel III; and Section 2.4.3 analyses the impact of a strengthening in the resolution framework and compares the main results for the two policy events.

2.4.1 The methodology

The panel-event study design allows us to estimate and analyze the dynamic effects of a policy intervention on an outcome variable of interest. The associated methodological literature has witnessed a substantial growth over the last few years; see e.g. Sun and

short time series length. See Section 1.5.1 for more details.

Abraham (2021) for an overview. We estimate the following standard panel event-study regression with two-way fixed effects (TWFE) using the sector-specific probability of default at a horizon of 6 months and 5 years, $PD^{(h)}_{c,t}$, as the outcome variable:

$$PD^{(h)}_{c,t} = \sum_{j=\underline{j}}^{\bar{j}} \delta_j d^j_{c,t} + X^{\top}_{c,t-1}\,\beta + \mu_c + \theta_t + \nu_{c,t}\,, \tag{2.2}$$

where $d^j_{c,t}$ is a policy treatment indicator for an event taking place at a potentially country-specific time e_c located within an event window indexed by $j \in [\underline{j}, \bar{j}]$ ranging from $\underline{j} < 0$ periods before the event to $\bar{j} \geq 0$ after the event; $X_{c,t-1}$ is a vector of lagged macro-financial controls introduced in Section 2.3; μ_c is a country fixed effect accounting for cross-country differences in the average default probabilities; θ_t is a year fixed effect capturing overall trends in probabilities of default at the sector level; and $\nu_{c,t}$ is an error term. We follow the approach of Freyaldenhoven et al. (2019) and define the treatment indicator $d^j_{c,t}$ as follows:

$$d^j_{c,t} = \begin{cases} \mathbb{1}[t = e_c + j] & \text{if} \quad \underline{j} < j < \bar{j}\,, \\ \mathbb{1}[t \geq e_c + j] \times \operatorname{sign}(j) & \text{if} \quad j \in \{\underline{j}; \bar{j}\}\,. \end{cases} \tag{2.3}$$

Borusyak et al. (2021) highlight an under-identification problem for dynamic treatment effects in fully dynamic panel event-study settings, i.e. using an event window which covers the entire set of observed data, as the dynamic treatment parameters δ_j cannot be separately identified from the time fixed effect θ_t. As shown by Schmidheiny and Siegloch (2019), restricting the event window to a finite length $[\underline{j}, \bar{j}]$ allows to circumvent this identification issue even in settings where all units are treated — which is the case in our empirical application. This comes however at a cost in terms of flexibility in the modelling of the dynamic effects of a policy intervention as it corresponds to assuming that the policy impact is constant outside the event window. An additional identification challenge arises from the perfect multicollinearity between the policy treatment indicators and the country fixed effect μ_c which requires to standardize one of the δ_j coefficients. We follow the standard approach in the literature and exclude the first lead of the treatment indicators, $d^{-1}_{c,t}$, which is equivalent to imposing the linear restriction $\delta_{-1} = 0$ in the estimation; see e.g. Freyaldenhoven et al. (2019). This implies that the coefficients δ_j, $\forall$ $j \geq 0$, will be interpreted as the effect of the policy on the outcome variable j time periods after its introduction compared to the level of the outcome variable one period prior to the policy intervention. In addition, the model specified in Equation (2.2) implicitly restricts the dynamic effects of the policy treatment to be homogeneous across countries. Therefore, the estimates of the δ_j coefficients should be interpreted as the average pre-treatment (resp. post-) effect of the policy j periods before (resp. after) its introduction for all $j < 0$ (resp. $j \geq 0$) compared to the average level of the outcome variable one period prior to the policy intervention.

As pointed out in Schmidheiny and Siegloch (2019), the econometric identification of the panel event-study model specified in Equation (2.2) under the restrictions set out in the previous paragraph implicitly relies on either i) the existence of at least one never-treated unit, or ii) a setting with staggered treatment timing which enables a recursive identification by comparing a unit's treatment window endpoints with a control unit whose treatment window does not contain these time points. Given that our empirical analysis is based on a setting in which all countries are exposed simultaneously to the policy treatment, we need to impose an additional restriction to achieve identification and we thus exclude the second lead of the treatment indicators, $d_{c,t}^{-2}$, which is equivalent to imposing the linear restriction $\delta_{-2} = 0$ in the estimation.

Freyaldenhoven et al. (2019) highlight that a common concern in the assessment of the causal impact of a policy intervention on an outcome variable using a panel even-study setting is the potential endogeneity of the policy intervention due to the existence of confounding factors correlated with both the outcome variable and the likelihood of a policy intervention. Specializing to our analysis, the existence of confounding factors which simultaneously drive variations in sector-specific default risk and impact the likelihood of a change in the macroprudential policy stance would result in biased estimates of the dynamic effects of the policy intervention. A common diagnostic approach to address endogeneity concerns is to investigate — either visually or through a formal test on the coefficient estimates of the panel event-study model — whether the outcome variable appears to react to the policy intervention before the actual occurrence of the policy intervention; a phenomenon known as pre-event trend in the outcome variable. We follow this approach by testing the hypothesis of no pre-event trend as $\delta_{\underline{j}} = \delta_{\underline{j}+1} = \ldots = \delta_{-3} = 0$, which we complement with an hypothesis test on post-event trend formulated as $\delta_0 = \delta_1 = \ldots = \delta_{\bar{j}} = 0$.[25]

The next two subsections will apply the panel event-study methodology to analyze the impact on default risk at the sector level of two major changes in the European regulatory framework: i) the transposition of the Basel III package of measures into European law; and ii) the introduction of a regulatory framework for the resolution of failing banks. In both cases, we will consider an event window spanning 5 quarters before and after our chosen reference date for the policy event. This choice of event window allows to appropriately account for potential pre-event trends in sector-specific default risks and for the progressive transmission of announced changes in the macroprudential policy stance — see Section 2.3.1 for further details. Furthermore, we investigate the potential impact of the assumption of homogeneous dynamic policy effects across countries by conducting the analysis on the full sample of countries and on subsamples of euro area (EA) and non-EA countries.

2.4.2 Impact of higher capital requirements in the banking system.

The Basel III global standards were introduced in 2010 to address the lessons learned during the Global Financial Crisis of 2008 (BCBS (2010a)). The reforms introduced were aimed at improving the ability of the financial system to withstand losses during periods of stress, thus reducing both the magnitude and likelihood of spillovers from the

[25] Freyaldenhoven et al. (2019) develop a 2-stage Least Square (2SLS) estimation approach which corrects the potential bias in estimated dynamic policy effects due to the presence of confounding factors even in the presence of pre-event trends in the outcome variable. We do not follow this approach in our analysis as no statistical evidence supporting the presence of pre-event trends in the sector-specific probabilities of default is found.

financial sector to the real economy — due e.g. to banks' procyclical deleveraging and the amplification role played by systemic institutions. The key measures to strengthen banks' loss-absorbing capacities were an increase in minimum requirements for going-concern Tier 1 capital from 4.5 to 6% of Risk-Weighted-Assets (RWA) — of which at least 4.5% were to be held in the form of Common Equity Tier 1 (CET1) capital — and the introduction of macroprudential capital buffers aimed respectively at promoting the conservation of capital (Capital Conservation Buffer, CCoB), increasing resilience against procyclicality (Countercyclical Capital Buffer, CCyB), addressing structural systemic risks (Systemic Risk Buffer, SRB), and imposing capital surcharges for global and domestic Systemically Important Institutions (G-SII and O-SII buffers).[26]

The Basel III standards were subsequently implemented in European law in June 2013 through the CRR/CRD IV package which was comprised of the Capital Requirements Regulation (CRR, Regulation 575/2013) and the Capital Requirements Directive (CRD IV, Directive 2013/36/EU). We choose this event date as our center point to construct the event window, ranging from March 2012 to September 2014, used in the panel event-study analysis. We consider that this event window is appropriate to capture the dynamic effects of increased capital requirements, including both minimum requirements and buffers, on sector-specific probabilities of default given the important concentration of policy announcement during this period. Indeed, 11 countries in our sample announced in June 2013 that the Basel III minimum capital requirements would be effective from January 2014.[27] The remaining countries announced at the same date that the new requirements would be effective from January 2015. Furthermore, 12 countries announced the implementation of a fully phased-in CCoB (2.5% of RWA) during the event window, among which 5 of them also activated at least one other capital buffer.[28]

[26]All the capital buffer requirements have to be met with the highest level of capital quality (CET1).

[27]The countries were Bulgaria, Estonia, Finland, Greece, Italy, Luxembourg, Latvia, Malta, the Netherlands, Romania, and Sweden.

[28]For the CCoB, the countries were Austria, Bulgaria, Cyprus, Czech Republic, Estonia, Finland, Hungary, Italy, Luxembourg, Latvia, Sweden, and Slovakia. Bulgaria, Czech Republic, Estonia, Hungary, and Sweden also activated their SRB during the period studied. Finally, Sweden set a 1% CCyB in

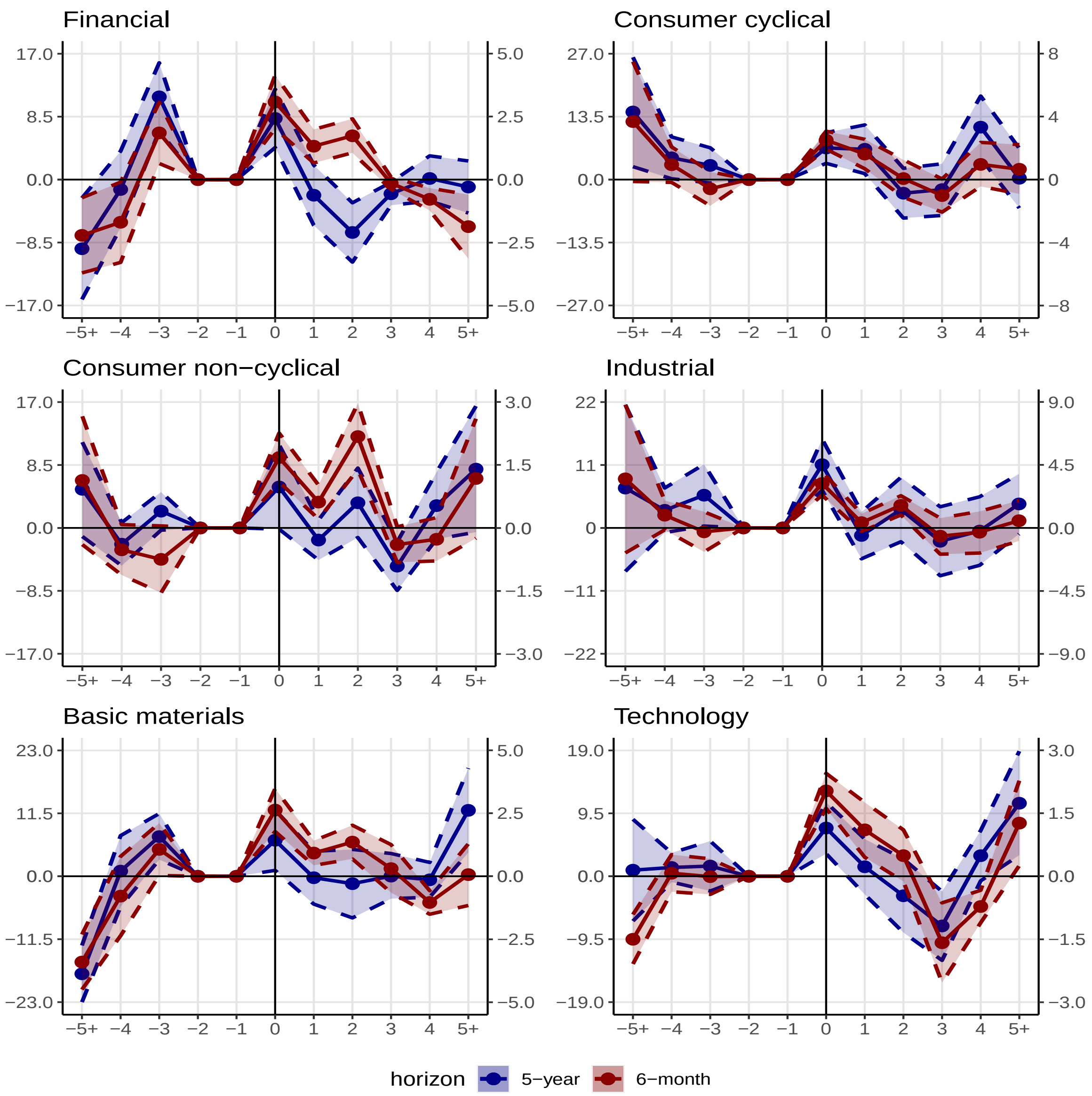
Figure 2.1 summarises the evolution of the median probabilities of default around the introduction of the CRR/CRD IV package for the six sectors under analysis. First, we generally do not find statistical evidence supporting the hypothesis of a pre-event trend.[29] This mitigates concerns about a potential bias in the estimates of the dynamic policy effects due to endogeneity. Second, the introduction of the policy package impacted short-term default risks in a statistically significant way as we reject the null hypothesis of no post-event trend on the 6-month DPs in all cases. This impact is less pronounced for long-term default risks as we only reject the null hypothesis of no post-event trend on the 5-year DPs for the consumer cyclical and technology sectors.

We now inspect in more details the impact of the introduction of the CRR/CRD IV policy package on default risks at the sector level. We observe an increase in both short- and long-term default risks around the event. The impact on 6-month DPs ranges from a 1.68 bps increase for the consumer non-cyclical sector to respectively 3.08 and 3.18 bps increases for the financial and industrial sectors. For the 5-year DPs, the impact ranges from a 5.53 bps increase for the consumer non-cyclical sector to respectively 8.26 and 11.05 bps increases for the financial and industrial sectors. The rise in default risk following the introduction of the regulatory package is also economically significant as a comparison with the median PD levels reported in Table 2.1 indicates that they translate into increases above median levels from 34% (consumer non-cyclical sector) to 62% (financial sector) for the 6-month default horizon, and from 4% (basic material sector) to 7% (financial sector) for the 5-year default horizon. An analysis of the impact of the policy change at a longer horizon provides evidence of a disconnect between the financial sector and non-financial ones. On the one hand, the default risk of the financial sector decreases progressively in the post-event period with e.g. a decrease of 7.14 bps for the 5-year DP two quarters after the event. The long-run impact of the introduction of the CRR/CRD IV package, captured by the estimate of δ_{5+} in equation (2.2), is a decrease in default risk by respectively 1.88 and 1 bps for the 6-month and 5-year DPs. The reduction in short-term default risk

September 2014.

[29]Notable exceptions are the 5-year DP for the consumer cyclical sector (p-val of 0.077) and the 6-month DPs for the basic materials and technology sectors (p-vals of 0.027 and 0.00 respectively).

Figure 2.1: Impact of the introduction of CRR



Note: This figure summarises the evolution of the median probabilities of default around the introduction of the CRR/CRD IV package for the six sectors analysed. The event window captures a period of 10 quarters around the event (x-axis). The y-axes display the estimated coefficients for the event window as specified in equation (2.2). The results for the 5-year (6-month) default horizon are reported in blue (red) with corresponding value on the left-hand (right-hand) y-axis. The shaded areas around the point estimates correspond to the 68% confidence intervals constructed based on standard errors clustered at the country level. The estimation is carried out on the full sample of countries.

is particularly substantial as it corresponds to a 38% decrease compared to the median level. Non-financial sectors, on the other hand, appear to experience a sustained increase in default risk following the introduction of the policy package.[30] The effect is particularly pronounced for long-term default risk, as the long-run impact on the 5-year DPs ranges from 4.19 bps (industrial sector) to 12.05 bps (basic material sector) — corresponding to increases above median levels ranging from 2.5 to 7.6%. The consumer non-cyclical and technology sectors also experience a marked increase in short-term default risk with a long-run increase of their 6-month DPs of respectively 1.18 and 1.27 bps — a 24% increase compared to their median levels.

The results for the financial sector are consistent with the intuition that increasing capital requirements can raise concerns in the short-term about the ability of financial institutions, in particular those which are less well-capitalized and/or less profitable, to meet increased standards of resilience. This leads to an increase in default risk in the early stage of the introduction of the policy package. However, the initial increase in default risk is progressively reversed as the CRR/CRD IV package leads to a strengthening in the resilience of the financial system and therefore reduces default risk in the long run. This is consistent with the long-run analysis in Jordà et al. (2021) showing how better capitalized banking systems are better equipped to withstand losses during banking crises, thus enabling banks to maintain a more stable supply of credit to the real economy and leading to shorter-lived economic downturns. The concurrent increase in default risk for non-financial sectors is also consistent with the literature studying how banks adjust their balance sheets in reaction to higher capital requirements and the implications for the real economy. When banks are faced with higher capital requirements, expressed in terms of CET1 capital to RWA, they are reluctant to meet them with higher equity levels and prefer instead considering options to shrink their RWA. This can be achieved through both a reduction in balance sheet exposure to retail and corporate borrowers (Gropp et al. (2018)) and a reduction in average risk weights — e.g. via a reallocation of credit supply from corporates to households (Juelsrud and Wold (2020)). Firms are

[30] The consumer cyclical sector is however not affected by this trend.

not always able to substitute this reduction in credit supply with alternative sources of funding and this reduced access to credit thus negatively impact the real economy through lower investment, employment, asset growth and sales (Gropp et al. (2018), Fraisse et al. (2020)). We complement these evidence on the real effects of higher capital requirements by documenting that the increase in default risk of the non-financial sectors is mainly apparent in long-term default risk, which likely reflects concerns about a structural change in access to credit after the phasing-in of the new regulatory regime. The consumer non-cyclical and technology sectors also show signs of increased short-term default risk which could mean that they are more vulnerable to a reduced credit supply from banks. Our findings also provide supporting empirical evidence to the literature highlighting how short-term transitional costs, e.g. through a reduction in credit supply and aggregate demand, can partially offset the long-term benefits of higher capital requirements arising from improved resilience in the financial system; see e.g. Mendicino et al. (2020).

We investigated the robustness of our results by re-estimating Equation (2.2) on the sub-samples of EA (euro area) and non-EA (non-euro area) countries. Results are reported respectively in Figures 2.7 and 2.9 of Appendix 3.B. For EA countries, we confirm our previous result of a lack of statistical evidence supporting the existence of a pre-event trend.[31] For non-EA countries, we find statistical evidence supporting a pre-event trend both in short- and long-term default risks for the basic material, consumer cyclical, and financial sectors. It is important to note that the existence of a pre-event trend in financial sector's default risk is not necessarily due to the presence of confounding factors potentially biasing the estimation of the dynamic policy effects over the event window. The relatively long implementation cycle of the Basel III package — from the initial agreement of the BCBS in 2010 to the effective introduction of the policy reforms between 2013 and 2015 — results in financial institutions, especially the non-EA ones, adjusting their behavior in anticipation of future policy changes, which would in turn be reflected in their default risk at the sector level. Our main conclusions on the statistically and economically significant

[31]The null hypothesis of no pre-event trend is only rejected for the 6-month DPs of the financial and technological sectors.

impact of the policy change on default risk are confirmed in the EA sub-sample but not in the non-EA one.

2.4.3 Impact of a strengthening in the resolution framework for failing banks

The Bank Recovery and Resolution Directive (BRRD, Directive 2014/59/EU) was introduced in May 2014 to provide a European framework to address failing banks at the national level and to promote a better coordination when dealing with cross-border banking failures. The BRRD represents the culmination of legislative efforts in the post-GFC period to transition away from a bailout regime, which relies heavily on recapitalizations from the public sector whose costs are eventually supported by tax payers, and towards a bail-in regime in which shareholders and creditors bear losses first and the public restructuring option is only considered after the application of the bail-in tool. The Directive aimed at ensuring a timely and efficient resolution of failing banks that would mitigate the risks of a significant adverse impact on other financial institutions and the real economy.[32] To this end, the key elements set out in the BRRD were the introduction of recovery and resolution planning to prepare for the resolution of failing banks through an adequately designed strategy; and providing resolution authorities with legal powers to intervene and resort to resolution tools in cases where a financial institution is at risk of failing.[33]

We choose December 2014, the latest date for the transposition of the BRRD into national laws, as our center point to construct the event window — which ranges from September 2013 to March 2016 — for the panel event-study analysis. We consider that

[32]See Article 31(2) of the Directive for a complete list of objectives.

[33]The set of resolution tools granted to authorities includes i) the sale to independent third parties of shares, assets, and liabilities of the failing institution; ii) the transfer of those to a fully- or partially-public legal entity (bridge institution); iii) transferring the management of the assets and liabilities of the failing institution to a publicly-owned asset management vehicle (special purpose vehicle); and iv) the ability to write down/off capital instruments and to convert existing debt instruments into equity to restore sufficient capitalization while avoiding bankruptcy proceedings (bail-in tool). See Philippon and Salord (2017) for a comprehensive overview of the BRRD.

this event window is appropriate to capture the dynamic effects of a strengthening in the resolution framework on the default risk of the financial and non-financial sectors of the economy for two reasons. First, the event window includes the key moments of the implementation of the resolution package as, in addition to the adoption of the directive in European law, it covers both the period around January 2015 — where BRRD's provisions not related to the implementation of the bail-in tool came into force — and the period around January 2016 where the Directive became fully binding for the regulation of EU banks' bail-ins. Second, Cutura (2021) documents that the threat of an enforcement of bail-in powers by resolution authorities was perceived as credible by investors given that banks' unsecured corporate bonds maturing after January 2016, and thus subject to the bail-in tool, started trading with a positive spread over their control group, i.e. unsecured corporate bonds from the same issuers but maturing before 2016, following the introduction of the BRRD.

Figure 2.2 details the evolution of the median probabilities of default of the different sectors around the introduction of the BRRD. Similar to our results presented in the previous section, we do not find statistical evidence supporting the presence of a pre-event trend in default risk prior to the introduction of the policy. We observe a rather muted impact of the introduction of the policy package in the short-run followed by a substantial long-run reduction in both short- and long-term default risks in all sectors. The reduction in the 6-month PDs ranges from 2.09 bps for the consumer cyclical sector to 3.77 bps for the financial sector; and up to 4.78 bps for the industrial sector.[34] Decreases in the 5-year PDs are comprised between 9.30 bps for the consumer non-cyclical sector and 20.44 bps for the financial sector. These reductions in default risk are sizeable as a comparison with figures in Table 2.1 shows that they translate into decreases below median PD levels ranging respectively from 47% (technology sector) to 76% (financial sector) for

[34]The basic materials sector experiences substantial reductions in default risk — of respectively 9.62 bps and 46.5 for the 6-month and 5-year PDs — following the introduction of the BRRD. Given the magnitude of the impact relative to the one for the financial sector, which serves as our benchmark, we decided not to elaborate on these results in the body of the text as they are likely to be driven to some extent by external factors outside the scope of our analysis.

the 6-month DPs, and from 6.7% (technology sector) to 17.3% (financial sector) for the 5-year DPs.

The results for the financial sector are consistent with the findings in Cutura (2021) that the perceived credibility of the newly introduced bail-in framework led to increased market discipline and a decrease in banks' risk taking reflected in a reduction in balance sheet's exposures to impaired and non-performing loans.[35] Our results suggest that the resulting improvement in the quality of banks' balance sheets, which translates into reduced funding cost on BRRD-sensitive instruments, also leads to lower default risk at the sector level. As the BRRD credibly increased investors' expectations about the likelihood of bail-ins, our results also provide supporting evidence on how transitioning away from a bailout regime — and its associated implicit government guarantees — can reduce banks' risk taking and improve financial stability through a reduction in financial sector's default risk; see e.g. Dam and Koetter (2012) and Duchin and Sosyura (2014) for evidence on respectively how bailout expectations and actual government recapitalizations increase banks' risk taking and default risk due to moral hazard.

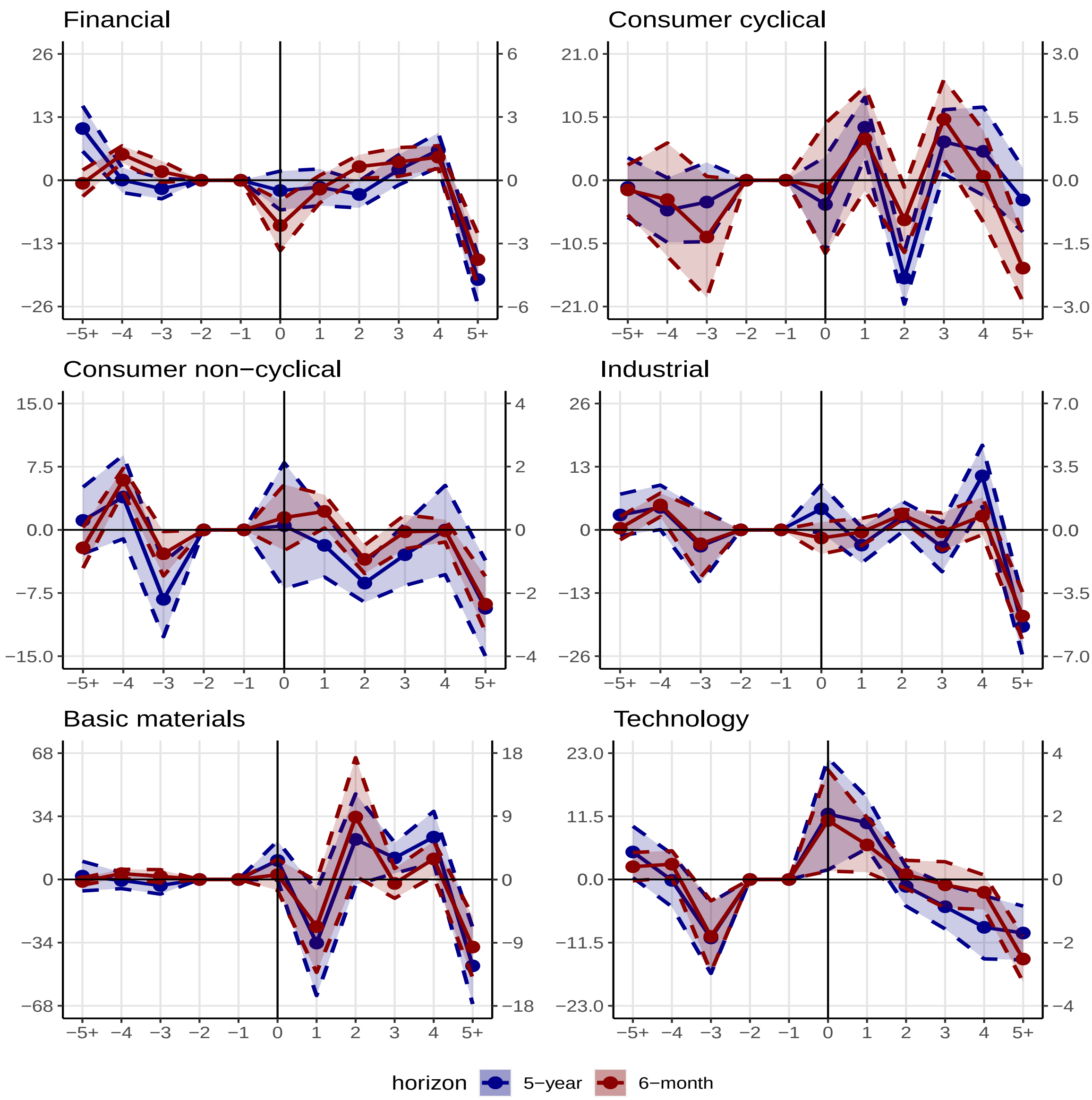
The positive impact of a strengthened resolution framework on financial stability spills over to the default risk of non-financial sectors of the economy. This result is consistent with the literature documenting how more resilient banks, as measured e.g. by their expected default frequency, are able to supply larger volumes of credit and can better insulate their credit supply from variations in the monetary policy stance and the macroeconomic environment (Altunbas et al., 2010; and Gambacorta and Mistrulli, 2014).[36] Our results thus suggest that the BRRD also had a positive impact on default risk in the non-financial sector through an improvement in access to credit resulting from the healthier balance sheet composition of the financial sector.

We provide the results for the robustness check on the subsamples of EA and non-EA countries in Figures 2.8 and 2.10 of Appendix 3.B. The main conclusions of our

[35] The author notes that the pattern is more pronounced for banks whose unsecured corporate bonds are more sensitive to the introduction of the BRRD, e.g. due to their lower capitalization levels.

[36] This effect is related to due to their better performance prospects and easier access to uninsured funding.

Figure 2.2: Impact of the introduction of BRRD



Note: This figure summarises the evolution of the median probabilities of default around the introduction of the BRRD package for the six sectors analysed. The event window captures a period of 10 quarters around the event (x-axis). The y-axes display the estimated coefficients for the event window as specified in equation (2.2). The results for the 5-year (6-month) default horizon are reported in blue (red) with corresponding value on the left-hand (right-hand) y-axis. The shaded areas around the point estimates correspond to the 68% confidence intervals constructed based on standard errors clustered at the country level. The estimation is carried out on the full sample of countries.

analysis are confirmed in both subsamples but we observe a lower level of precision in the estimates of the policy impact for the non-EA subsample. This result can be explained by the relatively smaller cross-section of countries available in this subsample and the higher degree of heterogeneity between them. The results set out in Sections 2.4.2 and 2.4.3 might be sensitive to our modelling choice of estimating each event separately. Particularly, pre-event variations prior to the introduction of BRRD might impact the assessment of the CRR/CRD IV package. Conversely, the impact of the CRR/CRD IV package on probabilities of default could introduce a local trend in the time series which impact the assessment of the BRRD reform. We argue that the main conclusions from the analysis are unlikely to be affected by our choice of modelling the events separately rather than jointly for two reasons. First, the specific features of the panel event-study setting outlined in Equations (2.2) and (2.3) make it robust to the potential impact of other events happening outside the event window considered. To see this, we first note that the definition of the treatment indicator in Equation (2.3) implies that the corresponding δ_j coefficients in Equation (2.2) capture the time-varying impact of the event within the window.[37] Any unmodelled sources of variations in probabilities of default across countries and time are captured respectively by the country (μ_c) and time (θ_t) fixed effects in Equation (2.2). This means that variations in PDs stemming from an event happening outside the window of the event being analyzed would be absorbed into the corresponding time fixed effect estimates. As a result, estimation results may be affected only in cases where the event windows of the different events overlap. In our case, this corresponds to the period ranging from June 2013 to September 2014; namely an overlap between the post CRR/CRD IV period and the pre-BRRD one. However, we have highlighted above that we do no find any statistical evidence supporting the existence of a pre-event trend in default risk prior to the introduction of BRRD. Therefore, we conclude that parameter estimates for the impact of the CRR/CRD IV introduction are unlikely to be affected by the pre-event

[37] As highlighted in Section 2.4.1, the use of a finite event window for identification purpose is equivalent to assuming that the impact of the event outside the window is constant and measured by $\delta_{\underline{j}}$ and $\delta_{\bar{j}}$ (resp. before/after).

period of the BRRD package.

Finally, it is useful to end this section by contrasting our results for the impact of the BRRD with the one obtained in Section 2.4.2 for the CRR/CRD IV package. Our analysis suggest that regulatory reforms incentivising banks' shareholders and creditors to monitor their risk-taking behaviour, such as the implementation of a credible bail-in framework for resolution, might be more effective in reducing default risk in the financial sector than measures targeting banks' loss-absorbing capacities through increased capital targets once the impact on the non-financial sectors of the economy is factored in. Indeed, the transmission of policy interventions to the default risk of the non-financial sectors is likely to be determined by how banks' credit supply is impacted by the policy. On the one hand, banks' react to higher capital requirements by reducing their RWA rather than increasing capital and the resulting reduction in credit supply increases default risk in non-financial sectors. On the other hand, the increased market discipline brought about by a strengthening in the resolution framework lowers banks' risk and increase their ability to supply credit, thereby contributing to a reduction in default risk of the non-financial sectors.

2.5 Conclusion

We provide a comprehensive analysis of the transmission of macroprudential regulation across both financial and non-financial sectors of the economy through the lens of its impact on short- and long-term probabilities of default at the sector level.

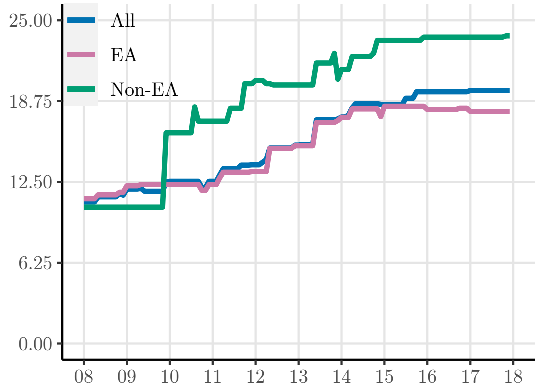
Combining a detailed database on macroprudential policies in European countries with data on probabilities of default for financial and non-financial sectors, we first investigate whether tighter macroprudential regulation also transmits to non-financial sectors of the economy and whether its impact is beneficial or detrimental. We find that tighter macroprudential regulation is beneficial to non-financial sectors of the economy on average and that the significance of the reduction in default risk — both economically and statistically — is comparable to the results obtained for the financial sector.

We then analyse how specific reforms in the macroprudential framework dynamically impact default risk in the financial and non-financial sectors. To this end, we study two important macroprudential reforms taking place at the European level: the phasing in of the Basel III standards on capital requirements, and the introduction of a resolution framework for failing banks. We find that higher capital requirements improve the resilience of the financial sector in the long run but at the cost of raising long-term default risk in non-financial sectors. On the contrary, a strengthening in the resolution framework has beneficial long-run effects on short- and long-term default risks of the financial and non-financial sectors. Our findings are consistent with papers documenting how banks adjust their balance sheet composition and credit supply in reaction to changes in their regulatory environment. However, an in-depth analysis of the effective channels of transmission is beyond the scope of the current paper and left for future research.

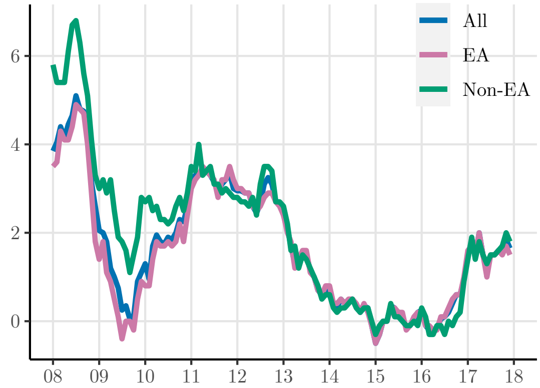
An important policy implication of our paper is that, although macroprudential regulation has on average beneficial effects on default risk in non-financial sectors, the impact of a policy reform can vary depending on the chosen instrument. Indeed, our results suggest that regulatory reforms incentivising better risk monitoring of banks by their shareholders and creditors might be more effective in reducing default risk in the financial sector than measures targeting banks' loss-absorbing capacities through increased capital targets — once the impact on default risk in the non-financial sectors default risk is taken into account. This is due to the fact that the transmission of a policy reform to the default risk of non-financial sectors is likely determined by how banks adjust their behaviour and credit supply in reaction to the policy change.

2.A Additional information on the data

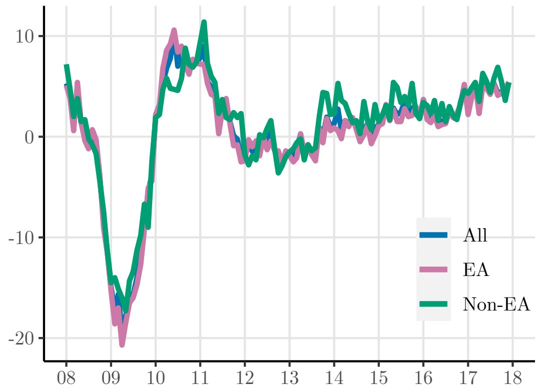
Figure 2.3: Explanatory variables



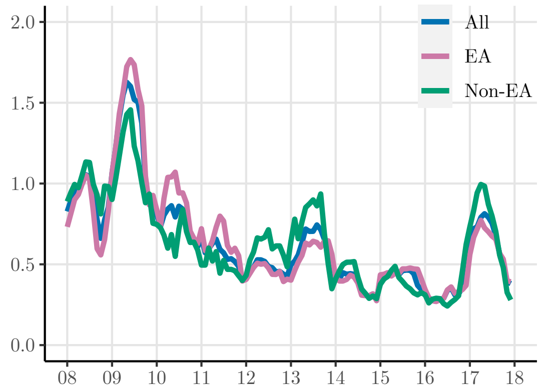
(a) MPI



(b) Inflation

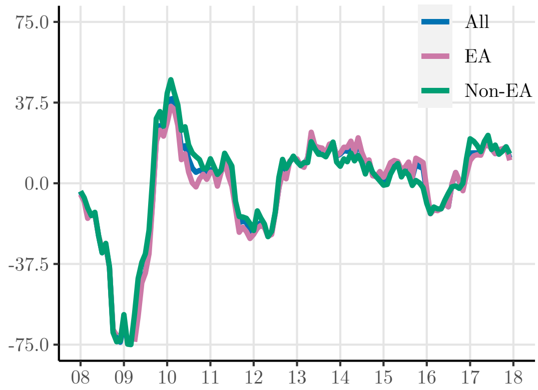


(c) Industrial production

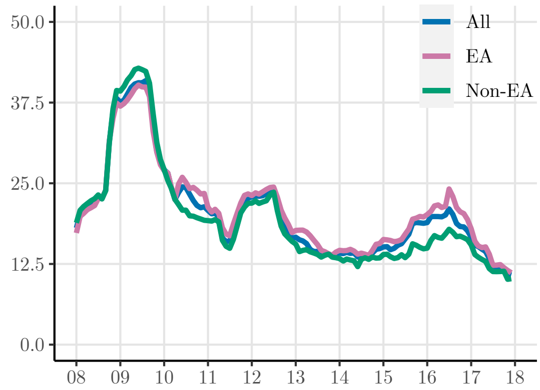


(d) Inflation volatility

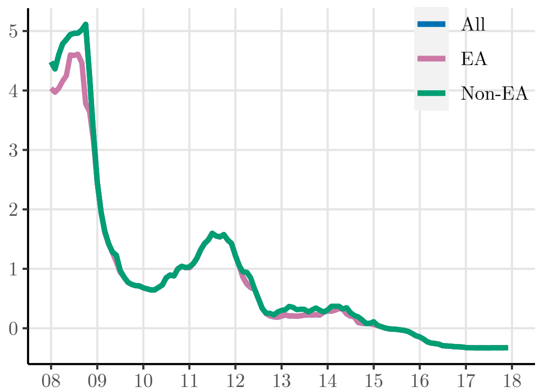
Figure 2.3 (Continued)



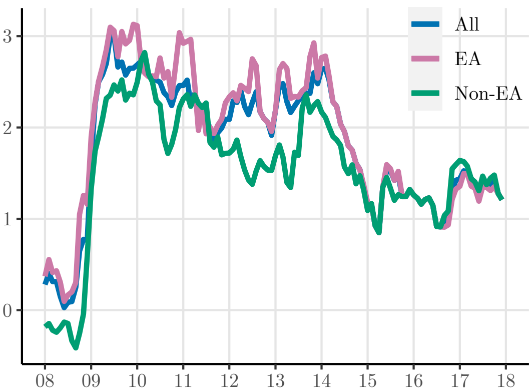
(e) Stock market return



(f) Stock market volatility



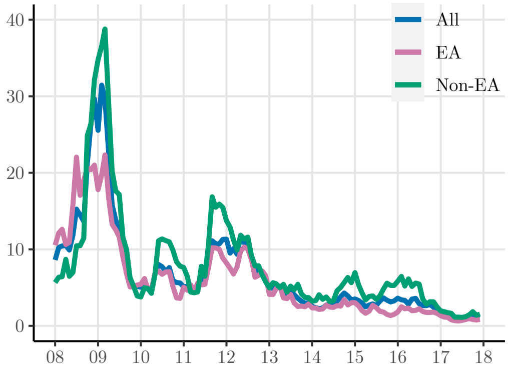
(g) Short rate



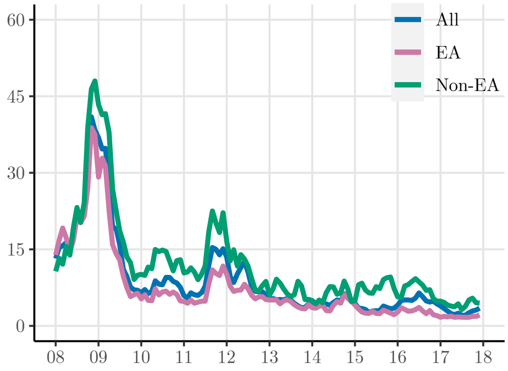
(h) Yield curve slope

Note: This figure plots the median value of each explanatory variable considered in the analysis across countries in a given reference group: All (blue line); EA countries (pink line); and Non-EA countries (green line).

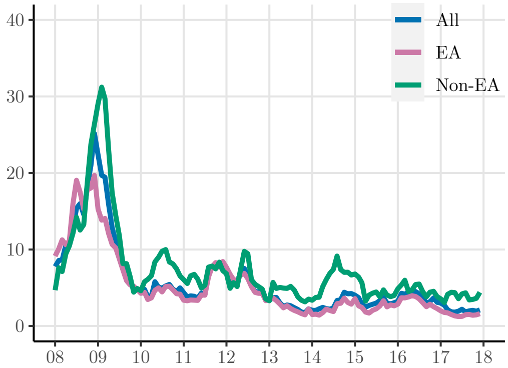
Figure 2.5: Probabilities of default at 6-month horizon for each sector



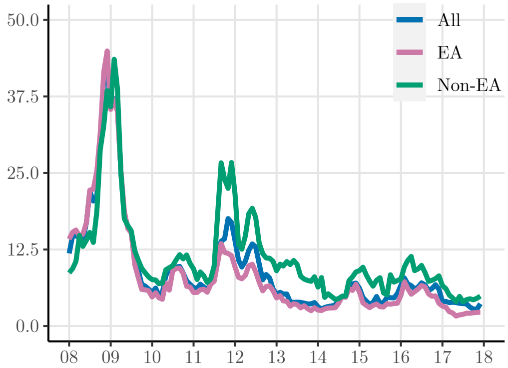
(a) Financial



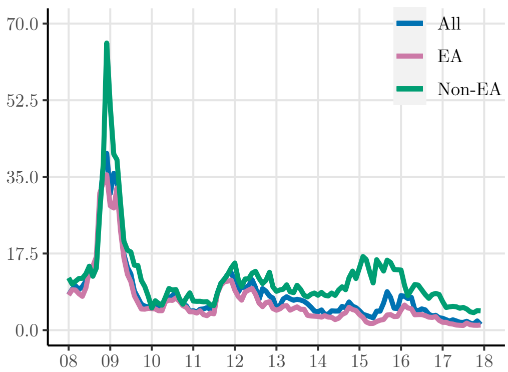
(b) Consumer cyclical



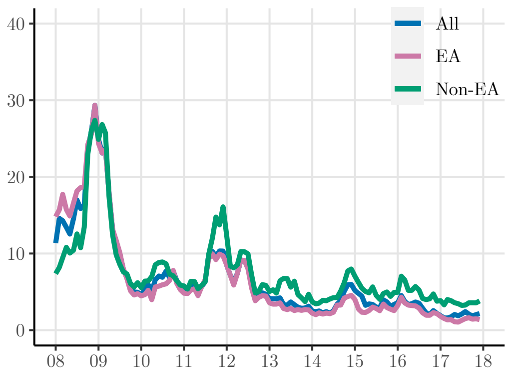
(c) Consumer non-cyclical



(d) Industrial



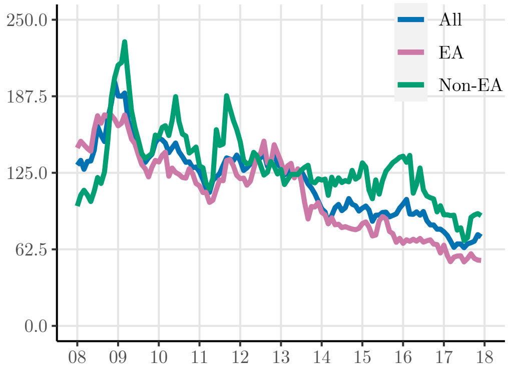
(e) Basic materials



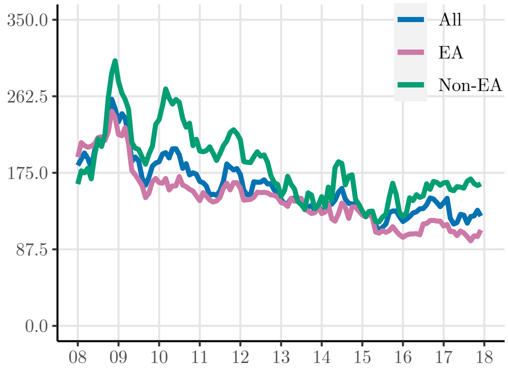
(f) Technology

Note: This figure plots the median value of the 6-month probability of default for each sector considered in the analysis (in basis points). The median is computed across countries in a given reference group: All (blue line); EA countries (pink line); and Non-EA countries (green line).

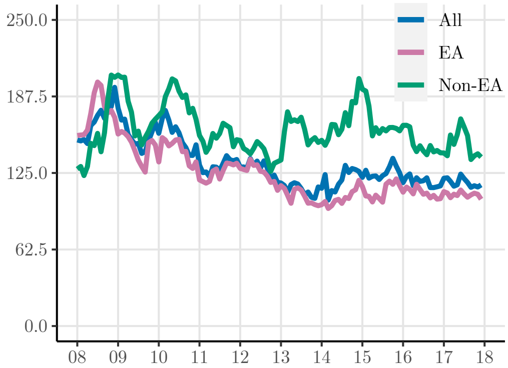
Figure 2.6: Probabilities of default at 5-year horizon for each sector



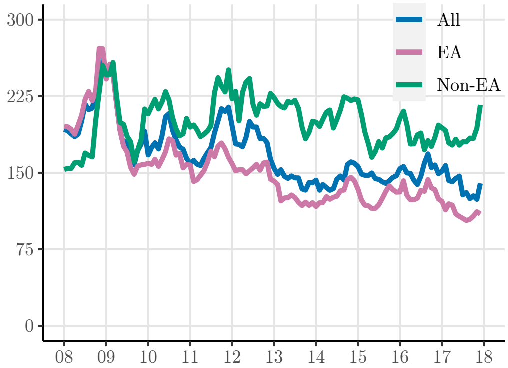
(a) Financial



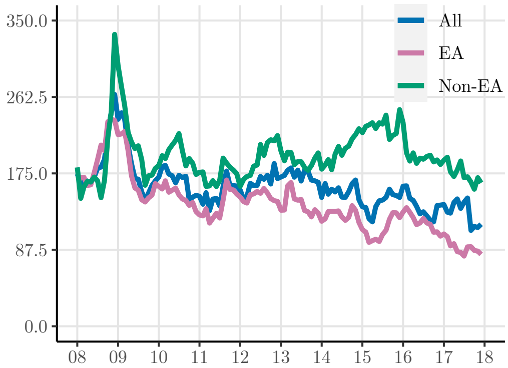
(b) Consumer cyclical



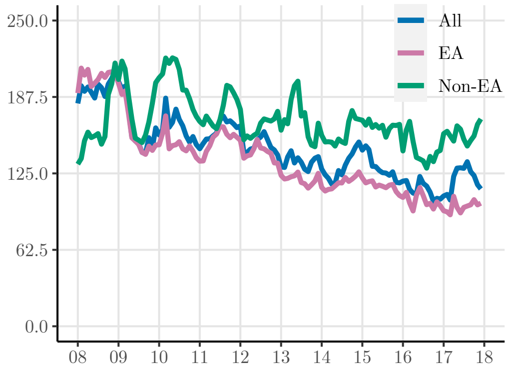
(c) Consumer non-cyclical



(d) Industrial



(e) Basic materials



(f) Technology

Note: This figure plots the median value of the 5-year probability of default for each sector considered in the analysis (in basis points). The median is computed across countries in a given reference group: All (blue line); EA countries (pink line); and Non-EA countries (green line).

2.B Dynamic linear panel model: simulation study on the performance of the OLS and GMM estimators

This section provides simulation evidence supporting the choice of the Least Squares estimator in our analysis given the long time series dimension of our data ($T = 120$ months). Indeed, the OLS estimator of the dynamic linear panel model with fixed effects is biased and inconsistent in settings with a short time series dimension ("*small T case*") where lags of the dependent variable are included as regressors — a phenomenon known as the Nickell (1981) bias. To investigate the potential impact of the Nickell bias on the results from our main analysis in Section 2.3.2, we focus on a first-order panel autoregression with unit-specific fixed effects in our simulation study:

$$y_{i,t} = \rho_0 y_{i,t-1} + \alpha_i + \varepsilon_{i,t}, \tag{2.4}$$

where $\alpha_i \sim \mathcal{N}(\mu_i, \sigma_i)$ is a unit-specific fixed effect, and $\varepsilon_{i,t} \sim \mathcal{N}(0, \sigma_\varepsilon)$ is an i.i.d. normal error term.[38] We will compare the performance of the OLS estimator with the one-step efficient difference GMM estimator of Arellano and Bond (1991), whose estimates will be denoted by $\hat{\rho}_{AB}$, which is tailored to the estimation of dynamic linear panel models with fixed effects in settings with *small T* and *large N*.

We consider a cross-sectional dimension of $N = 28$, which corresponds to the full set of countries in our empirical application, and time series dimensions $T \in \{12,\ 24,\ 36,\ 48,\ 60\}$. We also consider the implications of different degrees of time series persistence $\rho_0 \in \{0.6,\ 0.8,\ 0.95\}$. The moments for the distributions of the unit-specific fixed effects α_i and error terms $\varepsilon_{i,t}$ are calibrated based on the estimation results for the 5-year default probability of the financial sector (all countries) reported in Table 2.3 of Section 2.3.2. Finally, the Monte Carlo results for each data generating process (DGP) considered in the

[38] Note that we refrain from considering data generating processes with stationary covariates as Phillips and Sul (2007) show in their Proposition 2 that the bias of OLS coefficient estimates for exogenous covariates in dynamic panel models is smaller than for autoregressive coefficients.

tables below is based on $B = 10,000$ replications and each unit-specific simulated sample is initialized at the unconditional mean of the 5-year default probability of the financial sector (Table 2.1, Panel A) with a burn-in period of 0.5 T.

For each design, we evaluate the performance of the OLS and GMM estimators based on their bias, mean-squared error (MSE), and the variance (Var) of their distribution $\hat{\rho} - \rho_0$:

$$\widehat{\text{bias}}\,[\hat{\rho}] = \frac{1}{B}\sum_{b=1}^{B} \hat{\rho}_b - \rho_0 \ ,$$

$$\widehat{\text{MSE}}\,[\hat{\rho}] = \frac{1}{B}\sum_{b=1}^{B} (\hat{\rho}_b - \rho_0)^2 \ ,$$

$$\widehat{\text{Var}}\,[\hat{\rho}] = \widehat{\text{MSE}}\,[\hat{\rho}] - \left(\widehat{\text{bias}}\,[\hat{\rho}]\right)^2 \ .$$

Table 2.4 summarises the simulation results for DGPs with an autoregressive coefficient of $\rho_0 = 0.6$. We observe that parameter estimates are severely downward biased for small time series lengths, with the GMM estimator performing better than the OLS one. For $T = 12$, the GMM estimator also exhibits lower MSE but much higher distributional variance than its OLS counterpart. However, this only applies for small values of T as the OLS estimator is already performing better than the GMM one in terms of bias for $T = 24$, while also exhibiting lower MSE and variance. As T increases, the bias, MSE, and variance continue to decrease for both the OLS and GMM estimators — but with the OLS one still outperforming its GMM counterpart.

Tables 2.5 and 2.6 document the impact of more persistent time series dynamics, with the coefficient ρ_0 taking values of respectively 0.8 and 0.95. Higher levels of persistence appear to be particularly detrimental to the bias of the OLS estimator for small T. Particularly, the bias of the OLS estimator is still larger than the GMM one for $T = 24$ and $\rho_0 = 0.95$, though OLS still exhibits lower variance. Overall, OLS parameter estimates have smaller bias, MSE, and variance than the GMM ones in settings with larger T.

A comparison of the relative performance of the OLS and GMM estimators in settings with larger T is complicated by the fact that the Arellano and Bond (1991) one-step

Table 2.4: Simulation results: $\rho_0 = 0.6$

	Bias		MSE		Var	
T	$\hat{\rho}_{OLS}$	$\hat{\rho}_{AB}$	$\hat{\rho}_{OLS}$	$\hat{\rho}_{AB}$	$\hat{\rho}_{OLS}$	$\hat{\rho}_{AB}$
12	−0.165	−0.120	0.030	0.021	0.0027	0.0064
24	−0.091	−0.092	0.009	0.010	0.0012	0.0019
36	−0.066	−0.073	0.005	0.006	0.0008	0.0010
48	−0.055	−0.059	0.004	0.004	0.0006	0.0006
60	−0.047	−0.050	0.003	0.003	0.0004	0.0005

Note: Data generated as $y_{i,t} = \rho_0 y_{i,t-1} + \alpha_i + \varepsilon_{i,t}$ with $\alpha_i \sim \mathcal{N}(\mu_i, \sigma_i)$, $\varepsilon_{i,t} \sim \mathcal{N}(0, \sigma_\varepsilon)$, and $y_{i,0}$ initialized at the unconditional mean of the 5-year default probability of the financial sector (all countries). The columns report the bias, mean-squared error (MSE), and distribution variance (Var) for the OLS ($\hat{\rho}_{OLS}$) and one-step efficient difference GMM ($\hat{\rho}_{AB}$) estimators.

Table 2.5: Simulation results: $\rho_0 = 0.8$

	Bias		MSE		Var	
T	$\hat{\rho}_{OLS}$	$\hat{\rho}_{AB}$	$\hat{\rho}_{OLS}$	$\hat{\rho}_{AB}$	$\hat{\rho}_{OLS}$	$\hat{\rho}_{AB}$
12	−0.187	−0.175	0.037	0.040	0.0024	0.0093
24	−0.093	−0.107	0.010	0.013	0.0009	0.0019
36	−0.062	−0.077	0.004	0.007	0.0005	0.0008
48	−0.047	−0.055	0.003	0.004	0.0004	0.0005
60	−0.038	−0.043	0.002	0.002	0.0003	0.0003

Note: Data generated as $y_{i,t} = \rho_0 y_{i,t-1} + \alpha_i + \varepsilon_{i,t}$ with $\alpha_i \sim \mathcal{N}(\mu_i, \sigma_i)$, $\varepsilon_{i,t} \sim \mathcal{N}(0, \sigma_\varepsilon)$, and $y_{i,0}$ initialized at the unconditional mean of the 5-year default probability of the financial sector (all countries). The columns report the bias, mean-squared error (MSE), and distribution variance (Var) for the OLS ($\hat{\rho}_{OLS}$) and one-step efficient difference GMM ($\hat{\rho}_{AB}$) estimators.

Table 2.6: Simulation results: $\rho_0 = 0.95$

	Bias		MSE		Var	
T	$\hat{\rho}_{OLS}$	$\hat{\rho}_{AB}$	$\hat{\rho}_{OLS}$	$\hat{\rho}_{AB}$	$\hat{\rho}_{OLS}$	$\hat{\rho}_{AB}$
12	−0.109	−0.050	0.013	0.004	0.0011	0.0019
24	−0.064	−0.059	0.005	0.004	0.0004	0.0008
36	−0.052	−0.064	0.003	0.005	0.0002	0.0005
48	−0.044	−0.058	0.002	0.004	0.0002	0.0003
60	−0.038	−0.052	0.002	0.003	0.0001	0.0002

Note: Data generated as $y_{i,t} = \rho_0 y_{i,t-1} + \alpha_i + \varepsilon_{i,t}$ with $\alpha_i \sim \mathcal{N}(\mu_i, \sigma_i)$, $\varepsilon_{i,t} \sim \mathcal{N}(0, \sigma_\varepsilon)$, and $y_{i,0}$ initialized at the unconditional mean of the 5-year default probability of the financial sector (all countries). The columns report the bias, mean-squared error (MSE), and distribution variance (Var) for the OLS ($\hat{\rho}_{OLS}$) and one-step efficient difference GMM ($\hat{\rho}_{AB}$) estimators.

efficient GMM estimator is well suited to settings with small T and large N but becomes intractable for larger T. The reason is that the number of valid instruments, which is period specific, grows quadratically with T.[39] Therefore, we also provide in Table 2.7 Monte Carlo simulation results for the OLS estimator with T ranging from 72 to 120. We observe that the size of the downward bias continues to shrink as the length of the time series dimension increases. For $T = 120$, the bias ranges from 2% to 5.5% of the parameter value depending on the level of time series persistence in the simulation design.

Overall, these simulation evidence confirm that the OLS estimator of the dynamic linear panel model with fixed effects is appropriate for our empirical application with a long time series dimension ($T = 120$ months) and performs better than the GMM estimator in terms of bias, MSE, and variance.

[39] A workaround used in empirical applications is to restrict the number of instruments used in the GMM estimation. However, we do not pursue this avenue in the current simulation exercise as the results would become sensitive to the number of included instruments and, thus, be less informative.

Table 2.7: Simulation results: OLS estimator with $T \in [72, 120]$

T	Bias	MSE	Var
Panel A: $\rho_0 = 0.6$			
72	−0.04246	0.00217	0.00036
84	−0.03904	0.00184	0.00031
96	−0.03654	0.00161	0.00027
108	−0.03426	0.00142	0.00024
120	−0.03281	0.00130	0.00022
Panel B: $\rho_0 = 0.8$			
72	−0.03259	0.00129	0.00023
84	−0.02871	0.00101	0.00019
96	−0.02557	0.00082	0.00016
108	−0.02332	0.00069	0.00014
120	−0.02159	0.00059	0.00013
Panel C: $\rho_0 = 0.95$			
72	−0.03235	0.00115	0.00010
84	−0.02815	0.00088	0.00008
96	−0.02447	0.00066	0.00007
108	−0.02180	0.00053	0.00006
120	−0.01949	0.00043	0.00005

Note: Data generated as $y_{i,t} = \rho_0 y_{i,t-1} + \alpha_i + \varepsilon_{i,t}$ with $\alpha_i \sim \mathcal{N}(\mu_i, \sigma_i)$, $\varepsilon_{i,t} \sim \mathcal{N}(0, \sigma_\varepsilon)$, and $y_{i,0}$ initialized at the unconditional mean of the 5-year default probability of the financial sector (all countries). The columns report the bias, mean-squared error (MSE), and distribution variance (Var) for the OLS ($\hat{\rho}_{OLS}$) estimator.

2.C Dynamic linear panel model: model selection and specification analysis

This section carries out a model specification analysis on the specification used for the main results reported in Section 2.3.2, namely the model in Equation (2.1) with 3 lags of the default probability variable. To this end, we adopt the bias-corrected tests for serial correlation in panel models with fixed effects introduced in Born and Breitung (2016). The authors propose a Lagrange Multiplier (LM) test for zero autocorrelation at lag k, $\widetilde{LM}_k^*$; a Wald test for the hypothesis that the errors are not autocorrelated up to order p, $\widetilde{Q}(p)$; and a test for first-order serial correlation which is robust against time-dependent heteroskedasticity, $\widetilde{HR}$. Note that all tests are based on the estimated residuals augmented with the fixed effect:

$$\begin{aligned}\hat{e}_{c,t} &= PD_{c,t} - \sum_{l=1}^{L} \hat{\rho}_l PD_{c,t-l} - \hat{\delta} MPI_{c,t-1} - \sum_{k=1}^{K} \hat{\beta}_k X_{k,c,t-1} \\ &= \hat{\eta}_c + \hat{\varepsilon}_{c,t} \end{aligned} \tag{2.5}$$

The heteroskedasticity-robust $\widetilde{HR}$ statistic to test for first-order serial correlation is given by the following expression:

$$\begin{aligned}\widetilde{HR} &= \frac{\sum_{i=1}^{N} \hat{z}_{T,i}}{\sqrt{\sum_{i=1}^{N} \hat{z}_{T,i}^2 - \frac{1}{N}(\sum_{i=1}^{N} \hat{z}_{T,i})^2}} \ , \\ \hat{z}_{T,i} &= \sum_{t=3}^{T-1} \tilde{e}_{i,t}^f \tilde{e}_{i,t-1}^b \ , \\ \tilde{e}_{i,t}^f &= \hat{e}_{i,t} - \frac{1}{T-t+1} \left(\hat{e}_{i,t} + \ldots + \hat{e}_{i,T} \right) \ , \\ \tilde{e}_{i,t}^b &= \hat{e}_{i,t} - \frac{1}{t} \left(\hat{e}_{i,1} + \ldots + \hat{e}_{i,t} \right) \ ,\end{aligned} \tag{2.6}$$

and has a standard normal limiting distribution under the null hypothesis of zero first-order autocorrelation. The LM statistic to test for zero autocorrelation at lag k is given by the following expression:

$$\widetilde{LM}_k^* = \frac{\sum_{i=1}^{N} z_{k,i}}{\sqrt{\sum_{i=1}^{N} z_{k,i}^2 - \frac{1}{N}(\sum_{i=1}^{N} z_{k,i})^2}} \ , \tag{2.7}$$

$$z_{k,i} = \sum_{t=k+1}^{T} \left\{ (e_{i,t} - \bar{e}_{i,t})(e_{i,t-k} - \bar{e}_{i,t}) + \frac{1}{T-1}(e_{i,t-k} - \bar{e}_{i,t})^2 \right\} \ ,$$

and has a standard normal limiting distribution under the null hypothesis of zero autocorrelation at lag k. Finally, the Wald statistic to test for the hypothesis that the errors are not autocorrelated up to order p is given by the following expression:

$$\widetilde{Q}(p) = \left(\sum_{i=1}^{N} A_i\right) \left\{ \left(\sum_{i=1}^{N} A_i^\intercal A_i\right) - \frac{1}{N} \left(\sum_{i=1}^{N} A_i^\intercal\right) \left(\sum_{i=1}^{N} A_i\right) \right\}^{-1} \left(\sum_{i=1}^{N} A_i^\intercal\right) \ , \tag{2.8}$$

$$A_i = \hat{e}_i^\intercal M Z_i \ , \ Z_i = \left(L_1 \hat{e}_i, \ldots, L_p \hat{e}_i\right) \ , \ M = I_T - \frac{1}{T}\iota_T \iota_T^\intercal \ ,$$

$$L_k \hat{e}_i = \begin{pmatrix} 0_k \\ \hat{e}_{i,1} - \bar{e}_i \\ \vdots \\ \hat{e}_{i,T-k} - \bar{e}_i \end{pmatrix} + \left(\frac{T-k}{T^2 - T}\right) \hat{e}_i \ ,$$

and has a χ^2 limiting distribution with p degrees of freedom under the null hypothesis that the errors are not autocorrelated up to order p.

Tables 2.8 and 2.9 report the p-values from the tests carried out on the residuals obtained from our main specification with 3 lags estimated in Section 2.3.2. We see in the first row of Table 2.8 that we fail to reject the null hypothesis of no first-order serial correlation for all sectors and default horizons. Turning now to the LM test of serial correlation of order k, we fail to reject the null hypothesis of no serial correlation at the 5% significance level in the majority of the cases when lag orders from 1 to 12 are considered.[40]

[40] Exceptions include basic material ($k = 11$), financial ($k = 10$), consumer non-cyclical ($k = 5$), and consumer cyclical ($k \in \{5, 6, 10\}$) at the 6-month default horizon. For the 5-year default horizon, the exceptions are consumer non-cyclical ($k = 5$), basic material ($k \in \{4, 11\}$), financial ($k \in \{4, 6\}$), and consumer cyclical ($k \in \{4, 6, 10\}$).

Table 2.8: Test of serial correlation of order k: main specification

	Financial		Cons. cycl.		Cons. n-cycl.		Industrial		Basic mat.		Technology	
	6-M	5-Y	6-M	5-Y	6-M	5-Y	6-M	5-Y	6-M	5-Y	6-M	5-Y
$\widetilde{HR}$	0.350	0.782	0.965	0.954	0.616	0.770	0.812	0.741	0.991	0.978	0.767	0.712
$\widetilde{LM}^*_1$	0.278	0.695	0.858	0.877	0.705	0.846	0.777	0.636	0.783	0.730	0.910	0.984
$\widetilde{LM}^*_2$	0.591	0.833	0.820	0.943	0.906	0.948	0.550	0.424	0.821	0.930	0.827	0.656
$\widetilde{LM}^*_3$	0.074	0.195	0.131	0.179	0.206	0.190	0.138	0.105	0.288	0.070	0.620	0.753
$\widetilde{LM}^*_4$	0.256	0.045	0.115	0.026	0.913	0.739	0.346	0.156	0.083	0.020	0.532	0.665
$\widetilde{LM}^*_5$	0.356	0.580	0.043	0.175	0.015	0.045	0.694	0.707	0.520	0.342	0.266	0.186
$\widetilde{LM}^*_6$	0.094	0.010	0.033	0.001	0.120	0.091	0.179	0.247	0.514	0.485	0.828	0.340
$\widetilde{LM}^*_7$	0.856	0.502	0.334	0.364	0.514	0.445	0.058	0.283	0.528	0.419	0.851	0.489
$\widetilde{LM}^*_8$	0.916	0.867	0.384	0.886	0.800	0.849	0.340	0.469	0.235	0.288	0.151	0.994
$\widetilde{LM}^*_9$	0.162	0.126	0.897	0.432	0.382	0.552	0.207	0.630	0.289	0.250	0.848	1.00
$\widetilde{LM}^*_{10}$	0.035	0.051	0.022	0.005	0.349	0.134	0.115	0.289	0.276	0.337	0.964	0.770
$\widetilde{LM}^*_{11}$	0.778	0.954	0.386	0.515	0.621	0.544	0.386	0.538	0.044	0.004	0.410	0.856
$\widetilde{LM}^*_{12}$	0.903	0.454	0.052	0.679	0.867	0.208	0.298	0.922	0.602	0.170	0.515	0.748

Note: The table reports the p-values for the heteroskedasticity-robust test of first order serial correlation, $\widetilde{HR}$, and the Lagrange Multiplier test of serial correlation at order k, $\widetilde{LM}^*_k$, which were both introduced in Born and Breitung (2016). The columns cover the results for each sector at default horizons of 6 months and 5 years. All the models are estimated on the full sample of countries with data from 2008 to 2017.

Table 2.9: Test of serial correlation up to order p: main specification

	Financial		Cons. cycl.		Cons. n-cycl.		Industrial		Basic mat.		Technology	
	6-M	5-Y	6-M	5-Y	6-M	5-Y	6-M	5-Y	6-M	5-Y	6-M	5-Y
$\widetilde{Q}(1)$	0.279	0.696	0.859	0.879	0.707	0.847	0.777	0.637	0.882	0.790	0.911	0.984
$\widetilde{Q}(2)$	0.511	0.866	0.919	0.982	0.927	0.982	0.165	0.424	0.839	0.180	0.969	0.866
$\widetilde{Q}(3)$	0.049	0.031	0.120	0.106	0.099	0.034	0.157	0.384	0.691	0.053	0.937	0.820
$\widetilde{Q}(4)$	0.072	0.023	0.124	0.078	0.044	0.069	0.059	0.293	0.319	0.010	0.348	0.662
$\widetilde{Q}(5)$	0.053	0.044	0.00	0.008	0.026	0.045	0.008	0.022	0.057	0.00	0.247	0.583
$\widetilde{Q}(6)$	0.089	0.028	0.00	0.00	0.046	0.055	0.007	0.008	0.012	0.00	0.215	0.692
$\widetilde{Q}(7)$	0.003	0.007	0.00	0.00	0.037	0.069	0.010	0.003	0.00	0.00	0.248	0.734
$\widetilde{Q}(8)$	0.00	0.00	0.00	0.00	0.057	0.034	0.000	0.001	0.00	0.00	0.002	0.820
$\widetilde{Q}(9)$	0.00	0.00	0.00	0.00	0.082	0.038	0.000	0.002	0.00	0.00	0.00	0.844
$\widetilde{Q}(10)$	0.00	0.00	0.00	0.00	0.078	0.001	0.000	0.003	0.00	0.00	0.00	0.014
$\widetilde{Q}(11)$	0.00	0.00	0.00	0.00	0.007	0.001	0.00	0.00	0.00	0.00	0.00	0.021
$\widetilde{Q}(12)$	0.00	0.00	0.00	0.00	0.002	0.00	0.00	0.00	0.00	0.00	0.00	0.006

Note: The table reports the p-values for the test of serial correlation up to order p, $\widetilde{Q}(p)$, introduced in Born and Breitung (2016). The columns cover the results for each sector at default horizons of 6 months and 5 years. All the models are estimated on the full sample of countries with data from 2008 to 2017.

Table 2.9 reports the p-values of the Wald test of serial correlation up to order p, where we also consider lag orders ranging from 1 to 12 lags. Focusing first on the 6-month default horizon, we fail to reject at the 5% significance level the null hypothesis of no serial correlation up to lag order 4 in the majority of the cases.[41] However, the results provide supporting statistical evidence for the presence of autocorrelation at cumulative lag orders ranging from 5 to 12. The results for the 5-year default horizon are broadly comparable, with an absence of statistical evidence against the null hypothesis for lag orders up to 4 in the majority of the cases (5% significance level), but strong evidence supporting the rejection of the null hypothesis of no serial correlation for larger lag orders.[42]

Motivated by these statistical evidence, we investigate the sensitivity of the main results reported in Section 2.3.2 to the choice of the lag length for the estimation of Equation (2.1), and the potential impact of residual autocorrelation on the inference conducted on the estimated model parameters. Table 2.10 reports the Bayesian information criterion (BIC) obtained by estimating the model in Equation (2.1) for each sector and default horizon with lag orders ranging from 1 to 13. The BIC is minimized for lag orders ranging from 5 to 7 in the majority of the cases. Notable exceptions are the basic material and financial (5-year horizon) sectors for which the BIC is minimized at lag orders of 10-11. Data for the technology sector, on the other hand, seem to be appropriately modelled by a specification with 2 lags of the default probability variable.

Table 2.11 reports the parameter estimates obtained for each sector based on the model specification minimizing the BIC.[43] First, we observe that a tightening in the MPI significantly decreases the 5-year default probability (DP) of the financial sector — with a short-run impact of -0.417 bps and a 4.05 bps decrease in the long run. Our results also confirm the lack of statistical evidence supporting an impact of macroprudential regulation

[41] The two exceptions are the financial sector ($p = 3$) and the consumer non-cyclical sector ($p = 4$).

[42] Exceptions for lag orders ≤ 4 are the basic material ($p = 4$), consumer non-cyclical ($p = 3$), and financial ($p \in \{3, 4\}$) sectors.

[43] In the interest of conciseness, we focus on the results for the full set of countries but the conclusions from our main analysis in Section 2.3.2 also remain broadly valid for the subsamples of EA and non-EA countries.

on short-term default risk, measured by the 6-month DP. Second, coefficient estimates for the MPI in non-financial sectors confirm that tighter macroprudential regulation also significantly decreases default risk in these sectors. The short-run impact from a unit change in the MPI on the 5-year DP ranges from -0.25 bps (consumer cyclical sector) to -0.445 bps (industrial sector). The corresponding long-run impact ranges from -2.12 bps to -4.31 bps. The results reported in Table 2.11 also confirm the positive contribution of a better economic outlook, measured by IP, to the reduction of short- and long-term default risk in the financial and consumer cyclical sectors. Coefficient estimates for the yield curve slope, stock market returns, and inflation are also in line with the results of Section 2.3.2. This analysis confirms that our main conclusions regarding the significance and magnitude of the impact of macroprudential regulation — and of other predictors — on default risk are robust to the choice of different lag orders in the specification of the model in Equation (2.1).

We further investigate the potential impact of residual autocorrelation on the inference conducted on the estimated model parameters by reporting in Tables 2.12 and 2.13 the p-values from the tests carried out on the residuals obtained from the specifications minimizing the BIC. The first row of Table 2.12 confirms that we fail to reject the null hypothesis of no first-order serial correlation at conventional significance levels for all sectors and default horizons. For the LM test of serial correlation of order k, we fail to reject the null hypothesis of no serial correlation at the 5% significance level in almost all the cases when lag orders from 1 to 12 are considered.[44] Table 2.13 reports the p-values of the Wald test of serial correlation up to order p, with lag orders ranging from 1 to 12 lags. For the 6-month default horizon, we fail to reject at the 5% significance level the null hypothesis of no serial correlation up to lag order 7 in the majority of the cases.[45] We still find supporting statistical evidence for the presence of autocorrelation at cumulative lag orders ranging from 8 to 12. For the 5-year default horizon, we observe an absence of statistical evidence against the null hypothesis for lag orders up to 9 in the majority

[44] Exceptions include the industrial sector ($k = 11$) at the 6-month default horizon; and the consumer cyclical ($k = 10$) and basic material ($k = 11$) sectors at the 5-year default horizon.

[45] The two exceptions are the consumer cyclical sector ($p = 6$) and the industrial sector ($p = 7$).

of the cases (5% significance level), but still find evidence supporting the rejection of the null hypothesis at cumulative lag orders ranging from 10 to 12.[46]

Taken together, these evidence lead us to conclude that statistical inference on the parameter estimates reported in Table 2.11 is unlikely to be impacted by residual autocorrelation. This therefore reinforces our assessment on the robustness of the key results from the main analysis reported in Section 2.3.2.

[46]Exceptions for lag orders ≤ 9 are the basic material ($p = 8$) and financial ($p = 9$) sectors.

Table 2.10: Model selection based on information criteria

	Financial		Cons. cycl.		Cons. n-cycl.		Industrial		Basic mat.		Technology	
	6-M	5-Y	6-M	5-Y	6-M	5-Y	6-M	5-Y	6-M	5-Y	6-M	5-Y
Lag order = 1	23575	28811	17252	24352	16227	24724	18878	25703	17295	23268	11322	18560
Lag order = 2	23017	28443	17166	24315	15988	24604	18806	25646	17013	23081	**11234**	**18527**
Lag order = 3	22613	28227	17173	24323	15990	24607	18796	25649	16727	22952	11240	18532
Lag order = 4	22487	28214	17162	24320	15989	24613	18639	25618	16734	22960	11245	18537
Lag order = 5	**22485**	28215	17109	24301	15993	24621	18599	**25591**	16739	22965	11249	18545
Lag order = 6	22491	28219	**17103**	24303	15947	24612	**18585**	25598	16732	22945	11256	18551
Lag order = 7	22499	28225	17105	**24298**	**15912**	**24592**	18592	25606	16713	22935	11263	18558
Lag order = 8	22500	28221	17113	24306	15914	24599	18595	25612	16719	22923	11271	18566
Lag order = 9	22508	28224	17121	24312	15921	24605	18601	25617	16726	22912	11277	18573
Lag order = 10	22513	**28204**	17127	24316	15927	24613	18608	25624	16724	22918	11283	18580
Lag order = 11	22521	28206	17133	24323	15933	24614	18616	25628	**16688**	**22888**	11291	18587
Lag order = 12	22528	28213	17141	24331	15941	24619	18621	25636	16689	22894	11298	18591
Lag order = 13	22536	28221	17147	24339	15947	24627	18628	25644	16695	22902	11295	18589

Note: The table reports the Bayesian information criterion (BIC) for each sector at default horizons of 6 months and 5 years. Each panel corresponds to a different lag order for the probability of default, ranging from 1 to 13, and all the models are estimated on the full sample of countries with data from 2008 to 2017.

Table 2.11: Estimation results for the specification minimizing the BIC

	Financial		Cons. cycl.		Cons. n-cycl.		Industrial		Basic mat.		Technology	
	6-M	5-Y	6-M	5-Y	6-M	5-Y	6-M	5-Y	6-M	5-Y	6-M	5-Y
MPI	−0.075	−0.417*	−0.103***	−0.250*	−0.029	−0.077	−0.170***	−0.445***	−0.088	−0.654**	−0.101***	−0.328*
	(0.071)	(0.216)	(0.035)	(0.138)	(0.025)	(0.106)	(0.044)	(0.133)	(0.060)	(0.290)	(0.027)	(0.170)
Inf	0.585***	1.62***	0.341***	1.10***	0.258***	0.640***	0.288***	0.824***	0.427***	0.718*	0.196***	0.562*
	(0.218)	(0.459)	(0.095)	(0.314)	(0.068)	(0.240)	(0.081)	(0.254)	(0.156)	(0.405)	(0.054)	(0.308)
IP	−0.044***	−0.197***	−0.027**	−0.097*	0.002	0.025	−0.025	−0.084	−0.006	−0.021	−0.006	−0.014
	(0.016)	(0.056)	(0.014)	(0.057)	(0.011)	(0.051)	(0.018)	(0.060)	(0.021)	(0.088)	(0.009)	(0.053)
InfVol	−0.649	−1.91*	−0.066	0.412	−0.183	−0.565	−0.643*	−1.94	−0.813*	−3.04*	−0.235	0.701
	(0.394)	(0.970)	(0.381)	(1.24)	(0.174)	(0.882)	(0.385)	(1.18)	(0.448)	(1.57)	(0.225)	(1.21)
StockRet	−0.025	−0.013	−0.013**	0.030*	−0.005	0.025*	−0.014*	0.029	−0.027**	−0.022	−0.015***	0.022
	(0.015)	(0.019)	(0.006)	(0.018)	(0.005)	(0.015)	(0.008)	(0.020)	(0.013)	(0.039)	(0.005)	(0.019)
StockRetVol	0.009	0.036	0.004	0.070	0.001	0.050	0.006	0.058	−0.024	−0.094	−0.050***	−0.079
	(0.024)	(0.062)	(0.018)	(0.066)	(0.011)	(0.057)	(0.021)	(0.068)	(0.032)	(0.121)	(0.013)	(0.064)
ΔShortRate	−0.054	−0.402	−0.070	−0.714	−0.251	−0.779	−0.417	−1.65	0.195	0.386	0.086	0.461
	(0.477)	(1.54)	(0.317)	(1.02)	(0.215)	(0.866)	(0.338)	(1.08)	(0.561)	(1.91)	(0.385)	(1.43)
Slope	−0.489**	−1.20*	−0.200	−0.563	−0.219*	−0.586	−0.208	−0.649	−0.553***	−1.40**	−0.203**	−0.148
	(0.240)	(0.698)	(0.171)	(0.534)	(0.122)	(0.489)	(0.183)	(0.509)	(0.176)	(0.605)	(0.082)	(0.396)
Est. LR effect	−0.417	−4.05	−0.558	−2.12	−0.221	−1.09	−0.97	−4.31	−0.49	−5.87	−0.666	−3.46

Note: Estimation is carried out by OLS with one-way country fixed effect dummies. The estimation period is 2008-2017. The dependent variable is the median probability of default for the sector. All regressors are considered as lagged values and we do not report the coefficient estimates for the lags of the dependent variable. We report estimates with Driscoll Kraay standard errors between brackets which are robust to general forms of cross-sectional and temporal dependence (clustered at the country level). ***, **, and * indicate significance at the 1-, 5-, and 10-percent significance levels, respectively.

Table 2.12: Test of serial correlation of order k: specification minimizing the BIC

	Financial		Cons. cycl.		Cons. n-cycl.		Industrial		Basic mat.		Technology	
	6-M	5-Y	6-M	5-Y	6-M	5-Y	6-M	5-Y	6-M	5-Y	6-M	5-Y
$\widetilde{HR}$	0.932	0.977	0.996	0.975	0.704	0.751	0.999	0.928	0.934	0.952	0.873	0.775
$\widetilde{LM}_1^*$	0.858	0.881	0.797	0.879	0.686	0.909	0.858	0.515	0.783	0.730	0.790	0.942
$\widetilde{LM}_2^*$	0.983	0.894	0.793	0.905	0.960	0.833	0.674	0.828	0.964	0.960	0.763	0.554
$\widetilde{LM}_3^*$	0.537	0.914	0.842	0.874	0.906	0.682	0.802	0.742	0.628	0.147	0.661	0.831
$\widetilde{LM}_4^*$	0.738	0.736	0.944	0.948	0.997	0.890	0.956	0.948	0.676	0.566	0.458	0.536
$\widetilde{LM}_5^*$	0.097	0.813	0.746	0.759	0.556	0.653	0.571	0.796	0.897	0.957	0.138	0.289
$\widetilde{LM}_6^*$	0.806	0.895	0.338	0.789	0.802	0.738	0.867	0.699	0.872	0.926	0.759	0.276
$\widetilde{LM}_7^*$	0.604	0.495	0.805	0.882	0.231	0.869	0.311	0.695	0.796	0.976	0.958	0.357
$\widetilde{LM}_8^*$	0.635	0.243	0.997	0.652	0.789	0.719	0.623	0.641	0.995	0.863	0.100	0.908
$\widetilde{LM}_9^*$	0.294	0.259	0.150	0.269	0.751	0.503	0.166	0.465	0.492	0.537	0.782	0.912
$\widetilde{LM}_{10}^*$	0.163	0.313	0.220	0.045	0.193	0.082	0.620	0.574	0.693	0.909	0.973	0.639
$\widetilde{LM}_{11}^*$	0.601	0.242	0.931	0.772	0.306	0.362	0.024	0.545	0.061	0.009	0.400	0.937
$\widetilde{LM}_{12}^*$	0.944	0.887	0.567	0.954	0.781	0.324	0.934	0.536	0.406	0.548	0.534	0.800

Note: The table reports the p-values for the heteroskedasticity-robust test of first order serial correlation, $\widetilde{HR}$, and the Lagrange Multiplier test of serial correlation at order k, $\widetilde{LM}_k^*$, which were both introduced in Born and Breitung (2016). The columns cover the results for each sector at default horizons of 6 months and 5 years. All the models are estimated on the full sample of countries with data from 2008 to 2017.

Table 2.13: Test of serial correlation up to order p: specification minimizing the BIC

	Financial		Cons. cycl.		Cons. n-cycl.		Industrial		Basic mat.		Technology	
	6-M	5-Y	6-M	5-Y	6-M	5-Y	6-M	5-Y	6-M	5-Y	6-M	5-Y
$\widetilde{Q}(1)$	0.859	0.882	0.798	0.881	0.687	0.910	0.859	0.517	0.784	0.730	0.791	0.942
$\widetilde{Q}(2)$	0.979	0.989	0.952	0.983	0.910	0.976	0.904	0.757	0.897	0.640	0.926	0.772
$\widetilde{Q}(3)$	0.758	0.834	0.839	0.987	0.966	0.970	0.947	0.903	0.843	0.348	0.973	0.911
$\widetilde{Q}(4)$	0.788	0.917	0.932	0.996	0.815	0.993	0.981	0.944	0.913	0.194	0.572	0.441
$\widetilde{Q}(5)$	0.571	0.966	0.125	0.999	0.895	0.983	0.641	0.552	0.962	0.288	0.372	0.458
$\widetilde{Q}(6)$	0.333	0.965	0.001	0.997	0.941	0.721	0.177	0.354	0.668	0.068	0.394	0.571
$\widetilde{Q}(7)$	0.304	0.438	0.00	0.999	0.116	0.569	0.039	0.466	0.355	0.106	0.268	0.644
$\widetilde{Q}(8)$	0.382	0.528	0.00	0.876	0.101	0.294	0.001	0.485	0.022	0.00	0.00	0.734
$\widetilde{Q}(9)$	0.003	0.015	0.00	0.149	0.00	0.315	0.000	0.468	0.00	0.00	0.00	0.616
$\widetilde{Q}(10)$	0.00	0.022	0.00	0.00	0.00	0.00	0.000	0.381	0.00	0.00	0.00	0.008
$\widetilde{Q}(11)$	0.00	0.00	0.00	0.00	0.00	0.00	0.000	0.359	0.00	0.00	0.00	0.007
$\widetilde{Q}(12)$	0.00	0.00	0.00	0.00	0.00	0.00	0.000	0.000	0.00	0.00	0.00	0.003

Note: The table reports the p-values for the test of serial correlation up to order p, $\widetilde{Q}(p)$, introduced in Born and Breitung (2016). The columns cover the results for each sector at default horizons of 6 months and 5 years. All the models are estimated on the full sample of countries with data from 2008 to 2017.

2.D Dynamic linear panel: results with transformed probabilities of default

This section assesses the robustness of the key results outlined in Section 2.3.2 to potential model misspecifications arising from modelling probabilities of default with an i.i.d. Gaussian dynamic linear model. Indeed, the distribution of default probabilities displays high positive skewness given that they take values in $[0;1]$ with a mass of observations concentrated on the left-hand side of the support and periods of heightened default risk introducing a right tail in the distribution. To this end, we apply a log-transformation to the probabilities of default used in the estimation of Equation (2.1). Note that applying this transformation will impact the interpretation of the estimated coefficients. Taking as an example the parameter estimate for the MPI, $\hat{\delta}$, a one-unit increase in the MPI will be associated with an estimated $100\left(1-\exp(\hat{\delta})\right)\%$ variation in the probability of default.

Table 2.14 summarises the parameter estimates obtained for each sector based on the model specification applying a log-transform to the probabilities of default. We observe that tighter macroprudential regulation is significantly reducing default risk for all sectors. Compared with the results from Section 2.3.2, the statistical significance of the MPI parameter estimates is overall higher, and the MPI now also significantly reduces default risk at the 6-month horizon in both the financial and the consumer non-cyclical sectors. On the other hand, the MPI coefficient estimates for the 5-year PDs of the consumer cyclical and industrial sectors are no longer statically significant. The economic magnitude of these estimates is also significant, with a one unit increase in the MPI resulting in a short-term decrease in default risk ranging from 0.3% to 0.4% for the 5-year horizon and from 0.4% to 1.4% for the 6-month horizon.

Moving to the predictors of default risk, we note that IP is now significantly contributing to reducing default risk only in the financial sector and for longer default horizons (5 years). However, the parameter estimates for the slope of the yield curve — which incorporates markets' forward-looking assessment of the economic outlook — are now also significant for the consumer cyclical sector and for the industrial sector at the

6-month horizon.[47] For the stock market return, the decreasing effect of better stock market performance on short-term default risk is no longer statically significant, except for the technology sector. The positive relationship between stock market performance and longer-term default risk remains statistically significant for the consumer cyclical and industrial sectors. Higher inflation volatility is still a significant predictor of reduced default risk for the basic material and industrial sectors, but no longer for the consumer non-cyclical and financial sectors. However, higher stock market volatility is now significantly associated with a decrease in short-term default risk for all sectors. Finally, the sign and significance of the coefficient estimates for inflation are in line with our main results, with the exception of the technology sector for which the estimates are no longer significant.

Overall, our main conclusion that tighter macroprudential regulation decreases short- and long-term default risk appears to be robust to potential model misspecifications arising from our choice of modelling probabilities of default with a dynamic linear panel model estimated under the assumption of i.i.d. Gaussianity. Moreover, the results obtained for the default predictors are also broadly consistent with the key results from the main analysis reported in Section 2.3.2.

[47] On the other hand, the coefficient estimate for the technology sector at the 6-month horizon is no longer significant.

Table 2.14: Estimation results for the specification with log-transformed probabilities of default

	Financial		Cons. cycl.		Cons. n-cycl.		Industrial		Basic mat.		Technology	
	6-M	5-Y	6-M	5-Y	6-M	5-Y	6-M	5-Y	6-M	5-Y	6-M	5-Y
MPI	−0.008***	−0.003***	−0.006***	−0.001	−0.006***	−0.001	−0.004**	−0.001	−0.014***	−0.004***	−0.012***	−0.003***
	(0.0017)	(0.0007)	(0.0019)	(0.0007)	(0.0016)	(0.0006)	(0.0017)	(0.0007)	(0.0044)	(0.0016)	(0.0032)	(0.0009)
Inf	0.020***	0.007***	0.019***	0.006***	0.014***	0.003***	0.016***	0.005***	0.017***	0.003*	0.007	0.002
	(0.0028)	(0.0015)	(0.0040)	(0.0015)	(0.0025)	(0.0012)	(0.0023)	(0.0010)	(0.0037)	(0.0017)	(0.0059)	(0.0021)
IP	−0.0005	−0.0008**	−0.0004	−0.0003	0.0009	0.0002	−0.0006	−0.0007	−0.0004	−0.0002	0.0015	−0.0003
	(0.0008)	(0.0003)	(0.0011)	(0.0004)	(0.0008)	(0.0003)	(0.0010)	(0.0005)	(0.0013)	(0.0005)	(0.0021)	(0.0005)
InfVol	−0.014	−0.007	−0.0006	0.005	−0.016	−0.004	−0.026**	−0.012**	−0.027*	−0.014**	−0.008	0.007
	(0.0106)	(0.0051)	(0.0124)	(0.0052)	(0.0100)	(0.0050)	(0.0102)	(0.0050)	(0.0144)	(0.0060)	(0.0195)	(0.0086)
StockRet	0.0001	0.0001	−0.0002	0.0002**	−0.0002	0.0001	0.0003	0.0002**	−0.0007	0.00005	−0.0013*	0.00001
	(0.0002)	(0.00009)	(0.0002)	(0.00009)	(0.0002)	(0.00009)	(0.0002)	(0.0001)	(0.0005)	(0.0001)	(0.0007)	(0.0001)
StockRetVol	−0.002**	−0.00006	−0.0024***	0.0003	−0.002*	0.0003	−0.002**	0.0003	−0.005***	−0.0003	−0.005***	−0.0008
	(0.0009)	(0.0003)	(0.0009)	(0.0003)	(0.0009)	(0.0003)	(0.0008)	(0.0003)	(0.0014)	(0.0005)	(0.0016)	(0.0005)
ΔShortRate	0.004	0.0003	0.005	−0.003	−0.003	−0.003	−0.006	−0.004	−0.01	−0.003	0.012	0.004
	(0.0126)	(0.0061)	(0.0106)	(0.0042)	(0.0099)	(0.0042)	(0.0105)	(0.0039)	(0.0207)	(0.0096)	(0.0169)	(0.0076)
Slope	−0.013**	−0.005*	−0.009*	−0.003*	−0.008*	−0.003	−0.009**	−0.003	−0.016***	−0.005**	−0.0103	−0.00005
	(0.0050)	(0.0024)	(0.0050)	(0.0020)	(0.0043)	(0.0020)	(0.0043)	(0.0021)	(0.0061)	(0.0025)	(0.0065)	(0.0023)

Note: Estimation is carried out by OLS with one-way country fixed effect dummies. The estimation period is 2008-2017. The dependent variable is the log-transform of the median probability of default for the sector. All regressors are considered as lagged values and we do not report the coefficient estimates for the lags of the dependent variable. We report estimates with Driscoll Kraay standard errors between brackets which are robust to general forms of cross-sectional and temporal dependence (clustered at the country level). ***, **, and * indicate significance at the 1-, 5-, and 10-percent significance levels, respectively.

2.E Dynamic linear panel: accounting for the impact of unconventional monetary policies

This section assesses the potential implications for our results of overlooking the impact of unconventional monetary policies during the period analyzed. While our analysis captures the potential impact of conventional monetary policy through variations in short-term interest rates (ΔShortRate), central banks' policy rates have become constrained by the effective lower bound (ELB) in the aftermath of the GFC. Therefore, they had to resort to other unconventional monetary policy tools — including e.g. quantitative easing and negative interest rate policies — to further stimulate the real economy in an environment with weak economic growth and deflationary pressures. One way to capture the overall stance of monetary policy is to consider the shadow rate, i.e. the estimated short-term interest rate that would prevail in the absence of the effective lower bound. See e.g. Mouabbi and Sahuc (2019) and Wu and Zhang (2019) who introduce shadow rates as a tractable summary of both conventional and unconventional monetary policy tools in dynamic stochastic general equilibrium (DSGE) models. Given the scarcity in the availability of shadow rate estimates across countries, we collect data for the euro area and the UK which are based on the methodology of Wu and Xia (2020). We also obtain data for Sweden based on the methodology of De Rezende and Ristiniemi (2022). We use the euro area shadow rate data for the remaining seven non-EA countries.

Table 2.15 summarises the results obtained for each sector for the model specification where we introduce the shadow rate as a regressor instead of the short rate. We observe that both the significance and the magnitude of the coefficient estimates for the MPI are hardly impacted by the introduction of the shadow rate — except for the basic material sector where the statistical significance is slightly improved. The parameter estimates for the shadow rate are only significant for the consumer non-cyclical sector and for the technology sector at the 5-year horizon. The negative sign for the estimates is consistent with the literature documenting how a looser monetary policy stance can induce higher risk taking from banks in their lending decisions. This, in turn, can result in a higher likelihood of default ex-post (Jiménez et al., 2014; Heider et al., 2019). The significance of the shadow rate for the consumer non-cyclical sector, combined with the absence of significance for the MPI coefficient estimates, could be indicative of monetary policy — rather than macroprudential policy — being the main driver of variations in default risk. We observe the opposite result for the financial sector and other non-financial sectors, namely macroprudential regulation being the main driver of variations in default risk rather than (unconventional) monetary policy. Finally, the key conclusions regarding the sign and significance of the coefficient estimates for the other default predictors are unaffected by the introduction of the shadow rate.

Table 2.15: Estimation results for the specification with the shadow short rate

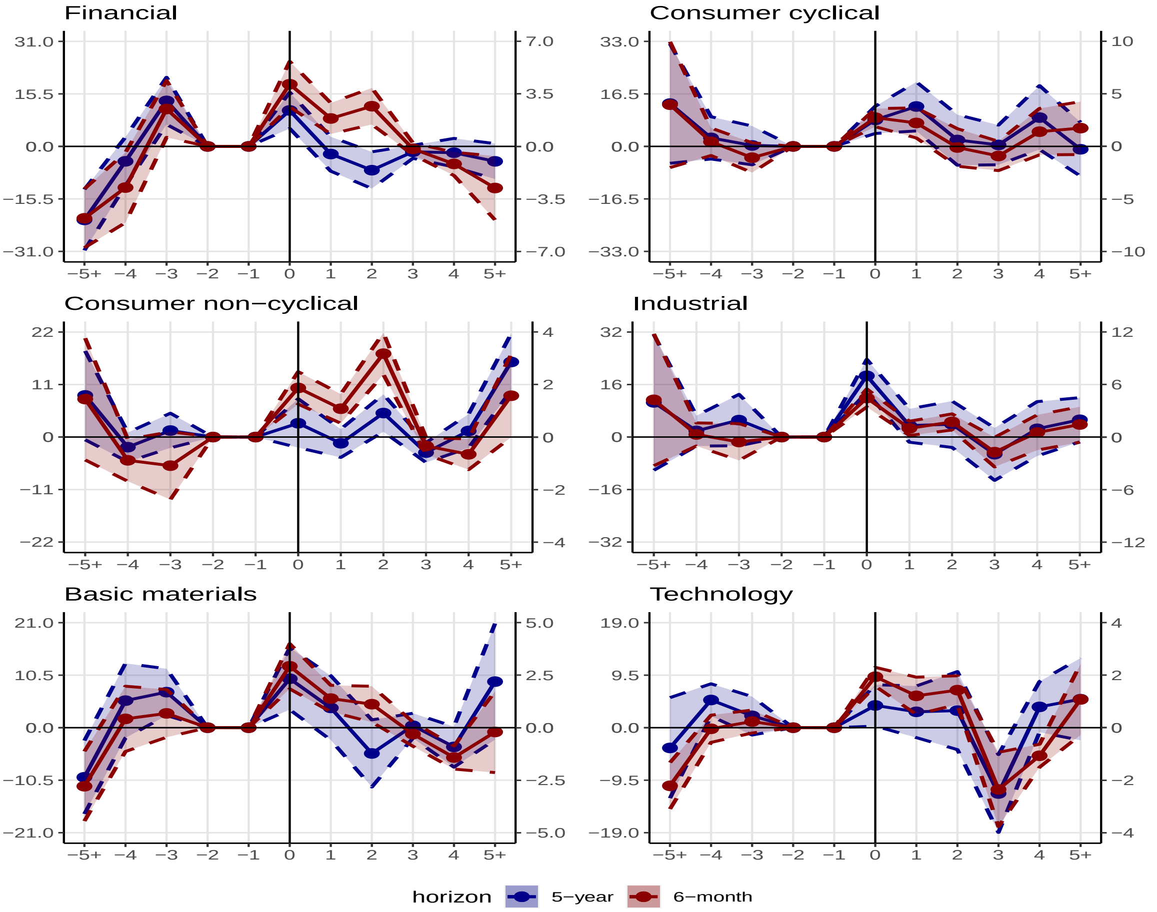
	Financial		Cons. cycl.		Cons. n-cycl.		Industrial		Basic mat.		Technology	
	6-M	5-Y	6-M	5-Y	6-M	5-Y	6-M	5-Y	6-M	5-Y	6-M	5-Y
MPI	−0.079	−0.434**	−0.104***	−0.254*	−0.034	−0.096	−0.140***	−0.394***	−0.126**	−0.728**	−0.104***	−0.342**
	(0.068)	(0.179)	(0.035)	(0.145)	(0.025)	(0.109)	(0.051)	(0.143)	(0.062)	(0.360)	(0.027)	(0.151)
Inf	0.623**	1.70***	0.402***	1.23***	0.301***	0.716***	0.481***	1.11***	0.490***	0.795*	0.204***	0.610**
	(0.252)	(0.511)	(0.099)	(0.317)	(0.084)	(0.259)	(0.107)	(0.279)	(0.181)	(0.431)	(0.055)	(0.311)
IP	−0.034*	−0.202***	−0.019	−0.109*	0.002	0.016	−0.013	−0.080	−0.0002	−0.028	−0.004	−0.010
	(0.018)	(0.054)	(0.014)	(0.061)	(0.011)	(0.050)	(0.018)	(0.060)	(0.026)	(0.112)	(0.009)	(0.054)
InfVol	−0.841**	−2.22**	−0.316	0.093	−0.297	−0.552	−1.05**	−2.39**	−1.12**	−3.68**	−0.209	0.912
	(0.426)	(1.08)	(0.347)	(1.15)	(0.192)	(0.859)	(0.458)	(1.19)	(0.542)	(1.64)	(0.218)	(1.17)
StockRet	−0.017*	0.014	−0.012*	0.039**	−0.001	0.037**	−0.008	0.035*	−0.024*	0.002	−0.013**	0.037*
	(0.010)	(0.017)	(0.006)	(0.019)	(0.004)	(0.016)	(0.007)	(0.019)	(0.014)	(0.041)	(0.006)	(0.020)
StockRetVol	0.001	0.053	−0.027	0.038	−0.004	0.042	−0.026	0.031	−0.050*	−0.095	−0.054***	−0.091
	(0.031)	(0.075)	(0.018)	(0.069)	(0.012)	(0.057)	(0.022)	(0.068)	(0.030)	(0.136)	(0.014)	(0.067)
ΔShadowRate	−1.06	−1.48	−0.451	−2.11	−0.798*	−2.68*	−1.01	−1.88	−0.599	−1.49	−0.472	−2.65**
	(0.782)	(1.57)	(0.436)	(1.44)	(0.454)	(1.36)	(0.771)	(1.58)	(0.915)	(2.63)	(0.371)	(1.21)
Slope	−0.649**	−1.26*	−0.252	−0.612	−0.197*	−0.477	−0.253	−0.706	−0.558***	−1.47**	−0.210**	−0.178
	(0.321)	(0.739)	(0.169)	(0.554)	(0.114)	(0.444)	(0.201)	(0.579)	(0.210)	(0.696)	(0.084)	(0.402)

Note: Estimation is carried out by OLS with one-way country fixed effect dummies. The estimation period is 2008-2017. The dependent variable is the median probability of default for the sector. All regressors are considered as lagged values and we do not report the coefficient estimates for the lags of the dependent variable. We report estimates with Driscoll Kraay standard errors between brackets which are robust to general forms of cross-sectional and temporal dependence (clustered at the country level). ***, **, and * indicate significance at the 1-, 5-, and 10-percent significance levels, respectively.

2.F Additional results for the main analysis

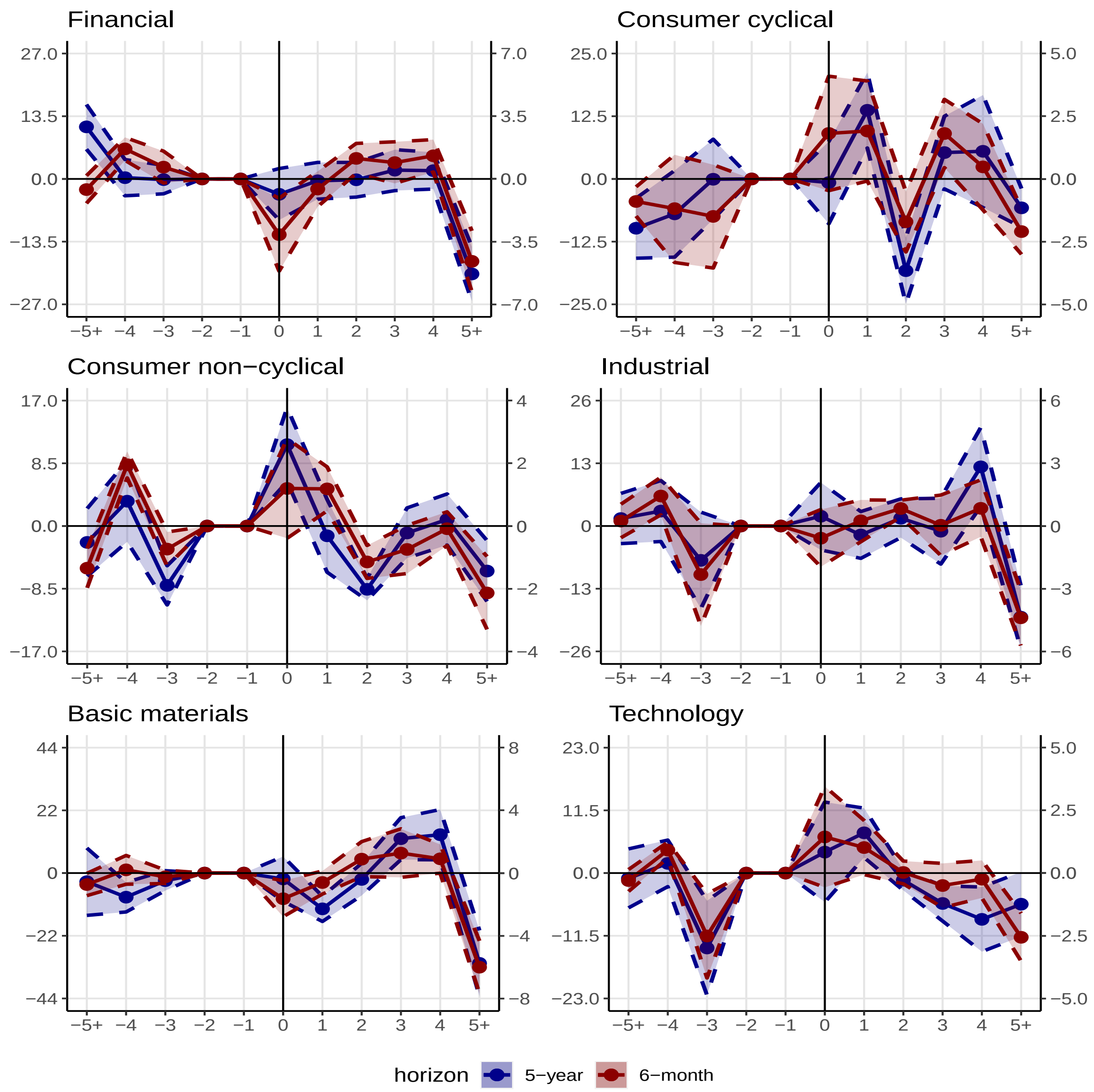
2.F.1 Panel even-study results for the subsample of EA countries

Figure 2.7: Impact of the introduction of CRR/CRD IV (EA countries)



Note: This figure summarises the evolution of the median probabilities of default around the introduction of the CRR/CRD IV package for the six sectors analysed. The event window captures a period of 10 quarters around the event (x-axis). The y-axes display the estimated coefficients for the event window as specified in equation (2.2). The results for the 5-year (6-month) default horizon are reported in blue (red) with corresponding value on the left-hand (right-hand) y-axis. The shaded areas around the point estimates correspond to the 68% confidence intervals constructed based on standard errors clustered at the country level. The estimation is carried out on the subsample of EA countries.

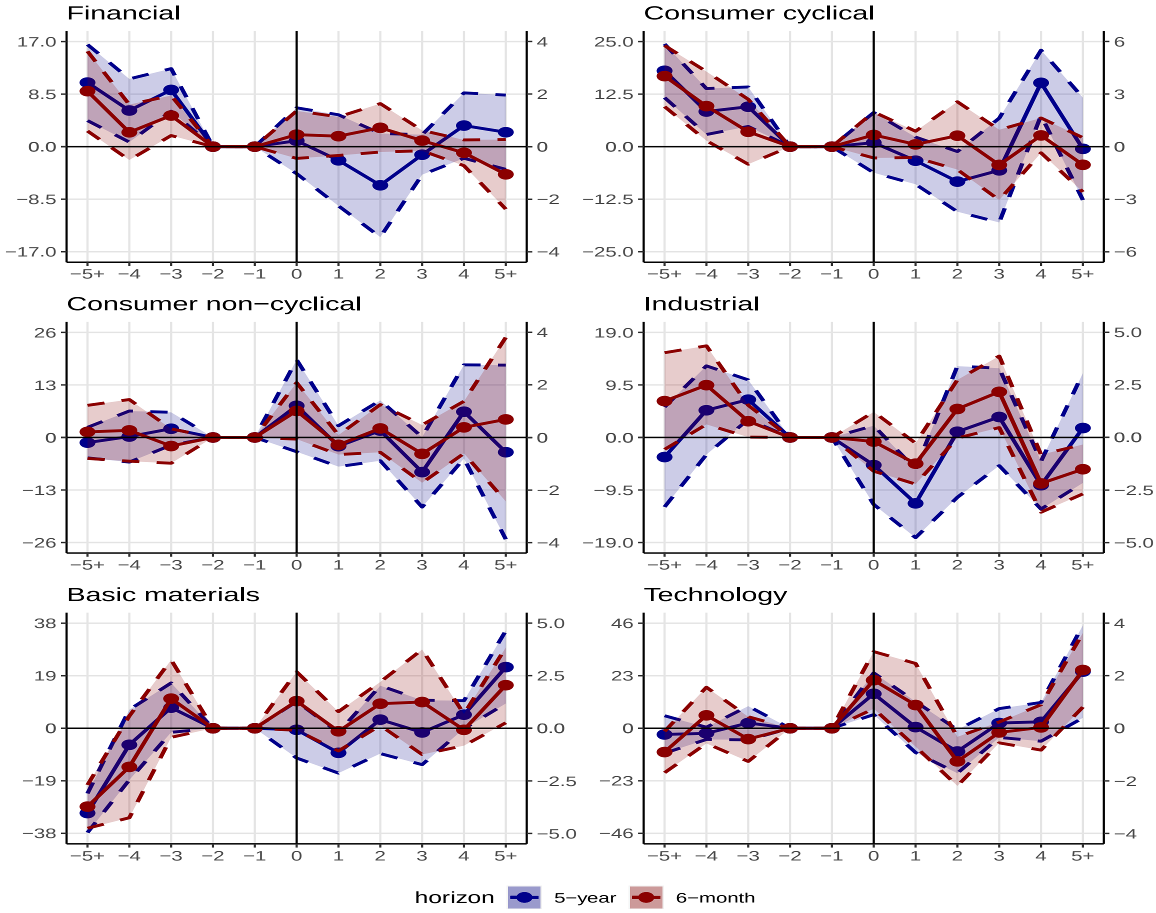
Figure 2.8: Impact of the introduction of BRRD (EA countries)



Note: This figure summarises the evolution of the median probabilities of default around the introduction of the BRRD for the six sectors analysed. The event window captures a period of 10 quarters around the event (x-axis). The y-axes display the estimated coefficients for the event window as specified in equation (2.2). The results for the 5-year (6-month) default horizon are reported in blue (red) with corresponding value on the left-hand (right-hand) y-axis. The shaded areas around the point estimates correspond to the 68% confidence intervals constructed based on standard errors clustered at the country level. The estimation is carried out on the subsample of EA countries.

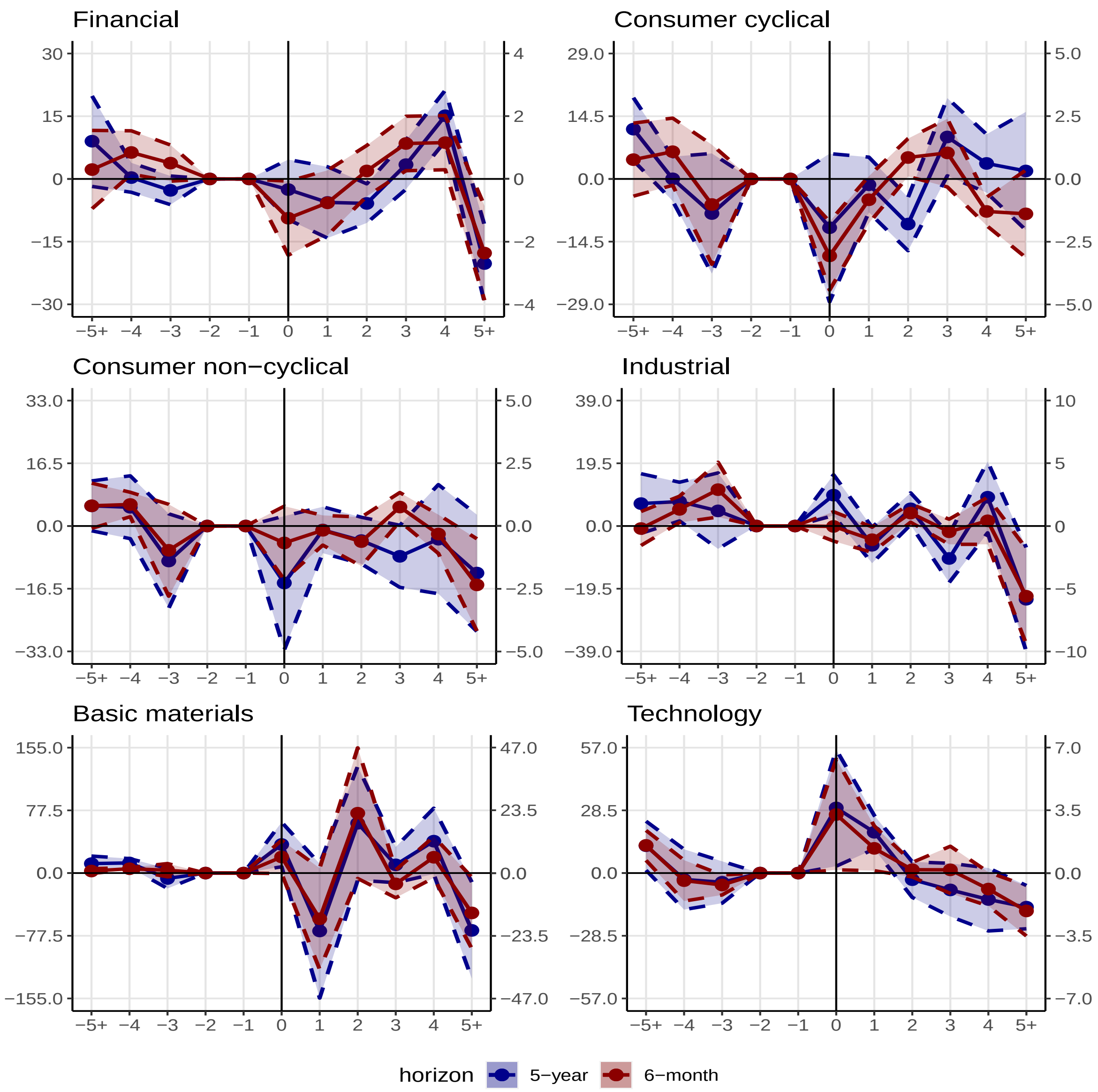
2.F.2 Panel even-study results for the subsample of Non-EA countries

Figure 2.9: Impact of the introduction of CRR/CRD IV (Non-EA countries)



Note: This figure summarises the evolution of the median probabilities of default around the introduction of the CRR/CRD IV package for the six sectors analysed. The event window captures a period of 10 quarters around the event (x-axis). The y-axes display the estimated coefficients for the event window as specified in equation (2.2). The results for the 5-year (6-month) default horizon are reported in blue (red) with corresponding value on the left-hand (right-hand) y-axis. The shaded areas around the point estimates correspond to the 68% confidence intervals constructed based on standard errors clustered at the country level. The estimation is carried out on the subsample of non-EA countries.

Figure 2.10: Impact of the introduction of BRRD (Non-EA countries)



Note: This figure summarises the evolution of the median probabilities of default around the introduction of the BRRD for the six sectors analysed. The event window captures a period of 10 quarters around the event (x-axis). The y-axes display the estimated coefficients for the event window as specified in equation (2.2). The results for the 5-year (6-month) default horizon are reported in blue (red) with corresponding value on the left-hand (right-hand) y-axis. The shaded areas around the point estimates correspond to the 68% confidence intervals constructed based on standard errors clustered at the country level. The estimation is carried out on the subsample of non-EA countries.

Chapter 3

Monitoring Tail Risks in the Economy Using CDS Spreads: A Score-Driven Approach [1]

3.1 Introduction

Systemic risk monitoring has become a central concern for macroprudential policy authorities across the globe since the 2008-2009 Global Financial Crisis (GFC) and the associated Great Recession in the US. This fostered a proliferation of academic research on systemic risk — with the ultimate goal of better identifying vulnerabilities in the financial system and designing regulatory measures to increase its resilience; see e.g. Benoit et al. (2017) for a comprehensive review of the relevant literature. A large part of this literature focuses on how buildup of systemic risk in the banking system can increase downside risks to the real economy; see e.g. Allen et al. (2012); Giglio et al. (2016); Adrian and Brunnermeier (2016); Brownlees and Engle (2017).

However, economic downturns — e.g. during the Great Recession or in the early stages of the Covid-19 pandemic — can lead to a surge in credit demand from the non-financial

[1] This chapter corresponds to Wijnandts J.-C. (2022): "Monitoring Tail Risks in the Economy Using CDS Spreads: A Score-Driven Approach."

sector. This can result in a materialization of balance-sheet liquidity risks in the financial sector, further amplifications of adverse shocks and potential financial stability implications (Acharya et al., 2021). This issue is particularly relevant given mounting evidence that large non-financial firms can also be systemic as their default can lead to contagion effects (Azizpour et al., 2018) and a realization of economic downside risks (Gourieroux et al., 2021). Moreover, systemic non-financial borrowers introduce an economically significant source of non-diversifiable granular credit risk on banks' balance sheets (Galaasen et al., 2020). Extending the existing monitoring framework to better account for two-way systemic spillovers between the financial and non-financial sectors would therefore support macroprudential authorities in achieving their financial stability objective.

Building on this insight, we propose to broaden the scope of systemic risk monitoring, which is centered around the financial sector, to encompass systemic risk originating in the non-financial sector and potential systemic risk spillovers across sectors. We focus on the modelling of daily CDS spread data for financial and non-financial Investment Grade corporates as this approach offers several benefits. First, Gourieroux et al. (2021) document that large firms entering the composition of CDS indices, such as the CDX in the US and the iTraxx in Europe, account for a large share of macroeconomic activity in their respective geographical areas. This implies that idiosyncratic shocks affecting these firms can impact aggregate fluctuations (Gabaix, 2011) and transmit to other firms through broad contagion channels (Azizpour et al., 2018). Second, market-based measures of credit risk, which include CDS spreads, provide timelier and more informative measurements than their lower-frequency accounting counterparts (Palazzo and Yamarthy, 2022). Second, CDS spreads contribute to the price discovery process of firm-specific credit risk information by incorporating information not reflected in the firm's corporate bond or stock data (Lee et al., 2018). This result can be explained by the relative ease with which investors can enter a CDS position compared to the corresponding corporate bond or loan (Bomfim, 2022) and the fact that banks acting as primary dealers in the CDS market use credit risk relevant information acquired through their lending relationships with the firm on which the CDS contract is written (Acharya and Johnson, 2007). Moreover, CDS spreads are less affected by buying/selling pressures from institutional investors (e.g. corporate bond funds and pension funds) which can, at times, drive a wedge between credit spreads and the level consistent with firms' credit risk (Haddad et al., 2021; Palazzo and Yamarthy, 2022). Lastly, CDS-based measures have been shown to outperform other measures based on interbank rates or stock market prices for the monitoring of systemic risk at high-frequency (Rodríguez-Moreno and Peña, 2013).

We build on the modelling framework of Oh and Patton (2018) who extend the factor copula model of Oh and Patton (2017) to a dynamic setting which is particularly well-suited to model time-varying multivariate conditional distributions in high dimensions. The key features of their modelling framework are first that it allows to estimate the different parts of the joint distribution, i.e. the marginal distributions and the copula function, in stages — therefore reducing the computational burden and allowing for more flexibility in the specification of the marginals. Second, the factor copula introduces dimension reduction where needed, i.e. in the modelling of the dependence, and the dynamics of the factor loadings are modelled using the score-driven (SD) approach of Creal et al. (2013) and Harvey (2013).

This flexible modelling framework allows us to derive measures of time-varying systemic risk which capture the dependence in failure across a large panel of firms; see Segoviano and Goodhart (2009) and Giesecke and Kim (2011) for a similar approach to systemic risk modelling in the banking system. The two measures we focus on are the Joint Probability of Distress (JPD) and the Expected Proportion in Distress (EPD). The JPD is the probability of a large fraction of the firms in the system being simultaneously in distress and thus captures the level of systemic risk in the economy inferred from CDS data. This links our contribution to the literature extracting information from financial instruments directly exposed to systemic risk, such as far out-of-the-money (OTM) put options written on equity indices (Backus et al., 2011; Bollerslev and Todorov, 2011) and Collateralized Debt Obligations (CDOs) (Longstaff and Rajan, 2008; Coval et al., 2009; Collin-Dufresne et al., 2012; and Seo and Wachter, 2018). These methodologies take an aggregate perspective by focusing on the tail risks inferred from a pool of entities (e.g.

equity index or portfolio of firms). We propose an alternative approach which exploits commonalities in tail risk across a large panel of firms by modelling them jointly (Kelly and Jiang, 2014). This way, we can also investigate how an individual firm contributes to the default risk of other firms and to aggregate tail risks (Adrian and Brunnermeier, 2016). This is achieved by our second measure, the EPD, which captures for a given firm the expected proportion of firms in distress conditional on this firm defaulting.

We make two main contributions. First, we extend the modelling framework of Oh and Patton (2018) by introducing a dynamic score model for the conditional volatility of the marginal distributions which is based on the Skew t distribution of Hansen (1994). The main benefits from the SD approach are first that the updating mechanism for the time-varying parameters is intuitive as the conditional score indicates the direction of steepest ascent to update the model's local fit in terms of likelihood. Second, the use of the conditional score from a heavy-tailed distribution, such as the Skew t, for the updating of the dynamic parameters introduces some robustness against the presence of outliers in the data. This is particularly relevant for the modelling of CDS spread data as their distribution is in general heavy-tailed; see e.g. Creal and Tsay (2015).[2] However, Blasques et al. (2022) point out that the SD approach imposes a strong link between the conditional distribution of the model and the updating equation for the dynamic parameters. This strong link might not always be supported empirically and the authors propose a Quasi Score-Driven (QSD) approach which generalizes the SD approach by allowing the updating equation for the time-varying parameters to be potentially decoupled from the distribution of the model innovations. We build on Blasques et al. (2022) and propose a QSD extension of the asymmetric Beta-t-EGARCH model of Harvey (2013). We document through several model specification tests that the flexibility of our asymmetric QSD-t-EGARCH model helps capturing the key features of the conditional marginal distribution of CDS data.

[2]Moreover, this modelling choice increases the overall coherence of the framework as the factor copula also uses a conditional score approach for the dynamics of the factor loadings based on the Skew t distribution.

Our second contribution is to apply this modelling framework to the analysis of CDS spread data for a panel of 75 US Investment Grade firms over the period from January 2007 to September 2022. Our analysis complements and extends the one in Oh and Patton (2018) which focuses on the period 2006-2012 and allows us to investigate the impact of different types of systemic stress — including a global financial crisis and a pandemic. We document first that the dependence between firms, measured based on the estimated time-varying factor loadings of the copula, has been steadily increasing across all sectors over the period from 2007 to end-2013. After a short period of stabilization, firms' dependence on the common factor resume its steady increase from 2018 until the end of the sample — reaching higher levels than during the GFC. We conclude from these results that higher dependence among firms appears to be driven by low-frequency factors relating to overall uncertainty and weaker global economic prospects, consistent with the existing literature documenting the co-cyclicality between corporate defaults and economic activity (Koopman and Lucas, 2005; Duffie et al., 2009; Koopman et al., 2009). Our analysis of time-varying systemic risk also highlights some interesting patterns. Although CDS spreads are more compressed in the second half of our sample than around the GFC, the JPD measure is markedly higher on average during the 2018-2022 period (particularly at the 1-year horizon). Furthermore, levels reached in 2019, at the onset of the Covid-19 pandemic, and in the first half of 2022 are broadly comparable to the ones observed at the peak of the GFC in 2009. The results for the EPD measure indicate that the expected proportion of firms in distress rise sharply during the GFC before coming down gradually but levelling off at higher levels than pre-crisis. In addition, the EPD fluctuates around higher levels on average in the most recent part of the sample, with peak values around historical highs. Finally, systemic spillover risks from the non-financial to the financial sector are higher than systemic spillovers from the financial to the non-financial sector over most of the sample. This highlights that the default of a large non-financial corporate can be an important trigger of stress in the financial sector, consistent with the literature documenting the impact of idiosyncratic shocks to large borrowers on banks' aggregate portfolio outcomes (Galaasen et al., 2020). We observe two exceptions where systemic spillovers from the financial to the non-financial sector peak at higher levels around end-2008 and at the beginning of the Covid crisis. This points to a stronger role of systemic spillovers from the financial sector to the real economy during economic downturns and highlights the role of the financial sector in amplifying adverse shocks during crises (Adrian and Brunnermeier, 2016).

The remainder of this paper is organized as follows. The next section introduces our CDS data and key stylized facts. Section 3.3 introduces the model specification for the marginal densities and the dynamic factor copula model used in the analysis, together with the procedure to estimate the systemic risk measures. In Section 3.4, we apply the model to a collection of daily CDS spreads on US firms and analyze the evolution of systemic risk over time. Section 3.5 concludes. Additional details on the empirical implementation and complementary results related to the empirical application are collected in Appendix 3.A and Appendix 3.B respectively.

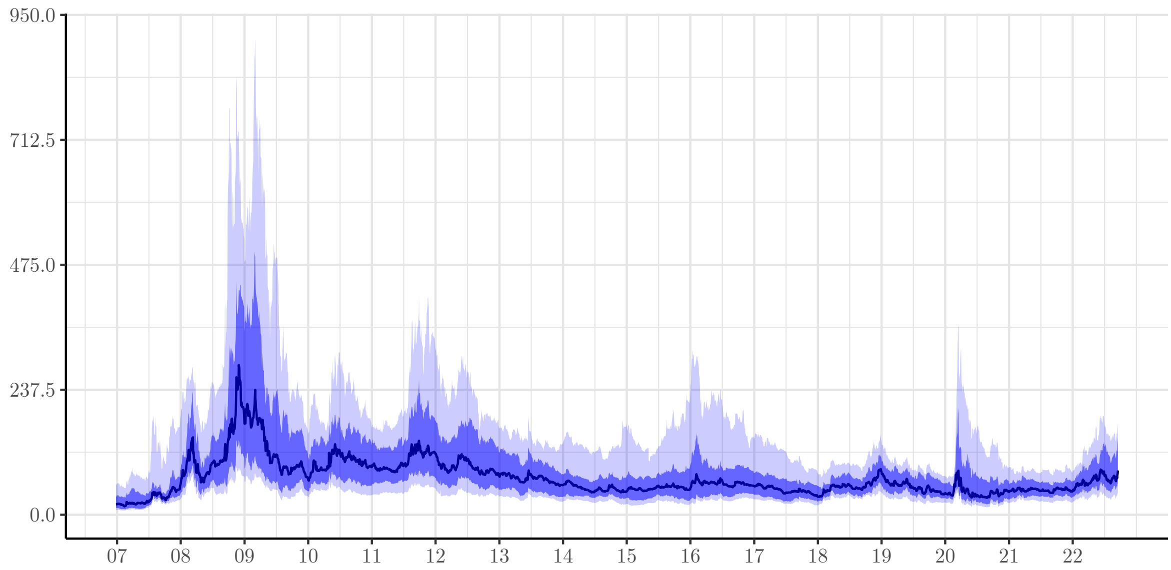
3.2 CDS data: stylized facts and descriptive statistics

CDS contracts provide insurance to the buyer against losses arising from a default of the reference entity — namely a corporate firm or sovereign entity — within a specified horizon. In exchange for this insurance, the buyer makes regular premium payments to the seller. We focus our analysis on "no restructuring" (XR) CDS contracts with a maturity of 5 years, the most liquid horizon, written on Investment Grade (IG) North American corporate entities listed in the Markit IG CDS index. We use the CDX NA IG Series 37 as reference (125 entities) and obtain CDS spread data for the period from 2007-01 to 2022-09. We only keep firms with less than 10 missing observations over the whole sample period. This yields a panel of 75 companies spread across 9 sectors of activity: basic materials (5); consumer goods (9); consumer services (15); energy (5); financials (18); healthcare (6); industrials (11); technology (2); and utilities (4).

We plot in Figure 3.1 the evolution of daily 5-year CDS spreads for our sample of

US IG firms. We see that the pre Global Financial Crisis (GFC) period is characterised by very compressed CDS spreads and low levels of market-implied default risk. The first uptick in CDS spreads occurs in the second half of 2007, marked by the collapse of two Bear Stearns leveraged credit funds over the summer and the start of an economic recession in the fourth quarter. As shown in Figure 3.2, this upward trend in spreads is generalised across sectors but more pronounced for financial firms. A first peak is reached in the first half of 2008 with the bankruptcy of Bear Stearns in March. The collapse of Lehman Brothers initiates a much more pronounced increase in spreads, with median values breaking above 250bps and financial sector spreads reaching record highs around 300-450bps; see e.g. Christoffersen et al. (2018) for a more detailed chronology of events. A series of events — including the unfolding of the European sovereign debt crisis from 2010 to 2012 and the US sovereign debt downgrade in August 2011 — sustain the widening in spreads in subsequent years and a return to pre-GFC levels is only achieved after 2014.

Figure 3.1: 5-year CDS spreads for US Investment Grade corporates (in bps)



Note: This figure plots the evolution over time of daily 5-year CDS spreads for 75 US Investment Grade corporates (in basis points). We consider from 2007-01 to 2022-09. The black line corresponds to the median CDS spread across firms; the dark- and light-blue shaded bands correspond respectively to the Inter Quartile Range (IQR) and the 10-90 percentile range.

Turning now to the period from 2014-01 to 2022-09, we observe an increased dispersion in CDS spreads around the beginning of 2016. This widening in spreads can be traced back to the financial market turmoil in China, starting during the summer 2015, which led to a material increase in global volatility and impeded the Federal Reserve's normalisation of monetary policy; see e.g. Carpenter and Whitelaw (2017) and Bian et al. (2021).[3] We also note a slight uptick in median spread levels starting from mid-2018 on. This period is associated with the escalation of the trade frictions between China and the US which have weighed on the global economic outlook and raised financial market volatility.

We also notice that sectors more affected by the trade frictions experience a larger increase in their mean CDS spreads; see e.g. the basic material and consumer goods sectors in Figure 3.2. The outset of the Covid-19 pandemic in March 2020 is associated with a marked increase in both median CDS spreads and their dispersion — resulting from the lockdown measures imposed by governments to contain the propagation of the virus. Sectors more exposed to the sharp decrease in economic activity worldwide experience a more pronounced increase in their median CDS spreads; see e.g. the energy and industrial sectors. In addition, consumer-facing sectors, such as consumer services, recover more slowly as consumers redirect their spendings towards goods consumption. Note that the relatively short-lived impact of the Covid shock on market-implied default risk can be partly explained by the support measures introduced by governments and central banks. For instance, Haddad et al. (2021) document that the introduction of the corporate bond purchase programme by the Federal Reserve, in particular the April extension extending the scope to "fallen angels" and high-yield ETFs, had a strong mitigating effect on firms who experienced large increases in their CDS spreads at the onset of the Covid pandemic.

Table 3.1 presents summary statistics for our CDS spread data on which we have applied a log-difference transformation. The top panel considers the sample ranging from 2007-01 to 2013-12, and the bottom panel covers the sample from 2014-01 to 2022-09. We

[3] Note that there are also idiosyncratic drivers for this uptick in CDS spreads. Figure 3.2 shows that the energy sector experienced a stark increase in its median spread during this period. This is mostly due to two companies: Devon Energy Corp., an oil and gas producer which experienced a period of distress amid declining oil prices; and William Companies Inc., a natural gas company confronted with a failed merger.

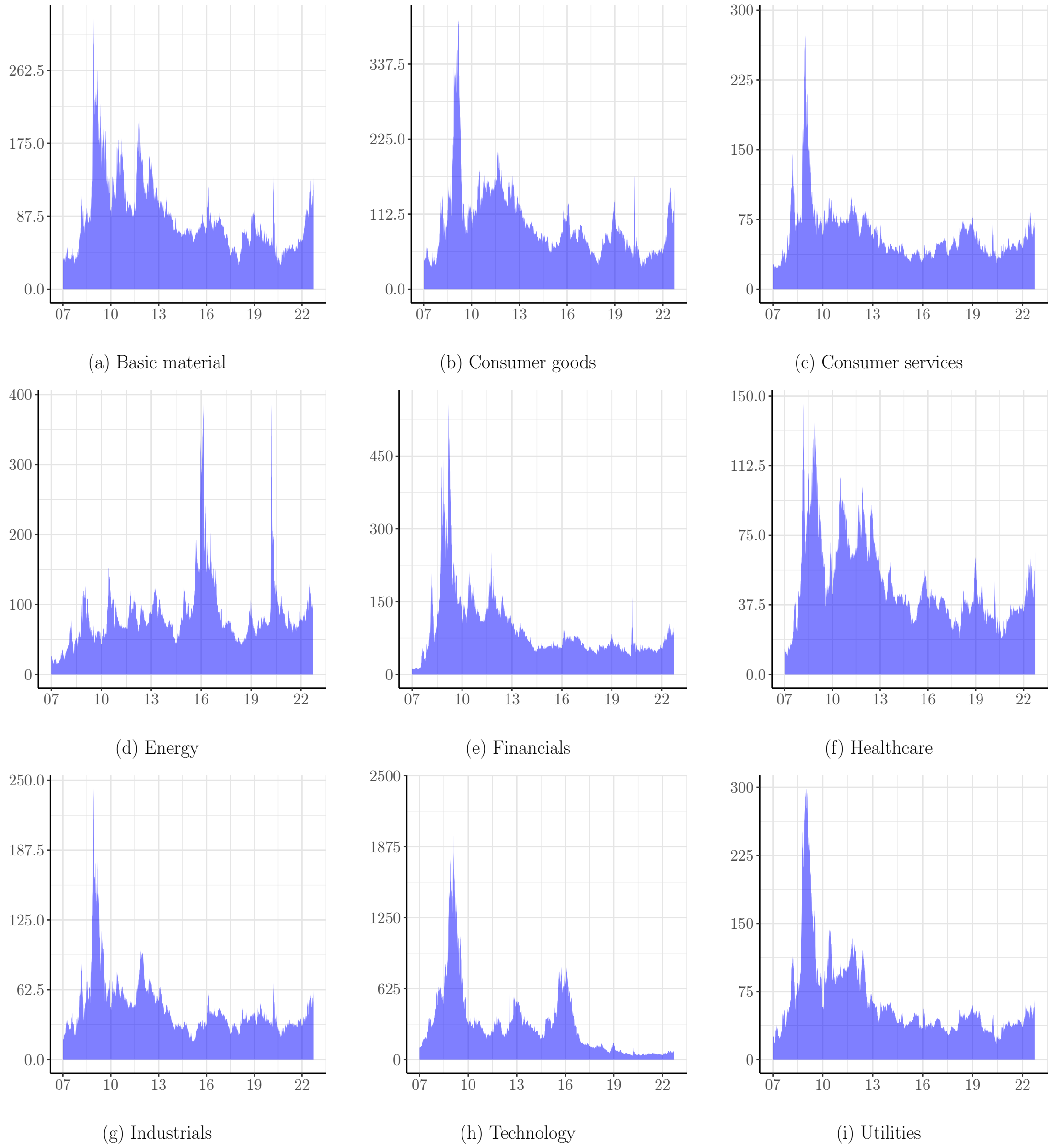
note that the data exhibit some degree of persistence with a median first-order correlation of 0.176 in the first subsample and ranging up to 0.279 for the 95^{th} percentile — values for the second subsample are broadly comparable, although slightly lower. Furthermore, the distribution of the data appears to depart from the Gaussian case as log-differenced CDS spreads data display positive skewness (median values around respectively 0.72 and 0.99) and fat tails (median kurtosis of respectively 15.55 and 22.52). These observations motivate our modelling approach aiming at capturing the relevant features of the data, which we outline in the next section.

Table 3.1: Descriptive statistics for 5-year CDS spreads in log-differences

	Mean	5%	25%	Median	75%	95%
Sample A: 2007/01 – 2013/12						
Mean	5.004	0.128	2.354	4.245	7.237	11.236
Std dev	370.685	280.226	325.513	352.566	385.088	546.676
1st-order autocorr	0.176	0.057	0.138	0.176	0.220	0.279
Skewness	0.915	−0.649	0.297	0.721	1.282	3.355
Kurtosis	24.899	8.454	11.381	15.546	28.833	58.999
5%	−498.938	−693.263	−540.687	−487.521	−447.289	−373.015
25%	−139.186	−198.872	−149.718	−137.760	−125.246	−92.997
Median	−2.603	−8.649	−3.550	−1.347	−0.364	0.000
75%	128.268	83.023	111.028	121.957	135.763	194.572
95%	553.944	412.740	499.004	541.696	594.399	759.246
Sample B: 2014/01 – 2022/09						
Mean	2.259	−1.422	0.753	2.508	3.929	5.567
Std dev	309.910	251.197	283.420	303.615	337.121	387.434
1st-order autocorr	0.137	−0.007	0.073	0.137	0.201	0.271
Skewness	1.808	−0.132	0.366	0.991	2.651	5.765
Kurtosis	40.771	11.949	15.767	22.520	41.320	121.053
5%	−391.077	−503.782	−429.684	−380.321	−347.361	−296.746
25%	−120.513	−156.408	−133.175	−118.637	−107.042	−91.762
Median	−10.021	−15.836	−12.857	−10.313	−7.528	−3.000
75%	99.998	68.284	86.707	95.883	113.672	138.957
95%	445.328	346.544	401.482	436.329	488.171	586.280

Note: Summary statistics for the log-differences of the 5-year CDS spreads (expressed in bps) of the 75 companies in our sample. The top panel considers the sample ranging from 2007-01 to 2013-12, and the bottom panel covers the sample from 2014-01 to 2022-09. The columns summarise the cross-sectional distribution (mean and key percentiles) of the respective statistics considered in each row.

Figure 3.2: Breakdown by sector of 5-year CDS spreads for US Investment Grade corporates (in bps)



(a) Basic material (b) Consumer goods (c) Consumer services

(d) Energy (e) Financials (f) Healthcare

(g) Industrials (h) Technology (i) Utilities

Note: This figure plots the evolution over time of daily 5-year CDS spreads for US Investment Grade corporates. We report sector-level median values in basis points and the period covered is 2007-01 to 2022-09. Note that the median values for the Technology sector (2 companies) are driven by the elevated levels of the CDS spread for Advanced Micro Devices Inc. (AMD).

3.3 Model specification and systemic risk measures

We introduce the dynamic copula model we will use in our application. We consider the log difference of firm i CDS spreads, $Y_{i,t} \equiv \Delta \log S_{i,t}$. Oh and Patton (2018) introduce a flexible modeling framework allowing for time-varying conditional marginal distributions and a time-varying dependence structure. We decompose the conditional joint distribution F_t of the log CDS differences for a collection of N firms, $\mathbf{Y}_t = \left[Y_{1,t}, \ldots, Y_{N,t}\right]'$, into their marginal distributions $F_{i,t}$ and a conditional copula C_t

$$\mathbf{Y}_t \mid \mathcal{F}_{t-1} \sim \mathbf{F}_t = \mathbf{C}_t \left(F_{1,t}, \ldots, F_{N,t}\right) \ , \tag{3.1}$$

where $\mathcal{F}_t$ is the information set generated by $\{\mathbf{Y}_t, \mathbf{Y}_{t-1}, \ldots\}$ and we have implicitly used Sklar's theorem for conditional distributions; see Patton (2006) for details. We now detail in the following subsections how we specify the different components of Equation (3.1).

3.3.1 Conditional mean and volatility models for the marginal distributions

Suppose that we have the following specification for the marginal distribution of each firm $i = 1, 2, \ldots, N$

$$Y_{i,t} = \mu_{i,t}\left(\phi_i^{\mu}\right) + \sigma_{i,t}\left(\phi_i^{\sigma}\right)\eta_{i,t} \ , \tag{3.2}$$

$$\eta_{i,t} \mid \mathcal{F}_{t-1} \sim F_{i,t}\left(\phi_i^{\eta}\right) \ , \tag{3.3}$$

where $\mu_{i,t}$ is the conditional mean of $Y_{i,t}$ and $\sigma_{i,t}$ is the conditional standard deviation. We denote the parameters for the conditional mean and volatility models respectively as ϕ_i^{μ} and ϕ_i^{σ}. Furthermore, $F_{i,t}\left(\phi_i^{\eta}\right)$ is a strictly increasing continuous parametric distribution with zero mean and unit variance. We denote its parameters as ϕ_i^{η} and we can thus collect the parameters of the marginal distribution of each firm in $\phi_i = \left[\phi_i^{\mu\prime}, \phi_i^{\sigma\prime}, \phi_i^{\eta\prime}\right]'$. Collecting these parameter vectors across the N firms, we write $\phi = \left[\phi_1', \ldots, \phi_N'\right]'$. In this paper, we use the Skew t distribution introduced in Hansen (1994) for the modelling of the marginal distribution of the standardized residuals, $\eta_{i,t}$, with degrees of freedom ν_i and asymmetry parameter ψ_i

$$\eta_{i,t} = \frac{e_{i,t}}{\sigma_{i,t}} \sim \text{ iid Skew } t\left(\nu_i, \psi_i\right) \ . \tag{3.4}$$

The marginal distribution of the standardized residuals thus allows for nonzero skewness and excess kurtosis. Log difference of CDS spreads exhibit more autocorrelation than what would be expected from other financial time series such as daily stock return series (see Table 3.1 in Section 3.2). Therefore, we specify a dynamic model for the conditional mean of the CDS spread log differences $Y_{i,t}$. We opt for an AR(p) model, which we augment with q lags of the market index — computed as the equal-weighted average across the N firms — to capture any dynamic spillover effects.

$$Y_{i,t} = \phi_{0,i} + \sum_{j=1}^{p} \phi_{j,i} Y_{i,t-j} + \sum_{k=1}^{q} \phi_{k,i}^{m} Y_{t-k}^{m} + e_{i,t} \ . \tag{3.5}$$

After estimating the conditional mean model, we can obtain the fitted residual term $e_{i,t}$ for each firm i which is then used as an input in our time-varying volatility model. For the conditional volatility, we consider the Beta-t-EGARCH volatility model with leverage effect proposed by Harvey (2013). The motivation for the leverage effect in this model is that "bad news" about a firm increase its future volatility more than "good news". For stock returns, bad news are associated with a negative residual. For CDS spreads, on the other hand, bad news are associated with a positive residual, and so we reverse the direction of the indicator variable in the Beta-t-EGARCH volatility model with leverage effect to reflect this stylized fact.[4] We specify the model for the log volatility $h_{i,t} := \log(V_{t-1}\left[e_{i,t}\right])$

$$h_{i,t} = \omega_i + \beta_i h_{i,t-1} + \alpha_i u_{i,t-1}^{h} + \delta_i sgn\left(e_{i,t-1}\right)\left(u_{i,t-1}^{h} + 1\right) \ , \tag{3.6}$$

where $u_{i,t}^{h}$ is the conditional score which by construction is a martingale difference sequence. We derive the analytical expression for the conditional score of the Beta-t-EGARCH volatility model specified above under the assumption that the density of the innovations $e_{i,t}$ is given by the Skew t distribution of Hansen (1994). Using results from

[4]Note that we only make this adjustment for internal consistency reasons as this would only affect the sign of the estimated coefficient δ_i.

Appendix B of Jondeau and Rockinger (2003), we obtain:

$$u_{i,t}^h = \frac{\partial \log f_{ST}(e_{i,t};\nu_i,\psi_i)}{\partial h_{i,t}} = \frac{\nu_i+1}{2m_{i,t}}\frac{2d_{i,t}}{\nu_i-2}\frac{b_i e_{i,t}}{(1-\psi_i\bar{s}_{i,t})\exp(h_{i,t})} - 1\,, \tag{3.7}$$

where $\log f_{ST}(e_{i,t};\nu_i,\psi_i)$ is the log-likelihood function for the Skew t distribution and we have defined the following quantities

$$\begin{aligned}
a_i &= 4\psi_i c_i \frac{\nu_i-2}{\nu_i-1}\,,\\
b_i &= \sqrt{1+3\psi_i^2-a_i^2}\,,\\
c_i &= \frac{\Gamma\left(\frac{\nu_i+1}{2}\right)}{\sqrt{\pi(\nu_i-2)}\Gamma\left(\frac{\nu_i}{2}\right)}\,,\\
d_{i,t} &= \frac{\left(\frac{b_i e_{i,t}}{\exp(h_{i,t})}+a_i\right)}{(1-\psi_i\bar{s}_{i,t})}\,,\\
m_{i,t} &= 1+\frac{d_{i,t}^2}{\nu_i-2}\,.
\end{aligned}$$

Note that the expression for $\bar{s}_{i,t}$ is defined as follows:

$$\bar{s}_{i,t} = \begin{cases} 1 & \text{if} \quad \left(\frac{b_i e_{i,t}}{\exp(h_{i,t})}+a\right) < 0\,,\\ -1 & \text{otherwise}\,. \end{cases}$$

The parameter ν_i plays a double role in the specification of the Beta-t-EGARCH in Equations (3.6) and (3.7). First, it acts as the shape parameter in the Skew t density of the residual term $e_{i,t}$. Second, it enters the specification of the conditional score in Equation (3.7) and bounds the impact of large innovations on the log volatility process $h_{i,t}$. However, Blasques et al. (2022) point out that the score-driven (SD) approach outlined above imposes a strong link between the conditional distribution of the model and the updating equation for the dynamic parameters. This strong link might not always be supported empirically and the authors propose a Quasi Score-Driven (QSD) approach which generalizes the SD approach by allowing the updating equation for the time-varying parameters to be potentially decoupled from the distribution of the model innovations. The authors illustrate their approach by extending the Beta-t-GARCH model of Harvey and Chakravarty (2008). They show through simulations that the model misspecification

— associated with using the more restrictive SD model instead of the QSD approach — can result in biased parameter estimates and a persistent underestimation of volatility following large shocks. Moreover, the use of a skewed density for the innovations seems to magnify the issues of the SD approach. They also document empirically, using a panel of 400 US stocks from the S&P500, that the restrictions associated with the Beta-t-GARCH model are rejected in respectively 50% and 100% of the cases for the symmetric and skewed distributions. Finally, the Probability Integral Transform (PIT) test of Diebold et al. (1997) indicates that the skewed version of their QSD model captures the key features of 88% of the stocks in the sample.

We build on Blasques et al. (2022) and propose a QSD extension of the asymmetric Beta-t-EGARCH model of Harvey (2013):

$$u^h_{i,t} = \frac{\nu^u_i + 1}{2m^u_{i,t}} \frac{2d^u_{i,t}}{\nu^u_i - 2} \frac{b^u_i e^u_{i,t}}{(1 - \psi^u_i \bar{s}_{i,t}) \exp(h_{i,t})} - 1 \;, \tag{3.8}$$

where we have introduced the additional parameters ν^u_i and ψ^u_i in the updating equation for the log volatility process $h_{i,t}$. We use the superscript u in the notation of Equation (3.8) to emphasize that the associated parameters are now decoupled from the ones entering the density of the residual term $e_{i,t}$. The estimation of the asymmetric QSD-t-EGARCH model defined by Equations (3.6) and (3.8) will be carried out by MLE based on the Skew t log-likelihood function of the residual term $\log f_{ST}(e_{i,t}; \nu_i, \psi_i)$.

3.3.2 Dynamic factor copula model

We define the conditional probability integral transforms of the data as

$$U_{i,t} = F_{i,t}\left(\frac{Y_{i,t} - \mu_{i,t}\left(\phi^\mu_i\right)}{\sigma_{i,t}\left(\phi^\sigma_i\right)}; \phi^\eta_i\right), \quad i = 1, 2, \ldots, N \;. \tag{3.9}$$

The conditional copula of $\mathbf{Y}_t \mid \mathcal{F}_{t-1}$ is equal to the conditional distribution of $\mathbf{U}_t \mid \mathcal{F}_{t-1}$, i.e.

$$\mathbf{U}_t \mid \mathcal{F}_{t-1} \sim \mathbf{C}_t\left(\gamma\right) \;. \tag{3.10}$$

As they are interested in high-dimensional applications, Oh and Patton (2018) introduce a factor structure where it is most needed, i.e. in the specification of the conditional dependence model, to achieve dimension reductions. For simplicity, we use a specification with one common factor, where the copula for the latent vector random variable $\mathbf{X}_t = \left[X_{1,t}, \ldots, X_{N,t}\right]'$ is implied by the following structure

$$X_{i,t} = \lambda_{i,t}\left(\gamma_\lambda\right) Z_t + \varepsilon_{i,t}, \quad i = 1, 2, \ldots, N \ , \tag{3.11}$$

$$\text{where } Z_t \sim F_{zt}\left(\gamma_z\right), \quad \varepsilon_{i,t} \sim \text{ iid } F_{\varepsilon t}\left(\gamma_\varepsilon\right), \quad Z_t \perp \varepsilon_{i,t} \text{ for } \forall i \ . \tag{3.12}$$

where we have introduced $F_{zt}\left(\gamma_z\right)$ and $F_{\varepsilon t}\left(\gamma_\varepsilon\right)$ to denote flexible parametric univariate distributions for the common factor and the idiosyncratic variables. $\lambda_{i,t}\left(\gamma_\lambda\right)$ is the time-varying loading on the common factor for firm i. We collect all the static parameters of the dynamic copula into the vector $\gamma = \left[\gamma_z', \gamma_\varepsilon', \gamma_\lambda'\right]'$. In our application, we consider that the common factor follows the Skew t distribution of Hansen (1994), i.e. $Z \sim \text{Skew}\, t\left(v_z, \psi_z\right)$, while the idiosyncratic variables are modelled by a t distribution, namely $\varepsilon_i \sim \text{iid}\, t\left(v_\varepsilon\right)$.

Analogous to $\mathbf{Y}_t$, the conditional joint distribution for $\mathbf{X}_t$ can be decomposed into:

$$\mathbf{X}_t \sim \mathbf{G}_t = \mathbf{C}_t\left(G_{1,t}(\gamma), \ldots, G_{N,t}(\gamma); \gamma\right) \ . \tag{3.13}$$

Note that we will only use the copula of $\mathbf{X}_t$, denoted $\mathbf{C}_t(\gamma)$, as a model for the copula of the observable data $\mathbf{Y}_t$. The marginal distributions of $\mathbf{X}_t$ can differ from the ones chosen for the observable data without implications. Therefore, we discard the marginals $G_{i,t}$ from our analysis.

We specify a Dynamic Conditional Score (DCS) model for the log factor loadings $\log \lambda_{i,t}$, i.e.

$$\log \lambda_{i,t} = \omega_i + \beta \log \lambda_{i,t-1} + \alpha s_{i,t-1}, \quad i = 1, 2, \ldots, N \ , \tag{3.14}$$

where $s_{i,t} = \partial \log \mathbf{c}\left(\mathbf{u}_t; \lambda_t, v_z, \psi_z, v_\varepsilon\right) / \partial \log \lambda_{i,t}$ is the conditional score and we have introduced the notation $\lambda_t = \left[\lambda_{1,t}, \ \ldots, \lambda_{N,t}\right]'$. To address the computational challenges that can arise with a large panel of firms, we adopt the "variance targeting" approach proposed in Oh and Patton (2018). In this case, Equation (3.14) is modified as follows

$$\log \lambda_{i,t} = E\left[\log \lambda_{i,t}\right](1 - \beta) + \beta \log \lambda_{i,t-1} + \alpha s_{i,t-1} \ , \tag{3.15}$$

where $E\left[\log \lambda_{i,t}\right]$ can be estimated using an approximation based on sample rank correlations. The targeting technique makes it feasible to estimate the model in high dimensional applications since it eliminates the need to optimize over the intercept parameters, ω_i.[5]

An alternative way of reducing the dimensionality of the problem is through the imposition of restrictions on the structure of the loadings on the common factor, such as "block equidependence".

$$X_{i,t} = \lambda_{g(i),t} Z_t + \varepsilon_{i,t}, \quad i = 1, 2, \ldots, N \, , \tag{3.16}$$

$$\log \lambda_{g,t} = \omega_g + \beta \log \lambda_{g,t-1} + \alpha s_{g,t-1}, g = 1, 2, \ldots, G \, , \tag{3.17}$$

where $g(i)$ is the group to which variable i belongs, and G is the number of groups. In our application, we focus on the case where groups are based on the sector information for each firm and assume that the parameters within a given group take the same value. Further restricting the ω_g to be identical across groups will result in the "dynamic equidependence" specification.

To summarise, we consider three specification of the copula Skew *t*-*t* model in this paper to capture the time-varying conditional dependence structure in the CDS spreads over time. To make it feasible to estimate the model in high dimensions, we first consider the more general heterogeneous dependence model ($G = N$). In this case, we use the targeting approach based on rank correlations to achieve dimension reduction. Second, we implement the dynamic block equidependence model (without targeting) to reduce the total number of parameters. Lastly, we also include the most restrictive dynamic equidependence model specification ($G = 1$) in our model comparison.

3.3.3 Time-varying systemic risk

We consider two measures of systemic risk which capture the dependence in failure across firms in the system. First, the Joint Probability of Distress (JPD) is the probability of a large fraction of the firms in the system being simultaneously in distress. Second, the Expected Proportion in Distress (EPD) of a firm measures the distress spillover effect from a single firm to the market as a whole.[6] See e.g. Segoviano and Goodhart (2009)

[5] More details on the implementation and the property of the estimator can be found in Section 2.3 of Oh and Patton (2018).

[6] The definitions and names of the two systemic risk measures are based on Oh and Patton (2018).

and Giesecke and Kim (2011) for a similar approach to systemic risk modelling in the banking system.

3.3.3.1 Joint Probability of Distress

To compute the JPD, we define a distress event as a firm's h-days ahead CDS spread rising above a given threshold. More specifically,

$$D_{i,t+h} = \mathbf{1}\left\{S_{i,t+h} > c^{*}_{i,t+h}\right\} \ , \tag{3.18}$$

where $c^{*}_{i,t+h}$ is a predetermined threshold which we set at the 99% conditional quantile of the individual CDS spread series in our application. We consider horizons of 3 months and 1 year ($h \in [63; 252]$) for the distress event.

The Joint Probability of Distress (JPD) measure can then be computed as

$$\text{JPD}^{h}_{t,k} = \Pr_t\left[\left(\frac{1}{N}\sum_{i=1}^{N} D_{i,t+h}\right) \geq \frac{k}{N}\right] \ , \tag{3.19}$$

where k is a user-defined threshold reflecting what constitutes a "large" proportion of the N firms. We will set k as the threshold corresponding to 40% of the N firms being in distress.

By measuring the conditional probability of the joint default of a considerable fraction of large entities, the JPD allows us to extract information on the level of systemic risk in the economy from CDS data. This approach is reminiscent of other methodologies extracting information from financial instruments directly exposed to systemic risk (Gourieroux et al., 2021). Examples include far out-of-the-money (OTM) put options written on equity indices (Backus et al., 2011; Bollerslev and Todorov, 2011) and Collateralized Debt Obligations (CDOs) (Longstaff and Rajan, 2008; Coval et al., 2009; Collin-Dufresne et al., 2012; and Seo and Wachter, 2018). These methodologies take an aggregate perspective by focusing on the tail risks inferred from a pool of entities (e.g. equity index or portfolio of firms). We propose an alternative approach which exploits commonalities in tail risk across a large panel of firms by modelling them jointly (Kelly and Jiang, 2014). This way, we can also investigate how an individual firm contributes to the default risk of other firms and to aggregate tail risks (Adrian and Brunnermeier, 2016). This is done through the EPD measure which is introduced below.

3.3.3.2 Expected Proportion in Distress

The EPD is computed as the expected proportion of firms in distress conditional on firm i being in distress

$$\mathrm{EPD}_{i,t}^{h} = E_t\left[\frac{1}{N}\sum_{j=1}^{N} D_{j,t+h} \mid D_{i,t+h} = 1\right] . \tag{3.20}$$

The EPD measure takes values ranging from $1/N$ to one with $1/N$ indicating no distress spillover from a single firm to the market and one meaning that the entire market is in distress conditional on this single firm failing. Therefore, the EPD summarises the systemic importance of a given firm by measuring how the firm's own default can result in a clustering of defaults from other firms through broad contagion channels (Azizpour et al., 2018). Finally, the EPD also relates to the theory of granular origins of aggregate fluctuations (Gabaix, 2011) as it captures the likelihood of idiosyncratic shocks affecting a systemic firm to lead to a material impact on aggregate economic fluctuations.

3.3.4 Summary of dynamic model estimation and time-varying systemic risk measure

The previous subsections presented the dynamic models used for conditional marginal and joint distributions, in addition to the construction of the time-varying systemic risk measures. In the following, we summarise the three-step procedure to estimate the dynamic models and the additional steps required to construct the systemic risk measures.

1. We estimate the dynamic conditional mean model specified in Equation (3.5) using an Ordinary Least squares (OLS) regression to obtain the parameter estimates of $\hat{\phi}_\mu$ and thus the de-meaned residual terms $\hat{e}_{i,t}$ for each firm i.

2. We estimate the dynamic conditional volatility (asymmetric QSD-t-EGARCH) model specified in Equations (3.6) and (3.8) using maximum likelihood estimation proce-

dure to obtain parameter estimates of $\hat{\phi}_\sigma$ and $\hat{\phi}_\eta$. The de-volatilized residuals $\hat{\eta}_{i,t}$ can be computed based on the estimated parameters; see Equation (3.4).

3. We estimate the Skew t-t factor copula models for the heterogeneous dependence (Equation (3.14)), the block equidependence (Equation (3.17)) and the equidependence (Equation (3.17) with $\omega_1 = \omega_2 = \ldots = \omega_G$) specifications, to obtain the estimated copula parameters $\hat{\gamma}$ for each model.

4. For each day where the systemic risk measures are computed, we draw 300 simulations of the common factor Z from a Skew t distribution and of the idiosyncratic variables ε_i from a t distribution for each firm i.

   - Using Z and ε_i, we can construct recursively the forecasts of the time-varying loadings $\lambda_{i,t}$ and thus $X_{i,t}$, which provides us with the forecasts of $\eta_{i,t}$, using the inverse CDF transform $F_{i,t}^{-1}$.
   - Similarly, the h-day-ahead forecast of the conditional volatility and mean can be computed recursively based on $\eta_{i,t}$ and Equations (3.5), (3.6) and (3.8).
   - Therefore, the h-day-ahead CDS spread $\hat{S}_{i,t+h}$ can be calculated based on the forecasts $[\hat{Y}_{i,t+1}, \ \ldots \ , \hat{Y}_{i,t+h}]$.

5. Based on the h-day-ahead forecast of the CDS spread $\hat{S}_{i,t+250}$, we compute the two systemic measures JPD and EPD as specified in Equations (3.19) and (3.20).

3.4 Empirical application

3.4.1 Conditional mean and volatility dynamics

We consider the sample ranging from 2007-01 to 2013-12 and a second period ranging from 2014-01 to 2022-09 to estimate the dynamic model for conditional mean specified in Equation (3.5) and the model for conditional volatility specified in Equations (3.6) and (3.8). We carried out a model selection exercise to determine the lag orders p and q in the conditional mean model based on the minimization of the Bayesian Information Criterion

(BIC) which led to a specification with $p = q = 3$ lags. We plot the estimation results for the conditional mean and volatility parameters respectively in Figure 3.11 (Appendix 3.B.1) and Figure 3.13 (Appendix 3.B.2). The key results for the conditional mean are summarised as follows.[7]

The conditional mean dynamics of CDS daily log-differences have a higher degree of persistence than what is usually observed for stock return data. For the period from 2007-01 to 2013-12, estimates of the first autoregressive coefficient can reach values up to 0.21 and are statistically significant at the 5% level for 60% of the firms. The second and third lags are statistically significant in respectively 40% and 28% of the cases, with values ranging from 0.1 to 0.17. For the period from 2014-01 to 2022-09, we observe a marked increase in the persistence of the data as coefficient estimates increase in magnitude for all lags and are significant in 76% of the cases for the first lag and 67-68% for lags 2 and 3. We find strong evidence of market spillovers in the first subsample with estimates of the first lag being significant in 96% of the cases. The strength of market spillover effects decreases somewhat in the second subsample, both in terms of the magnitude of the coefficient estimates and their statistical significance.

For the conditional volatility dynamics, Figure 3.3 below plots a summary of the estimated volatility dynamics in both subsamples. The black line corresponds to the median fitted volatility across the 75 firms and the dark- and light-blue shaded areas correspond respectively to the Inter Quartile Range (IQR) and 10-90 percentile range. The first subsample is marked by a sustained period of elevated volatility starting with the GFC and continued with the unfolding of the European sovereign debt crisis and the US sovereign debt downgrade in August 2011. This period is followed by a prolonged, more persistent, low-volatility regime starting from mid-2013 and marked by short-lived episodes of elevated volatility in 2016, 2018, and at the onset of the Covid-19 pandemic. Lastly, we note that volatility start trending upward from end-2021 on.

These features of the fitted volatility dynamics are consistent with the parameter

[7]More details on the interpretation of the estimation results of the dynamic conditional mean and conditional volatility model parameters can be found respectively in Appendix 3.B.1 and Appendix 3.B.2.

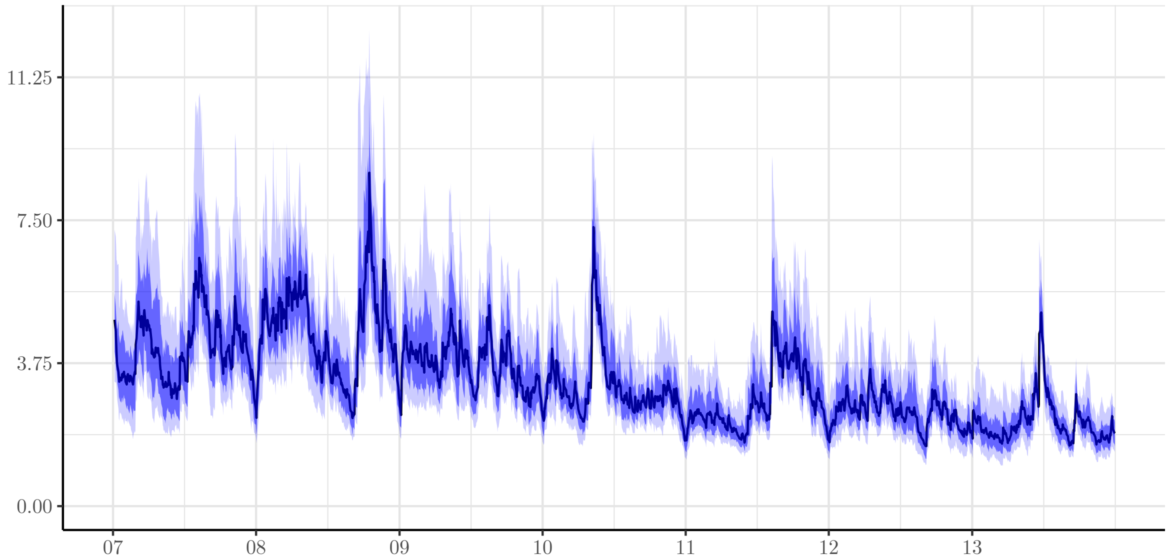
estimates of the asymmetric QSD-t-EGARCH model reported in Figure 3.13 of Appendix 3.B.2. We document a high degree of persistence in the dynamics, with median estimates around 0.966 in both samples. This pattern is particularly pronounced in the second subsample where the distribution of the estimates is more concentrated at higher levels of persistence ranging from 0.925 to 0.99. Furthermore, bad news increasing a firm's CDS level also increase its conditional volatility. Higher values of the estimates for the parameter δ_i indicate that firms have become more sensitive to this driver of the log volatility process since 2014. Firms' standardized residuals are fat-tailed and positively skewed, with the latter becoming more pronounced in the second subsample we analyze.

Finally, the flexibility of the asymmetric QSD-t-EGARCH helps capturing key differences between the shape and skewness parameters entering the density of the innovations (ν_i and ψ_i) and the updating equation for the log-volatility process (ν_i^u and ψ_i^u). Indeed, allowing the parameters of the updating equation to be decoupled from the ones entering the innovation density leads to a lower down-weighting of large innovations in the first subsample than what would be implied by its Beta-t-EGARCH counterpart (higher degrees of freedom estimates in the quasi score update). Results for the second subsample are more comparable, although there is more dispersion in the range of values taken by ν_i^u and a tilt towards higher degrees of freedom estimates. The larger positive gap between the ν_i^u and ν_i estimates in the first subsample suggests that allowing for a steep news impact curve is important during sustained periods of elevated volatility such as the GFC period.[8] On the other hand, the gap between ν_i^u and ν_i estimates narrows during calmer periods with short-lived episodes of high volatility, implying a flatter news impact curve for large innovations due to the fat-tailed distribution. Comparing estimates for the skewness parameters, we see that the ψ_i^u estimates take a much broader range of both positive and negative values than what would be implied by the SD approach as the ψ_i estimates are mainly concentrated at smaller positive values.

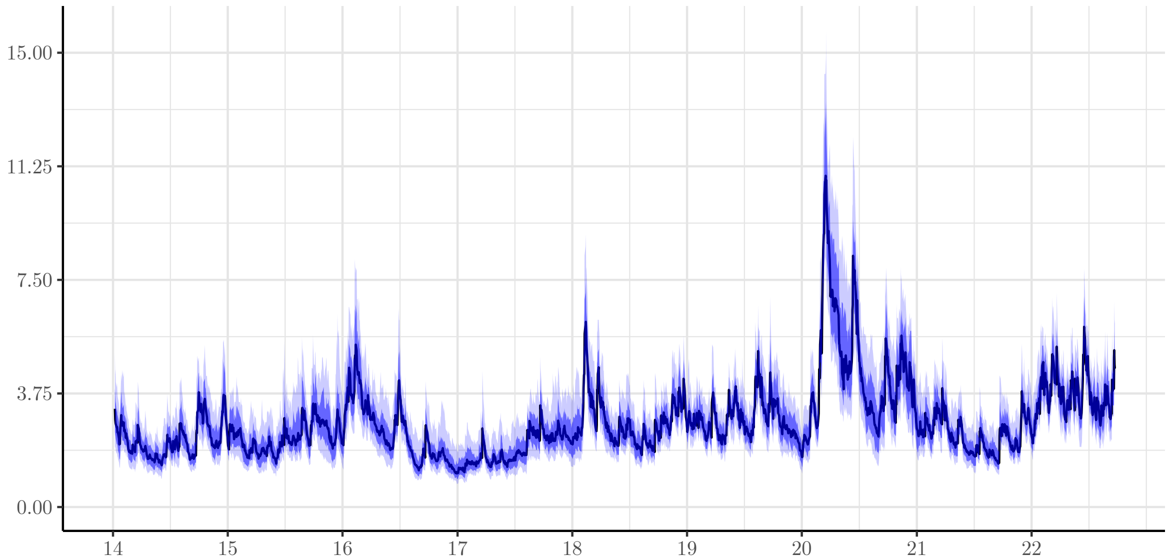
We assess how well the models we specified for the conditional mean and volatility dy-

[8]See Figure 3.15 is Appendix 3.B.2 for a plot of the estimates of the shape and skewness parameters for each of the 75 firms in our sample.

Figure 3.3: Estimated volatility (in percentage points)



(a) Period from 2007/01 to 2013/12



(b) Period from 2014/01 to 2022/09

Note: This figure plots the quantiles of the fitted volatilities for the log-differences of the 5-year CDS spreads. We plot daily quantiles across the 75 firms in our sample. The top panel considers the results for the sample ranging from 2007-01 to 2013-12, and the bottom panel covers the results for the sample from 2014-01 to 2022-09. In each panel, the black line corresponds to the median fitted volatility across firms; the dark- and light-blue shaded bands correspond respectively to the Inter Quartile Range (IQR) and the 10-90 percentile range.

namics fit the conditional marginal distributions of our CDS data. Table 3.3 in Appendix 3.B.2 reports descriptive statistics for the standardized residuals $\eta_{i,t}$ and the number of rejections, using a 5% significance level, for several model specification tests. The tests include the Box-Pierce (BP) tests, using a maximum lag length of 25, on the standardized residuals and their squares; and Kolmogorov-Smirnov tests on the standardized residuals following a Skew t distribution. We conclude that the models specified in Equations (3.5), (3.6), and (3.8) for the conditional mean and volatility dynamics provide a good fit to the CDS data and their marginal distributions. In the next section, we move to the estimation of the dynamic copula models, which are based on the $U_{i,t}$ estimates obtained by applying the Probability Integral Transform (PIT) to the estimated standardized residuals using their respective marginal distributions.

3.4.2 Conditional copula dynamics

Table 3.2 summarises the estimation results for the Skew t-t factor copula model specified in Equations (3.10), (3.11) and (3.14). First, estimates for the autoregressive parameter β are indicative of high levels of persistence in the dynamics of the loadings. Estimated values range from 0.924 for the equidependence specification to 0.996 for the heterogeneous dependence specification.

The parameter α controls how the time-varying loadings process, and therefore dependence across firms, reacts to new information through the score update. We first observe that the sensitivity of dependence to new information seems to increase in the second sample ranging from 2014 to 2022. Second, we see a different pattern in each subsample for the evolution of parameter estimates across the different specifications. In the first sample, the estimates indicate that dependence across firms becomes comparatively more responsive to new information in specifications with more flexibility in the modelling of firms' loadings on the common factor. In the second sample, estimates are rather stable across specifications. This result could indicate that time-varying dependence across firms reacts more to new information during prolonged periods of elevated volatility.

Considering now the results for the degrees of freedom parameters of the common

Table 3.2: Estimation results for different copula specifications

	Equidependence		Block equidependence		Heterogeneous dependence	
	Sample 1	Sample 2	Sample 1	Sample 2	Sample 1	Sample 2
$\omega_{1\to G}$	-0.009	-0.044	–	–	–	–
α	0.006	0.069	0.019	0.062	0.044	0.057
β	0.940	0.924	0.952	0.927	0.995	0.996
ν_z	5.291	8.065	10.638	7.092	9.346	5.952
ν_ε	6.250	5.714	5.435	4.202	5.435	3.968
ψ_z	0.114	0.269	0.159	0.274	0.067	0.090
No. of parameters	6		14		80	
$\log \mathcal{L}$	38,219	62,805	38,299	68,744	38,818	71,621
AIC	$-76,425$	$-125,599$	$-76,569$	$-137,460$	$-77,477$	$-143,081$
BIC	$-76,392$	$-125,565$	$-76,492$	$-137,379$	$-77,036$	$-142,623$

Note: This table reports the parameter estimates for the Skew t-t factor copula model specified in Equations (3.10), (3.11) and (3.14). We consider three specifications for dependence which range from equidependence ($G = 1$), to block equidependence at the sector level ($G = 9$), and heterogeneous dependence where each firm has its own time-varying loadings. The number of parameters for each specification are reported at the bottom of the table, together with the log-likelihood and the corresponding Akaike and Bayesian Information Criteria. Sample 1 ranges from 2007/01 to 2013/12 and Sample 2 covers the period from 2014/01 to 2022/09.

factor and idiosyncratic term, ν_z and ν_ε, we conclude that the hypothesis of normality for the factor copula is not supported by the data as the estimates are between 4 and 11. Furthermore, estimates for the second subsample indicate fatter-tailed distributions for the common factor and idiosyncratic term. More flexible dependence specifications appear to be associated with a less heavy-tailed distribution for the common factor in the first subsample but the converse is true in the second subsample. For the idiosyncratic term, more flexible specifications are associated with heavier-tailed distributions across both samples.

We also consider the level of tail dependence implied by the degrees of freedom estimates. As shown in Oh and Patton (2017), tail dependence for the factor Skew t-t copula will be zero or one respectively when $\nu_z > \nu_\varepsilon$ and $\nu_z < \nu_\varepsilon$; tail dependence will be in the interval $[0, 1]$ when the two parameters are equal. Applying these results to our estimates, we observe that $\hat{\nu}_z > \hat{\nu}_\varepsilon$ in all the cases but one.[9] Therefore, the estimated factor copula models imply zero dependence between extreme variations in CDS spreads. This is consistent with the results reported in Oh and Patton (2018) (Table 4, page 189) who notice that this result on tail dependence applies only in the limit but not for "near-extreme" variations.

Finally, we observe that the estimates for the asymmetry parameter ψ_z of the common factor are all positive, which is indicative of greater dependence for upward moves in CDS spreads. We therefore find empirical support in the data for the view that financial market dependence increases during periods of market stress, which are typically associated with rising CDS spreads. Asymmetry estimates are relatively larger in specifications with less flexibility in the modelling of dependence across firm and they also tend to increase in the second subsample for the more recent period.

We assess which specification for dependence provides the best fit to the data. In both subsamples, the data appears to support the most flexible specification with heterogeneous dependence. This is confirmed by the large gains in log-likelihood achieved when moving

[9] The exception is for the equidependence specification in the first subsample for which estimates are consistent with a tail dependence of one.

from a restricted model to a more flexible one. In addition, the Information Criteria (Akaike and Bayesian) are minimized for the heterogeneous dependence specification — despite the fact that they penalize for models with a larger number of parameters to estimate.

In summary, we opt for the copula factor Skew t-t model with heterogeneous dependence in the time-varying loadings as it provides the best fit to the conditional dependence in CDS spreads over the studied period. The model parameter estimates reveal a high degree of persistence in the loadings; heavier tails for the common factor and idiosyncratic term than in the Gaussian case; and positive asymmetry in the common factor which implies higher dependence between upward moves in CDS spreads — although the estimates are associated with zero tail dependence for extreme variations. We will focus on this model specification in the rest of our analysis.

3.4.3 Time-varying factor loadings

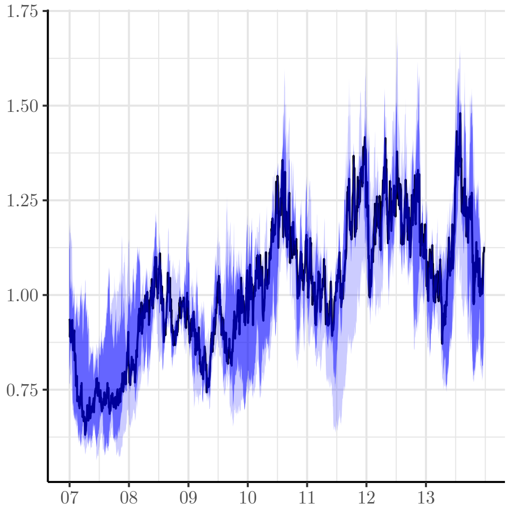
Figures 3.4 and 3.6 summarise the evolution of the median value of the time-varying factor loadings $\lambda_{i,t}$ across firms in each sector for the heterogeneous dependence specification; respectively over the period 2007-2013 and 2014-2022. For the first subsample, we observe that — unlike for the CDS spreads plotted in Figure 3.1 — dependence on the common factor Z_t does not peak around the start of the GFC before progressively going down. Rather, factor loadings appear to experience a steady increase before levelling off at higher levels compared to the beginning of the sample. Interestingly, there is some degree of asynchronicity across sectors in the timing of this increased dependence on the common factor — with the majority of the sectors experiencing this increase in the early stage of the subprime crisis (2007-2008) and others, such as the energy and utility sectors, only starting around 2010-2011.

We observe in Figure 3.6 that factor loadings stabilize in the period from 2014 to end-2017 before experiencing a second phase of rising dependence on the common factor. In this respect, dependence appears to be less responsive to the period of increased volatility resulting from the financial market turmoil in China (2015-2016) compared to the reaction observed for CDS spreads and their conditional volatilities in Figures 3.1 and 3.3.[10] Factor loadings increase markedly from 2018 to mid-2019 — rising above dependence levels observed in the first part of the sample.[11] Afterwards, dependence goes down progressively until mid-2020 — in stark contrast with the acute increase in CDS spreads and their volatility observed at the onset of the Covid-19 pandemic. Common factor loadings then resume their sustained increasing trend to reach their highest levels towards the beginning of 2022 and stabilize at these elevated levels towards the end of the sample, concurrently with rising levels of CDS spreads and volatility (see Figures 3.1 and 3.3).

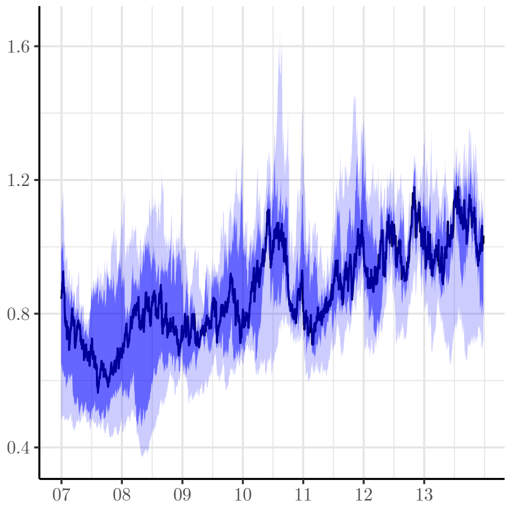
[10] One notable exception is the industrial sector which experiences a spike in dependence over the second half of 2016.

[11] A potential caveat to this type of comparison across subsamples is that other factors then increasing dependence could be driving differences in the sector level of factor loadings, such as changes in parameter estimates for the model.

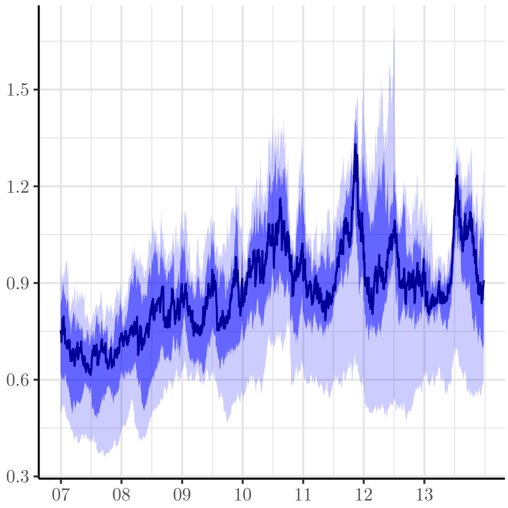
Figure 3.4: Estimated factor loadings for each sector (2007-2013)



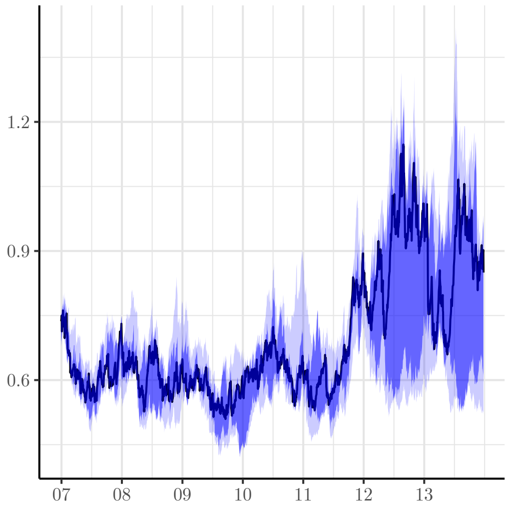
(a) Basic materials



(b) Consumer goods

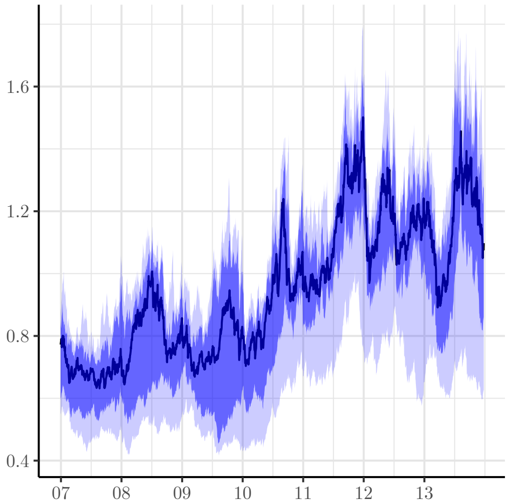


(c) Consumer services

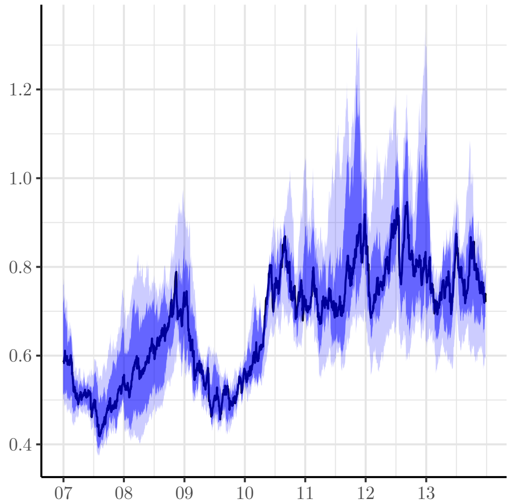


(d) Energy

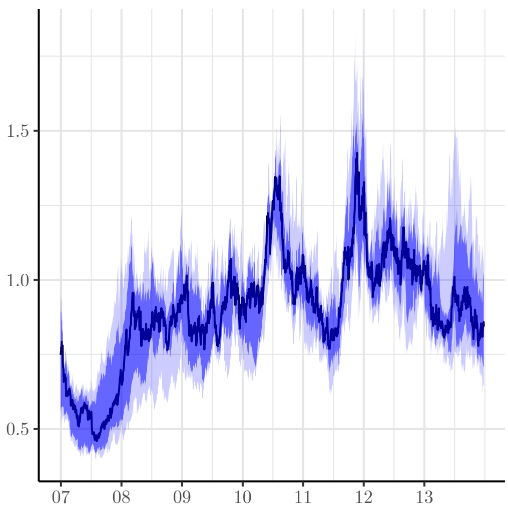
Figure 3.5: (Continued)



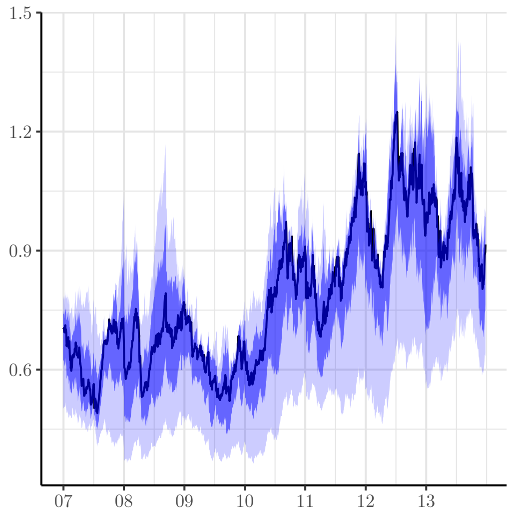
(e) Financials



(f) Healthcare



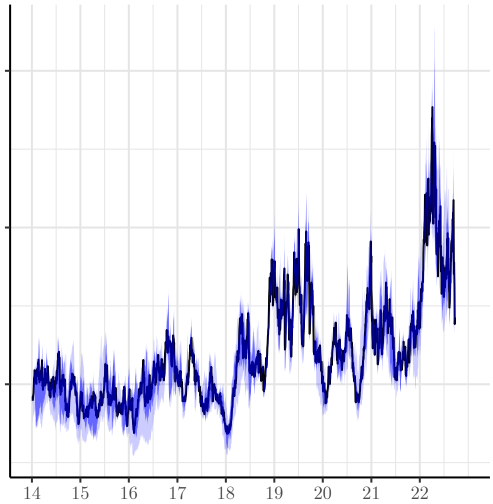
(g) Industrials



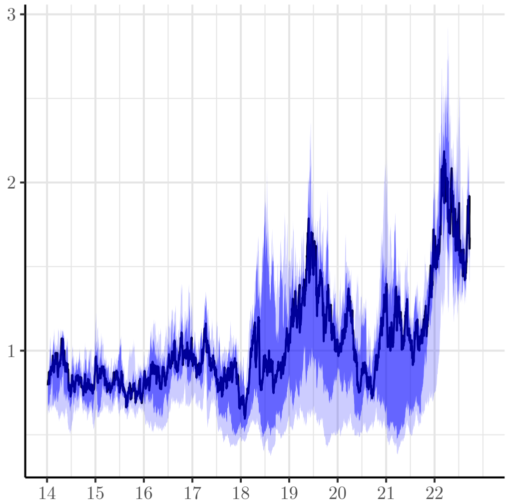
(h) Utilities

Note: This figure plots the evolution of the estimated time-varying loadings of the respective sectors over the period 2007-2013 based on our preferred model specification. In each panel, the black line corresponds to the median fitted volatility across firms; the dark- and light-blue shaded bands correspond respectively to the Inter Quartile Range (IQR) and the 10-90 percentile range.

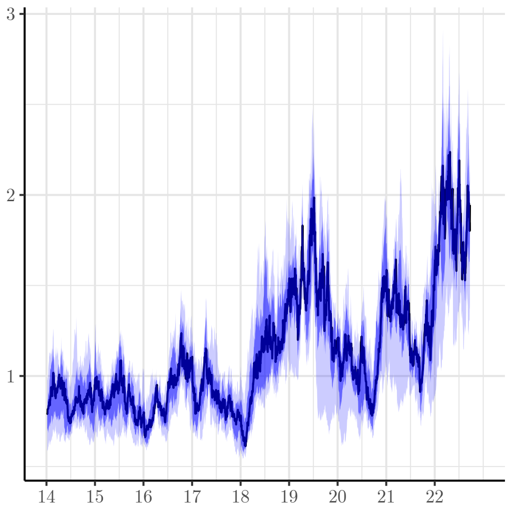
Figure 3.6: Estimated factor loadings for each sector (2014-2022)



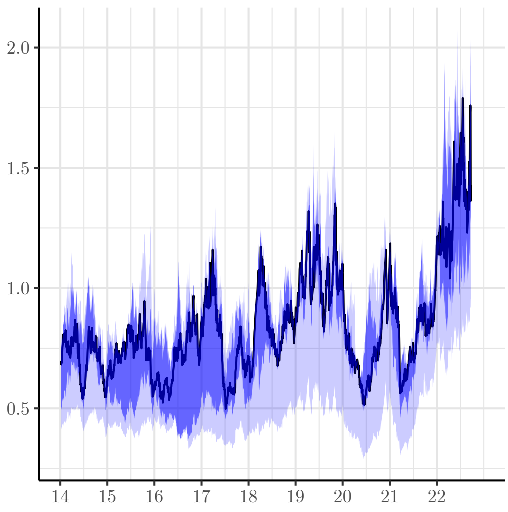
(a) Basic materials



(b) Consumer goods

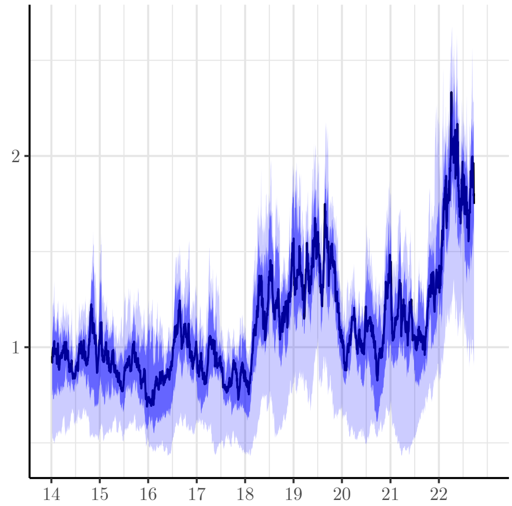


(c) Consumer services

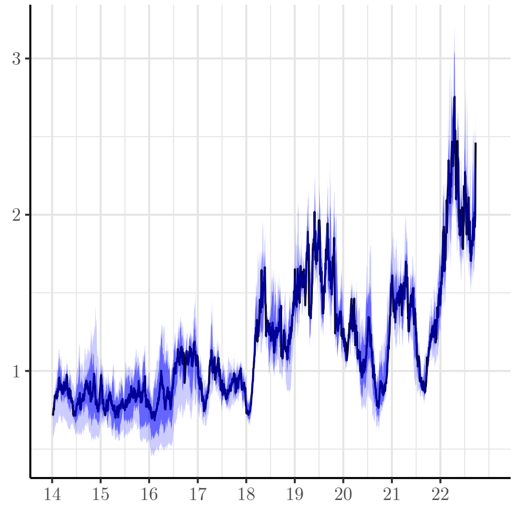


(d) Energy

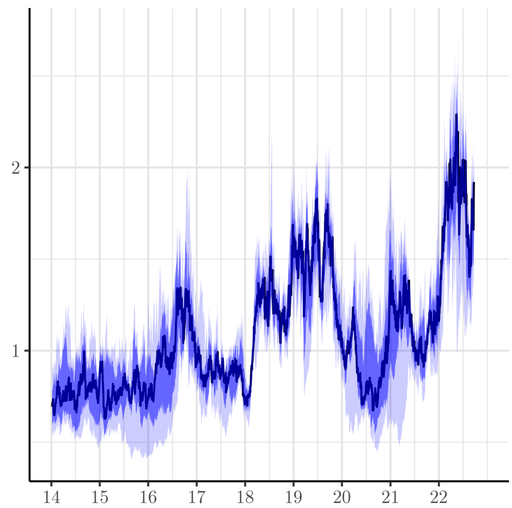
Figure 3.7: (Continued)



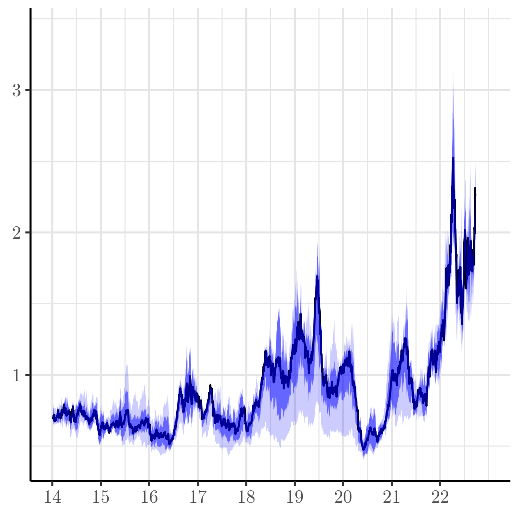
(e) Financials



(f) Healthcare



(g) Industrials



(h) Utilities

Note: This figure plots the evolution of the estimated time-varying loadings of the respective sectors over the period 2014-2022 based on our preferred model specification. In each panel, the black line corresponds to the median fitted volatility across firms; the dark- and light-blue shaded bands correspond respectively to the Inter Quartile Range (IQR) and the 10-90 percentile range.

We conclude from this analysis that dependence between firms, as measured by variations in firms' loadings $\lambda_{i,t}$ on the common factor Z_t, seems to be less responsive to periods of heightened financial market stress and volatility than the corresponding CDS spreads or their volatility.[12] However, firms' loadings on the common factor appear to be driven by lower-frequency factors. Indeed, periods associated with rising uncertainty and a weakening in global economic prospects appear to drive increases in dependence. This is evidenced by i) the GFC period which triggered a global recession and precipitated the European sovereign debt crisis; ii) the slowdown in global economic activity around 2018-2019 associated with the escalation of trade tensions between China and the US; iii) the Covid-19 pandemic which led to a sharp and sudden decline in global output followed by a protracted recovery phase; and iv) the global tightening in financial conditions associated with major central banks' response to elevated inflationary pressures. A more formal investigation of the short- and long-term drivers of dependence across firms and sectors would shed additional light on our results. This is however outside of the scope of our current analysis and left for future research. We focus in the next section on the analysis of the systemic risk measures derived from our multivariate model combining the conditional mean, volatility, and copula dynamics.

3.4.4 Time-varying systemic risk

We first consider the Joint Probability of Distress (JPD), computed based on Equation (3.19), which measures the probability of a large proportion of firms experiencing a default at the same time. Figure 3.8 summarises the evolution of the JPD over time for the heterogeneous dependence specification. As explained in Section 3.3.3, we set a firm specific distress threshold, $c^*_{i,t+h}$, based on the corresponding 99% CDS spread quantile of the firm. We consider horizons of 3 months ($h = 63$, upper panels in Figure 3.8) and 1 year ($h = 252$, lower panels in Figure 3.8). Our reported results focus on a 40% threshold for the proportion of firms in distress but the dynamics of the JPD are broadly

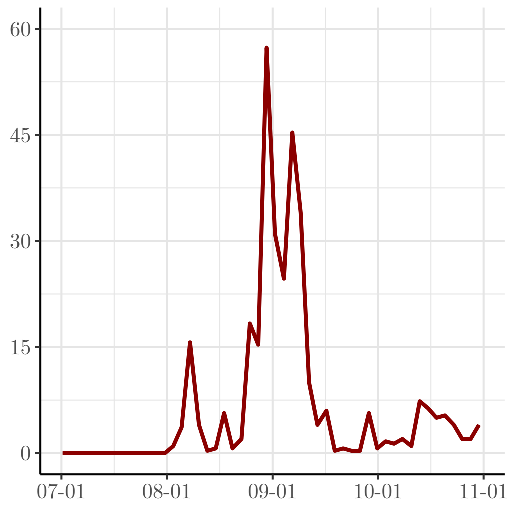
[12] This is particularly apparent for the GFC, the financial market turmoil in China (2015-2016) and the onset of the Covid-19 pandemic in March 2020.

comparable for other threshold values in the same range. The early part of the sample (left panels) is associated with near-zero risks of joint distress at both horizons. The first uptick in the JPD occurs around the bankruptcy of Bear Stearns in March 2008. The collapse of Lehman Brothers in September 2008 sparks a sharp increase in the systemic distress indicator which reaches its highest recorded level in the sample around the end of the year and stays at elevated levels for a few months (particularly at 1-year horizon). The JPD then returns progressively to lower levels in the first half of 2009 while still remaining higher than in the pre-GFC period. Other spikes are more contained: in 2010 due to concerns on the implications for the global economic outlook, and the impact for US corporates, of the European sovereign debt crisis; and following US sovereign debt downgrade in August 2011. The JPD is markedly higher at the end of 2010 than in the pre-GFC era.

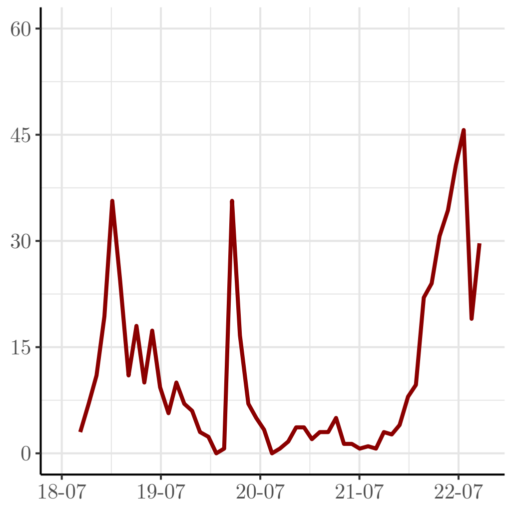
The more recent part of the sample (2018-2022, right panels) is associated with a higher average risk level for the joint default of a large proportion of firms.[13] The systemic risk measure spikes in the second half of 2018 during the escalation of the trade frictions between China and the US (2018-2019) before progressively coming back down to lower level by the beginning of of 2020. This is followed by a second large spike at the onset of the Covid-19 pandemic (March 2020). This period of elevated systemic risk is again short-lived, potentially reflecting the effectiveness of the coordinated policy response. Lastly, the JPD started a steep increasing phase around end-2021 against a background of rising inflationary pressures globally and an associated tightening in financial conditions as the outlook for economic activity weakened. This trend accelerated around March 2022 with the beginning of the monetary tightening cycle by the Federal Reserve and increased expectations of an economic recession nearing. Systemic risk appears to have peaked around July but remained elevated afterwards by historical standards. Note that the the three spikes in the JPD measure observed during the period 2018-2022 are relatively close to the ones observed during the GFC — highlighting that the JPD can potentially uncover

[13]The same caveat as in the comparison of time-varying factor loadings across subsamples applies here. See Footnote 11 in Section 3.4.3 for more details.

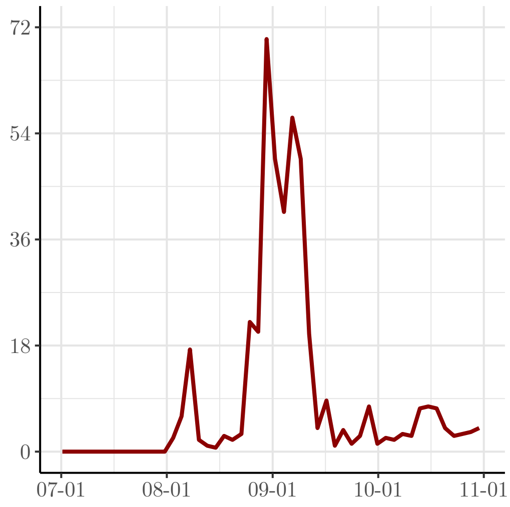
Figure 3.8: Evolution of the joint probability of distress ($\frac{k}{N} = 40\%$)



(a) 3-month horizon: 2007-01 to 2010-12



(b) 3-month horizon: 2018-09 to 2022-09



(c) 1-year horizon: 2007-01 to 2010-12

(d) 1-year horizon: 2018-09 to 2022-09

Note: This figure plots the evolution of the Joint Probability of Distress (JPD) computed based on Equation (3.19) for the heterogeneous dependence specification (in pp). We define distress based on firms' respective 99% CDS spread quantile in each subsample and set the threshold for the proportion of firms in distress at 40%, corresponding to 30 firms. The upper panels correspond to the 3-month horizon and the lower panels to the 1-year horizon.

buildups of systemic risk during less volatile periods. This is consistent with the literature documenting how systemic risk accumulates during expansionary phases characterized by compressed volatility (Adrian and Brunnermeier, 2016).

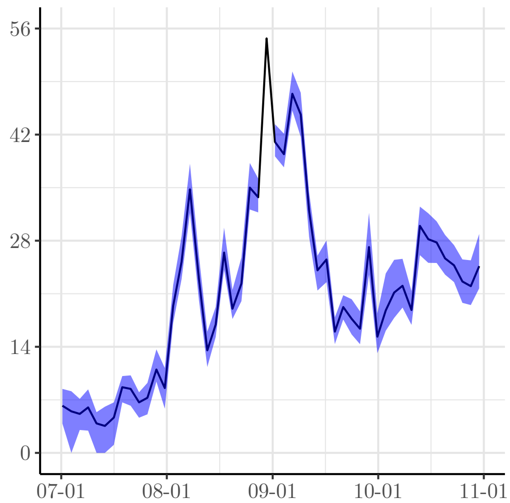
We turn to the analysis of our second measure of systemic risk, the Expected Proportion in Distress (EPD), which captures the proportion of firms at risk of default conditional on a given firm defaulting, and is computed based on Equation (3.20).

Focusing first on the period from 2007-01 to 2010-12 displayed in the left panels of Figure 3.9, we observe that the EPD offers a more granular view of the systemic risk developments prior to the GFC. In particular, we see that the systemic risk measure start increasing from mid-2007, around the time of the collapse of two Bear Stearns leveraged credit funds. This increase is particularly pronounced at the 1-year horizon (bottom panels of Figure 3.9). The expected proportion of firms in distress rises from an average level of around 5% before the crisis to more than 50% in late 2008. The EPD fluctuates around 20-30% in the period directly after the GFC, which is markedly higher than pre-crisis. For the more recent part of the sample (2018-2022), we observe that both the 3-month and 1-year EPD measures fluctuate around higher levels of approximately 35%. Consistent with our results for the JPD measure, the period is associated with three spikes in systemic risk (early 2019, onset of Covid crisis, and end-2021) whose levels are comparable to the GFC period.

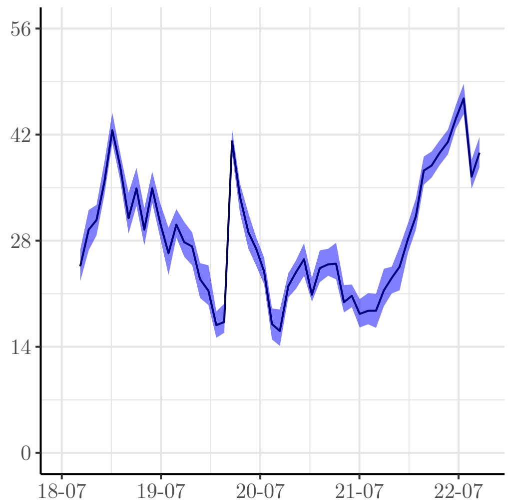
Our EPD measure also allows us to quantify the potential systemic risk spillovers that a distressed firm in a given sector (e.g. financials) can transmit to another sector (e.g. non-financials). To this end, Figure 3.10 summarises the evolution of the expected proportion of financial firms being in distress conditional on one non-financial firm being in distress (blue line) and the expected proportion of non-financial firms being in distress conditional on one financial firm being in distress (red line).

We first observe that the direction of the transmission of systemic risk spillovers in the early stages of the GFC is broadly balanced across the financial and non-financial sectors. The expected proportion of non-financial firms in distress conditional on one distressed financial firm is initially higher. The systemic risk spillovers from the non-financial to

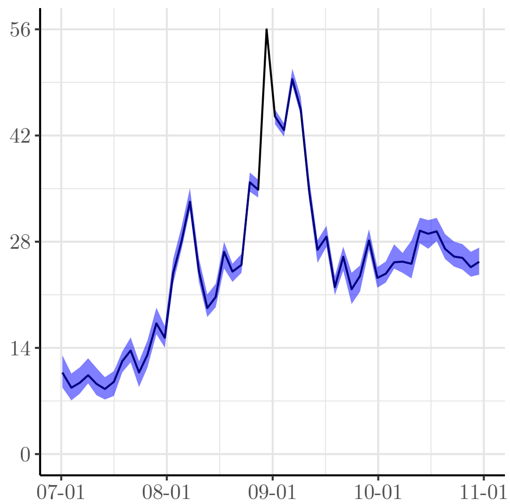
Figure 3.9: Evolution of the expected proportion of firms in distress



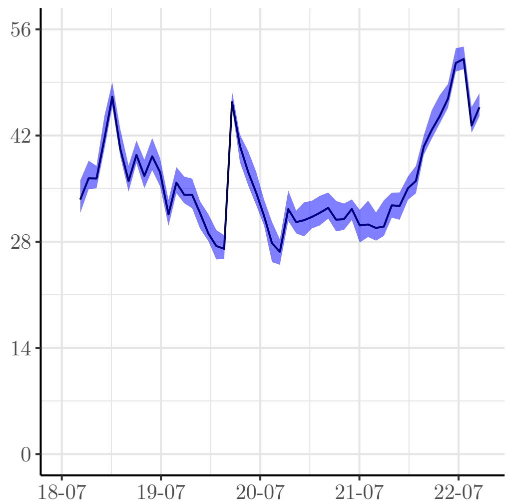
(a) 3-month horizon: 2007-01 to 2010-12



(b) 3-month horizon: 2018-09 to 2022-09



(c) 1-year horizon: 2007-01 to 2010-12



(d) 1-year horizon: 2018-09 to 2022-09

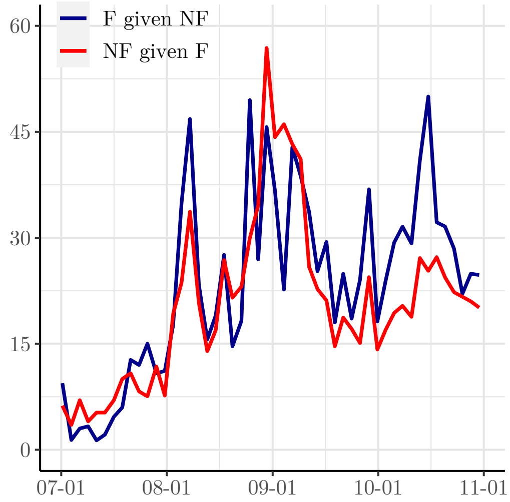
Note: This figure plots the evolution of the Expected Proportion in Distress (EPD) computed based on Equation (3.20) for the heterogeneous dependence specification (in pp). The black line corresponds to the median EPD across firms and the blue-shaded band corresponds to the 20-80 percentile range. We define distress based on firms' respective 99% CDS spread quantile in each subsample. The upper panels correspond to the 3-month horizon and the lower panels to the 1-year horizon.

the financial sector start increasing in the second half of 2007 with the collapse of the Bear Stearns funds and accelerate after the fourth quarter as the US economy enters a recession. Spillover effects from the financial to the non-financial sector also pick up markedly around that period. They both reach a first peak around the bankruptcy of Bear Stearns. Afterwards, the spillovers from non financials to financials reach a second peak around the collapse of Lehman Brothers in September 2008. The expected proportion of non-financial firms in distress conditional on one distressed financial firm increases more gradually during that period, reaching a peak at the end of 2008 as General Motors and Chrysler receive short-term bailout funds under the Troubled Asset Relief Program (TARP), which was initially targeted at the financial sector (Gourieroux et al., 2021). Both series come down gradually as the US economy exits recession around mid-2009 — although they remain at elevated levels compared to the pre-GFC period. Systemic spillover risks from the non-financial to the financial sector remain high subsequently with two more peaks around end-2009 and mid-2010.

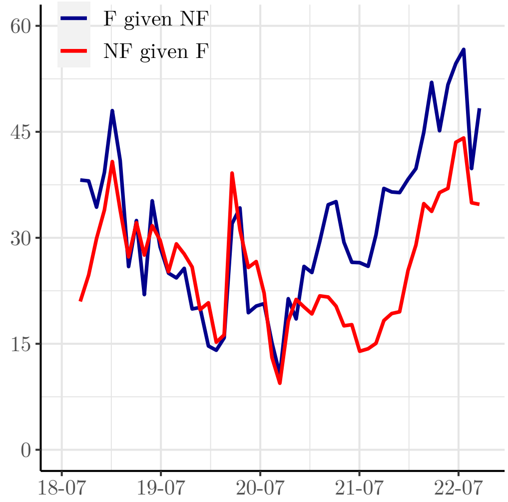
Consistent with our results for the EPD displayed in panels b) and d) of Figure 3.9, both systemic risk spillover measures fluctuate around higher values in the more recent part of the sample. We note that spillovers from the financial to the non-financial sector appear to be stronger at the 1-year horizon than at the 3-month horizon. Interestingly, short-term systemic risk spillovers seem to play a more important role around beginning-2019 than at the onset of the Covid-19 pandemic (Panel b). The levels are more comparable for longer-term systemic spillovers (Panel d). Both systemic risk spillover series experience a strong upward trend over 2022, reaching levels comparable to the heights of the GFC period.

As a summary, the two measures of systemic risk provide consistent results that the pre-GFC period is associated with low levels of systemic risk. They then rise materially during the crisis before progressively decreasing to levels that are noticeably higher than pre-crisis. Furthermore, the more recent part of the sample (2018-2022) is associated with higher levels of systemic risk on average for both measures and the three peaks observed in 2019, at the onset of Covid, and in July 2022 display levels of systemic risk broadly comparable to the GFC.Lastly, systemic spillover risks from the non-financial to the financial sector are higher than systemic spillovers from the financial to the non-financial sector over most of the sample. This highlights that the default of a large non-financial corporate can be an important trigger of stress in the financial sector, consistent with the literature documenting the impact of idiosyncratic shocks to large borrowers on banks' aggregate portfolio outcomes (Galaasen et al., 2020). We observe two noticeable exceptions where systemic spillovers from the financial to the non-financial sector peak at higher levels: end-2008 — a particularly acute phase of the US Great Recession — and at the beginning of the Covid-19 pandemic which was marked by a severe but short-lived economic downturn. These findings point to a stronger role of systemic spillovers from the financial sector to the real economy during economic downturns. They complement the existing literature documenting the co-cyclicality between corporate defaults and economic activity (Koopman and Lucas, 2005; Duffie et al., 2009; Koopman et al., 2009) by highlighting the role of the financial sector in amplifying adverse shocks during crises (Adrian and Brunnermeier, 2016). This is also consistent with the literature documenting that a buildup of systemic risk in the financial sector increases downside risks to the real economy, therefore raising the spillovers to the non-financial sector from financial sector distress. See e.g. Allen et al. (2012), Giglio et al. (2016), and Brownlees and Engle (2017) for empirical analysis along these lines.

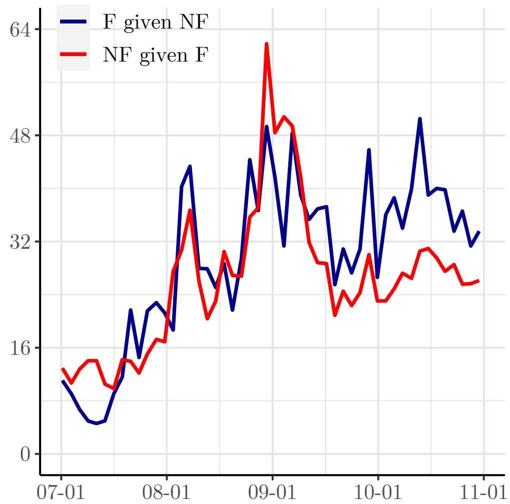
Figure 3.10: Breakdown of the evolution of systemic spillovers across sectors (financial and non-financial sectors)



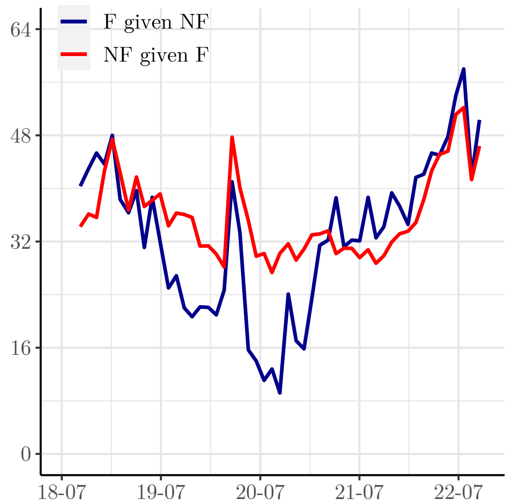
(a) Period from 2007-01 to 2010-12



(b) Period from 2018-09 to 2022-09



(c) Period from 2007-01 to 2010-12



(d) Period from 2018-09 to 2022-09

Note: This figure plots the evolution of the expected proportion of financial firms in distress conditional on one non-financial firm being in distress ("F given NF" in blue) and of non-financial firms in distress conditional on one financial firm being in distress ("NF given F" in red). Our panel of firms comprises 18 financial firms and 57 non-financial firms. The upper panels correspond to the 3-month horizon and the lower panels to the 1-year horizon.

3.5 Conclusion

We model systemic risk through the dependence in failure across firms in the system, measured from the information contained in their CDS spread data. Our framework encompass both systemic risk originating from the financial and non-financial sectors, together with potential systemic risk spillovers across sectors.

Using CDS spread data for a panel of 75 US Investment Grade firms over the period from January 2007 to September 2022, we fit a flexible dynamic factor copula model which is particularly well-suited to track time-varying multivariate conditional distributions in high dimensions. In addition, we introduce a dynamic score model for the conditional volatility of the marginal distributions. This approach provides some robustness against the presence of outliers in the data, which is particularly relevant for the modelling of CDS spread data as their distribution is in general heavy-tailed. Building on recent contributions generalizing the Score-Driven (SD) approach (Blasques et al., 2022), we propose a Quasi-Score-Driven (QSD) extension of the asymmetric Beta-t-EGARCH model of Harvey (2013). The added flexibility of our QSD-t-EGARCH — which arises from allowing the updating of the log-volatility process to be decoupled from the density of the model innovations — helps capturing the key features of the conditional marginal distribution of CDS data. This is confirmed through several model specification tests.

Our modelling framework, combined with a long sample, allow us to investigate the impact of different types of systemic stress — including a global financial crisis and a pandemic. We document first that the dependence between firms, measured based on the estimated time-varying factor loadings of the copula, has been steadily increasing across all sectors over the period from 2007 to end-2013. After a short period of stabilization, firms' dependence on the common factor resume its steady increase from 2018 until the end of the sample — reaching higher levels than during the GFC. We conclude from these results that higher dependence among firms appears to be driven by low-frequency factors relating to overall uncertainty and weaker global economic prospects.

Our two measures of systemic risk provide consistent results that the pre-GFC period is associated with low levels of systemic risk. They then rise materially during the crisis before progressively decreasing to levels that are noticeably higher than pre-crisis. Furthermore, the more recent part of the sample (2018-2022) is associated with higher levels of systemic risk on average for both measures and the three peaks observed in 2019, at the beginning of the Covid-19 pandemic, and in 2022 display levels of systemic risk broadly comparable to the GFC. Finally, systemic spillover risks from the non-financial to the financial sector are higher than the respective spillover risks from the financial to non-financial sector over most of the sample. We observe two notable exceptions where systemic spillovers from the financial to the non-financial sector peak at higher levels around end-2008 and at the beginning of the Covid crisis.

3.A Evaluation of the factor copula likelihood

Consider the factor structure specified in Equations (3.11)-(3.13) in Section 3.4.2. Our objective is to evaluate the copula density of $\mathbf{X}_t$ which can be computed as

$$\mathbf{c}_t\left(u_1,\ldots,u_N\right)=\frac{\mathbf{g}_t\left(G_{1,t}^{-1}\left(u_1\right),\ldots,G_{N,t}^{-1}\left(u_N\right)\right)}{g_{1,t}\left(G_{1,t}^{-1}\left(u_1\right)\right)\cdot\cdots\cdot g_{N,t}\left(G_{N,t}^{-1}\left(u_N\right)\right)}\ . \tag{3.21}$$

where $\mathbf{g}_t\left(x_1,\ldots,x_N\right)$ is the joint density of $\mathbf{X}_t$, $g_{i,t}\left(x_i\right)$ is the marginal density of $X_{i,t}$, and $\mathbf{c}_t\left(u_1,\ldots,u_N\right)$ is the copula density. The expression for this likelihood is not available in closed form, but can be evaluated using numerical integration technique.

To construct the copula density, we need to obtain the value of each function that appears on the right-hand side of Equation (3.21) above, namely $g_{i,t}\left(x_i\right), G_{i,t}\left(x_i\right), \mathbf{g}_t\left(x_1,\ldots,x_N\right)$ and $G_{i,t}^{-1}\left(u_i\right)$. The independence of Z and ε_i implies that

$$f_{X_i|Z,t}\left(x_i \mid z\right)=f_{\varepsilon_i}\left(x_i-\lambda_{i,t}z\right)\ , \tag{3.22}$$

$$F_{X_i|Z,t}\left(x_i \mid z\right)=F_{\varepsilon_i}\left(x_i-\lambda_{i,t}z\right)\ , \tag{3.23}$$

$$\mathbf{g}_{\mathbf{X}|Z,t}\left(x_{1,\ldots,}x_N \mid z\right)=\prod_{i=1}^{N}f_{\varepsilon_i}\left(x_i-\lambda_{i,t}z\right)\ . \tag{3.24}$$

Based on these conditional distributions, we can obtain the marginals via one dimensional integration, i.e.

$$\begin{aligned}
g_{i,t}\left(x_i\right) &= \int_{-\infty}^{\infty} f_{X_i,Z,t}\left(x_i,z\right)dz \\
&= \int_{-\infty}^{\infty} f_{X_i|Z,t}\left(x_i \mid z\right)dF_{Zt}(z) \\
&= \int_{-\infty}^{\infty} f_{\varepsilon_i}\left(x_i-\lambda_{i,t}z\right)dF_{Zt}(z) \\
&= \int_{0}^{1} f_{\varepsilon_i}\left(x_i-\lambda_{i,t}F_{Zt}^{-1}(u)\right)du\ .
\end{aligned} \tag{3.25}$$

where the last step is to convert the integration to bounded integrals using a change of variables, $u = F_{Zt}(z)$. Similarly, we can obtain

$$G_{i,t}\left(x_i\right) = \int_0^1 F_{\varepsilon_i}\left(x_i - \lambda_{i,t} F_{Zt}^{-1}(u)\right) du \ , \tag{3.26}$$

$$\mathbf{g}_t\left(x_1, \ldots, x_N\right) = \int_0^1 \prod_{i=1}^{N} f_{\varepsilon_i}\left(x_i - \lambda_{i,t} F_{Zt}^{-1}(u)\right) du \ . \tag{3.27}$$

Thus, to calculate the factor copula density, we only require the computation of one-dimensional integrals. We use the Gauss-Legendre quadrature method for the computation of the integration using Q nodes where we choose $Q = 50$ following the simulation study results of Oh and Patton (2018).

Finally, we need a method to invert $G_{i,t}\left(x_i\right)$ which is a function of both x and the factor loading $\lambda_{i,t}$, with $G_{i,t} = G_{j,s}$ if $\lambda_{i,t} = \lambda_{j,s}$. We estimate the inverse of $G_{i,t}$ by creating a grid of 100 points for x in the interval $[x_{\min}, x_{\max}]$ and 50 points for λ in the interval $[\lambda_{\min}, \lambda_{\max}]$. We then evaluate G at each of those points and use a two dimensional linear interpolation to obtain $G^{-1}(u;\lambda)$ given u and λ. This two-dimensional approximation substantially reduces the computational burden, especially when λ is time-varying, as we can evaluate the function G prior to the estimation, rather than re-estimating it for each likelihood evaluation.

3.B Additional results for the main analysis

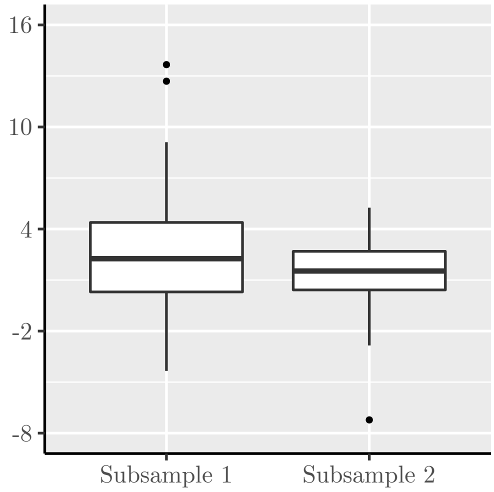
3.B.1 Conditional mean dynamics

We summarise in Figure 3.11 the estimation results from the model for conditional mean dynamics specified in Equation (3.5). Our results support the observation made in Section 3.2 that daily log-differences in CDS data have a higher degree of persistence than what is usually observed for stock return data. Focusing first on the sample ranging from 2007/01 to 2013/12, we document that the median for the estimates of the $\phi_{j,i}$ autoregressive parameters across firms ranges from 0.017 for the AR(1) parameter to 0.02-0.05 for lags 3 and 2 respectively. In addition, these estimates can go as high 0.21 for the AR(1) parameter and from 0.1 to 0.17 for the other lags. We also document strong statistical significance of the parameter estimates. The AR(1) estimates are significant at the 5% level in the majority of cases (60%) while the second and third lags are significant in respectively 40% and 28% of the cases.

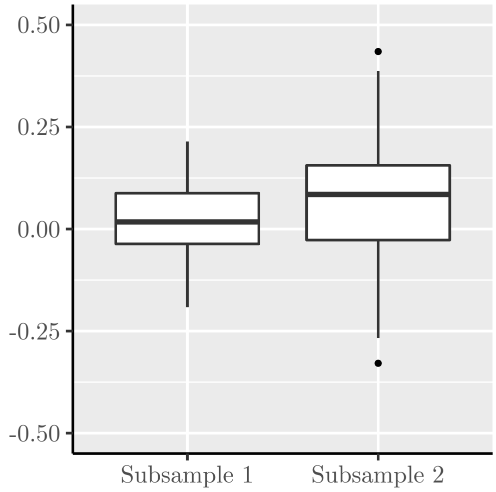
We contrast these results with the one obtained for the sample ranging from 2014/01 to 2022/09. Our main observation is that the degree of persistence in the data increases materially. Indeed, the magnitude of the median AR(1) estimate is multiplied by a factor of almost 5 while the magnitude of the median estimates for lags 2 and 3 is multiplied by a factor of respectively 1.75 and 3. This increase in persistence in the second subsample is also reflected in the statistical significance of the parameter estimates. The three lags are significant at the 5% level for the majority of firms, with 76% of significant AR(1) estimates and 67-68% for lags 2 and 3.

We turn to the analysis of the results for the coefficient estimates of the $\phi^m_{k,i}$ parameters. These parameters capture the dynamic spillover effects from the market, modelled as the equally-weighted average of all firms, to a given firm. We find strong evidence of market spillovers in the first subsample as the first market lag is significant at the 5% level for 72 out of 75 firms. The median estimate is 0.36 with values going as high as 0.62. We also find milder evidence of statistical significance for the second and third market lags with respectively 16 and 21% of firms having estimates significant at the 5% level.

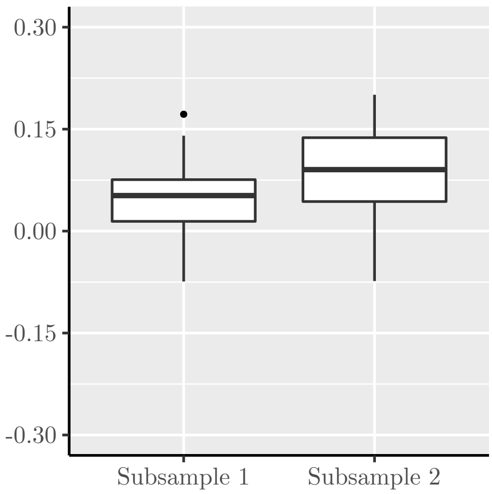
Figure 3.11: Conditional mean parameters



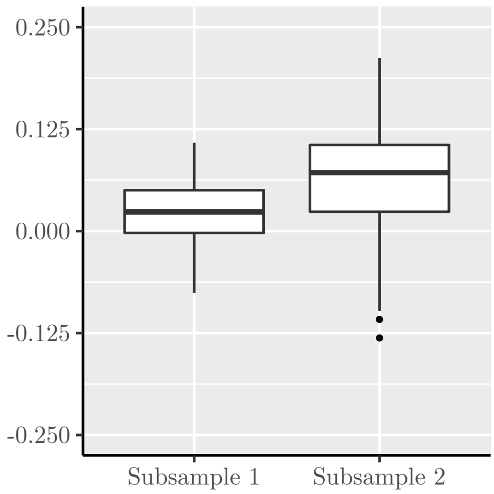
(a) $\phi_{0,i} \times 10^4$



(b) $\phi_{1,i}$

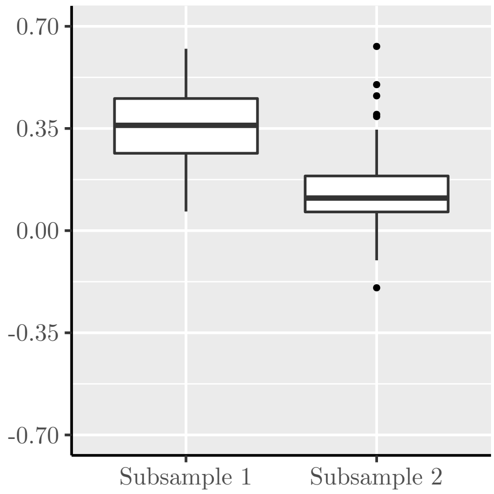


(c) $\phi_{2,i}$

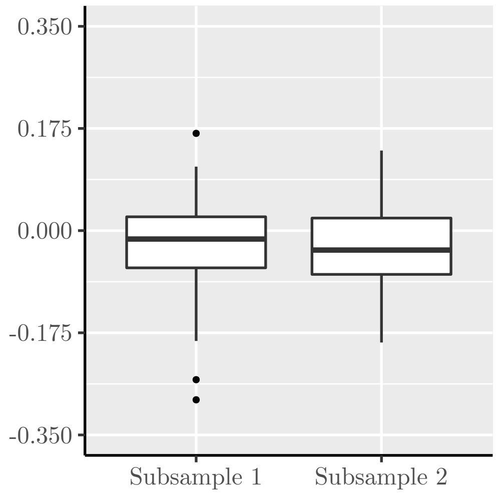


(d) $\phi_{3,i}$

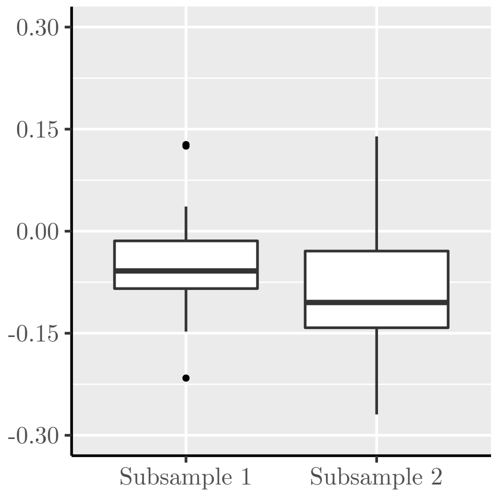
Figure 3.12: (Continued)



(e) $\phi^m_{1,i}$



(f) $\phi^m_{2,i}$



(g) $\phi^m_{3,i}$

Note: The figures summarise the distribution of parameter estimates for the model of conditional mean dynamics specified in Equation (3.5). Subsample 1 ranges from 2007/01 to 2013/12 and Subsample 2 covers the period from 2014/01 to 2022/09. The boxplots provide the median value of the parameter estimates across the 75 firms (horizontal black line) together with the corresponding interquartile range (IQR, the edges of the box). The vertical black lines indicate estimates within $1.5 \times IQR$ from the respective first (below) and third (above) quartiles. Estimates outside this range are represented by a black dot.

In addition, the median estimates are negative which indicates that the initial strong spillover effect from the market is subsequently dampened. Moving to the analysis of the second subsample, we observe a deterioration in the strength of market spillover. This is evidenced by a drop in the proportion of firms with a statistically significant estimate for the first market lag dropping to 68% and the median estimate falling down to 0.11. Results for the second and third market lags are broadly comparable with the ones above. However, it is worth noticing that the share of firms with a statistically significant estimate for the third market lag increases to 60%, compared to 21% in the first subsample, with a median estimate of -0.105.

To summarise, data on daily log-differences in CDS exhibit more persistence in their conditional mean dynamics than what is usually observed for other financial data such as stock returns. This feature of the data seems even more relevant for the recent period as we observe a material increase in persistence estimates for the second subsample ranging from 2014/01 to 2022/09. Dynamic spillover effects from the market are also relevant for modelling and, although their relevance has decreased in the recent period, they remain an important contributor to CDS conditional mean dynamics in the earlier subsample. We develop in the next section our analysis on the modelling of conditional volatility dynamics. The estimation is based on the estimated residuals $\hat{e}_{i,t}$ which are obtained as a by-product of the results produced in this section.

3.B.2 Conditional volatility dynamics

Figure 3.13 summarises the estimation results from the asymmetric QSD-t-EGARCH model for conditional volatility dynamics specified in Equations (3.6) and (3.8). First, the estimates of the autoregressive parameter β_i indicate a high degree of persistence in CDS conditional volatility dynamics. This is true in both subsamples as the median estimates are almost identical at around 0.966. The two subsamples differ however in the degree of dispersion around this median value. Namely, the first subsample displays more variability with estimates ranging from 0.914 to almost 1 and a few outlying observations (4 firms) whose estimates are comprised between 0.85 and 0.9. The estimates in second subsample, on the other hand, range from 0.925 to 0.99 and outliers (3 firms) are located between 0.88 and 0.92. We therefore conclude that the log volatility process is more persistent in the second subsample due to a more concentrated distribution of estimates towards higher persistence levels.

We now turn to the estimates of the parameters α_i and δ_i which control how the log volatility process reacts to new information through the score update. Median estimates of α_i are comparable across subsamples, respectively 0.089 and 0.097; the range of estimates is comprised between 0.07 and 0.12 in both cases. We observe more outliers in the second subsample (5 firms vs. 1) with values ranging from 0.18 to 0.30. The parameter δ_i captures the incremental effect of bad news, measured by a positive innovation $e_{i,t-1}$ to the daily CDS log-difference, on the updating of the log volatility process. The magnitude of the estimates is noticeably lower than for α_i, which ensures that an increase in the absolute value of a standardized observation does not decrease volatility; see Harvey (2013) page 105. We observe that the sensitivity of the log volatility process to the occurrence of bad news increases markedly in the more recent period. Estimates for the first subsample range from 0.01 to 0.0275 with a median value of 0.015. The range of parameter estimates in the second subsample shifts up towards 0.02-0.05 with a median value of 0.033.

The distribution of estimates for the degrees of freedom parameter ν_i is comparable across subsamples with values ranging from 2.65 to 3.45 and median estimates around 3.05. These results indicate heavy tails in the distribution of the standardized residuals $\eta_{i,t} = e_{i,t}/\sigma_{i,t}$. In addition, estimates for the skewness parameter ψ_i indicate that firms' standardized residuals are overall positively skewed. While positive skewness is less pronounced in the first subsample, ranging from 0.025 to 0.058 with median value of 0.037, it increases noticeably in the second subsample to reach a median value of 0.094 with estimates in the range 0.07-0.12.

We move now to the estimation results for the parameters ν_i^u and ψ_i^u entering the updating equation of the log-volatility process. The results differ markedly across subsamples for the degrees of freedom parameter ν_i^u, with estimates in the first subsample ranging from 4.5 to 11 and a median 6.42 but with a long right tail of estimates going up to 22.81. The estimates for the second subsample range from 2.5 to 4.5 with a median of 3.23. These lower estimates indicate that the updating equation of the log-volatility process down weigh more strongly the impact of large innovations on volatility compared to the first subsample. For the skewness parameter ψ_i^u, the distribution of the estimates is broadly comparable across subsamples, ranging from -0.04 to 0.31 with median values of respectively 0.06 and 0.14. We note however that there is more dispersion in the first subsample with a few large positive (1 firm) and negative (2 firms) outliers.

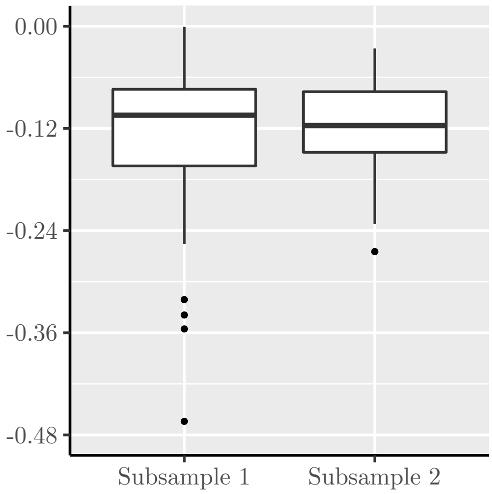
Comparing these results for the updating equation with the ones obtained for the parameters ν_i and ψ_i entering the density of the innovations highlights the added flexibility of the asymmetric QSD-t-EGARCH model. Indeed, allowing the parameters of the updating equation to be decoupled from the ones entering the innovation density leads to a lower down-weighting of large innovations in the first subsample than what would be implied by its Beta-t-EGARCH counterpart (higher degrees of freedom estimates in the quasi score update). Results for the second subsample are more comparable, although there is more dispersion in the range of values taken by ν_i^u and a tilt towards higher degrees of freedom estimates. Comparing estimates for the skewness parameters, we see that the ψ_i^u estimates take a much broader range of both positive and negative values than what would be implied by the SD approach as the ψ_i estimates are mainly concentrated at smaller positive values.

To better visualize how the added flexibility of the QSD-t-EGARCH model impact the estimation at a firm-specific level, Figure 3.15 compares for each of the 75 firms in our sample (x-axis) the estimates of degrees of freedom (top panel) and skewness parameters (bottom panel) entering respectively the density of the innovations (black dots) and the updating equation for the log-volatility process (red squares). Starting with the degrees of freedom parameters, we observe that the majority of the ν_i^u estimates are substantially larger than the ones for ν_i for the subsample from 2007-01 to 2013-12 (top-left panel). Imposing $\nu_i^u = \nu_i$, as in the Beta-t-EGARCH, would therefore lead to down weigh large innovations to the log-volatility process too much compared with what is suggested by the data. However, this can vary over time as we observe in the top-right panel for the subsample from 2014-01 to 2022-09 that the ν_i^u estimates are still different from their ν_i counterparts but the magnitude of this difference is much smaller than in the first sample. The larger positive gap between the ν_i^u and ν_i estimates in the first subsample suggests that allowing for a steep news impact curve is important during sustained periods of elevated volatility such as the GFC period. On the other hand, the gap between ν_i^u and ν_i estimates narrows during calmer periods with short-lived episodes of high volatility, implying a flatter news impact curve for large innovations due to the fat-tailed distribution. For the skewness parameters, the results are broadly comparable across subsamples as we see that ψ_i^u estimates fluctuate a lot from one firm to another and cover a large range of both positive and negative values. This is in stark contrast with the ψ_i estimates which are narrowly concentrated in a range of small positive values. Taken together, these observations highlight the flexibility of the QSD-t-EGARCH model compared to the SD approach in handling different settings where the parameters for the updating equation of the time-varying parameters differ from what would be implied by the corresponding parameters of the innovation density.

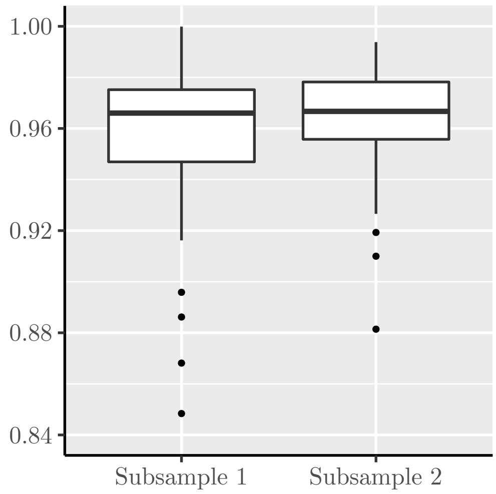
Concerning the statistical significance of the estimated parameters for the conditional volatility dynamics, standard errors — computed based on the inverse Hessian matrix of the log likelihood evaluated at the optimum — indicate that almost all parameter estimates are significant at the 5% level.[14] However, these estimates must be considered conservatively as the standard errors fail to account for the multi-stage dimension of the estimation, i.e. they neglect estimation errors introduced in the first-stage estimation of the conditional mean dynamics. Alternative approaches to address this concern would be to consider the robust Multi-Stage Maximum Likelihood (MSML) covariance matrix estimator (Patton, 2013) or the bootstrap approach proposed by Gonçalves et al. (2022) for multi-stage Quasi Maximum Likelihood (QML) estimators. Nevertheless, we do not pursue these here as the relevance for our application is limited.

[14]Exceptions are 1 firm having an insignificant δ_i estimate in Subsample 2 and 3 firms having insignificant ω_i estimates (1 firm in Subsample 1 and 2 firms in Subsample 2).

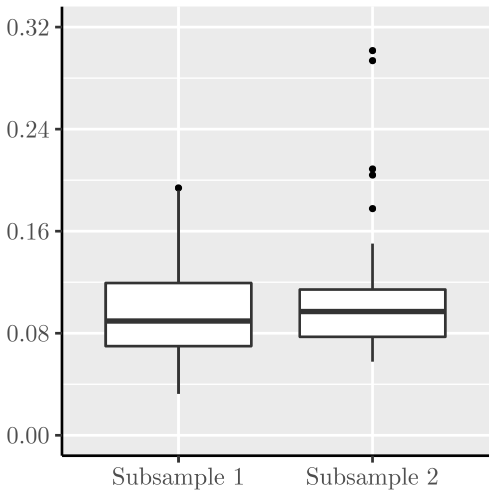
Figure 3.13: Conditional volatility parameters



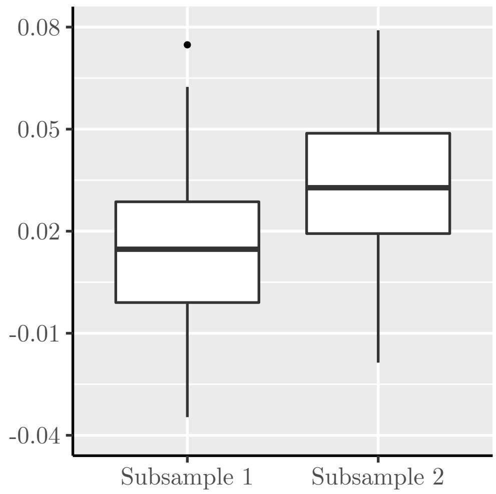
(a) ω_i



(b) β_i

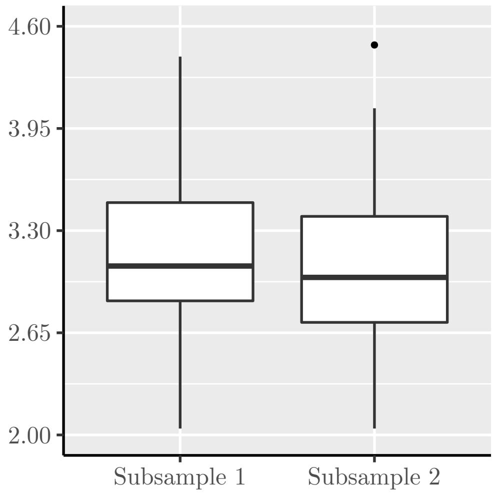


(c) α_i

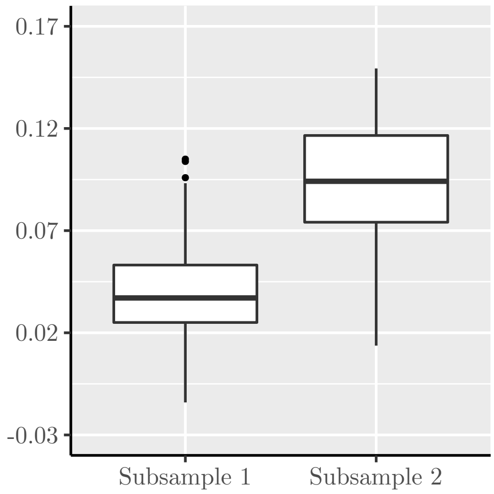


(d) δ_i

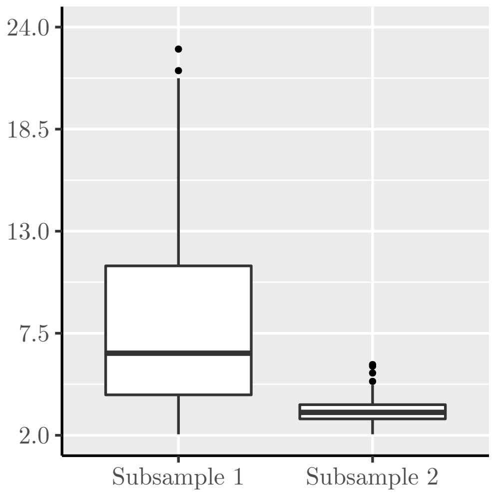
Figure 3.14: (Continued)



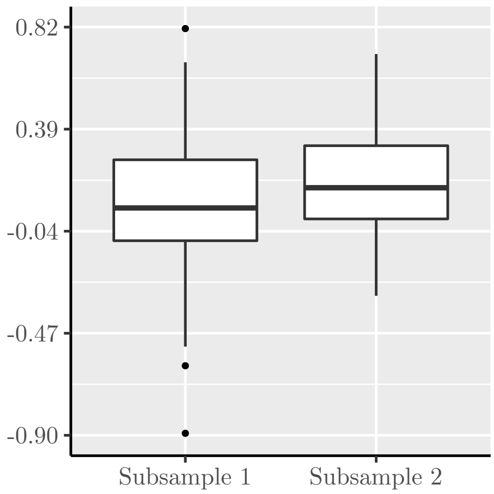
(e) ν_i



(f) ψ_i



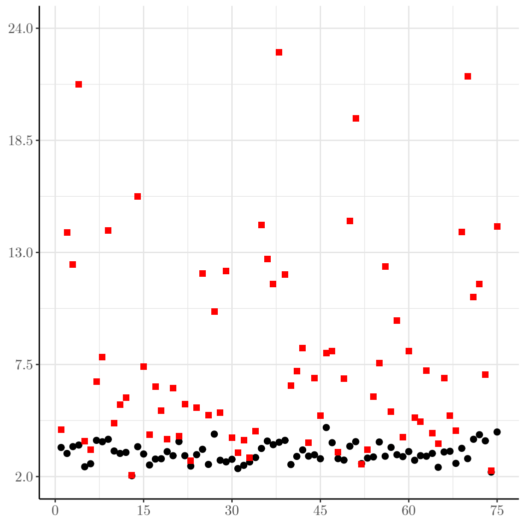
(g) ν_i^u



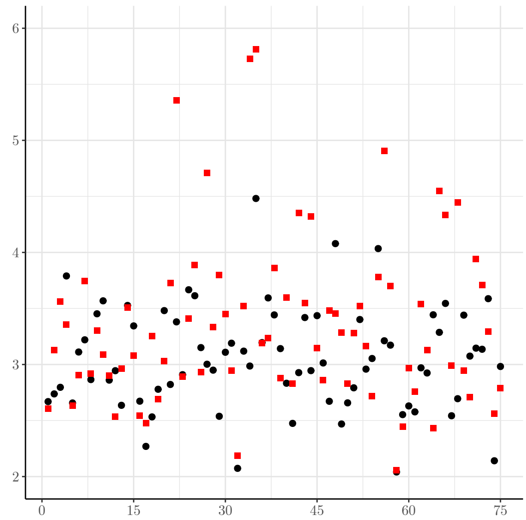
(h) ψ_i^u

Note: The figures summarise the distribution of parameter estimates for the asymmetric QSD-t-EGARCH model of conditional volatility dynamics specified in Equations (3.6) and (3.8). Subsample 1 ranges from 2007/01 to 2013/12 and Subsample 2 covers the period from 2014/01 to 2022/09. The boxplots provide the median value of the parameter estimates across firms (horizontal black line) together with the corresponding interquartile range (IQR, the edges of the box). The vertical black lines indicate estimates within $1.5 \times IQR$ from the respective first (below) and third (above) quartiles. Estimates outside this range are represented by a black dot.

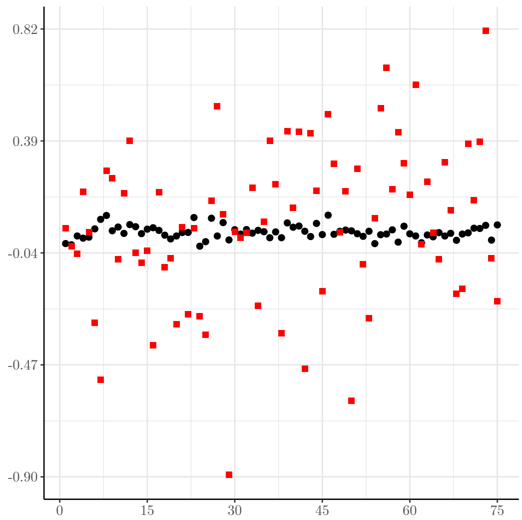
Figure 3.15: Estimates of the shape and skewness parameters



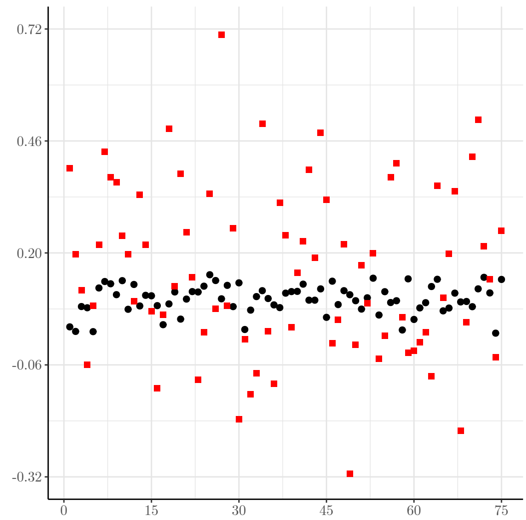
(a) ν_i and ν_i^u : 2007/01 to 2013/12



(b) ν_i and ν_i^u : 2014/01 to 2022/09



(c) ψ_i and ψ_i^u : 2007/01 to 2013/12



(d) ψ_i and ψ_i^u : 2014/01 to 2022/09

Note: This figure reports the estimates of the shape and skewness parameters for each of the 75 firms in our sample (x-axis). ν_i and ψ_i enter the density of the innovations (black dots) and ν_i^u and ψ_i^u (red squares) enter the updating equation for the log-volatility process. Subsample 1 ranges from 2007/01 to 2013/12 (panels on the left) and Subsample 2 covers the period from 2014/01 to 2022/09 (panels on the right).

Summarising the main results of this section, we documented that conditional volatility dynamics exhibit a high degree of persistence — even more so in the more recent part of the data. Furthermore, bad news increasing a firm's CDS level also increase its conditional volatility. Firms have become more sensitive to this driver of the log volatility process since 2014. Firms' standardized residuals are fat-tailed and positively skewed, with the latter becoming more pronounced in the second subsample we analyze. Finally, the flexibility of the asymmetric QSD-t-EGARCH helps capturing key differences between the shape and skewness parameters entering the density of the innovations and the updating equation for the log-volatility process.

Before moving to the estimation of the conditional copula dynamics, we assess how well the models we specified for the conditional mean and volatility dynamics fit the conditional marginal distributions of our CDS data. Table 3.3 below reports descriptive statistics for the standardized residuals $\eta_{i,t}$, which are expected to have mean zero and a standard deviation of one. This is broadly consistent with the distribution of the estimates across firms — although we note that standardized residuals appear to be closer to their theoretical distribution in the second subsample. Sample estimates for the skewness and kurtosis are also consistent with our estimation results above which point to fat-tailed and positively skewed standardized residuals.

We also report in Table 3.3 the number of rejections, using a 5% significance level, for several model specification tests. The Box-Pierce (BP) tests, using a maximum lag length of 25, on the standardized residuals and their squares indicate that we cannot reject the null hypothesis of zero autocorrelation in the majority of the cases. Comparing across subsamples, we see that the rejection frequency in the first subsample is higher than the 5% nominal level of the tests (resp. 9% and 16% for the residuals and their squares) while this is not the case in the second subsample (8% and 4%). However, these results are not necessarily indicative of a model misspecification as we would already expect to reject the null hypothesis 5% of the time due to type I errors and multiple testing. The null hypothesis of the BP test on the conditional score is not rejected for a majority of firms (17%-20% of rejections), which lends support to the validity of the martingale difference property of the conditional score underpinning the SD approach and its QSD extension. Finally, the Kolmogorov-Smirnov tests on the standardized residuals following a Skew t distribution indicate that our assumption for the conditional marginal distributions is supported by the data in the majority of the cases (5% of rejections).

We conclude that the models specified in Equations (3.5), (3.6) and (3.8) for the conditional mean and volatility dynamics provide a satisfactory fit to the CDS data and their marginal distributions. In Section 3.4.2, we move to the estimation of the dynamic copula models, which are based on the $U_{i,t}$ estimates obtained by applying the Probability Integral Transform (PIT) to the estimated standardized residuals using their respective marginal distributions.

Table 3.3: Descriptive statistics for standardized residuals

	Mean	5%	25%	Median	75%	95%
Sample A: 2007/01 – 2013/12						
Mean	-0.013	-0.029	-0.020	-0.012	-0.006	0.002
Std dev	0.934	0.838	0.912	0.947	0.973	1.017
1st-order autocorr	0.004	-0.028	-0.013	0.003	0.017	0.041
Skewness	0.934	-0.361	0.221	0.570	1.079	3.389
Kurtosis	21.413	6.560	8.021	10.473	17.870	69.377
					No. of rejections	
BP test for standardized residuals					7	
BP test for squared standardized residuals					12	
BP test for conditional score					13	
KS test on dist of standardized residuals					4	
Sample B: 2014/01 – 2022/09						
Mean	0.002	-0.012	-0.001	0.002	0.007	0.013
Std dev	0.945	0.806	0.923	0.977	0.998	1.028
1st-order autocorr	0.005	-0.041	-0.012	0.003	0.020	0.052
Skewness	1.598	0.476	1.239	1.877	2.286	3.821
Kurtosis	29.896	8.280	14.237	19.195	27.448	57.142
					No. of rejections	
BP test for standardized residuals					6	
BP test for squared standardized residuals					3	
BP test for conditional score					15	
KS test on dist of standardized residuals					4	

Note: Summary statistics for the standardized residuals η_{it} estimated based on Equations (3.5), (3.6) and (3.8). The top panel considers the sample ranging from 2007/01 to 2013/12 and the bottom panel covers the sample from 2014/01 to 2022/09. The columns summarise the cross-sectional distribution (mean and key percentiles) across the 75 firms of the respective statistics considered in each row. We also report for each panel the number of rejections (using a 5% significance level) for the Box-Pierce tests with a maximum lag length of 25 on the standardized residuals, their squares, and the conditional scores. In addition, we report the number of rejections for the Kolmogorov-Smirnov tests on the standardized residuals following a Skew t distribution.

Conclusion

This dissertation has made three contributions to the literature on financial stability and macroprudential regulation. Chapter 1 focused on assessing the effectiveness of the existing macroprudential framework in delivering on its intended goals to enhance the resilience of the financial system and reduce the occurrence of systemic banking crises. To this end, we introduced a novel empirical setup accounting for the simultaneous effects of macroprudential policies on the probability of financial crises and economic growth. This empirical setup allowed us to capture both the direct and indirect effects that macroprudential policies can have on banking crises and to evaluate their net effect. We documented the empirical relevance of both direct and indirect channels of transmission and showed that macroprudential policies have a positive net effect on financial stability.

Chapter 2 considered the potential unintended consequences of macroprudential policy reforms. We analyzed the transmission of macroprudential regulation across both financial and non-financial sectors of the economy through the lens of its impact on short- and long-term probabilities of default at the sector level. We documented that tighter macroprudential regulations lower default risk in both financial and non-financial sectors on average. However, this aggregate result hid heterogeneous effects across different instruments and short-term transitional costs. This was highlighted in our panel event-study analysis where we showed that higher capital requirements improved the long-run resilience of the financial sector while raising long-term default risk in non-financial sectors. A strengthening in the resolution framework for failing banks, on the other hand, had beneficial long-run effects on financial and non-financial sectors.

Lastly, Chapter 3 developed new monitoring methods for macroprudential risks enabling regulators to better anticipate and build resilience against the next source of shock to financial stability. We proposed to broaden the scope of systemic risk monitoring, which is centered around the financial sector, to encompass systemic risk originating in the non-financial sector and potential systemic risk spillovers across sectors. We applied this framework to US financial and non-financial firms by fitting a flexible dynamic factor copula model to their CDS spread data, which allowed us to model the evolution of aggregate systemic risk in the US economy and its breakdown by sectors.

I would like to conclude this dissertation by outlining some fruitful avenues for future research which could play an instrumental role in shaping the evolution of the macroprudential framework. First, there has been increased interest in academic and central banking circles over the past few years to better understand the interactions between monetary policy, financial stability, and macroprudential regulation. See inter alia Martin et al. (2021); Bussière et al. (2021); Ajello et al. (2022); and Boyarchenko et al. (2022) for overviews of the relevant empirical and theoretical literature. This literature builds on the recognition that monetary policy can impact the buildup of financial vulnerabilities — which can amplify adverse shocks to the real economy — through its effects on asset prices, borrowers' and financial intermediaries' leverage, and overall risk-taking in the economy (Ajello et al., 2022). An understudied area of this research agenda, which would greatly benefit current policy debates, relates to quantifying the contribution of prolonged periods of accomodative monetary policy to the buildup of vulnerabilities.

Second, mounting evidence suggest that accomodative (unconventional) monetary policies could have played a role in the buildup of vulnerabilities among Non-Bank Financial Intermediaries (NBFIs). One channel of transmission is through an increase in risk-taking and reach-for-yield behaviors (Foley-Fisher et al., 2016; Di Maggio and Kacperczyk, 2017; Choi and Kronlund, 2018). Accomodative monetary policy also contributed to this buildup by facilitating an increase in leverage of financial intermediaries and institutional investors (Adrian and Shin, 2010; Adrian and Shin, 2014). Therefore, furthering our understanding of the interactions between monetary policy and financial stability is even more crucial given the important growth in Market-Based Finance (MBF) in the post-GFC era and the financial stability challenges associated with NBFI vulnerabilities.

Finally, the question of whether a tightening in the monetary policy stance might also contribute to increasing financial stability risks is becoming central. Indeed, central banks across the world are now rapidly raising their policy rates to contain high inflationary pressures and progressively return inflation to its medium-term target. Moreover, many central banks have now started unwinding the asset purchases carried out under their different Quantitative Easing (QE) programmes. A first important consideration is whether this sharp tightening in the monetary policy stance, and the associated increase in financial market volatility, could reveal existing fault lines in the financial system. The research agenda outlined in the previous paragraph can help identify which NBFIs are most vulnerable to this tightening and their degree of interconnectedness with the rest of the financial system. This, in turn, will support the assessment of the systemic risks that could materialize as a result and guide the implementation of preemptive policy measures to contain their impact on the real economy. A separate, but complementary, question is whether a monetary tightening cycle could exacerbate the trend observed after the GFC of a shift in financial intermediation from the banking sector to the less-regulated MBF segment. See e.g. Xiao (2020) for US evidence using money market funds data and a theoretical justification of the underlying mechanism.

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