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Preface

In this dissertation, I contribute to the field of empirical banking and financial market structure. I focus on how financial institutions and markets respond to external shocks—whether monetary, macroprudential, behavioral, or environmental—and the implications for credit allocation and asset prices. Across the chapters, I combine structural modeling, high-frequency identification strategies, novel data collection, and advanced textual analysis to uncover causal relationships and deepen our understanding of the mechanisms that shape bank behavior and financial markets under different constraints and incentives.

In Chapter 1, titled *Monetary Policy, Binding Regulatory Capital Constraints and Bank Lending*, I show how monetary policy can have asymmetric effects on bank lending depending on bank capitalization. First, I develop a theoretical model showing how weakly capitalized banks, do not react to monetary policy easing, because of their binding capital constraints, while strongly capitalized banks expand lending. As capital constraints only impose an upper bound on lending, both types of banks similarly reduce lending in reaction to monetary policy tightening. Second, I empirically confirm these predictions using bank-level lending data, loan exposure data, and confidential capital ratio information for German banks. In particular, I find that, on average, a one basis point monetary policy easing shock increases lending by 0.17 percent more for banks with a one-percentage point higher CET1 ratio. In contrast, monetary policy tightening has a uniform effect across banks with different CET1 ratios, in line with the model's predictions. Third, to address the potential endogeneity of bank capital ratios to bank lending, I build a new dataset of exogenous surprises around macroprudential policy announcements. I use these surprises as a proxy for the sensitivity of each bank to each announcement. In line with my previous results, I find that, following a constraining surprise, the least sensitive banks increase their lending more than the most sensitive ones in reaction to monetary policy easing, and reduce their lending less in reaction to monetary policy tightening. This happens because strongly treated banks, following a macroprudential constraining surprise, have to reduce their lending more than weakly treated banks in reaction to macroprudential constraining surprise, which makes their capital constraints more binding.

Chapter 2, named *Through Rose-Tinted or Dark Lenses: How Bank Manager Sentiment Affects Lending and Risk*, is co-authored with Frank Brueckbauer. In this chapter, we present evidence on how bank managers' systematic over-optimism or over-pessimism (bank manager sentiment) affects both the amount and the riskiness of credit that banks supply to the real sector. We first use textual analysis methods (using both dictionary and machine learning approaches) to build a textual score measuring the tone of bank earnings press release documents. Our analysis focuses on medium-sized and large European banks at the banking group level, from the first quarter of 2006 to the second quarter of 2019. We then define bank manager sentiment as the variation in the textual tone score that is orthogonal to bank-specific and macroeconomic fundamentals. We show that bank manager sentiment is related to past fundamentals and is strongly auto-correlated, implying that risk-taking behavior of banks and contemporaneous economic fundamentals might be systematically disconnected. For instance, we find that a one standard deviation increase in GDP growth in the past six months is associated with an average increase in contemporaneous bank manager sentiment by approximately 0.08 standard deviation. We also find that a higher bank manager sentiment is associated to a credit supply reallocation on the part of banks from low- to high-risk borrowers. In particular, a one standard deviation increase in bank manager sentiment raises bank share in the syndicated loan to a given borrower by 0.15 to 0.24 percentage points in the next six months, conditional on this borrower's risk profile being higher by 1%. Finally, we show that bank manager sentiment spills over to their equity investors, who seem to perceive banks with high manager sentiment as having a lower systemic risk, and conversely. Specifically, a one standard deviation increase in bank manager sentiment is on average associated with a 0.03 standard deviation decrease in the bank's systemic risk in the next six months.

Chapter 3, named *The Green Bond Market Elasticity*, is co-authored with Maurice Bun. In this chapter, we examine how supply and demand shocks for green bonds affect the green spread — the yield differential between existing green and equivalent conventional bonds. To identify exogenous supply shocks, we exploit daily announcements of future green bond issuances from different financial market actors, such as corporates or public entities. To identify exogenous demand shocks, we collect ECB announcements related to the incorporation of climate considerations in its different policy tools. Using a narrative approach, we classify each announcement as being in favor of, neutral to, or against this incorporation. In line with economic theory, we find that supply shocks increase the green spread. However, this effect is economically very small and short-lived: on average, the green spread increases by 0.05 basis points following the announcement of a USD 1bn green bond issuance and is only significant for a few days. We highlight, nonetheless, interesting heterogeneity dimensions. In particular, we find that the effect of local supply shocks is stronger: a USD 1bn green bond issuance announcement by an entity of a given country increases the green spread of bond pairs that have been issued by entities from the same country by around 0.26 basis points. Additionally, we find that the size of the announcement matters, with large announcements (more than USD 5bns) having the strongest effect on the green spread (0.09 basis points per USD bn announced). Regarding demand shocks, we find that those significantly and persistently reduce the green spread. We show that, every time the ECB makes an announcement in favor of the incorporation of climate considerations in its different policy tools, the green spread decreases by around 0.5 basis points. This effect is primarily driven by general announcements, greening asset purchase programmes or collateral framework announcements.

Chapter 1

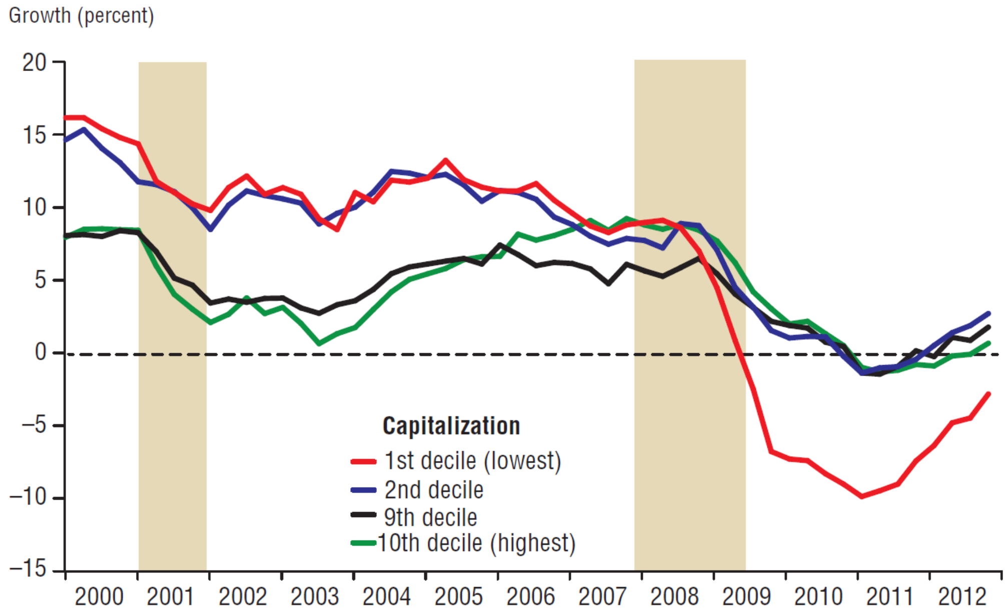
Monetary Policy, Binding Regulatory Capital Constraints and Bank Lending

1.1 Introduction

In response to the Global Financial Crisis (GFC), central banks around the world implemented extensive monetary stimulus programs aimed at reviving bank lending and economic growth. While succeeding in boosting aggregate lending, the recovery was uneven across banks. As shown in Figure 1.1, although aggregate lending gradually rebounded following the GFC, it took significantly longer for weakly capitalized banks to recover. This slower recovery might be attributed either to a dampened effect of monetary policy easing on the lending of weakly capitalized banks, or to a more severe impact of the GFC on weakly capitalized banks compared to better capitalized banks. In contrast, during the period from July 2004 to July 2006, marked by strong economic growth and a steady increase in the Federal Funds rates, weakly capitalized banks managed to sustain higher lending growth than their strongly capitalized counterparts. This higher growth might be due either to a stronger resilience of weakly capitalized banks to monetary policy tightening, or because they benefited more from the favorable economic conditions than strongly capitalized banks. These two episodes underscore the importance and the difficulty for policymakers to evaluate the effects of monetary policy easing and tightening on the lending of banks with different levels of capitalization.

In this paper, I examine how bank capitalization affects the effectiveness of the bank lending channel of monetary policy, both during easing and tightening episodes. Understanding these dynamics carries important policy implications. For example, if a weakened bank lending channel is observed for weakly (strongly) capitalized banks, it suggests that the existence

Figure 1.1. Year/Year lending growth of US commercial banks by capitalization level.



Notes: Note: This figure shows the year-over-year lending growth of US commercial banks by capitalization decile. The capitalization measure used in this chart is the capital-over-assets ratio. Source: Cooke and Koch (2014).

of numerous weakly (strongly) capitalized banks in the economy could undermine the effectiveness of monetary policy stimulus (i.e., easing). Conversely, if an enhanced bank lending channel is observed for weakly (strongly) capitalized banks, it suggests that the existence of numerous weakly (strongly) capitalized banks in the economy could exacerbate the moderation of monetary policy contraction (i.e., tightening).

To explore these dynamics, I first build on the work of Gödl-Hanisch (2023) by employing the Monti-Klein model of the banking sector, which incorporates monopolistic competition and introduces capital constraints that limit banks' lending-over-equity ratio. In addition, I assume that loans are risky and that each bank has its own specific repayment probability and recovery rate on these loans, hence generating differences across banks in how binding their capital constraints are. The model predicts asymmetric effects of monetary policy, with easing and tightening producing different outcomes. In response to monetary policy tightening, all banks would raise both lending and deposit rates while reducing lending volumes. On the contrary, following monetary policy easing, banks' reaction depends on how binding their capital constraints are. While banks with non-binding capital constraints have the exact opposite reaction to monetary policy easing compared to tightening, banks with binding capital constraints do not react to monetary policy easing. This result occurs because the capital constraints are binding only in one direction, imposing an upper bound on lending volume without a corresponding lower bound.

Second, I empirically test the predictions of the theoretical model by exploiting the unique characteristics of the German banking system. Germany's banking system comprises few large banks and a vast number of smaller banks, each holding a small share of the loan market. Furthermore, these banks vary widely in terms of business models and capitalization levels. To account for this diversity and to take advantage of the heterogeneity in German banks' capitalization, I employ a bank-panel local projection framework (Jordà, 2005) with fixed effects. This approach allows me to study the bank-level lending response over subsequent time horizons of banks with different CET1 ratios to monetary policy shocks. I obtain the monthly bank balance sheet information from Bundesbank's BISTA database and the CET1 information from Bundesbank's COREP dataset. I perform the empirical analysis over the period from the beginning of 2014 to the end of 2021. The results support the predictions of the theoretical model: on average, a one basis point stimulus monetary policy easing shock (i.e. a surprise decrease of the monetary policy rate by one basis point) increases lending by 0.17 percent more for banks with a one-percentage point higher CET1 ratio. Given that a one-standard deviation monetary policy surprise is around 4.4 basis points, this result implies that a bank with a CET1 ratio of 10 percent increases its lending by 3.7 percent more than a bank with a 5 percent-CET1 ratio, following a one standard deviation stimulus monetary policy easing, which is economically large. In contrast, monetary policy tightening has a uniform effect across banks with different CET1 ratios, in line with the model's predictions. One potential limitation of the analysis using bank-level data is the influence of loan demand, which could bias the results. To address this, I use quarterly loan exposure data from the credit register of loans of €1.0 million or more from Bundesbank and include borrower-time fixed effects in the model, following the approach of Khwaja and Mian (2008). The results remain robust with this adjustment: a one basis point monetary policy easing shock increases lending by 0.2 percent more for banks with a one-percentage point higher CET1 ratio. On the contrary, monetary policy tightening has a completely uniform effect across banks with different CET1 ratios.

Third, I identify an exogenous measurement of the capital constraints faced by German banks. Although a bank's CET1 ratio is an intuitive proxy for how binding their capital constraints are, it may suffer from endogeneity to its lending. To address this issue, I build a dataset of macroprudential policy surprises specific to German credit institutions, which serves as an alternative to the CET1 ratio. These surprises are derived from daily variations in bank bond yields around macroprudential policy announcements affecting German banks. Given that bonds are issued by both large and small banks, this approach enables an analysis which is representative of the entire German banking system, with bond yield data available for 824 different credit institutions located in Germany. To study the impact of these surprises on bank lending, I proceed in several steps. I first extract the stance of each macroprudential policy announcement from the bond yields by studying the sign of the reaction of these yields to macroprudential policy announcements, controlling for daily market conditions and bond-year-month fixed effects. If bank bond yields increase (decrease) in reaction to a given announcement, I interpret the event as a macroprudential loosening (constraining) surprise, signaling that financial markets perceive an increased (reduced) risk profile for banks.[1] I then calculate an abnormal bond return for each bank and hypothesize that the banks which are the most sensitive to each announcement will react the most in terms of abnormal bond returns on the announcement day. In line with this hypothesis, I find that, for macroprudential loosening (constraining) surprises, banks with lower capital ratios exhibit a significantly stronger increase (decrease) in abnormal bond return compared to banks with higher capital ratios. I then focus on the macroprudential policy constraining surprises and group banks by treatment intensity for each announcement, based on their sensitivity to the announcement. Finally, I examine how these groups differ in their lending behavior in response to monetary policy shocks that are subsequent to the constraining macroprudential policy surprises.

My results show that, following a macroprudential constraining surprise, weakly treated banks (i.e. banks with low sensitivity to the surprise, as indicated by their near-zero abnormal returns) increase their lending significantly more than strongly treated banks (i.e. banks with high sensitivity to the surprise, as indicated by their strongly negative abnormal returns) in response to subsequent monetary policy easing shocks, confirming the results obtained using the CET1 ratio. Furthermore, I find that weakly treated banks reduce their lending less than strongly treated banks in reaction to subsequent monetary policy tightening shocks. This new finding can be explained by the fact that, following a macroprudential constraining surprise, strongly treated banks have to reduce their lending more than weakly treated banks due to the effect of the macroprudential constraining surprise, which makes their capital constraints more binding, adding to the contractionary effect of the monetary policy tightening shock. When refining the treatment intensity to the least vs most treated banks (e.g the top vs bottom 10% of banks in terms of sensitivity for each macroprudential policy announcement), I find that these results become even stronger in economic size.

[1] In the rest of the paper, I use the macroprudential policy "loosening" and "constraining" wording instead of macroprudential policy "easing" and "tightening" to avoid any confusion with monetary policy "easing" and "tightening", respectively.

The rest of the paper is organized as follows. In Section 1.2, I summarize the related literature and lay out my contributions. In Section 1.3, I present the Monti-Klein model of the banking sector with monopolistic competition from which I derive predictions. In Section 1.4, I present the empirical strategy I adopt, which exploits bank capital ratios, to test the predictions of the theoretical model. In Section 1.5, I describe the German banking system and the data used for the empirical analysis. In Section 1.6, I present the main empirical results. In Section 1.7, I show that the use of bank capital ratios can lead to biased estimates, and I introduce the macroprudential policy surprises as a solution. In Section 1.8, I present the data used for computing the macroprudential policy surprises and estimate them. In Section 1.9, I present the empirical strategy to test the predictions of the model by exploiting the macroprudential policy surprises and present the results. Finally, in Section 1.10, I conclude.

1.2 Related Literature

This paper contributes to three strands of research. First, it contributes to the literature studying the asymmetric transmission of monetary policy through bank capital constraints, where the capital constraint is treated as given. In particular, my paper focuses on the regulatory capital constraint channel: low-capitalized banks face regulatory constraints that can limit their response to monetary easing (A. Kashyap and J. Stein, 1994; Van den Heuvel et al., 2002; Niepmann, Schmidt-Eisenlohr, and Liu, 2021; Gödl-Hanisch, 2023). My paper is most closely related to Gödl-Hanisch (2023) and Niepmann, Schmidt-Eisenlohr, and Liu (2021). Gödl-Hanisch (2023) theoretically shows that low-capitalized banks adjust their lending rates more in response to monetary policy shocks, hence amplifying the transmission of monetary policy. Conversely, Niepmann, Schmidt-Eisenlohr, and Liu (2021) provide some empirical evidence that capital-constrained banks are unable to expand lending following monetary easing, as doing so would deteriorate their capital ratios. On the contrary, they show that in case of monetary policy tightening, a bank can still reduce its loans, whatever the level of its regulatory capital. My paper contributes to this literature both theoretically and empirically. On the theoretical side, I build on the model of Gödl-Hanisch (2023) and bring two extensions. I incorporate risky loans with bank-specific repayment probability and recovery rate on these loans, thus generating differences across banks in how binding their capital constraints are. Furthermore, I explicitly distinguish between monetary policy easing and tightening and derive distinct predictions for each stance. I show that, in such a framework, monetary policy has an asymmetric effect: monetary policy easing is effective on the lending rates and quantity of banks with non-binding capital constraints only, while monetary policy tightening decreases (increases) the lending quantity (rate) of all banks independently of their capitalization. On the empirical side, I exploit a combination of unique datasets, namely the individual domestic monetary financial institutions' balance sheet statistics from Bundesbank (BISTA) combined with capital ratio data and the credit register of loans of €1.0 million or more from Bundesbank. This combination enables me to study the full spectrum of German banks and hence the full heterogeneity of the German banking system in terms of bank capitalization while isolating credit supply from credit demand (Khwaja and Mian, 2008). To the best of my knowledge, this paper is finally the first to use a bank-panel local projection framework to study the long-term effects of monetary policy easing and tightening on the lending behavior of well-capitalized banks compared to weakly capitalized banks, while taking into account serial correlation.

The second strand of literature this paper contributes to is the one measuring bank capital constraints. This is usually done by exploiting exogenous shifts in the macroprudential policy stance. Different methods have been used so far to estimate this stance, each of them having pros and cons. A first method consists in building an aggregate indicator of the stance of macroprudential policies in a certain country at a certain time, and then reduce the endogeneity bias [2] (Cerutti, Claessens, and Laeven, 2017; Meeks, 2017; Akinci and Olmstead-Rumsey, 2018; Richter, Schularick, and Shim, 2019; Brandao-Marques et al., 2020; Budnik and Rünstler, 2020; Meuleman and Vander Vennet, 2020; Nier, Olafsson, and Rollinson, 2020; Ahnert et al., 2021; Altavilla, Laeven, and Peydró, 2021; Hristov, Hülsewig, and Kolb, 2021; Gelos et al., 2022; Rojas, Vegh, and Vuletin, 2022). A second method uses directly exogenous macroprudential policy-related events, mostly stress-tests (Bassett and Berrospide, 2017; Acharya, Berger, and Roman, 2018; Acharya et al., 2022; Raz, McGowan, and Zhao, 2022; Shahhosseini, 2022; Chronopoulos, Wilson, and Yilmaz, 2023; Kok et al., 2023). A third method exploits bank-specific changes in capital requirements (Aiyar, Calomiris, and Wieladek, 2014). In this paper, I adopt an alternative method recently introduced to measure exogenously the treatment intensity of different macroprudential policies on each bank of my sample. This method relies on macroprudential policy surprises built in a similar way to monetary policy surprises. It consists in measuring daily variations of bank-level financial market variables around the announcement of macroprudential policy events. Compared to the three methods described above, this method enables to have an estimate which is simultaneously bank-specific, exogenous with respect to financial and macroeconomic developments, unanticipated, and that can be measured for multiple macroprudential policy events. To the best of my knowledge, only two papers have computed similar surprises so far. Bluw-

[2] The most common ways to reduce this bias in the existing literature are by using for lags combined with the GMM estimator, a residual approach, a VAR structure or a narrative approach.

stein and Patozi (2022) have focused on the CDS spreads and stock prices reaction of UK banks to different types of local macroprudential policy events and have used them to study the effect on banks' SRISK. Couaillier and Henricot (2023) have computed these stock prices and CDS spreads surprises for banks located in eighteen European countries (including Germany), but only for announcements related to countercyclical capital buffer requirements. Compared to these papers, I introduce a new exogenous measurement of the strength of a broad type of macroprudential policy announcements for Germany, which I use as an exogenous variation of how binding are the capital constraints of German banks. Moreover, this paper is the first one to focus on bank bond yields rather than stock prices or CDS spreads, ensuring that my analysis is representative of the entire German banking system, as bonds are issued by both large and small banks.

Third, this paper contributes to the growing literature on the interaction between monetary and macroprudential policies, with a particular focus on their joint effects on bank lending. Despite the increasing importance of the coordination between these two policies — in particular in case of adverse economic or financial shocks such as the COVID-19 pandemic — a large majority of the existing literature is theoretical and relies on general equilibrium models with financial frictions (Angelini, Neri, and Panetta, 2014; Brunnermeier and Sannikov, 2016; Farhi and Werning, 2016; Collard et al., 2017; Gelain and Ilbas, 2017; Kiley and Sim, 2017; Paoli and Paustian, 2017; Martinez-Miera and Repullo, 2019; Van der Ghote, 2021). Empirical evidence on this interaction is far more limited, partly due to significant endogeneity between monetary and macroprudential policies [3], and between those policies and bank lending. Among the few empirical papers, findings on the interaction between monetary and macroprudential policies remains inconclusive. On the one hand, Imbierowicz, Löffler, and Vogel (2021), who also study German banks [4], find that more constraining capital requirements attenuate the stimulative effect of monetary policy easing on corporate lending rates, but not lending volumes. Similarly, Aiyar, Calomiris, and Wieladek (2016) investigate the interaction between capital requirements and monetary policy in the UK banking sector find no significant interaction effects between changes in monetary policy and capital requirements. On the other hand, Altavilla, Laeven, and Peydró (2021), who use granular loan-level data from credit registers across several European countries, find that monetary policy easing (tightening) increases (decreases) bank lending, and that this effect is dampened (amplified)

[3] Both types of policies often respond to common objectives such as financial stability, making it difficult to disentangle their individual and interactive effects on bank lending.

[4] Imbierowicz, Löffler, and Vogel (2021) use the Bundesbank's MFI interest rate statistics which covers a representative sample of about 220 banks in the German banking system, instead of the credit register of loans of €1.0 million or more from Bundesbank.

by a more constraining macroprudential environment. Maddalonia and Peydró (2018) also show that low policy rates tend to soften lending standards, but that this effect is mitigated by tighter capital requirements or loan-to-value ratios. To the best of my knowledge, this paper is the first to exploit exogenous macroprudential policy surprises to identify their causal impact on bank lending, as well as their interaction with monetary policy shocks. Doing so, I show that macroprudential constraining surprises dampen (amplify) the lending channel of subsequent monetary policy easing (tightening) shocks for the most sensitive banks to the surprises.

1.3 Theoretical model

In this section I highlight how the asymmetric effect of monetary policy between banks with different capital constraints emerges using a simple theoretical model. The model builds on the Monti-Klein framework of banking sector with monopolistic competition, extending it with capital constraints (as in (Gödl-Hanisch, 2023)) and, in addition, a two-period structure ($t = 0$ and $t = 1$) and risky loans. In period $t = 0$, the bank i is endowed with some exogenous equity E_i, collects deposits D_i and allocates its funding to risky loans L_i or to safe reserves R_i held at the central bank. The stylized balance sheet for bank i in period $t = 0$ is structured as follows:

Assets	Liabilities
Loans (L_i)	Deposits (D_i)
Reserves (R_i)	Equity (E_i)

In period $t = 1$, the loans are either fully repaid with a return r_i^l with a probability p_i, or default with a probability $(1 - p_i)$ in which case the bank recovers only a fraction α_i of L_i with $\alpha_i < 1$. Importantly, note that both the repayment probability of the risky loans p_i and the recovery rate in case of default α_i are specific to each bank i, reflecting variations in both the borrowers' risk profile and in banks' risk assessment. This should be realistic regarding the German banking system given all the different categories of banks and hence of their investment strategies.[5] Bank i also receives a safe return r^f on its reserves R_i and pays a deposit rate r_i^d on its deposits D_i. Furthermore, I assume that the loan demand addressed to bank i ($L(r_i^l)$) is decreasing in r_i^l with $L(r_i^l) = \left(\frac{r_i^l}{\bar{r}^l}\right)^{-\varepsilon^l} \bar{L}$, where ε^l is the loan elasticity of

[5] For instance, the savings banks (Sparkassen in German), which is one type of German banks, are controlled by their local government and in general have a public mandate to serve their local stakeholders and communities

substitution, $\overline{r}^l$ is the average loan rate in the economy and $\overline{L}$ is a constant that shifts aggregate loan demand. Conversely, deposit supply offered to bank i ($D(r_i^d)$) is increasing in r_i^d, with $D(r_i^d) = \left(\frac{r_i^d}{\overline{r}^d}\right)^{\varepsilon^d} \overline{D}$, where ε^d is the deposit elasticity of substitution, $\overline{r}^d$ is the average deposit rate in the economy and $\overline{D}$ is a constant that shifts aggregate deposit supply. Each bank i faces capital requirements represented by the constraint $E_i \geq v * L_i$ where v is the capital adequacy ratio. As a simplification, I assume that the reserves (R_i) of bank i have a weight equal to 0, which is realistic as following Basel III regulation.

In period $t = 0$, bank i chooses its lending rate r_i^l and deposit rate r_i^d to maximize its expected profit in $t = 1$:

$$\max_{r_i^l, r_i^d} \ \Pi_i \ = \ p_i(1 + r_i^l)L_i + (1 - p_i)\alpha_i L_i + (1 + r^f)R_i - (1 + r_i^d)D_i - L_i - R_i + D_i$$

$$\text{such that} \begin{cases} E_i \geq vL_i \\ L_i = L(r_i^l) \\ D_i = D(r_i^d) \\ L_i + R_i = D_i + E_i \end{cases}$$

i.e. bank i maximizes its profits such that (i) the capital constraint holds, (ii) the loan quantity supplied by bank i equals its loan demand, (iii) the deposit quantity used by bank i equals its deposit supply, and (iv) the balance sheet constraint holds.
Plugging the balance sheet constraint in the profit equation allows to write the Lagrangian as follows:

$$\mathscr{L} \ = \ \left[r_i^l p_i - (1 - \alpha_i)(1 - p_i)\right]L_i + r^f(D_i + E_i - L_i) - r_i^d D_i + \phi_i(E_i - vL_i)$$

The first-order conditions are:

$$\frac{\partial \mathscr{L}}{\partial r_i^l} \ = \ 0 \Rightarrow p_i L_i + \frac{\partial L_i}{\partial r_i^l}\left[p_i r_i^l - (1 - \alpha_i)(1 - p_i)\right] - r^f \frac{\partial L_i}{\partial r_i^l} - \phi_i v \frac{\partial L_i}{\partial r_i^l} \ = \ 0$$

$$\frac{\partial \mathscr{L}}{\partial r_i^d} \ = \ 0 \Rightarrow r^f \frac{\partial D_i}{\partial r_i^d} - D_i - \frac{\partial D_i}{\partial r_i^d} r_i^d \ = \ 0$$

The solution is given by:

$$r_i^l = \frac{\varepsilon^l}{p_i(\varepsilon^l - 1)}\left(r^f + v\phi_i + (1-\alpha_i)(1-p_i)\right) \tag{1.1}$$

$$r_i^d = \frac{\varepsilon^d}{\varepsilon^d + 1} r^f \tag{1.2}$$

Optimal loan and deposit quantities are given by their respective functions:

$$L_i = \left(\frac{\frac{\varepsilon^l}{p_i(\varepsilon^l-1)}\left(r^f + v\phi_i + (1-\alpha_i)(1-p_i)\right)}{\bar{r}^l} \right)^{-\varepsilon^l} \bar{L} \tag{1.3}$$

and

$$D_i = \left(\frac{\frac{\varepsilon^d}{\varepsilon^d+1} r^f}{\bar{r}^d} \right)^{\varepsilon^d} \bar{D} \tag{1.4}$$

Finally, R_i is directly deduced from the balance sheet constraint. Intuitively, banks with a higher repayment probability p_i and recovery rate α_i (i.e.low risk-loans) offer lower loan rates r_i^l hence maximizing lending under their capital constraints, which will be binding. Conversely, banks with a lower repayment probability p_i and a lower recovery rate α_i (i.e high risk-loans) raise loan rates to reduce the loan demand addressed to them and shift funds into safe reserves, implying that their capital constraints will not be binding.

In this setting, the effect of monetary policy will depend on whether the capital constraint faced by bank i is binding or not. If the capital constraint is not binding (i.e. bank i is sufficiently capitalized), then $\phi_i = 0$ and monetary policy easing and tightening have a symmetric effect, where the effects of a monetary policy tightening are the following:

$$\frac{\partial r_i^l}{\partial r^f} = \frac{\varepsilon^l}{p_i(\varepsilon^l - 1)} > 0 \Rightarrow \frac{\partial L(r_i^l)}{\partial r^f} < 0$$

and

$$\frac{\partial r_i^d}{\partial r^f} = \frac{\varepsilon^d}{\varepsilon^d + 1} > 0 \Rightarrow \frac{\partial D(r_i^d)}{\partial r^f} > 0$$

The effects of a monetary policy easing are the exact opposite of the effects of a monetary policy tightening:

$$\frac{\partial r_i^l}{-\partial r^f} = -\frac{\varepsilon^l}{p_i(\varepsilon^l - 1)} < 0 \Rightarrow \frac{\partial L(r_i^l)}{-\partial r^f} > 0$$

and

$$\frac{\partial r_i^d}{-\partial r^f} = -\frac{\varepsilon^d}{\varepsilon^d + 1} < 0 \Rightarrow \frac{\partial D(r_i^d)}{-\partial r^f} < 0$$

If the capital constraint is binding (i.e. if the bank i is weakly capitalized), then $\phi_i > 0$. From the function of loan demand addressed to bank i and equation 1.1, and by the binding capital constraint, ϕ_i can be calculated as:

$$\phi_i = \frac{1}{v}\left[\left(\frac{v\bar{L}}{E_i}\right)^{\frac{1}{\varepsilon^l}} \bar{r}^l \frac{p_i(\varepsilon^l - 1)}{\varepsilon^l} - r^f - (1 - \alpha_i)(1 - p_i)\right] \tag{1.5}$$

As the constraint is binding only in one direction (as it only imposes an upper bound on L_i, but no lower bound), monetary policy tightening will have the same effects as before:

$$\frac{\partial r_i^l}{\partial r^f} = \frac{\varepsilon^l}{p_i(\varepsilon^l - 1)} > 0 \Rightarrow \frac{\partial L(r_i^l)}{\partial r^f} < 0$$

and

$$\frac{\partial r_i^d}{\partial r^f} = \frac{\varepsilon^d}{\varepsilon^d + 1} > 0 \Rightarrow \frac{\partial D(r_i^d)}{\partial r^f} > 0$$

However, the effects of monetary policy easing on lending rates and volume are this time muted:

$$\frac{\partial r_i^l}{-\partial r^f} = -\frac{\varepsilon^l}{p_i(\varepsilon^l - 1)}\left(1 + v * \frac{\partial \phi_i}{\partial r^f}\right) = 0 \Rightarrow \frac{\partial L(r_i^l)}{-\partial r^f} = 0$$

To summarize, the presence of an upper bound on lending supply should impair the bank lending channel of monetary policy easing for banks with binding capital constraints (i.e. weakly capitalized banks). Conversely, the absence of a lower bound on lending supply should not prevent banks with binding capital constraints to reduce lending in reaction to monetary policy tightening, as would do banks with non-binding capital constraints. In the rest of the paper, I approximate the bank capital constraints and test empirically these predictions.

1.4 Empirical strategy

In this section, I describe an intuitive proxy that can be used to capture how binding are bank capital constraints. I then describe the empirical strategy used to study its effect on bank lending and how it interacts with monetary policy easing and tightening shocks.

1.4.1 From the theoretical model to the empirical testing

One key element of the model that needs to be approximated is how binding is the capital constraint $E_i \geq \nu L_i$ of bank i or equivalently $\frac{E_i}{L_i} \geq \nu$. The proxy I use here relies on using directly observable data for the variables composing the constraints, i.e. $\frac{E_i}{L_i}$ and ν for a given bank i. Such a proxy for $\frac{E_i}{L_i}$ consists in existing regulatory capital ratios, e.g. the Common Equity Tier 1 ratio of bank b at time t ($CET1ratio_{i,t}$ hereafter):

$$CET1ratio_{i,t} = \frac{Common \quad Equity \quad Tier \quad 1 \quad Capital_{i,t}}{Risk \quad Weighted \quad Assets_{i,t}}$$

The numerator of $CET1ratio_{i,t}$ (i.e. $Common \quad Equity \quad Tier \quad 1 \quad Capital_{i,t}$) is composed of regulatory capital of the highest quality, as it absorbs losses immediately when they occur.[6] The denominator (i.e. $Risk \quad Weighted \quad Assets_{i,t}$) measures the risks a bank has on its books. As its name indicates, it is the sum of the assets of the bank, weighted by a factor increasing with the risk profile of each asset [7]. The CET1 ratio has been enforced by Basel III regulation since 2014 and has to be above 4.5% (which is represented by the capital adequacy ratio ν in the theoretical model).

1.4.2 Bank-level lending analysis

The main specification I implement relies on a bank-panel local projection framework (Jordà, 2005). The local projection framework allows to take into account the autocorrelation of the variables while studying the persistence of the shocks of interest. This method does not require solving or iterating through a full system of equations as in a vector autoregression (VAR) model. Instead, for a given shock occurring at time t, each impact at time $t+h$ (where

[6] The Common Equity Tier 1 is the sum of common shares and stock surplus, retained earnings, other comprehensive income, qualifying minority interest and regulatory adjustments

[7] The factors applied depend on several parameters: the approach chosen by the bank (standardized or based on internal ratings, the type of borrower as well as its credit rating. For instance, according to the standardized approach, exposures to covered bonds having an external rating between AAA and AA- have a factor of 10%. Exposures to other banks or corporates, which are considered riskier, with the same external rating have a factor of 20%. More details are available in this link.

$h \in [0,H]$) is estimated separately by directly regressing the outcome of interest at time $t+h$ on the shock and other control variables at time t:

$$\begin{aligned} y_{i,t+h} - y_{i,t-1} = \; & \alpha_i + \beta_t + \phi^h * CET1ratio_{i,t} + \beta^h_{E,CET1} * MPS_t * (-\mathbb{I})\{Easing\}_t * CET1ratio_{i,t} \\ & + \beta^h_{T,CET1} * MPS_t * \mathbb{I}\{Tightening\}_t * CET1ratio_{i,t} + \mu * M_{i,t} + controls + u_{i,t+h} \end{aligned} \tag{1.6}$$

where $y_{i,t}$ represents the logarithm of total loans of bank i in month t. MPS_t is the monetary policy shock in month t, averaged to a monthly frequency. $\mathbb{I}\{Easing\}_t$ and $\mathbb{I}\{Tightening\}_t$ represent the monetary policy stance for each measure of monetary policy shock.[8] Importantly, note that I multiply $\mathbb{I}\{Easing\}_t$ by (-1) so that the corresponding coefficient $\beta^h_{E,CET1}$ can be interpreted as the effect of a monetary policy stimulus shock (in the rest of the paper, I will refer to it as a stimulus monetary policy easing shock). $CET1ratio_{i,t}$ represents the CET1 ratio of bank i in month t.[9] The vector $M_{i,t}$ contains all the pairwise interactions between MPS_t, $\mathbb{I}\{easing\}_t$, $\mathbb{I}\{tightening\}_t$] and $CET1ratio_{i,t}$ that are not already present in the equation above. The vector *controls* contains bank-time control variables (total assets, cash-over-asset ratio and deposit-over-asset ratio) and 12 lags of MPS_t, $\mathbb{I}\{easing\}_t$, $\mathbb{I}\{tightening\}_t$, $CET1ratio_{i,t}$ and of their interaction. Bank-level and time-level unobserved variables are captured by the bank fixed effects α_i and the time fixed effects β_t, respectively. The coefficients of interest $\beta^h_{E,CET1}$ and $\beta^h_{T,CET1}$ capture how much more, in percent, loans of bank i at horizon $t+h$ react to a monetary policy easing shock and to a monetary policy shock tightening occurring in month t, respectively, when the CET1 ratio of bank i is higher by one percentage point.

1.4.3 Isolating credit supply

As shown by the literature, the use of bank-level data may suffer from an omitted-variable bias (Anil K Kashyap and Jeremy C Stein, 2000; Khwaja and Mian, 2008). In particular, as shown by Khwaja and Mian (2008), it is important to distinguish two separate channels when studying bank liquidity shocks: the credit supply channel, i.e., the inability of banks to cushion borrowing firms against bank-specific liquidity shocks; and the firm borrowing channel, i.e., the inability of firms to smooth out bank lending channel effects by borrowing

[8] $\mathbb{I}\{Easing\}_t$ is a dummy equal to 1 if $MPS_t < 0$ and $\mathbb{I}\{Tightening\}_t$ is a dummy equal to 1 if $MPS_t > 0$
[9] I only have quarterly data for the CET1 ratio, so I assume it is constant over the three months of a given quarter.

from alternative sources of financing. In the case of this paper, assume that a given bank in my sample is specialized in lending to a specific sector. Assume as well that this specific sector is more sensitive to monetary policy shocks than other sectors. Then a monetary policy shock would strongly affect the total loan quantity of this bank, not only because of its effect on lending supply, but also because of its effect on the loan demand addressed to this bank, independently of this bank's capital ratio. In such a case, the bank-level results would be biased. In order to isolate loan supply from loan demand, I use loan-level data. Such a granularity allows to include borrower-time fixed effects that control for borrower-specific credit demand, as shown by Khwaja and Mian (2008). Concretely, the main specification I estimate is the following one:

$$\begin{aligned} y_{i,f,t+h} - y_{i,f,t-1} \ = \ & \alpha_i + \phi^h * CET1ratio_{i,t} + \beta^h_{E,CET1} * MPS_t * (-\mathbb{I})\{Easing\}_t * CET1ratio_{i,t} \\ & + \beta^h_{T,CET1} * MPS_t * \mathbb{I}\{Tightening\}_t * CET1ratio_{i,t} + \mu * M_{i,t} + controls + \gamma_{f,t} + u_{i,t+h} \end{aligned} \tag{1.7}$$

where $y_{i,f,t}$ represents the logarithm of loans of bank i to firm f in quarter t. Importantly, the presence of borrower fixed effects ($\gamma_{f,t}$) allows to control for loan demand (Khwaja and Mian, 2008). The other variables are the same as in regression 1.6.

1.5 Data

The focus of the empirical analysis is on German banks. I first present the German banking system and show how it fits the research question of this paper, and then present the datasets I use to implement the empirical specifications.

1.5.1 The German banking system

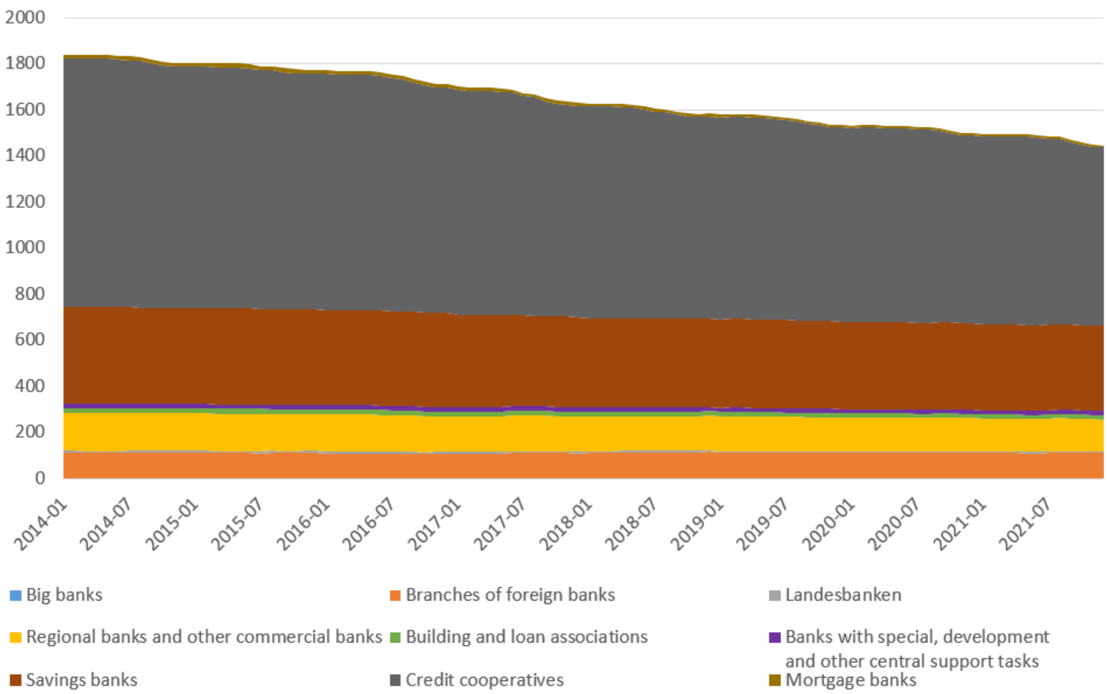
The German banking system is composed of nine categories of banks as classified by the Bundesbank: big banks, branches of foreign banks, Landesbanken, regional banks and other commercial banks, building and loan associations, banks with special, development and other central support tasks, savings banks, credit cooperatives and mortgage banks.[10] For each category, I show the evolution between 2014 and 2021 of the number of banks (Figure 1.2), the

[10] More details can be found in this link.

share in the German lending market (Figure 1.3) and the average capital-over-asset ratio [11] (Figure 1.4).

As shown by Figure 1.2, the number of banks in each category has been stable over time (except for the credit cooperatives whose number has decreased steadily). At the end of 2021, there were in total around 1,450 banking institutions operating in Germany. The most represented institutions were cooperative banks (773), savings banks (371), regional banks and other commercial banks (139) and the branches of foreign banks (109). At the same time, the German banking system is characterized by quite few building and loan associations and banks with special, development and other central support tasks (18 banks each), mortgage banks (9), Landesbanken (6) and big banks (3).

Figure 1.2. Number of banks by category of banks (end-of-month)



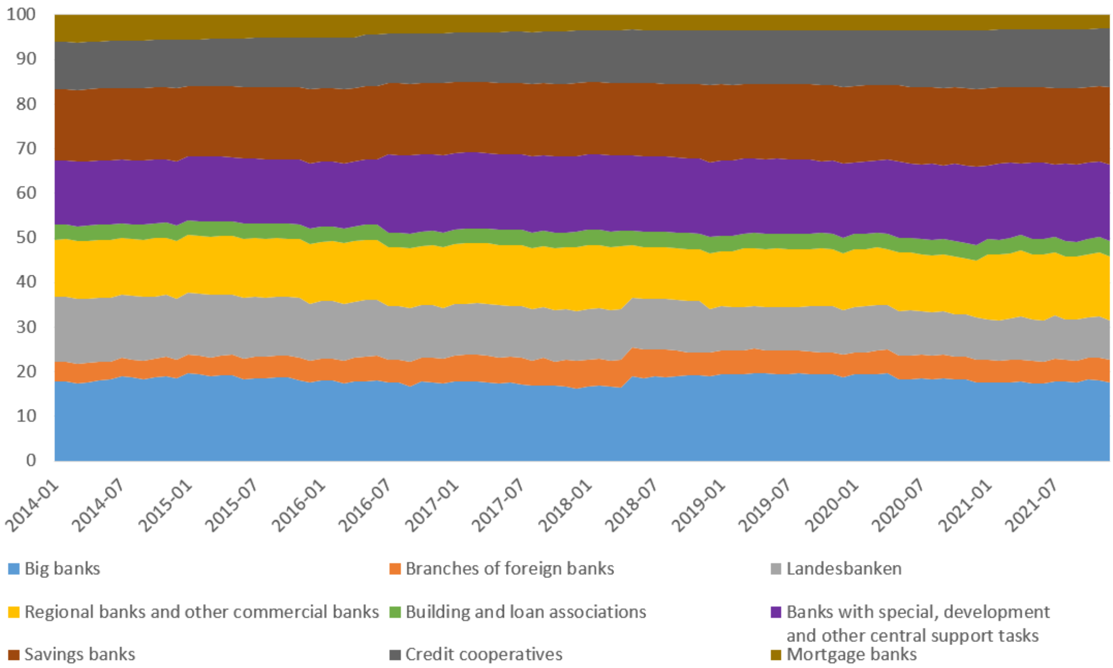
Source: Deutsche Bundesbank Statistical Series Banking statistics 2024-08-29

As shown by Figure 1.3, each category of banks has a quite stable share in the German lending market. Interestingly, no category seems to gather most of the market shares, with

[11] To compute the capital-over-asset ratio, I use the ratio of capital including published reserves, participation rights capital and fund for general banking risks over the total balance sheet, for a given category of banks at the end of each year. These data at the bank category-level are available here.

the highest share possessed by the big banks and the savings banks (around 17% each). On the opposite side, the mortgage banks and the building and loan associations only have around 3% of the market shares each. Hence, it appears that the German lending market has a low level of concentration.

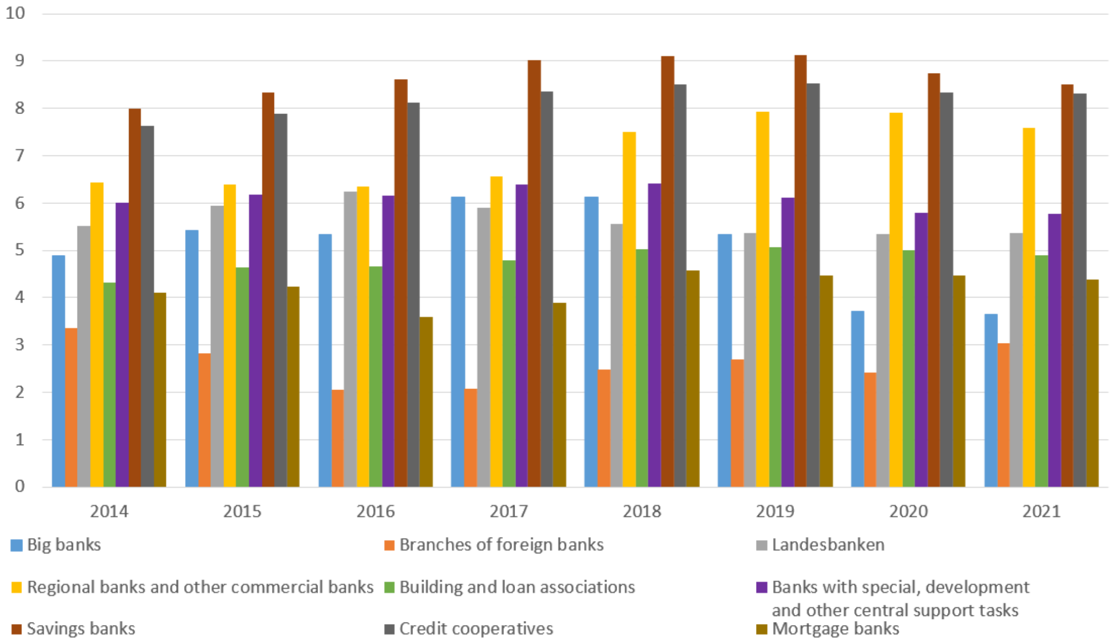
Figure 1.3. Market share in the German lending market by category of banks (in %, end-of-month)



Source: Deutsche Bundesbank Statistical Series Banking statistics 2024-08-29

Regarding the average capital-over-asset ratio, Figure 1.4 indicates a lot of heterogeneity and divergent trends over time between the different categories of banks. While the average capital-over-asset ratio of the savings banks, of the credit cooperatives and of the regional banks and other commercial banks has slightly increased (by 0.5 to 1 percentage point), the one of big banks has decreased by around 1.2 percentage points overall, in particular during the last three years of the sample. As shown by Figure 1.4, there is also a lot of heterogeneity in terms of the level of average capital-over-asset ratio between the different categories of banks. At the end of 2021, the savings banks, the credit cooperatives and the regional banks and other commercial banks had the highest average capital-over-asset ratio (more than 7.5%). Conversely, the big banks and the branches of foreign banks had the lowest average capital-over-asset ratio (less than 4%).

Figure 1.4. Bank capital over total assets by category of banks (in %, end-of-year)



Source: Deutsche Bundesbank Statistical Series Banking statistics 2024-08-29

To summarize, the German banking system is composed of a huge number of banks, including a few large banks having important but non dominant lending market shares, the rest of the lending market being shared by a multitude of smaller banks. This aspect supports the need to use granular banking data to have a representative sample of the overall German banking system. Furthermore, both large and small banks have very different capital-over-asset ratio levels and trends. I use this heterogeneity between banks to study how banks with different capitalization react differently to monetary policy easing and tightening.

1.5.2 Main datasets

In order to test empirically the predictions of my model, I use four main datasets. First, I compute monthly monetary policy shocks using the monetary policy surprises from Altavilla et al. (2019). These monetary policy surprises consist in intraday price changes in the euro area around monetary policy announcements for a broad class of assets and various maturities, including Overnight Index Swaps (OIS), sovereign yields, stock prices, and exchange rates. I focus on the one-year OIS rate changes (expressed in basis points) in the relevant window. I obtain monthly monetary policy shocks by aggregating the monetary policy surprises occurring on a given month. Using high frequency price changes allows to ensure that the monetary policy shocks are orthogonal to economic conditions that might have led to the monetary policy decision, hence preventing endogeneity concerns. Also the high frequency around monetary policy announcements ensures the absence of concurrent events that could have polluted the price changes.

Regarding the bank-level variables, I use two datasets from Bundesbank. The bank-level total loans and bank-level control variables come from the BISTA database. The BISTA database contains individual domestic monetary financial institutions' balance sheet statistics for Germany, at a monthly frequency starting from January 1999. [12] I get the CET1 ratios from the COREP (Common Reporting) dataset . COREP is a framework given by the European Banking Authority for reporting capital information to the regulator and applicable to all credit institutions in the European Union. Importantly, COREP requires consolidated reporting as well as entity-by-entity reporting. The CET1 ratio is available since its implementation in 2014. Since the CET1 ratio is only available at a quarterly frequency, I assume that it is stable over each month of a given quarter so that I can conduct the bank-level lending analysis at a monthly frequency.

In order to isolate the credit supply channel, I use the credit register of loans of €1.0 million or more from Bundesbank as a fourth dataset. The credit register of loans of €1.0 million or more from Bundesbank contains the loan exposure of bank i to firm f at time t for banks located in Germany and exposures above or equal to €1.0 million. [13, 14] The dataset is available starting from 2002 at a quarterly frequency, which is the frequency I use for the loan-level analysis to isolate credit supply. Both when using bank-level data and loan exposure data, my final sample covers the period 2014-2021.

1.6 Results

I start by presenting the results of the analysis using the bank-level lending data (regression 1.6) in Figure 1.5. As shown by Figure 1.5, strong asymmetries are present. On the one hand, stimulus monetary policy easing shocks have a significantly positive and persistent effect on

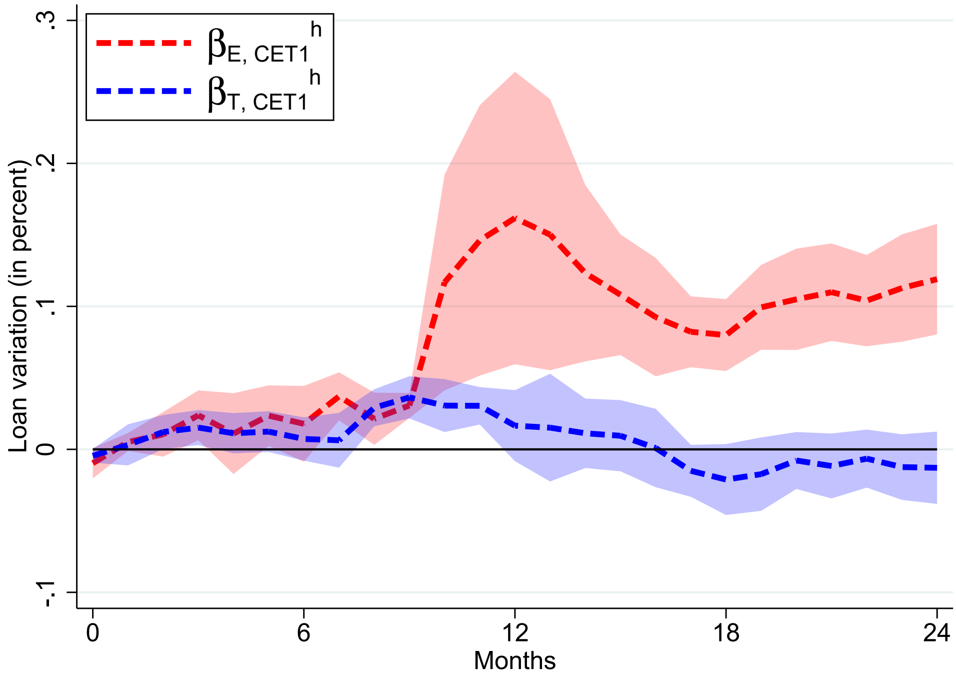
[12] For a description of the BISTA dataset at Deutsche Bundesbank, please refer to Gomolka, Schäfer, and Stahl (2022).

[13] The reporting threshold for the credit register was lowered to €1.0 million only from January 2015 onwards; before that period, the reporting threshold was set at €1.5 million.

[14] For a description of the credit register of loans of €1.0 million or more from Bundesbank, please refer to Schmieder (2006).

the lending of banks with a higher CET1 ratio, as predicted by the theoretical model. The effect reaches its peak after one year: on average, a one basis point stimulus monetary policy easing shock increases lending by 0.17 percent more for banks with a one-percentage point higher CET1 ratio. Given that a one-standard deviation monetary policy surprise is around 4.4 basis points, this result implies that a bank with a CET1 ratio of 10 percent increases its lending by 3.7 percent more than a bank with a 5 percent-CET1 ratio, following a one standard deviation stimulus monetary policy easing shock. On the other hand, the effect of a monetary policy tightening shock is mostly the same for banks with different CET1 ratios, also as predicted by the theoretical model. Interestingly, monetary policy tightening shocks seem to be slightly attenuated (i.e. less contractionary on lending) for banks with a higher CET1 ratio between seven months and twelve months after the shocks occurs. Over this horizon, a one basis point monetary policy tightening shock decreases lending by around 0.04 percent less for banks with a one-percentage point higher CET1 ratio.

Figure 1.5. Response of bank loans to stimulus monetary policy easing vs tightening shocks interacted with CET1 ratio ($\beta^h_{E,CET1}$ vs $\beta^h_{T,CET1}$ in regression 1.6).

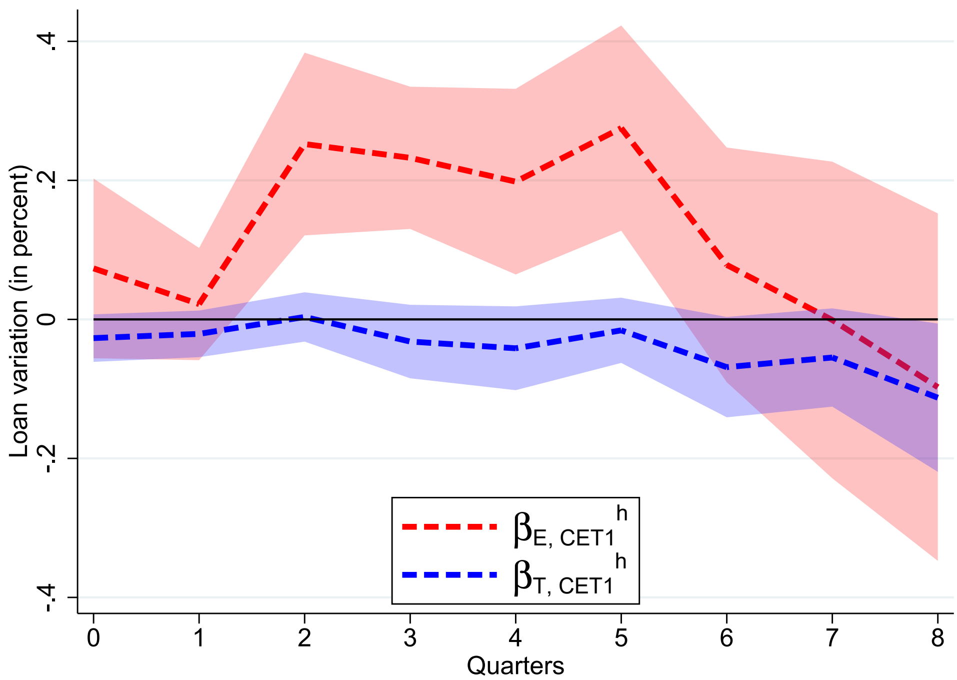


Source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BISTA and COREP datasets, 2014-2021, own calculations.

Note: In this figure, I plot the effect of the interaction between a one basis point stimulus monetary policy easing shock and the CET1 ratio of bank i in month t (expressed in percent) compared to the effect of a one basis point monetary policy tightening shock also interacted with the CET1 ratio of bank i in month t on bank loans over different time horizons h where $h = 0, 1, ..., 24$ months. The red dashed line represents the coefficient for the stimulus monetary policy easing shock interacted with the CET1 ratio of bank i in month t (i.e. $\beta^h_{E,CET1}$) for each horizon h. The light red area represents the 90 percent confidence bands of each coefficient $\beta^h_{E,CET1}$. The blue dashed line represents the coefficient for the monetary policy tightening shock interacted with the CET1 ratio of bank i in month t (i.e. $\beta^h_{T,CET1}$) for each horizon h. The light blue area represents the 90 percent confidence bands of each coefficient $\beta^h_{T,CET1}$.

In Figure 1.6, I show the results of the analysis using the CET1 ratio as a proxy for bank capital constraints, but exploiting the credit register of loans of €1.0 million or more from Bundesbank to isolate credit supply from credit demand using borrower-time fixed effects (regression 1.7). As shown by Figure 1.6, the asymmetries shown previously using bank-lending data are confirmed when isolating credit supply from credit demand . Stimulus monetary policy easing shocks have a significantly positive and quite persistent effect on the lending of banks with a higher CET1 ratio. The effect reaches its peak two to five quarters after the monetary policy shock occurred. On average, a one basis point stimulus monetary policy easing shock increases lending by 0.2 percent more for banks with a one-percentage point higher CET1 ratio. As for the analysis using bank-level lending data, the effect is still economically large. This result indeed implies that a bank with a CET1 ratio of 10 percent increases its lending by 4.4 percent more than a bank with a 5 percent-CET1 ratio, following a one standard deviation stimulus monetary policy easing (which is equal to 4.4 basis points). In contrast, the effect of a monetary policy tightening shock is similar for banks with different CET1 ratios.

Figure 1.6. Response of bank loan supply to stimulus monetary policy easing vs tightening shocks interacted with CET1 ratio ($\beta^h_{E,CET1}$ vs $\beta^h_{T,CET1}$ in regression 1.7), controlling for loan demand.



Source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BISTA, credit register of loans of €1.0 million or more from Bundesbank and COREP datasets, 2014-2021, own calculations. *Note*: In this figure, I plot the effect of the interaction between a one basis point stimulus monetary policy easing shock and the CET1 ratio of bank i in quarter t (expressed in percent) compared to the effect of a one basis point monetary policy tightening shock also interacted with the CET1 ratio of bank i in quarter t on bank loans over different time horizons h where $h = 0, 1, ..., 8$ quarters. The specification is based on the credit register of loans of €1.0 million or more from Bundesbank, allowing me to include borrower-time fixed effects, hence controlling for loan demand. The red dashed line represents the coefficient for the stimulus monetary policy easing shock interacted with the CET1 ratio of bank i in quarter t (i.e. $\beta^h_{E,CET1}$) for each horizon h. The light red area represents the 90 percent confidence bands of each coefficient $\beta^h_{E,CET1}$. The blue dashed line represents the coefficient for the monetary policy tightening shock interacted with the CET1 ratio of bank i in quarter t (i.e. $\beta^h_{T,CET1}$) for each horizon h. The light blue area represents the 90 percent confidence bands of each coefficient $\beta^h_{T,CET1}$.

The above analyses could be biased because of a wrong monetary policy shock identification. As shown by Jarociński and Karadi (2020), the monetary announcements around which the monetary policy surprises are estimated can convey two types of information: about monetary policy stance and about the central bank's assessment of the economic outlook. In order to focus on the effect of monetary policy, it is hence important to clean the surprises from this second type of information. Hence, as a robustness check, I follow the "poor man"'s approach from Jarociński and Karadi (2020) and keep only the surprises (measured by the one-year OIS rate) that have a negative co-movement with the EuroStoxx 50 over the same high frequency time window. The results are presented in Appendix 1.A and lead to similar conclusions, both for the bank-level lending analysis and when isolating credit supply.

1.7 The macroprudential policy surprises

The identification above has several limitations. One main reason is the potential reverse causality between a given bank's lending and CET1 ratio. For instance, if a bank decides to gain market shares on the lending market, its Risk Weighted Assets will increase, and hence its CET1 will decrease, assuming that its Common Equity Tier 1 Capital remains unaffected. In this section, I integrate this caveat conceptually in the previous theoretical model. I then show how it can be avoided by developing an alternative identification strategy and describe how to concretely implement it.

1.7.1 The endogeneity issues with the current model

I start by extending the theoretical model presented in Section 1.3. In the extended version of the model, let's assume there are two types of banks. The first type of banks (which we denote by the dummy variable $\lambda_i = 0$) has as a unique objective profit maximization, as in the Section 1.3. The second type of banks (which we denote by the dummy variable $\lambda_i = 1$) has as an objective of utility maximization, where the utility of the bank is composed of its profits (as the first type of bank) and of an additional gain stemming from the increase in its market shares on the lending market [15].

Integrating those elements in the theoretical model, the maximization programme of bank i becomes:

$$\max_{r_i^l, r_i^d} \; U_i \;=\; \Pi_i + \lambda_i S(L_i)$$

[15] Such an "empire building" strategy, where a CEO expands firm size or market share, even at the expense of shareholder value or profit maximization, has been shown extensively in the existing literature, for instance Baumol (1959), Williamson (1964), Jensen (1986), Rajan, Servaes, and Zingales (2000), and Gabaix and Landier (2008).

$$\text{such that} \begin{cases} E_i \geq \nu L_i \\ L_i = L(r_i^l) \\ D_i = D(r_i^d) \\ L_i + R_i = D_i + E_i \end{cases}$$

where Π_i is the accounting profit of bank i as in Section 1.3:

$$\Pi_i = p_i(1 + r_i^l)L_i + (1 - p_i)\alpha_i L_i + (1 + r^f)R_i - (1 + r_i^d)D_i - L_i - R_i + D_i$$

Plugging the balance sheet constraint in the profit equation allows to write the Lagrangian as follows:

$$\mathcal{L} = \left[r_i^l p_i - (1 - \alpha_i)(1 - p_i)\right]L_i + r^f(D_i + E_i - L_i) - r_i^d D_i + \lambda_i S(L_i) + \phi_i(E_i - \nu L_i)$$

The first-order conditions are:

$$\frac{\partial \mathcal{L}}{\partial r_i^l} = 0 \Rightarrow p_i L_i + \frac{\partial L_i}{\partial r_i^l}\left[p_i r_i^l - (1 - \alpha_i)(1 - p_i)\right] - r^f \frac{\partial L_i}{\partial r_i^l} + \lambda_i S'(L_i)\frac{\partial L_i}{\partial r_i^l} - \phi_i \nu \frac{\partial L_i}{\partial r_i^l} = 0$$

$$\frac{\partial \mathcal{L}}{\partial r_i^d} = 0 \Rightarrow r^f \frac{\partial D_i}{\partial r_i^d} - D_i - \frac{\partial D_i}{\partial r_i^d} r_i^d = 0$$

The solution is given by:

$$r_i^l = \frac{\varepsilon^l}{p_i(\varepsilon^l - 1)}\left(r^f + \nu\phi_i + (1 - \alpha_i)(1 - p_i) - \lambda_i S'(L_i)\right) \tag{1.8}$$

$$r_i^d = \frac{\varepsilon^d}{\varepsilon^d + 1} r^f \tag{1.9}$$

Optimal loan and deposit quantities are then given by their respective functions:

$$L_i = \left(\frac{\frac{\varepsilon^l}{p_i(\varepsilon^l - 1)}\left(r^f + \nu\phi_i + (1 - \alpha_i)(1 - p_i) - \lambda_i S'(L_i)\right)}{\overline{r}^l}\right)^{-\varepsilon^l} \overline{L} \tag{1.10}$$

and

$$D_i = \left(\frac{\frac{\varepsilon^d}{\varepsilon^d+1} r^f}{\overline{r}^d} \right)^{\varepsilon^d} \overline{D} \tag{1.11}$$

Compared to the version of the model in Section 1.3, the results change for the bank lending decision. Banks focusing on increasing market shares on the lending markets (i.e. with $\lambda_i = 1$) offer lower lending rates r_i^l to attract a higher share of the total loan demand, which translates into a higher lending quantity L_i. In this extension of the model, the reverse causality issue between bank i's lending L_i and its capital ratio $\frac{E_i}{L_i}$ appears when $\lambda_i = 1$: in that case, bank i will increase its lending L_i to gain market shares, which will in turn mechanically decrease its capital ratio $\frac{E_i}{L_i}$ and make it more likely to have a binding capital constraint.

1.7.2 Alternative strategy : Using an exogenous shift in v

I now present an alternative identification strategy that addresses the endogeneity concerns raised previously. This strategy exploits exogenous shifts in the capital adequacy ratio requirement imposed to banks (v) and constructs a measure of how each individual bank is exposed to this shift. Adopting this strategy presents several advantages. First, exogenous shifts in v are decided independently on each individual bank i's situation, in particular each bank i's lending (L_i). This contrasts with directly using the observed capital ratio of bank i, which is likely to be endogenous with L_i as shown in Subsection 1.7.1. Second, exploiting a measure that captures the sensitivity of each bank to this exogenous shift in v enables to take into account the bank-specific strategies, for instance their focus on gaining market shares or not (i.e. λ_i). An ideal proxy for that bank-specific sensitivity is a bank-level market variable observed around some exogenous changes in v. Such a measure captures how financial markets assess the impact of the regulatory shift on individual banks, integrating forward-looking information about each bank's business model, capital buffer, and strategic orientation. Furthermore, market variables are usually observed at a high-frequency, hence ensuring that their variation captures only the exogenous shifts in v and no other confounding event.

I implement the strategy described above by focusing on exogenous changes in macroprudential requirements affecting German banks [16]. One challenge related to changes in macroprudential requirements is their typically countercyclical nature. Macroprudential loosening

[16] Even though the CET1 requirement of 4.5% did not change since its implementation in 2014, other capital ratios evolved over time, such as the capital conservation buffer or the countercyclical capital buffer.

policies are generally triggered during crises, in tandem with other policies (e.g. during the COVID-19 pandemic when both fiscal and monetary policies were used to counter the economic damages of the crisis). Conversely, macroprudential constraining decisions are usually taken during periods of rising vulnerabilities (e.g. credit booms), or conversely when the financial cycle reaches a peak (e.g. before a credit bust). Hence, using an aggregate score of the macroprudential policy stance as usually done by the existing literature [17] may lead to underestimating or overestimating the effect of these macroprudential policies on bank lending. To mitigate these biases, I adopt an approach analogous to the identification of monetary policy surprises. Monetary policy surprises are derived from high-frequency changes in financial market variables (e.g., market interest rates) around monetary policy announcements. The use of high-frequency data ensures that the observed changes in asset prices reflect only the unexpected component of the announced monetary policy decision, and excludes confounding events that would have otherwise influenced the change in these financial market instruments. I adapt this approach to macroprudential policy. My methodology proceeds in five steps. First, I identify macroprudential policy announcements affecting the banks in my sample. I do so by compiling a list of macroprudential policy announcements relevant to these banks. Second, I retain only the policies relevant for this paper, i.e. I focus on policies related to bank capital ratios (either the announcements of new frameworks such as Basel III introducing a new set of capital ratios, or the announcements regarding a specific capital ratio).[18] I also eliminate announcement days that coincide with confounding events.[19] Third, I collect bond yield data for the banks of my sample, compute their daily variations, and use these variations to determine the surprise stance of each macroprudential policy announcement $a \in A$ separately. Focusing on bank bond yields rather than other financial market variables such as stock prices or CDS spreads enables to have an analysis which is representative of the entire German banking system, as bonds are issued by both large and small banks.[20] To

[17] This score is generally computed by summing the number of constraining macroprudential policies and subtracting the number of loosening macroprudential policies that were implemented during a certain time period.

[18] Conversely, I exclude certain categories of policies, in particular bans on short selling of bank related securities, policies related to bank separation and changes in capital ratios affecting only systematically important financial institutions. Depending on which capital ratio is concerned, changes in capital ratios affecting exclusively systematically important financial institutions concern only one to twelve banks.

[19] For instance, I exclude the reserve requirement ratio reduction announced by the ECB on the 8^{th} of December 2011 as the ECB announced it monetary policy decisions at the same time, making it impossible to disentangle the effect of the reserve requirement ratio decision from the monetary policy decision. Another example of announcement I exclude is the recommendation of the German financial regulator (Bafin) made on the 24^{th} of March 2020 to German financial institutions to use looser accounting standard and banks under its direct supervision to refrain from making dividend distributions and performing share buy-backs in order to mitigate the effects of COVID-19. I exclude this event, as, on the same day, rumors about the implementation of a massive fiscal stimulus package in the United States made the DAX index rise by 11%.

[20] As shown later on in the Data Section, I indeed find bonds for 824 different credit institutions located in Germany, while if I were focusing on stock prices or CDS spreads, I would have data for only 60 and 9 different credit institutions, respectively.

determine the surprise stance of each macroprudential policy announcement, I regress the daily change in bond yields for German banks on a set of dummies indicating each policy announcement day, controlling for the daily variation in several financial market variables, as well as bond-month-year level fixed effects:

$$\Delta yield_{b(i),t} = \alpha_{b(i),my(t)} + \sum_{a=1}^{A} \beta_a * \mathbb{I}\{t = a\} + market\_controls_t + \epsilon_{b(i),t} \tag{1.12}$$

where $\Delta yield_{b(i),t}$ is the change in the yield of bond b issued by bank i at the end of day t compared to the end of day $(t-1)$. $\mathbb{I}\{t=a\}$ is a dummy equal to 1 if the macroprudential policy announcement a has been released on day t. $market\_controls_t$ is a vector of daily market controls, namely the daily change in the VIX, in the spread between the 10-year Italian and German sovereign yields, in the 3-month OIS spread, and the daily percentage change in the EuroStoxx 600. $\alpha_{b(i),my(t)}$ represents bond-month-year fixed effects (where $my(t)$ represents the month and year of day t). Including bond-month-year fixed effects allows to control for bond-level characteristics (such as bond seniority) and bond-time-level characteristics (such as the remaining maturity of the bonds). The coefficient of interest is β_a, which captures the bank bond yield reaction to the macroprudential policy announcement a. If β_a is positive, I consider that macroprudential policy announcement a is perceived by the financial markets as increasing the risk profile of banks, and hence I interpret this announcement as being a macroprudential policy loosening surprise, i.e. that macroprudential policy announcement a is looser than expected by the market. Conversely, if β_a is negative, I consider that the corresponding macroprudential policy announcement a is perceived by the financial markets as decreasing the risk profile of banks, and hence I interpret this announcement as being a macroprudential policy constraining surprise, i.e. that macroprudential policy announcement a is more constraining than expected by the market. The macroprudential constraining (loosening) surprises provide an exogenous increase (decrease) in macroprudential requirements, hence making some banks exogenously more (less) capital-constrained. Given that this paper aims at studying how capital-constrained banks react differently from capital-unconstrained banks to monetary policy easing and tightening, I focus on the macroprudential policy constraining surprises and hence keep only those. Fourth, I estimate again regression 1.12 but without the dummy for macroprudential policy announcement release days:

$$\Delta yield_{b(i),t} = \alpha_{b(i),my(t)} + market\_controls_t + \xi_{b(i),t} \tag{1.13}$$

I define bank-level abnormal returns for each macroprudential policy announcement as the average across bonds of the residuals from regression 1.13 at the bank-level for each macroprudential policy announcement day a:

$$AR_{i,a} = \frac{1}{B(i,a)} * \sum_{b(i)=1}^{B(i,a)} \xi_{b(i),t=a} \tag{1.14}$$

where $B(i,a)$ represents the number of outstanding bonds of bank b on announcement day a. The above metric captures the average abnormal movement in bond yields attributable to the policy announcement for each bank. Fifth, I use the bank-level abnormal returns calculated in (1.14) as a measure of treatment intensity to distinguish between strongly treated banks and weakly treated banks. I classify banks as being strongly treated if they exhibit strong negative abnormal returns in response to macroprudential policy announcement a, indicating they were more sensitive to the constraining surprise, and hence are considered by the financial markets as having a lower risk profile. Conversely, weakly treated banks are those with near-zero abnormal returns, indicating little sensitivity to the constraining surprise. Importantly, note that the strongly and weakly treated banks can be different between the different announcements $a \in A$, reflecting the different responses of a same given bank to different announcements.

1.8 Data and estimation

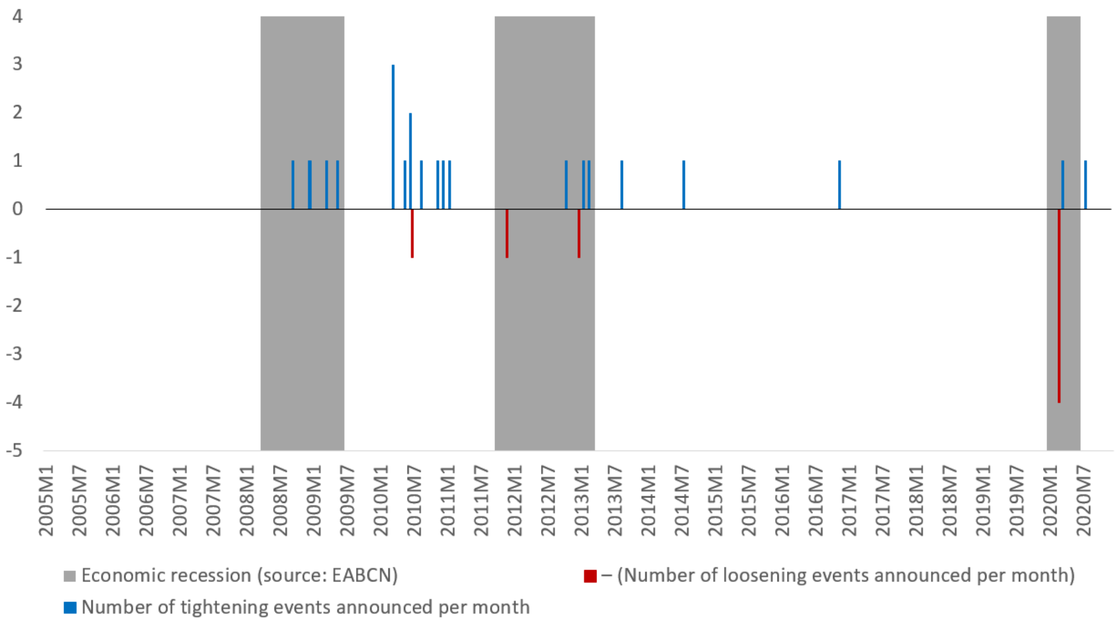
In this section, I present the data used to compute the macroprudential policy surprises and I estimate them.

To estimate macroprudential policy surprises, I use data on macroprudential policy events and bank bond yields. Information on macroprudential policy events are taken from two databases largely used in the existing literature: the MaPPED database from Budnik and Kleibl (2018) and the iMaPP database from Alam et al. (2019). The MaPPED database includes macroprudential policy events for 28 EU countries between 1995 and 2017 [21]. For each policy, this database contains information about the policy type, the stance (constraining, loosening or neutral) and the implementation date. With regard to Germany, Budnik and Kleibl (2018) report information on a total of 34 events. The iMaPP database covers 134 countries from January 1990 to December 2021. It also contains information on the stance, the implementation date as well as the category of the policy and, for some policies, the month of announcement. Concerning Germany, this database reports 45 events. I merge both databases for Germany and compile a list of the exact announcement dates of these measures (Table 1.D.1 of Appendix 1.D). Each of these policy measures is taken either by the ECB, the German financial regulator (Bafin), the German government or the German

[21] For more recent periods, it is possible to complete the database using ESRB public data.

Parliament, but some of them have to follow a complex and long legislative process. As the main idea is to capture the surprise component of these measures, I focus on the first time those were announced as well as when they were officially voted. Since the exact announcement date is not included for most policies, I collect this information from various external sources (e.g., Refinitiv Eikon, Lexis-Nexis, EUR-Lex) and find the announcement dates of 46 macroprudential policy measures between 2000 and the end of 2021. In Figure 1.7, I show the number of macroprudential policy announcements per month and by stance (loosening or constraining, as classified by the MaPPED and the iMaPP databses). Most of the macroprudential loosening events are announced during economic recessions. Conversely, even if this is not as clear, a majority of the constraining events are announced outside of recession periods. This confirms the need to use some high frequency variation around these events, as I do with the macroprudential policy surprises framework.

Figure 1.7. Number of macroprudential policies announcements per month by stance.



Sources: EABCN, MaPPED and iMaPP databases.

From these different announcements, I retain only the policies relevant for answering the research question of this paper, i.e. I focus on policies related to bank capital ratios (either the announcements of new frameworks such as Basel III introducing a new set of capital ratios, or the announcements regarding a specific capital ratio). Concretely, I keep only the policies in the following categories: accounting standards, bank levy [22], Basel II / CRD (Capital Requirements Directive), Basel III / CRD IV, CCB (capital conservation buffer), CCyB (countercyclical capital buffer), CRD II, LCR, leverage ratio, reserve requirement ratio. Conversely, I ignore the policies in the following categories: GBSA (German Bank Separation Act; "Trennbankengesetz" in German), restrictions on dividend distribution, short-selling restrictions, SIFIs (systemically important financial institutions) [23]. I also eliminate announcement days that coincide with confounding events, for instance monetary policy decisions announced on the same day, or concurrent news affecting the bank bond market. The final list of events I consider is presented in Table 1.1.

To construct a measure of macroprudential policy surprises, I then gather the daily bond yield variation for the banks in my sample. Focusing on bank bond yields rather than other financial market variables such as stock prices or CDS spreads enables to have a broad cross-section of German banks, as bonds are issued by both large and small banks, hence ensuring to have a comprehensive representation of the German banking system. Using Refinitiv Eikon, I collect daily bank bond yield data from the beginning of 2005 to the end of 2021, hence covering the full period of macroprudential policy announcements included in my analysis (see Table 1.1). I exclude callable bonds given their specific characteristics as well as bonds denominated in a foreign currency to avoid the confounding influence of exchange rates.[24] The final dataset includes bond yields for 824 different credit institutions located in Germany.[25] In Tables 1.2 and 1.3, I present summary statistics of the bonds included in my sample. As shown in both tables, the bonds included in my sample exhibit substantial heterogeneity. On average, the daily bond yield variation is slightly negative, with a mean of -0.4 basis points, and shows considerable dispersion (a standard deviation of 3.5 basis points, a 5^{th} percentile of -6.2 basis points and a 95^{th} percentile of +5.2 basis points, as reported in Panel A of Table 1.2). The number of outstanding bonds per bank also varies widely. While banks in the sample have on average 81 outstanding bonds during the observation period (2005-2021), the median is only 28 outstanding bonds. Also, at least 5% of the banks in my sample have only one outstanding bond on the estimation period and 5% have at least 214 outstanding bonds. When restricting the analysis to macroprudential policy announcement days (Panel B of Table 1.2), the distribution of the bond yield variation on these days is simi-

[22] Even if the bank levy is not a capital ratio, I still consider it as the German bank levy was aimed at penalizing excessive leverage, with the levy base being total liabilities minus liabilities toward customers and own funds (relevant liabilities).
[23] The SIFIs policies affect only one to twelve banks.
[24] Callable bonds are bonds that can be redeemed by its issuer before maturity. The issuer has an incentive to redeem a callable bond whenever the market interest rates drop below the coupon rate of the bond. Consequently, the yield of callable bonds is higher and more sensitive to call features, issuer-specific risks, and market interest rate variations than otherwise similar non-callable bonds.
[25] In comparison, using stock prices or CDS spreads would have limited the sample to 60 and 9 credit institutions, respectively.

lar to the overall sample distribution. The average yield variation on these days is still slightly negative, but more centered around 0 (-0.1 basis point). Interestingly, the dispersion is still very large (3.2 basis points of standard deviation, a 5^{th} percentile of -5.1 basis points and a 95^{th} percentile of +4.9 basis points) suggesting that the bond yield variations observed on macroprudential policy announcement days are among the largest in the overall sample.

Bonds also have very different remaining maturities on macroprudential policy announcement days. While the average remaining maturity is 2.9 years, 5% of the bonds have a remaining maturity of less than 0.2 years (i.e. less than 3 months) while 5% have a remaining maturity of at least 8 years. The bonds in my sample also differ significantly in terms of seniority (Table 1.3). While half of the bonds are subordinated (i.e. have the lowest rank in terms of seniority), 37% are senior unsecured (i.e. have the priority over subordinated bonds in case of default) and the remaining 13% are senior secured (i.e. have the priority over subordinated bonds and are also backed by some collateral assets in case of default). Given the substantial heterogeneity between the bonds in my sample both in terms of remaining maturity and seniority, it is crucial to control for bond-month-year fixed effects, which is done throughout the subsequent analysis.

Table 1.1. List of macroprudential policies included in the analysis

Announcement date	Category [a]	Event
15/02/2006	Basel II /CRD	The German federal government approved a draft law by the Finance Minister to implement the new Basel II capital adequacy guidelines.
20/12/2006	Basel II /CRD	Publication in the German official journal of the "Solvabilitätsverordnung", which comes as a complement of the Basel II standards for German banks.
26/03/2010	CRD II	Draft law issued by the German federal government to amend the Kreditwesengesetz (KWG) due to the "CRD II-Umsetzungsgesetz".
31/03/2010	Bank levy	The German federal government announced that it adopted the key points for a future law to impose a bank levy in Germany.
22/06/2010	Bank levy	Joint statement by the French, UK and German governments proposing the introduction of bank levies s based on banks' balance sheets.
29/06/2010	Bank levy	Draft law from the Ministry of Finance published.
25/08/2010	Bank levy	Draft law adopted by the German federal government.
14/12/2010	Bank levy	Publication of the final law in the German official journal.
16/12/2010	Basel III / CRD IV	First publication of the Basel III regulation by the Basel committee.
06/01/2013	LCR	The Liquidity Coverage Ratio introduced by the Basel III regulation was revised (the minimum requirement will begin on 1 January 2015 at 60% with annual increases of 10 percentage points until it reaches 100% in 2019 instead of reaching 100% directly on 1 January 2015 as initially planned).
27/06/2013	Basel III / CRD IV	Publication in the official journal of the EU of the CRD IV regulation.
03/09/2013	Basel III / CRD IV	Publication in the German official journal of the transposition of the CRD IV regulation in the German law.
30/07/2014	Bank levy	Publication in the official journal of the EU of the new regulation related to the Single Resolution Mechanism and a Single Resolution Fund.
29/11/2016	Accounting standards	Announcement of the EU regulation No. 2016/2067 (effective January 1, 2018) implementing International Financial Reporting Standard 9 (IFRS 9) which introduced a forward-looking approach to loan loss provisions.
20/03/2020	Accounting standards	The ECB recommended banks under its direct supervision (that is, significant institutions) to (1) opt to apply the transitional IFRS 9 provisions and (2) avoid excessively procyclical assumptions in their expected credit loss estimations, considering the extraordinary uncertainty during the COVID-19 pandemic. This guidance is applicable to significant institutions in Germany.

Sources: MaPPED and iMaPP databases

[a] The acronyms for the different categories mean the following: CRD (Capital Requirements Directive), SIFIs (Systemically Important Financial Institutions), GBSA (German Bank Separation Act; "Trennbankengesetz" in German), LCR (Liquidity coverage ratio), CCyB (Countercyclical capital buffer), CCB (Capital Conservation Buffer).

Table 1.2. Bond data summary statistics

Panel A: Entire sample						
Variable	N	mean	std	p5	p50	p95
Yield daily variation (in bps)	47,927,308	-0.37	3.50	-6.22	-0.20	5.20
Number of bonds per bank	824	81.45	290.46	1	28	214
Panel B: Bond sample on macroprudential policy announcement days only						
Variable	N	mean	std	p5	p50	p95
Yield daily variation (in bps)	262,151	-0.08	3.22	-5.10	-0.09	4.90
Remaining maturity (in years)	267,278	2.92	3.13	0.18	2.13	8.06

Source: Refinitiv Eikon
Note: In Panel A, I present summary statistics for the entire bond sample. In Panel B, I present summary statistics for the bond sample only on days when a macroprudential policy was announced, as defined in Table 1.1.

Table 1.3. Bond seniority summary statistics

Seniority	N	Share (in %)
Senior secured	9,004	13.42
Senior unsecured	24,617	36.68
Subordinated	33,484	49.9

Source: Refinitiv Eikon

I use these bond yields to determine the surprise stance of each macroprudential policy announcement separately by estimating regression 1.12. The results are shown in Table 1.4. Over the 15 announcements listed in Table 1.1, 7 are macroprudential policy loosening surprises (i.e. with $\beta_a > 0$) while the 8 remaining ones are macroprudential policy tightening surprises (i.e. with $\beta_a < 0$). β_a is significant at the 1% level for each announcement, except for the 6^{th} of January 2013 when the Liquidity Coverage Ratio implementation was revised [26]. Noticeably, the stance of the macroprudential policy surprises significantly differs from the stance of the corresponding policy as classified by the MaPPED and the iMaPP databases. In particular, among the 15 announcements I retain for my analysis in Table 1.1, 9 concern constraining policies, 1 concerns a loosening policy, and 5 concern ambiguous policies. Among the 9 constraining policies, only 4 have an announcement which I classify as a constraining surprise while the 5 other ones have an announcement classified as loosening surprises. The only loosening macroprudential policy included in my analysis [27] has an announcement classified as a constraining surprise given the strongly negative and statistically significant bond yield reaction on that day (see Table 1.4). Finally, among the 5 ambiguous policies, I classify 2 of them as being loosening surprises and 3 of them as being constraining

[26] I keep this event in the rest of the analysis, but the conclusions are similar when excluding it
[27] The 20^{th} of March 2020 when the ECB recommended significant credit institutions to implement looser accounting standards.

surprises. The differences between the macroprudential policy stance and the macroprudential surprise stance highlights the importance to focus on the unexpected exogenous component of macroprudential policy announcements rather than using the macroprudential policy decision itself to define the macroprudential policy stance. I hence use the macroprudential surprise stance to classify the different announcements as being loosening or constraining events.

Table 1.4. German banks' bond yields reaction around the announcement of macroprudential policies

a	15/02/06	20/12/06	26/03/10	31/03/10	22/06/10	29/06/10	25/08/10	14/12/10
$\mathbb{I}\{t=a\}$	-0.63***	-1.60***	2.19***	-0.35***	1.10***	2.48***	-0.31***	0.83***
	(0.01)	(0.01)	(0.02)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)
Constant	-0.36***	-0.36***	-0.36***	-0.36***	-0.36***	-0.36***	-0.36***	-0.36***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Security-month-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	44,215,761	44,215,761	44,215,761	44,215,761	44,215,761	44,215,761	44,215,761	44,215,761
R^2	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20
$Adj.R^2$	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0.16

a	16/12/10	06/01/13	27/06/13	03/09/13	30/07/14	29/11/16	20/03/20
$\mathbb{I}\{t=a\}$	1.73***	-0.04	-3.19***	0.43***	0.40***	-1.19***	-2.46***
	(0.02)	(0.03)	(0.04)	(0.02)	(0.03)	(0.03)	(0.10)
Constant	-0.36***	-0.36***	-0.36***	-0.36***	-0.36***	-0.36***	-0.36***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Security-month-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	44,215,761	44,215,761	44,215,761	44,215,761	44,215,761	44,215,761	44,215,761
R^2	0.20	0.20	0.20	0.20	0.20	0.20	0.20
$Adj.R^2$	0.16	0.16	0.16	0.16	0.16	0.16	0.16

Sources: MaPPed and iMaPP databses, Refinitiv Eikon

I then define bank-level abnormal returns for each macroprudential policy announcement day by implementing regression 1.13 and equation 1.14. I present summary statistics for the bank-level abnormal returns in Table 1.5. I first present statistics on the abnormal returns for the entire preriod of estimation (Panel A). The abnormal returns are on average equal to 0, and vary between -3.5 and +3.6 basis points (5^{th} and 95^{th} percentiles, respectively). In Panel B, I focus on the abnormal returns for macroprudential policy announcement days, distinguishing them by surprise stance (i.e. loosening or constraining). On average, the bank-level abnormal returns for macroprudential loosening surprises is +1.4 basis points, varying between -0.6 and +4.0 basis points (5^{th} and 95^{th} percentiles, respectively). The bank-level abnormal returns for macroprudential constraining surprises is -0.8 basis points with some dispersion, varying between -3.7 and +2.5 basis points (5^{th} and 95^{th} percentiles, respectively). I then check the relationship between the bank-level abnormal returns and the observed bank capital ratios. I find that, for most macroprudential loosening (constraining) surprises, banks with lower capital ratios exhibit a significantly stronger increase (decrease) in abnormal bond return compared to banks with higher capital ratios. However, for a few macroprudential policy announcements, no significant relationship is found, hence emphasizing the importance of using macroprudential surprises as they enable to capture both observed and unobserved bank capital constraints [28].

Table 1.5. Bank-level daily abnormal returns summary statistics

Panel A: Entire sample						
Variable	N	mean	std	p5	p50	p95
Daily abnormal returns (in bps)	1,856,416	0.00	2.22	-3.45	0.01	3.57
Panel B: Daily abnormal returns for macroprudential policy announcement days only						
Variable	N	mean	std	p5	p50	p95
Daily abnormal returns for macroprudential policy loosening surprises (in bps)	4,108	1.39	1.50	-0.55	1.21	3.99
Daily abnormal returns for macroprudential policy constraining surprises (in bps)	4,378	-0.82	1.94	-3.71	-0.78	2.47

Source: Refinitiv Eikon
Note: In Panel A, I present summary statistics for the entire sample. In Panel B, I present summary statistics only for macroprudential policy loosening and constraining surprises, respectively, as defined in Table 1.4.

The macroprudential constraining (loosening) surprises provide an exogenous increase (decrease) in macroprudential requirements, hence making some banks exogenously more (less) capital-constrained. Given that this paper aims at studying how capital-constrained banks react differently from capital-unconstrained banks to monetary policy easing and tightening, I focus on the macroprudential policy constraining surprises in the rest of the paper. I use the bank-level abnormal returns as a measure of treatment intensity to distinguish between strongly treated banks and weakly treated banks. I classify banks as being strongly treated if they exhibit strong negative abnormal returns in response to macroprudential policy announcement a, indicating they were more sensitive to the constraining surprise. Conversely, weakly treated banks are those with near-zero or positive abnormal returns, indicating little sensitivity to the constraining surprise. To quantify the treatment intensity, I use the bank-level abnormal returns on each macroprudential policy announcement days as a continuous variable. The bank-level abnormal returns directly measure a relative treatment intensity, in the sense that lower (i.e. more negative) returns capture stronger treatment while higher (i.e. close to zero or positive) returns capture weak treatment. As an alternative, I classify banks by abnormal return percentiles on each macroprudential policy announcement day, enabling me to refine the treatment intensity by comparing the least vs

[28] Those results are currently checked by Bundesbank in order to be sure that no confidential information is released. As a consequence, I am not allowed to disclose any numbers as for now, but only to describe the results.

most treated banks. In particular, in the empirical analysis section, I compare the top vs bottom 10, 25, and 50% banks in terms of abnormal bond returns on a given macroprudential policy announcement day, respectively.

1.9 Empirical strategy and results

In this section, I describe the empirical strategy used to study the effect of macroprudential policy surprises on bank lending and how they interact with monetary policy easing and tightening shocks. I then present the results.

1.9.1 Lending analysis using the macroprudential policy surprises

I use the classification of weakly and strongly treated banks defined in Section 1.8 to study how the most sensitive and the least sensitive banks to each macroprudential policy constraining announcement differ in their lending behaviour in response to subsequent monetary policy easing and tightening shocks. Concretely, for each macroprudential policy constraining surprise, I restrict my sample to the groups of weakly and strongly treated banks exclusively. Then, I check how the lending of weakly treated group reacts over time to the subsequent monetary policy easing and tightening shocks, compared to the group of strongly treated banks. I focus on the monetary policy easing and tightening shocks occurring up to D (alternatively 1, 3 or 12) months after each macroprudential policy announcement a, by using the bank-level lending data and estimating the following bank-panel local projection setup $\forall d \in \{1, ..., D\}$:

$$y_{i,m(a)+d+h} - y_{i,m(a)-1} = \alpha_i + \beta_{m(a)} + \phi^h * weaktreat_{i,a} + \beta^h_{E,weak} * MPS_{m(a)+d} * (-\mathbb{I})\{Easing\}_{m(a)+d} * weaktreat_{i,a} + \beta^h_{T,weak} * MPS_{m(a)+d} * \mathbb{I}\{Tightening\}_{m(a)+d} * weaktreat_{i,a} + \mu * M_{i,a} + controls + u_{i,m(a)+d+h} \tag{1.15}$$

where $y_{i,m(a)}$ represents the logarithm of total loans of bank i in month $m(a)$, with $m(a)$ being the month when macroprudential policy announcement a has been released. The regressor of interest, $weaktreat_{i,a}$, is a measure capturing the relative treatment intensity of bank i for macroprudential policy announcement a, with a lower value of *weaktreat* indicating a stronger treatment, and a higher value of *weaktreat* indicating a weaker treatment. [29] I use

[29] Using a relative treatment intensity variable is less intuitive than using a more classic treatment intensity variable (i.e. which takes higher values for stronger treatment) but enables a direct comparison of the results with the ones from the previous analysis studying high-CET1-ratio banks compared to their low-CET1-ratio counterparts.

two alternative measures for *weaktreat*: the bank-level abnormal returns on macroprudential policy announcement a directly, or a dummy equal to 1 if bank i belongs to the top 10, 25, or 50% in terms of abnormal bond returns for macroprudential policy announcement a, and 0 if it belongs to the bottom 10, 25, or 50%, respectively. [30] The vector $M_{i,a}$ contains MPS_a, $\mathbb{I}\{easing\}_a$, $\mathbb{I}\{tightening\}_a]$, $weaktreat_{i,a}$ and all their pairwise interactions that are not already present in the equation above. The vector *controls* contains bank-time control variables (total assets, cash-over-asset ratio and deposit-over-asset ratio) and 12 lags of MPS_a, $\mathbb{I}\{easing\}_a$, $\mathbb{I}\{tightening\}_a$, $weaktreat_{i,a}$ and of their interaction. Bank-level and time-level unobserved variables are captured by the bank fixed effects α_i and the time fixed effects β_t, respectively. The coefficients of interest $\beta^h_{E,weak}$ and $\beta^h_{T,weak}$ capture how much more, in percent, loans of weakly treated bank i at horizon $t+h$ react to a monetary policy easing shock occurring up to d months after the macroprudential policy announcements and to a monetary policy tightening shock occurring up to d months after the macroprudential policy announcements, respectively, compared to the strongly treated banks. The other variables are the same as before. In an alternative setup, I also control for loan demand, by using the credit register of loans of €1.0 million or more from Bundesbank and by including borrower-time fixed effects as in the previous subsection:

$$
\begin{aligned}
&y_{i,f,m(a)+d+h} - y_{i,f,m(a)-1} = \alpha_i + \gamma_{f,m(a)} + \phi^h * weaktreat_{i,a} + \beta^h_{E,weak} * MPS_{m(a)+d} * \\
&(-\mathbb{I})\{Easing\}_{m(a)+d} * weaktreat_{i,a} + \beta^h_{T,weak} * MPS_{m(a)+d} * \mathbb{I}\{Tightening\}_{m(a)+d} * weaktreat_{i,a} + \\
&\mu * M_{i,a} + controls + u_{i,f,m(a)+d+h}
\end{aligned}
\tag{1.16}
$$

where $y_{i,f,m(a)}$ represents the logarithm of loans of bank i to firm f in month $m(a)$, and $\gamma_{m(a),f}$ represents borrower-time fixed effects capturing loan demand.

1.9.2 Results

In Figure 1.8, I show the results using the macroprudential policy constraining surprises, i.e. estimating regression 1.15, for monetary policy easing and tightening shocks occurring up to 3 months after each macroprudential policy announcement. As a relative treatment intensity variable, I use the bank-level abnormal returns directly (Figure 1.8a), or alternatively, I focus on the top compared to the bottom 50, 25, and 10% banks in terms of abnormal bond returns

[30] As explained in the previous section, given that I focus on macroprudential policy constraining surprises, the corresponding bank-level abnormal returns are on average negative by construction. Hence the higher the abnormal return of bank i on macroprudential policy announcement day a, the weaker the treatment. Conversely, the more negative the abnormal return, the stronger the treatment.

respectively for each macroprudential policy announcement (Figures 1.8b, 1.8c and 1.8d, respectively). The results using the macroprudential policy surprises confirm the previous results using the CET1 ratio regarding the effect of monetary policy easing shocks, both when using the bank-level abnormal returns directly as a relative treatment intensity variable, or when focusing on the percentiles of banks in terms of abnormal returns. As shown by Figure 1.8a, a one basis point stimulus monetary policy easing shock occurring up to 3 months after a macroprudential constraining surprise increases lending by 0.18 percent more for banks which abnormal return decreased by one less basis point, after one year. The effect is statistically significant from the 4^{th} to the 18^{th} month after the monetary policy shock occurred.

Interestingly, I find that weakly treated banks resist also more (i.e. reduce their lending less) than strongly treated banks in reaction to subsequent monetary policy tightening shocks. As shown by Figure 1.8a, a one basis point monetary policy tightening shock occurring up to 3 months after a macroprudential constraining surprise increases lending by 0.28 percent more for banks which abnormal return decreased by one less basis point, after one year. Compared to the stimulus monetary policy easing shock, the effect is hence stronger, but does not last as long, being statistically significant from the 4^{th} to the 8^{th} month after the monetary policy shock occurred. Compared to the analysis using the CET1 ratio, this different result for monetary policy tightening shocks can be explained by the fact that the constraining macroprudential policy surprises consist in an upward shift in the capital requirement of banks, which leads to more binding capital constraints for strongly treated banks. Hence, strongly treated banks have to reduce their lending more than weakly treated banks due to the macroprudential constraining surprise.

When refining the treatment intensity to the least vs most affected banks only, I find that this result becomes even stronger in economic size. When comparing the 50% least vs most affected banks (Figure 1.8b), I find that the 50% least affected banks increase their lending by 0.28 percent more compared to the 50% most affected banks, 13 months after a one basis point stimulus monetary policy easing shock occurred in the 3 months following a macroprudential constraining surprise. When refining the treatment intensity and focusing on the 25% (10%) least vs most affected banks (Figures 1.8c and 1.8d, respectively), I find that the 25% (10%) least affected banks increase their lending by 0.31 (0.32) percent more compared to the 25% (10%) most affected banks, 6 (4) months after a one basis point stimulus monetary policy easing shock occurred in the 3 months following a macroprudential constraining surprise, even though the effect is significant for a very short period of time. The conclusion is similar regarding monetary policy tightening shocks. When comparing the 50% least vs most affected banks (Figure 1.8b), I find that the 50% least affected banks increase their lending by 0.44 percent more compared to the 50% most affected banks, 5 months after a one basis point monetary policy tightening shock occurred in the 3 months following a macroprudential constraining surprise. When refining the treatment intensity and focusing on the 25% (10%) least vs most affected banks (Figures 1.8c and 1.8d, respectively), I find that the 25% (10%) least affected banks increase their lending by 0.90 (0.90) percent more compared to the 25% (10%) most affected banks, 6 (4) months after a one basis point stimulus monetary policy easing shock occurred in the 3 months following a macroprudential constraining surprise.

As robustness checks, I follow the "poor man"'s approach from Jarociński and Karadi (2020) to measure the monetary policy surprises shocks, and I take into account different time lengths of monetary policy shocks occurring after a macroprudential constraining surprise (i.e. taking into account monetary policy shocks occurring either in the month or in the 12 months following a macroprudential constraining surprise). The results hold in both cases (see Appendix 1.B).

In Figure 1.9, I present the results using the macroprudential policy constraining surprises while controlling for loan demand, i.e. by estimating regression 1.16 and by exploiting the quarterly data of the credit register of loans of €1.0 million or more from Bundesbank. As a baseline analysis, I focus on monetary policy easing and tightening shocks occurring up to 2 quarters after each macroprudential policy announcement. [31], which lead to similar conclusions to the ones of the baseline analysis. As in the previous part, I use alternatively the bank-level abnormal returns directly as a relative treatment intensity variable (Figure 1.9a), or I focus on the top compared to the bottom 50, 25, and 10% banks in terms of abnormal bond returns respectively for each macroprudential policy announcement (Figures 1.9b, 1.9c and 1.9d, respectively). Controlling for loan demand reduces the significance of the previous results regarding monetary policy easing shocks. As shown in Figure 1.9a, when using the bank-level abnormal returns directly as a relative treatment intensity variable, the significance of the effect of monetary policy easing shocks on the lending of weakly vs strongly treated banks disappears. On the contrary, monetary policy tightening shocks still have a significant effect: a one basis point monetary policy tightening shock occurring up to 2 quarters after a macroprudential constraining surprise increases lending by 0.33 percent more for banks which abnormal return decreased by one less basis point, 2 quarters after the monetary policy tightening shock occurred.

As before (i.e. without controlling for loan demand, Figure 1.8), the refinement of the treatment intensity to the least vs most affected banks leads to stronger results in terms of economic size for both monetary policy easing and tightening shocks, and also highlights important non-linearities when controlling for loan demand. When comparing the 50% least

[31] Focusing on monetary policy shocks occurring up to 1 quarter gives too imprecise results, in particular for the monetary policy tightening shocks because of too few quarterly shocks in the sample.

vs most affected banks (Figure 1.9b), I find that the 50% least affected banks increase their lending by 1.74 percent more compared to the 50% most affected banks, the effect being significant up to 3 quarters after a one basis point stimulus monetary policy easing shock occurred in the 2 quarters following a macroprudential constraining surprise. When refining the treatment intensity and focusing on the 25% (10%) least vs most affected banks (Figures 1.9c and 1.9d, respectively), I find that the 25% (10%) least affected banks increase their lending by 2.25 (3.61) percent more compared to the 25% (10%) most affected banks, 1 quarter after a one basis point stimulus monetary policy easing shock occurred in the 2 quarters following a macroprudential constraining surprise, even though the effect is non-significant again starting from the second quarter. Interestingly, as shown by Figure 1.9c, the effect starts to be significant again after 7 quarters for the 10% least affected banks compared to the 10% most affected banks. The non-linearities are also present when focusing on the effect of monetary policy tightening shocks. When comparing the 50% least vs most affected banks (Figure 1.9b), I find that the 50% least affected banks reduce their lending by 1.86 percent less compared to the 50% most affected banks, the effect being significant up to 4 quarters after a one basis point monetary policy tightening shock occurred in the 2 quarters following a macroprudential constraining surprise. When refining the treatment intensity and focusing on the 25% least vs most affected banks (Figure 1.9c), I find that the 25% least affected banks reduce their lending by 2.55 percent less compared to the 25% most affected banks, even though the effect is statistically significant only starting from 6 quarters after a one basis point stimulus monetary policy easing shock occurred in the 2 quarters following a macroprudential constraining surprise. Refining even more the treatment intensity and focusing on the 10% least vs most affected banks (Figure 1.9d) leads to stronger economic results, the 10% least affected banks reducing their lending by 1.16 percent less than the 10% most affected banks, 1 quarter after a one basis point tightening monetary policy shock occurred in the 2 quarters following a macroprudential constraining surprises. The longer term effects are also stronger than when focusing on the 50% and 25% least vs most affected banks, for both monetary policy easing and tightening shocks. The 10% least affected banks reduce (increase) their lending by 5.98 percent less (12.60 percent more) than the 10% most affected banks, starting from 6 quarters and up to 8 quarters after a one basis point monetary policy tightening (easing) shock occurred in the 2 quarters following a macroprudential constraining surprise.

The results remain robust when following the "poor man"'s approach from Jarociński and Karadi (2020) to measure the monetary policy surprises shocks, and when taking into account a different time length of monetary policy shocks occurring after a macroprudential constraining surprise (i.e. taking into account monetary policy shocks occurring in the 4 quarters following a macroprudential constraining surprise, see Appendix 1.C).

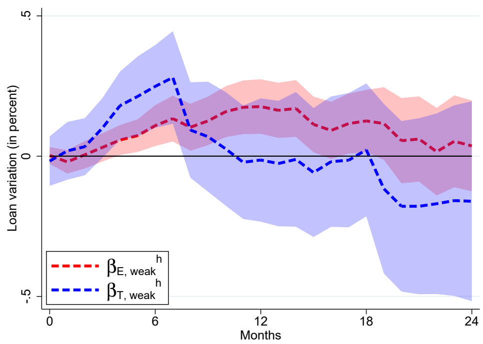
Two mechanisms may explain the strong and persistent lending response to monetary policy shocks of weakly affected banks compared to strongly affected banks when controlling for loan demand. A first explanation is related to the sample size. As the horizon extends, the sample size diminishes, particularly for smaller subgroups of banks, and when focusing on monetary policy tightening shocks [32]. This small size can inflate the estimated responses and increase their variance (see the 25% and 10% least vs most affected banks, Figures 1.9c and 1.9d). A second explanation related to the use of borrower-time fixed effects (Khwaja and Mian, 2008) and to likely heterogeneity in the lending responses. Specifically, since the Khwaja and Mian (2008) identification strategy focuses on multi-bank firms and excludes firms borrowing from only one bank—often the smallest and riskiest—one possible mechanism is a reallocation of credit. Over time, well-capitalized banks disproportionately expand credit to larger and safer firms, while weakly capitalized banks shift toward smaller and riskier borrowers [33]. This reallocation may only become apparent with a lag due to loan maturity structures or persistent relationship lending frictions. This would also explain why this persistent effect of monetary policy only appears when using borrower-time fixed effects, but is absent when using total bank lending. This interpretation is consistent with prior empirical and theoretical research, in particular when focusing on monetary policy easing shocks. For instance, Gambacorta and Shin (2018) document that well-capitalized banks benefit from lower funding costs and exhibit stronger loan growth in response to monetary easing. Similarly, Miyakawa, Oikawa, and Ueda (2022) develop a New Keynesian model in which monetary easing induces a reallocation of resources toward more productive firms, which are typically larger and more established (Leung, Meh, and Terajima, 2008; Hsieh and Klenow, 2009; Silveira, 2022).

[32] The period we study here, i.e. from the start of 2005 to the end of 2021, is mostly marked by monetary policy easing rather than tightening shocks

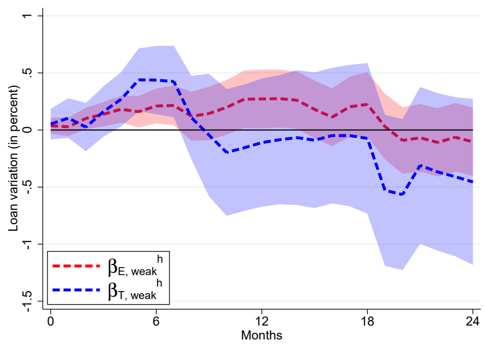
[33] This is consistent with the main model presented in Section 1.3 as capitally-constrained banks tend to offer a higher lending rate than capitally-unconstrained banks

Figure 1.8. Response of bank loans to alternative weak treatment variables for macroprudential announcements interacted with stimulus monetary policy easing vs tightening shocks occurring up to 3 months afterwards ($\beta^h_{E,weak}$ vs $\beta^h_{T,weak}$ in regression 1.15)

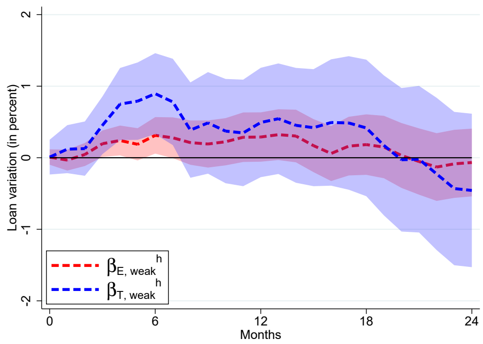
(a) Continuous variable of weak treatment



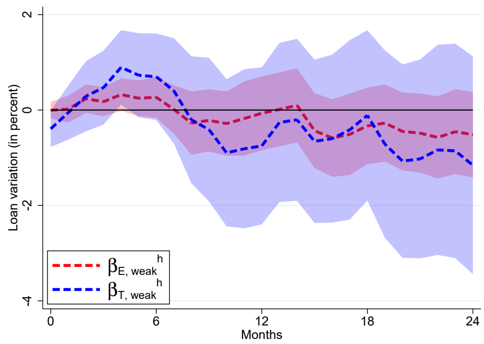
(b) Top vs bottom 50% banks



(c) Top vs bottom 25% banks



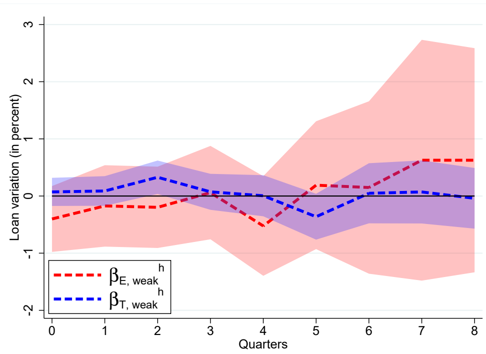
(d) Top vs bottom 10% banks



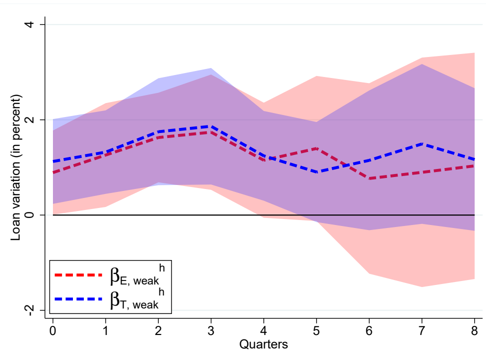
Source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BISTA and COREP datasets, 2005-2021, own calculations.
Note: In these figures, I plot the effect of the interaction between a one basis point stimulus monetary policy easing shock occurring up to 3 months after a given macroprudential policy announcement was released, and a measure of weak treatment for this macroprudential policy announcement on bank loans over different time horizons h where $h = 0, 1, ..., 24$ months. I compare it to the effect of a one basis point monetary policy tightening shock occurring up to 3 months after a given macroprudential policy announcement was released, interacted with the same measure of weak treatment for this macroprudential policy announcement. Four alternative measures of weak treatment are used: the bank-level abnormal returns used as a continuous variable directly (Figure 1.8a), or using a dummy equal to 1 if bank i belongs to the top 10, 25, or 50% in terms of abnormal bond returns for a given macroprudential policy announcement, and 0 if it belongs to the bottom 50, 25, or 10% respectively (Figures 1.8b, 1.8c, and 1.8d, respectively). In each figure, the red dashed line represents the coefficient for the stimulus monetary policy easing shock interacted with the measure of weak treatment for a given macroprudential policy announcement (i.e. $\beta^h_{E,weak}$) for each horizon h. The light red area represents the 90 percent confidence bands of each coefficient $\beta^h_{E,weak}$. The blue dashed line represents the coefficient for the monetary policy tightening shock interacted with the measure of weak treatment for a given macroprudential policy announcement (i.e. $\beta^h_{T,weak}$) for each horizon h. The light blue area represents the 90 percent confidence bands of each coefficient $\beta^h_{T,weak}$.

Figure 1.9. Response of bank loans to alternative weak treatment variables for macroprudential announcements interacted with stimulus monetary policy easing vs tightening shocks occurring up to 2 quarters afterwards ($\beta^h_{E,weak}$ vs $\beta^h_{T,weak}$ in regression 1.16), controlling for loan demand

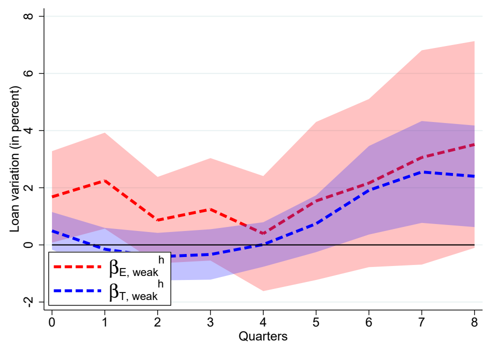
(a) Continuous variable of weak treatment



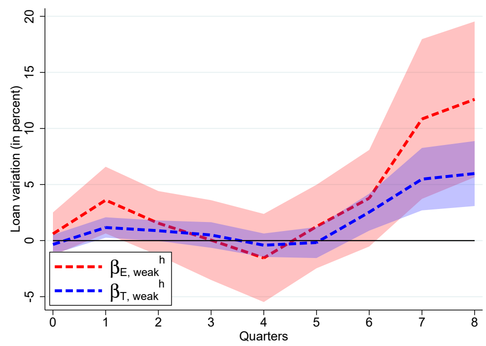
(b) Top vs bottom 50% banks



(c) Top vs bottom 25% banks



(d) Top vs bottom 10% banks



Source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BISTA, credit register of loans of €1.0 million or more from Bundesbank and COREP datasets, 2005-2021, own calculations.
Note: In these figures, I plot the effect of the interaction between a one basis point stimulus monetary policy easing shock occurring up to 2 quarters after a given macroprudential policy announcement was released, and a measure of weak treatment for this macroprudential policy announcement on bank loans over different time horizons h where $h = 0, 1, ..., 8$ quarters. The specification is based on the credit register of loans of €1.0 million or more from Bundesbank, allowing me to include borrower-time fixed effects, hence controlling for loan demand. I compare it to the effect of a one basis point monetary policy tightening shock occurring up to 2 quarters after a given macroprudential policy announcement was released, interacted with the same measure of weak treatment for this macroprudential policy announcement. Four alternative measures of weak treatment are used: the bank-level abnormal returns used as a continuous variable directly (Figure 1.9a), or using a dummy equal to 1 if bank i belongs to the top 10, 25, or 50% in terms of abnormal bond returns for a given macroprudential policy announcement, and 0 if it belongs to the bottom 50, 25, or 10% respectively (Figures 1.9b, 1.9c, and 1.9d, respectively). In each figure, the red dashed line represents the coefficient for the stimulus monetary policy easing shock interacted with the measure of weak treatment for a given macroprudential policy announcement (i.e. $\beta^h_{E,weak}$) for each horizon h. The light red area represents the 90 percent confidence bands of each coefficient $\beta^h_{E,weak}$. The blue dashed line represents the coefficient for the monetary policy tightening shock interacted with the measure of weak treatment for a given macroprudential policy announcement (i.e. $\beta^h_{T,weak}$) for each horizon h. The light blue area represents the 90 percent confidence bands of each coefficient $\beta^h_{T,weak}$.

1.10 Conclusion

In this paper, I provide theoretical and empirical evidence on the differential impact of monetary policy easing and tightening on banks' lending, conditional on their capital constraints. I find that, following a monetary policy easing shock, well-capitalized banks expand their lending more than weakly capitalized banks, which are constrained by their capital buffers hence resulting in muted responses. Conversely, I find that both well- and weakly capitalized banks reduce lending in a similar way in response to monetary policy tightening shocks. This asymmetry is important for policymakers, as it underscores the uneven transmission of monetary policy across the banking sector. Furthermore, when making bank capital constraints exogenously more binding by using surprises around several macroprudential policy announcements, I find that the least sensitive banks to the announcements expand their lending more than the most sensitive ones in reaction to monetary policy easing shocks, but also reduce their lending less in response to monetary policy tightening shocks. This finding suggests that capital regulations, in particular macroprudential constraining shocks, can amplify the asymmetric effects of monetary policy. Future research could explore the long-term implications of these dynamics, particularly in periods of prolonged low interest rates or financial stress, to further refine policy design aimed at maintaining financial stability and promoting economic growth.

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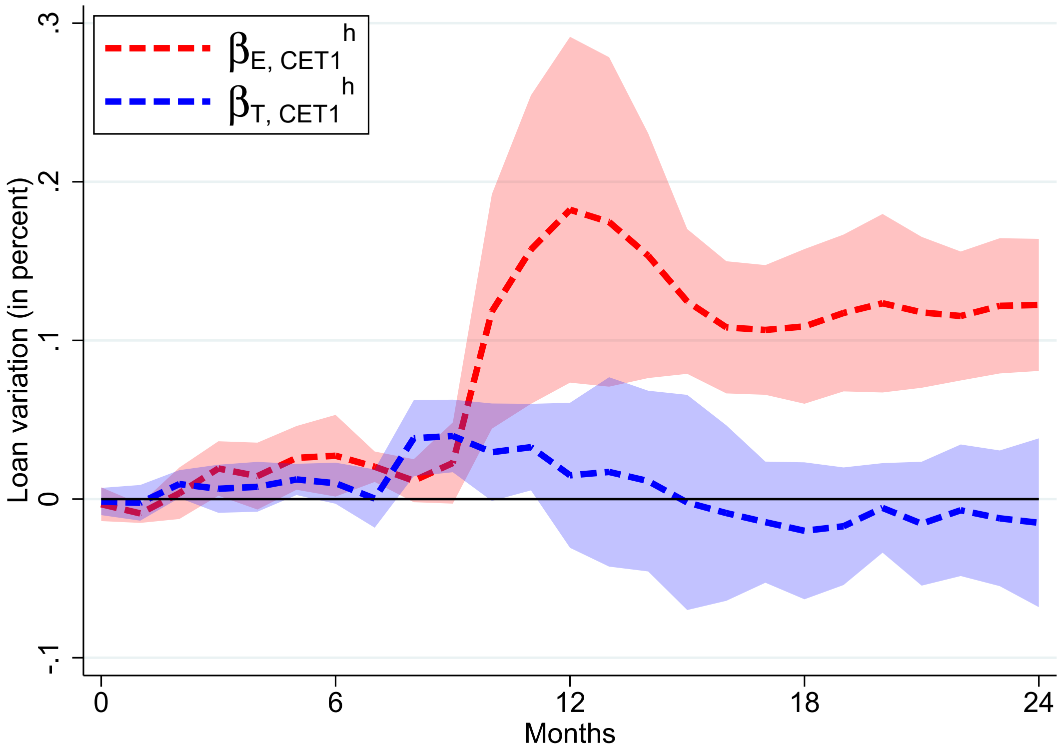
Appendices to Chapter 1

Appendix 1.A Results using the CET1 ratio and the "poor man"'s approach of Jarociński and Karadi (2020)

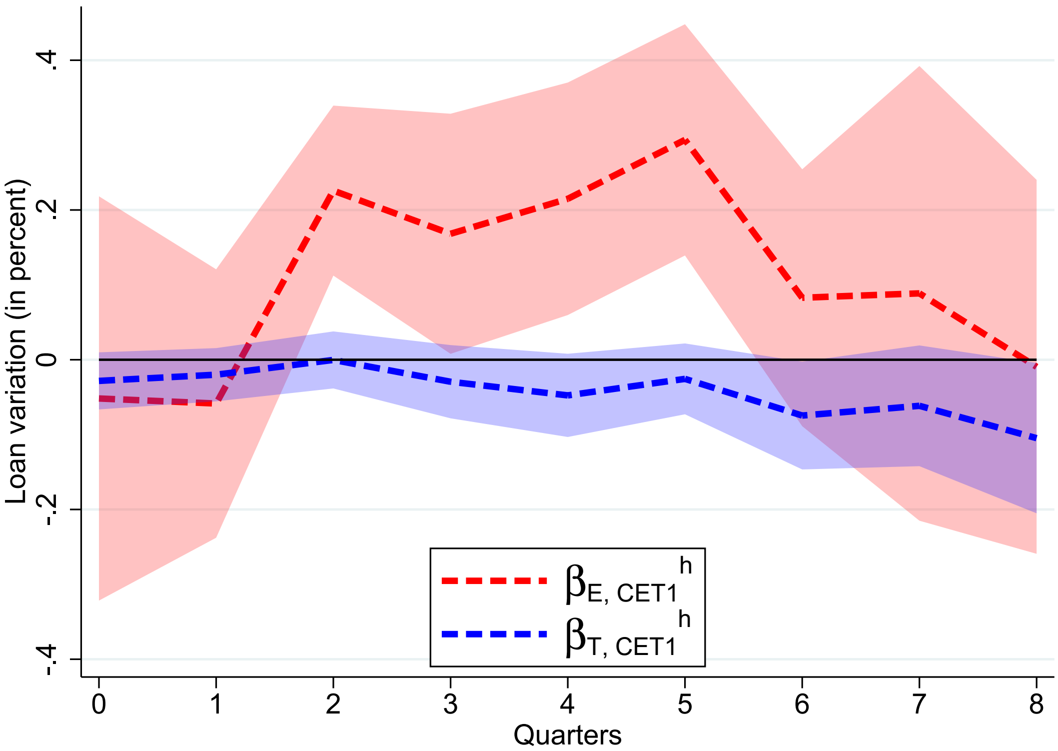
Figure 1.A.1. Response of bank loans to stimulus monetary policy easing vs tightening shocks interacted with CET1 ratio ($\beta^h_{E,CET1}$ vs $\beta^h_{T,CET1}$ in regression 1.6), "poor man"'s approach from Jarociński and Karadi (2020)



Source: Source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BISTA and COREP datasets, 2014-2021, own calculations.

Note: In this figure, I plot the effect of the interaction between a one basis point stimulus monetary policy easing shock and the CET1 ratio of bank i in month t (expressed in percent) compared to the effect of a one basis point monetary policy tightening shock also interacted with the CET1 ratio of bank i in month t on bank loans over different time horizons h where $h = 0, 1, ..., 24$ months. The red dashed line represents the coefficient for the stimulus monetary policy easing shock interacted with the CET1 ratio of bank i in month t (i.e. $\beta^h_{E,CET1}$) for each horizon h. The light red area represents the 90 percent confidence bands of each coefficient $\beta^h_{E,CET1}$. The blue dashed line represents the coefficient for the monetary policy tightening shock interacted with the CET1 ratio of bank i in month t (i.e. $\beta^h_{T,CET1}$) for each horizon h. The light blue area represents the 90 percent confidence bands of each coefficient $\beta^h_{T,CET1}$. The monetary policy surprises are here cleaned from the central bank information component following the "poor man"'s approach from Jarociński and Karadi (2020).

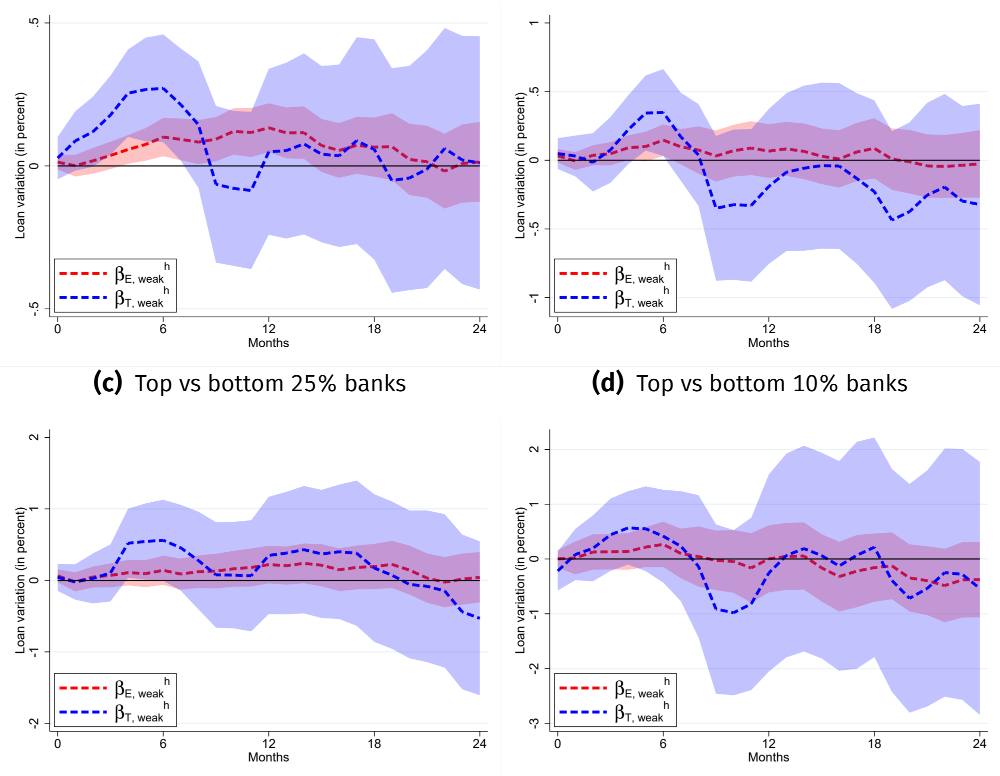
Figure 1.A.2. Response of bank loan supply to stimulus monetary policy easing vs tightening shocks interacted with CET1 ratio ($\beta^h_{E,CET1}$ vs $\beta^h_{T,CET1}$ in regression 1.7), "poor man"'s approach from Jarociński and Karadi (2020), controlling for loan demand



Source: Source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BISTA, credit register of loans of €1.0 million or more from Bundesbank and COREP datasets, 2014-2021, own calculations.
Note: In this figure, I plot the effect of the interaction between a one basis point stimulus monetary policy easing shock and the CET1 ratio of bank i in quarter t (expressed in percent) compared to the effect of a one basis point monetary policy tightening shock also interacted with the CET1 ratio of bank i in quarter t on bank loans over different time horizons h where $h = 0, 1, ..., 8$ quarters. The specification is based on the credit register of loans of €1.0 million or more from Bundesbank, allowing me to include borrower-time fixed effects, hence controlling for loan demand. The red dashed line represents the coefficient for the stimulus monetary policy easing shock interacted with the CET1 ratio of bank i in quarter t (i.e. $\beta^h_{E,CET1}$) for each horizon h. The light red area represents the 90 percent confidence bands of each coefficient $\beta^h_{E,CET1}$. The blue dashed line represents the coefficient for the monetary policy tightening shock interacted with the CET1 ratio of bank i in quarter t (i.e. $\beta^h_{T,CET1}$) for each horizon h. The light blue area represents the 90 percent confidence bands of each coefficient $\beta^h_{T,CET1}$. The monetary policy surprises are here cleaned from the central bank information component following the "poor man"'s approach from Jarociński and Karadi (2020).

Appendix 1.B Additional results using the macroprudential policy surprises

Figure 1.B.1. Response of bank loans to alternative weak treatment variables for macroprudential announcements interacted with stimulus monetary policy easing vs tightening shocks occurring up to 3 months afterwards ($\beta^h_{E,weak}$ vs $\beta^h_{T,weak}$ in regression 1.15), "poor man"'s approach from Jarociński and Karadi (2020)



(a) Continuous variable of weak treatment

(b) Top vs bottom 50% banks

(c) Top vs bottom 25% banks

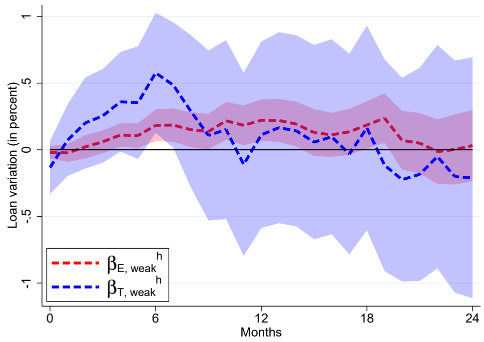
(d) Top vs bottom 10% banks

Source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BISTA and COREP datasets, 2005-2021, own calculations.

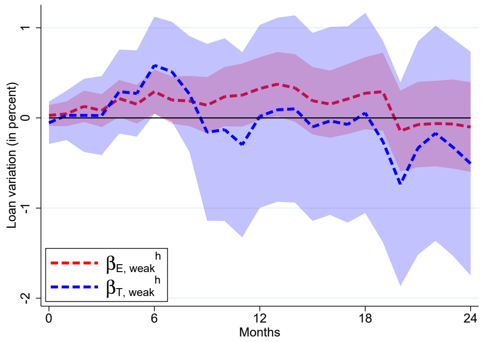
Note: In these figures, I plot the effect of the interaction between a one basis point stimulus monetary policy easing shock occurring up to 3 months after a given macroprudential policy announcement was released, and a measure of weak treatment for this macroprudential policy announcement on bank loans over different time horizons h where $h = 0, 1, ..., 24$ months. I compare it to the effect of a one basis point monetary policy tightening shock occurring up to 3 months after a given macroprudential policy announcement was released, interacted with the same measure of weak treatment for this macroprudential policy announcement. Four alternative measures of weak treatment are used: the bank-level abnormal returns used as a continuous variable directly (Figure 1.B.1a), or using a dummy equal to 1 if bank i belongs to the top 10, 25, or 50% in terms of abnormal bond returns for a given macroprudential policy announcement, and 0 if it belongs to the bottom 50, 25, or 10% respectively (Figures 1.B.1b, 1.B.1c, and 1.B.1d, respectively). In each figure, the red dashed line represents the coefficient for the stimulus monetary policy easing shock interacted with the measure of weak treatment for a given macroprudential policy announcement (i.e. $\beta^h_{E,weak}$) for each horizon h. The light red area represents the 90 percent confidence bands of each coefficient $\beta^h_{E,weak}$. The blue dashed line represents the coefficient for the monetary policy tightening shock interacted with the measure of weak treatment for a given macroprudential policy announcement (i.e. $\beta^h_{T,weak}$) for each horizon h. The light blue area represents the 90 percent confidence bands of each coefficient $\beta^h_{T,weak}$. The monetary policy surprises are here cleaned from the central bank information component following the "poor man"'s approach from Jarociński and Karadi (2020).

Figure 1.B.2. Response of bank loans to alternative weak treatment variables for macroprudential announcements interacted with stimulus monetary policy easing vs tightening shocks occurring 1 month afterwards ($\beta^h_{E,weak}$ vs $\beta^h_{T,weak}$ in regression 1.15)

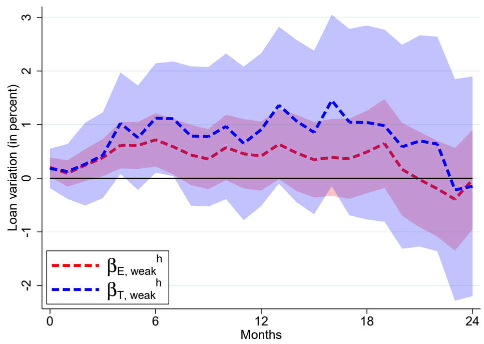
(a) Continuous variable of weak treatment



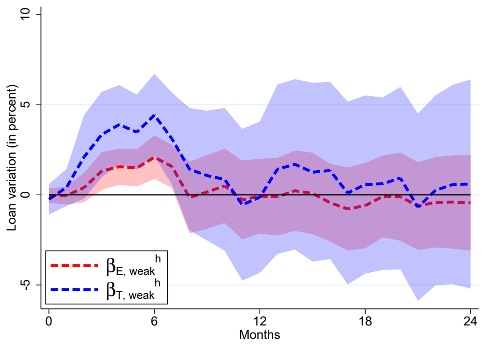
(b) Top vs bottom 50% banks



(c) Top vs bottom 25% banks



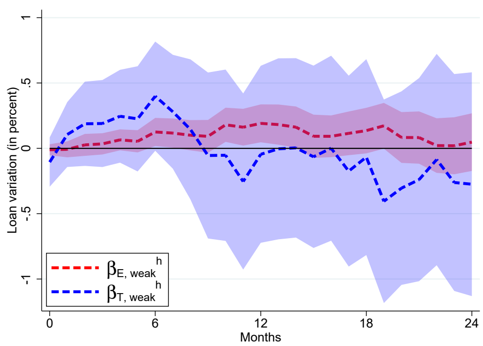
(d) Top vs bottom 10% banks



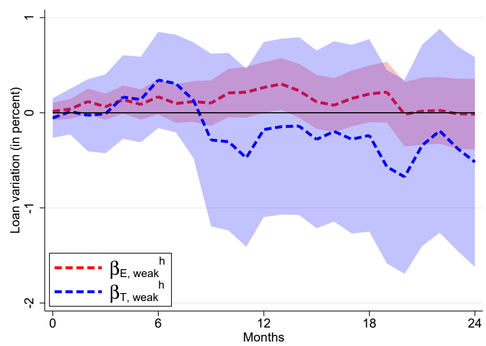
Source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BISTA and COREP datasets, 2005-2021, own calculations.
Note: In these figures, I plot the effect of the interaction between a one basis point stimulus monetary policy easing shock occurring 1 month after a given macroprudential policy announcement was released, and a measure of weak treatment for this macroprudential policy announcement on bank loans over different time horizons h where $h = 0, 1, ..., 24$ months. I compare it to the effect of a one basis point monetary policy tightening shock occurring 1 month after a given macroprudential policy announcement was released, interacted with the same measure of weak treatment for this macroprudential policy announcement. Four alternative measures of weak treatment are used: the bank-level abnormal returns used as a continuous variable directly (Figure 1.B.2a), or using a dummy equal to 1 if bank i belongs to the top 10, 25, or 50% in terms of abnormal bond returns for a given macroprudential policy announcement, and 0 if it belongs to the bottom 50, 25, or 10% respectively (Figures 1.B.2b, 1.B.2c, and 1.B.2d, respectively). In each figure, the red dashed line represents the coefficient for the stimulus monetary policy easing shock interacted with the measure of weak treatment for a given macroprudential policy announcement (i.e. $\beta^h_{E,weak}$) for each horizon h. The light red area represents the 90 percent confidence bands of each coefficient $\beta^h_{E,weak}$. The blue dashed line represents the coefficient for the monetary policy tightening shock interacted with the measure of weak treatment for a given macroprudential policy announcement (i.e. $\beta^h_{T,weak}$) for each horizon h. The light blue area represents the 90 percent confidence bands of each coefficient $\beta^h_{T,weak}$.

Figure 1.B.3. Response of bank loans to alternative weak treatment variables for macroprudential announcements interacted with stimulus monetary policy easing vs tightening shocks occurring 1 month afterwards ($\beta^h_{E,weak}$ vs $\beta^h_{T,weak}$ in regression 1.15), "poor man"'s approach from Jarociński and Karadi (2020)

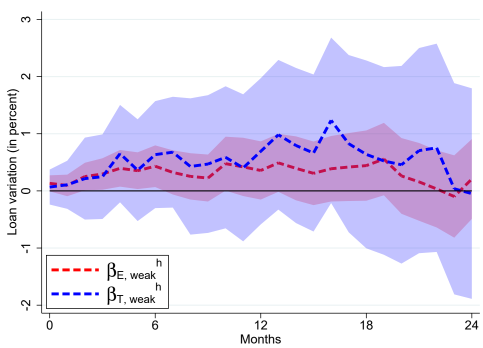
(a) Continuous variable of weak treatment



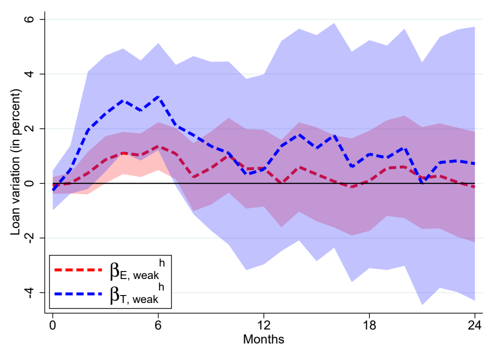
(b) Top vs bottom 50% banks



(c) Top vs bottom 25% banks



(d) Top vs bottom 10% banks

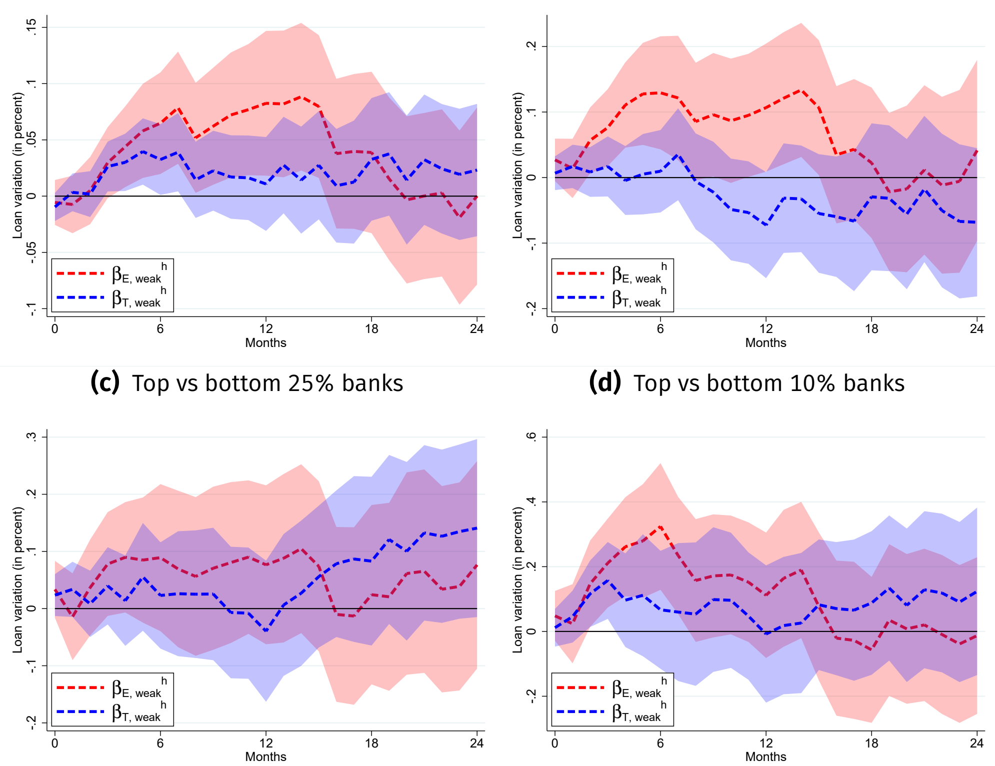


Source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BISTA and COREP datasets, 2005-2021, own calculations.
Note: In these figures, I plot the effect of the interaction between a one basis point stimulus monetary policy easing shock occurring 1 month after a given macroprudential policy announcement was released, and a measure of weak treatment for this macroprudential policy announcement on bank loans over different time horizons h where $h = 0, 1, ..., 24$ months. I compare it to the effect of a one basis point monetary policy tightening shock occurring 1 month after a given macroprudential policy announcement was released, interacted with the same measure of weak treatment for this macroprudential policy announcement. Four alternative measures of weak treatment are used: the bank-level abnormal returns used as a continuous variable directly (Figure 1.B.3a), or using a dummy equal to 1 if bank i belongs to the top 10, 25, or 50% in terms of abnormal bond returns for a given macroprudential policy announcement, and 0 if it belongs to the bottom 50, 25, or 10% respectively (Figures 1.B.3b, 1.B.3c, and 1.B.3d, respectively). In each figure, the red dashed line represents the coefficient for the stimulus monetary policy easing shock interacted with the measure of weak treatment for a given macroprudential policy announcement (i.e. $\beta^h_{E,weak}$) for each horizon h. The light red area represents the 90 percent confidence bands of each coefficient $\beta^h_{E,weak}$. The blue dashed line represents the coefficient for the monetary policy tightening shock interacted with the measure of weak treatment for a given macroprudential policy announcement (i.e. $\beta^h_{T,weak}$) for each horizon h. The light blue area represents the 90 percent confidence bands of each coefficient $\beta^h_{T,weak}$. The monetary policy surprises are here cleaned from the central bank information component following the "poor man"'s approach from Jarociński and Karadi (2020).

Figure 1.B.4. Response of bank loans to alternative weak treatment variables for macroprudential announcements interacted with stimulus monetary policy easing vs tightening shocks occurring up to 12 months afterwards ($\beta^h_{E,weak}$ vs $\beta^h_{T,weak}$ in regression 1.15)

(a) Continuous variable of weak treatment **(b)** Top vs bottom 50% banks

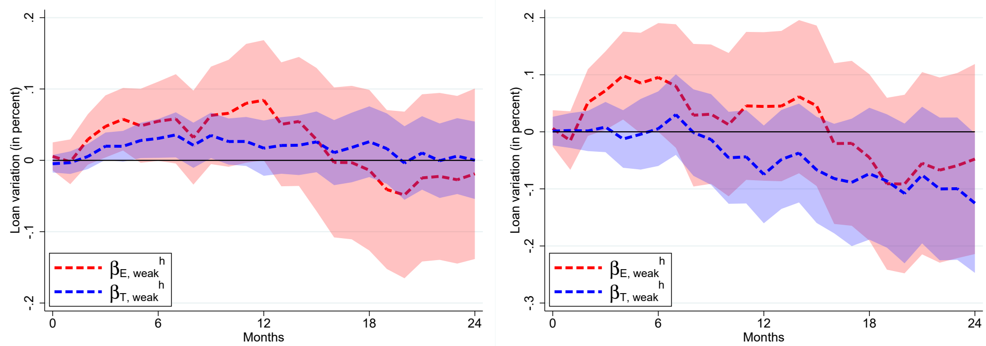
(c) Top vs bottom 25% banks **(d)** Top vs bottom 10% banks



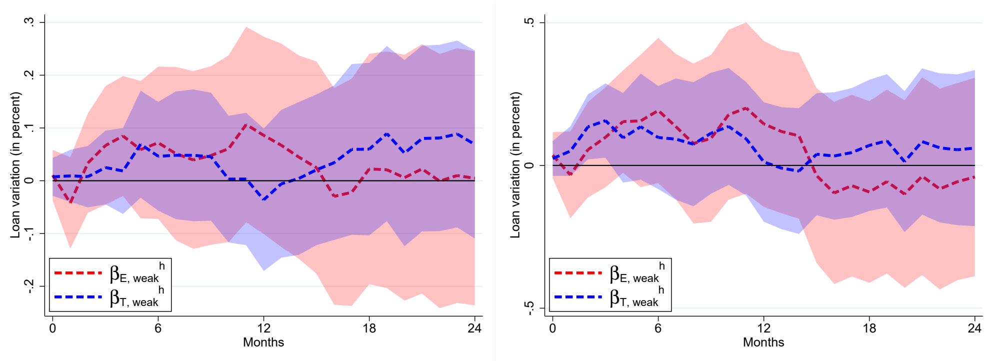
Source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BISTA and COREP datasets, 2005-2021, own calculations.
Note: In these figures, I plot the effect of the interaction between a one basis point stimulus monetary policy easing shock occurring up to 12 months after a given macroprudential policy announcement was released, and a measure of weak treatment for this macroprudential policy announcement on bank loans over different time horizons h where $h = 0, 1, ..., 24$ months. I compare it to the effect of a one basis point monetary policy tightening shock occurring up to 12 months after a given macroprudential policy announcement was released, interacted with the same measure of weak treatment for this macroprudential policy announcement. Four alternative measures of weak treatment are used: the bank-level abnormal returns used as a continuous variable directly (Figure 1.B.4a), or using a dummy equal to 1 if bank i belongs to the top 10, 25, or 50% in terms of abnormal bond returns for a given macroprudential policy announcement, and 0 if it belongs to the bottom 50, 25, or 10% respectively (Figures 1.B.4b, 1.B.4c, and 1.B.4d, respectively). In each figure, the red dashed line represents the coefficient for the stimulus monetary policy easing shock interacted with the measure of weak treatment for a given macroprudential policy announcement (i.e. $\beta^h_{E,weak}$) for each horizon h. The light red area represents the 90 percent confidence bands of each coefficient $\beta^h_{E,weak}$. The blue dashed line represents the coefficient for the monetary policy tightening shock interacted with the measure of weak treatment for a given macroprudential policy announcement (i.e. $\beta^h_{T,weak}$) for each horizon h. The light blue area represents the 90 percent confidence bands of each coefficient $\beta^h_{T,weak}$.

Figure 1.B.5. Response of bank loans to alternative weak treatment variables for macroprudential announcements interacted with stimulus monetary policy easing vs tightening shocks occurring up to 12 months afterwards ($\beta^h_{E,weak}$ vs $\beta^h_{T,weak}$ in regression 1.15), "poor man"'s approach from Jarociński and Karadi (2020)

(a) Continuous variable of weak treatment **(b)** Top vs bottom 50% banks



(c) Top vs bottom 25% banks **(d)** Top vs bottom 10% banks



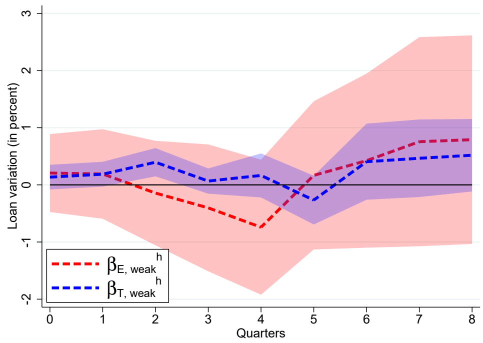
Source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BISTA and COREP datasets, 2005-2021, own calculations.

Note: In these figures, I plot the effect of the interaction between a one basis point stimulus monetary policy easing shock occurring up to 12 months after a given macroprudential policy announcement was released, and a measure of weak treatment for this macroprudential policy announcement on bank loans over different time horizons h where $h =$ 0, 1, ..., 24 months. I compare it to the effect of a one basis point monetary policy tightening shock occurring up to 12 months after a given macroprudential policy announcement was released, interacted with the same measure of weak treatment for this macroprudential policy announcement. Four alternative measures of weak treatment are used: the bank-level abnormal returns used as a continuous variable directly (Figure 1.B.5a), or using a dummy equal to 1 if bank i belongs to the top 10, 25, or 50% in terms of abnormal bond returns for a given macroprudential policy announcement, and 0 if it belongs to the bottom 50, 25, or 10% respectively (Figures 1.B.5b, 1.B.5c, and 1.B.5d, respectively). In each figure, the red dashed line represents the coefficient for the stimulus monetary policy easing shock interacted with the measure of weak treatment for a given macroprudential policy announcement (i.e. $\beta^h_{E,weak}$) for each horizon h. The light red area represents the 90 percent confidence bands of each coefficient $\beta^h_{E,weak}$. The blue dashed line represents the coefficient for the monetary policy tightening shock interacted with the measure of weak treatment for a given macroprudential policy announcement (i.e. $\beta^h_{T,weak}$) for each horizon h. The light blue area represents the 90 percent confidence bands of each coefficient $\beta^h_{T,weak}$. The monetary policy surprises are here cleaned from the central bank information component following the "poor man"'s approach from Jarociński and Karadi (2020).

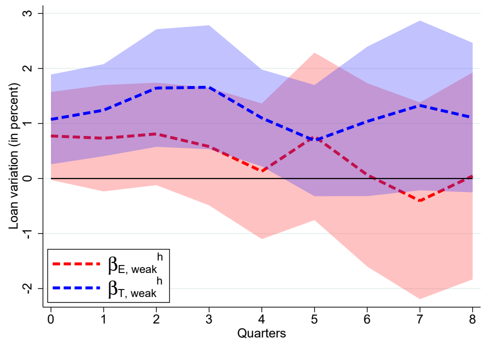
Appendix 1.C Additional results using the macroprudential policy surprises, controlling for loan demand

Figure 1.C.1. Response of bank loans to alternative weak treatment variables for macroprudential announcements interacted with stimulus monetary policy easing vs tightening shocks occurring up to 2 quarters afterwards ($\beta^h_{E,weak}$ vs $\beta^h_{T,weak}$ in regression 1.16), "poor man"'s approach from Jarociński and Karadi (2020), controlling for loan demand

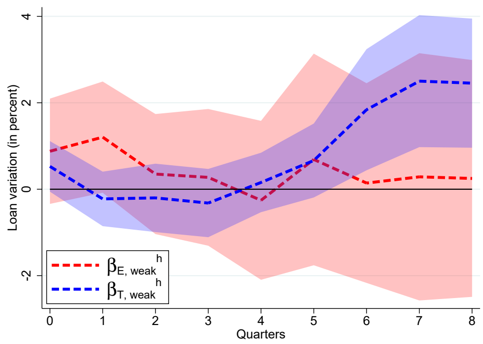
(a) Continuous variable of weak treatment



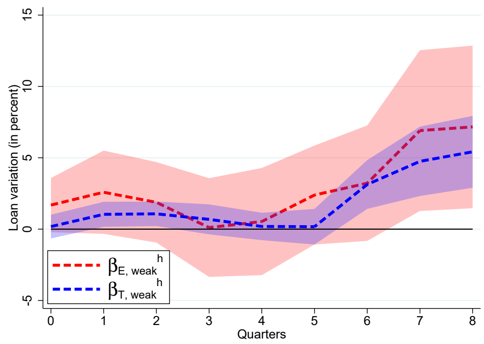
(b) Top vs bottom 50% banks



(c) Top vs bottom 25% banks



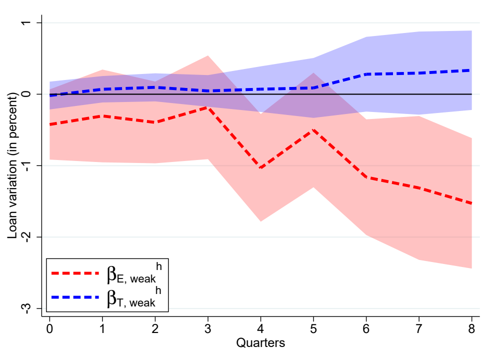
(d) Top vs bottom 10% banks



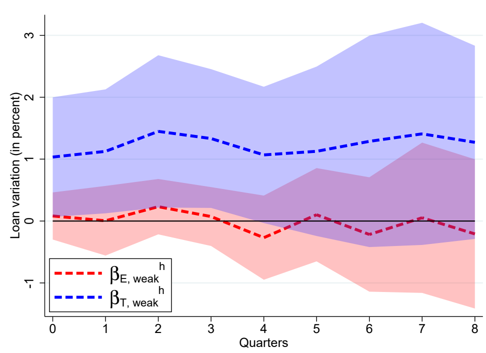
Source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BISTA, credit register of loans of €1.0 million or more from Bundesbank and COREP datasets, 2005-2021, own calculations.
Note: In these figures, I plot the effect of the interaction between a one basis point stimulus monetary policy easing shock occurring up to 2 quarters after a given macroprudential policy announcement was released, and a measure of weak treatment for this macroprudential policy announcement on bank loans over different time horizons h where $h = 0, 1, ..., 8$ quarters. The specification is based on the credit register of loans of €1.0 million or more from Bundesbank, allowing me to include borrower-time fixed effects, hence controlling for loan demand. I compare it to the effect of a one basis point monetary policy tightening shock occurring up to 2 quarters after a given macroprudential policy announcement was released, interacted with the same measure of weak treatment for this macroprudential policy announcement. Four alternative measures of weak treatment are used: the bank-level abnormal returns used as a continuous variable directly (Figure 1.C.1a), or using a dummy equal to 1 if bank i belongs to the top 10, 25, or 50% in terms of abnormal bond returns for a given macroprudential policy announcement, and 0 if it belongs to the bottom 50, 25, or 10% respectively (Figures 1.C.1b, 1.C.1c, and 1.C.1d, respectively). In each figure, the red dashed line represents the coefficient for the stimulus monetary policy easing shock interacted with the measure of weak treatment for a given macroprudential policy announcement (i.e. $\beta^h_{E,weak}$) for each horizon h. The light red area represents the 90 percent confidence bands of each coefficient $\beta^h_{E,weak}$. The blue dashed line represents the coefficient for the monetary policy tightening shock interacted with the measure of weak treatment for a given macroprudential policy announcement (i.e. $\beta^h_{T,weak}$) for each horizon h. The light blue area represents the 90 percent confidence bands of each coefficient $\beta^h_{T,weak}$. The monetary policy surprises are here cleaned from the central bank information component following the "poor man"'s approach from Jarociński and Karadi (2020).

Figure 1.C.2. Response of bank loans to alternative weak treatment variables for macroprudential announcements interacted with stimulus monetary policy easing vs tightening shocks occurring up to 4 quarters afterwards ($\beta^h_{E,weak}$ vs $\beta^h_{T,weak}$ in regression 1.16), controlling for loan demand

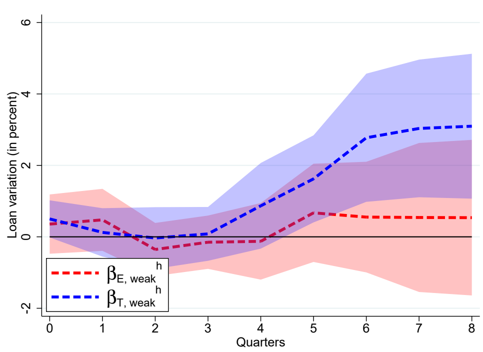
(a) Continuous variable of weak treatment



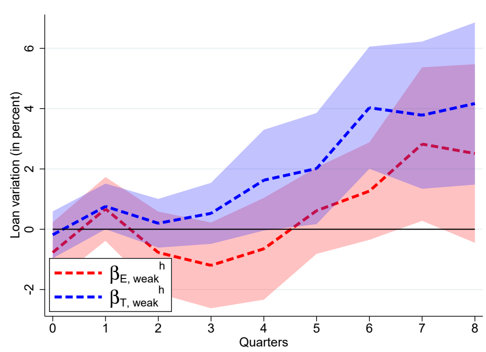
(b) Top vs bottom 50% banks



(c) Top vs bottom 25% banks



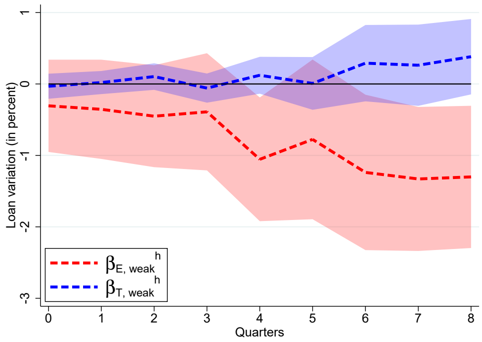
(d) Top vs bottom 10% banks



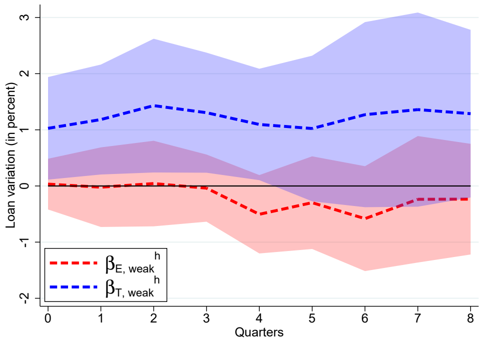
Source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BISTA, credit register of loans of €1.0 million or more from Bundesbank and COREP datasets, 2005-2021, own calculations.
Note: In these figures, I plot the effect of the interaction between a one basis point stimulus monetary policy easing shock occurring up to 4 quarters after a given macroprudential policy announcement was released, and a measure of weak treatment for this macroprudential policy announcement on bank loans over different time horizons h where $h = 0, 1, ..., 8$ quarters. The specification is based on the credit register of loans of €1.0 million or more from Bundesbank, allowing me to include borrower-time fixed effects, hence controlling for loan demand. I compare it to the effect of a one basis point monetary policy tightening shock occurring up to 4 quarters after a given macroprudential policy announcement was released, interacted with the same measure of weak treatment for this macroprudential policy announcement. Four alternative measures of weak treatment are used: the bank-level abnormal returns used as a continuous variable directly (Figure 1.C.2a), or using a dummy equal to 1 if bank i belongs to the top 10, 25, or 50% in terms of abnormal bond returns for a given macroprudential policy announcement, and 0 if it belongs to the bottom 50, 25, or 10% respectively (Figures 1.C.2b, 1.C.2c, and 1.C.2d, respectively). In each figure, the red dashed line represents the coefficient for the stimulus monetary policy easing shock interacted with the measure of weak treatment for a given macroprudential policy announcement (i.e. $\beta^h_{E,weak}$) for each horizon h. The light red area represents the 90 percent confidence bands of each coefficient $\beta^h_{E,weak}$. The blue dashed line represents the coefficient for the monetary policy tightening shock interacted with the measure of weak treatment for a given macroprudential policy announcement (i.e. $\beta^h_{T,weak}$) for each horizon h. The light blue area represents the 90 percent confidence bands of each coefficient $\beta^h_{T,weak}$.

Figure 1.C.3. Response of bank loans to alternative weak treatment variables for macroprudential announcements interacted with stimulus monetary policy easing vs tightening shocks occurring up to 4 quarters afterwards ($\beta^h_{E,weak}$ vs $\beta^h_{T,weak}$ in regression 1.16), "poor man"'s approach from Jarociński and Karadi (2020), controlling for loan demand

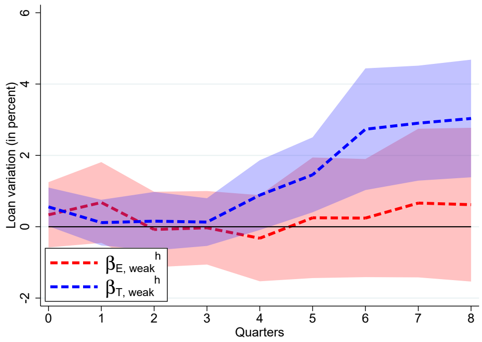
(a) Continuous variable of weak treatment



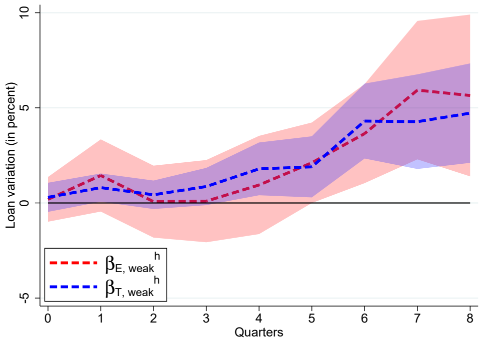
(b) Top vs bottom 50% banks



(c) Top vs bottom 25% banks



(d) Top vs bottom 10% banks



Source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, BISTA, credit register of loans of €1.0 million or more from Bundesbank and COREP datasets, 2005-2021, own calculations.
Note: In these figures, I plot the effect of the interaction between a one basis point stimulus monetary policy easing shock occurring up to 4 quarters after a given macroprudential policy announcement was released, and a measure of weak treatment for this macroprudential policy announcement on bank loans over different time horizons h where $h = 0, 1, ..., 8$ quarters. The specification is based on the credit register of loans of €1.0 million or more from Bundesbank, allowing me to include borrower-time fixed effects, hence controlling for loan demand. I compare it to the effect of a one basis point monetary policy tightening shock occurring up to 4 quarters after a given macroprudential policy announcement was released, interacted with the same measure of weak treatment for this macroprudential policy announcement. Four alternative measures of weak treatment are used: the bank-level abnormal returns used as a continuous variable directly (Figure 1.C.3a), or using a dummy equal to 1 if bank i belongs to the top 10, 25, or 50% in terms of abnormal bond returns for a given macroprudential policy announcement, and 0 if it belongs to the bottom 50, 25, or 10% respectively (Figures 1.C.3b, 1.C.3c, and 1.C.3d, respectively). In each figure, the red dashed line represents the coefficient for the stimulus monetary policy easing shock interacted with the measure of weak treatment for a given macroprudential policy announcement (i.e. $\beta^h_{E,weak}$) for each horizon h. The light red area represents the 90 percent confidence bands of each coefficient $\beta^h_{E,weak}$. The blue dashed line represents the coefficient for the monetary policy tightening shock interacted with the measure of weak treatment for a given macroprudential policy announcement (i.e. $\beta^h_{T,weak}$) for each horizon h. The light blue area represents the 90 percent confidence bands of each coefficient $\beta^h_{T,weak}$. The monetary policy surprises are here cleaned from the central bank information component following the "poor man"'s approach from Jarociński and Karadi (2020).

Appendix 1.D Complete list of macroprudential policies for Germany

Table 1.D.1. Complete list of macroprudential policies

Announcement date	Category [a]	Event	Sources event	Sources announcement date
26/06/2004	Basel II /CRD	Basel II regulation was published during the G10.	MaPPED	Bundesbank
15/02/2006	Basel II /CRD	The German federal government approved a draft law by the Finance Minister to implement the new Basel II capital adequacy guidelines.	MaPPED	Refinitiv Eikon, Nexis
30/06/2006	Basel II /CRD	Publication in the official journal of the EU of the Directives 2006/48/ and 2006/49/C (Capital Requirements Directive) implementing the Basel II standards	MaPPED	EUR-Lex
20/12/2006	Basel II /CRD	Publication in the German official journal of the "Solvabilitätsverordnung", which comes as a complement of the Basel II standards for German banks.	MaPPED	Bundesgesetzblatt-Archiv
19/09/2008	Short-selling restrictions	General Decree of BaFin on short selling: The decree banned transactions that result in a short position or in an increase in a short position in shares issued by 11 companies from the financial sector. Name-to-follow transactions ("Aufgabegeschäfte") by lead brokers ("Skontroführer") and transactions by market makers and designated sponsors were exempted from the ban. The ban is initially valid until 31 December 2008.	MaPPED	Refinitiv Eikon
17/12/2008	Short-selling restrictions	First extension of the ban on short selling, valid until the 31 March 2009.	MaPPED	Nexis
30/03/2009	Short-selling restrictions	Second extension of the ban on short selling, valid until the 31 May 2009.	MaPPED	Refinitiv Eikon
29/05/2009	Short-selling restrictions	Third extension of the ban on short selling, valid until the 31 January 2010.	MaPPED	Refinitiv Eikon
04/03/2010	Short-selling restrictions	Restrictions on uncovered short sales in shares and debt securities as well as naked credit default swaps. Additionally, any covered net short-selling position of at least 0.2% of the issued shares of a company that are traded in a regulated market of a German stock exchange has to be reported to the BaFin by the owner of the short-selling position.	MaPPED	Bafin
26/03/2010	CRD II	Draft law issued by the German federal government to amend the Kreditwesengesetz (KWG) due to the "CRD II-Umsetzungsgesetz".	MaPPED	Bundestag

31/03/2010	Bank levy	The German federal government announced that it adopted the key points for a future law to impose a bank levy in Germany.	iMapp and MaPPED	Bundestag
18/05/2010	Short-selling restrictions	General Decree of BaFin on the prohibition of naked short-selling transactions in certain shares, in debt securities of Member States of the EU whose legal currency is the euro and on contracting a credit derivative or entering into a transaction on the same if a no more than insignificant reduction of the protection buyer's risk is achieved thereby.	MaPPED	Refinitiv Eikon
26/07/2010	Short-selling restrictions	General Decree of 26 July 2010 by BaFin to revoke the General Decrees banning naked short-selling transactions in shares and debt securities as well as naked credit default swaps.	MaPPED	Bafin
22/06/2010	Bank levy	Joint statement by the French, UK and German governments proposing the introduction of bank levies s based on banks' balance sheets.	iMapp and MaPPED	UK Treasury
29/06/2010	Bank levy	Draft law from the Ministry of Finance published.	iMapp and MaPPED	Nexis
25/08/2010	Bank levy	Draft law adopted by the German federal government.	iMapp and MaPPED	Nexis
24/11/2010	CRD II	Publication of the law amending the Kreditwesengesetz (KWG) due to the "CRD II-Umsetzungsgesetz" in the German official journal.	MaPPED	Bundes-gesetzblatt-Archiv
14/12/2010	Bank levy	Publication of the final law in the German official journal.	iMapp and MaPPED	Bundes-gesetzblatt-Archiv
16/12/2010	Basel III / CRD IV	First publication of the Basel III regulation by the Basel committee.	MaPPED	BIS
31/01/2011	Short-selling restrictions	Extension of the restrictions on uncovered short sales in shares and debt securities as well as naked credit default swaps. Additionally, the Act imposes a reporting obligation on the owner of the short-selling position pursuant to which any covered net short-selling position of at least 0.2% of the issued shares of a company that are traded in a regulated market of a German stock exchange has to be reported to the BaFin.	MaPPED	Bafin
4/11/2011	SIFIs	The Financial Stability Board (FSB) published the initial list of global SIFIs (G-SIFIs) based on the BCBS methodology, as well as policy measures to address the systemic and moral hazard risks associated with SIFIs.	iMapp	FSB
08/12/2011	Reserve requirement ratio	The ECB lowered the reserve requirement ratio from 2% to 1%.	iMapp	ECB
22/08/2012	Basel III / CRD IV	The German federal government publishes a draft law to transpose Basel III in the German law .	MaPPED	Refinitiv Eikon
02/10/2012	GBSA	Liikanen report recommending a separation between retail and investment banks.	MaPPED	Nexis

06/01/2013	LCR	The Liquidity Coverage Ratio introduced by the Basel III regulation was revised (the minimum requirement will begin on 1 January 2015 at 60% with annual increases of 10 percentage points until it reaches 100% in 2019 instead of reaching 100% directly on 1 January 2015 as initially planned).	iMapp	BIS
30/01/2013	GBSA	First draft law issued by the German finance ministry for the "Trennbankengesetz".	MaPPED	Nexis
06/02/2013	GBSA	German government proposal for the "Trennbankengesetz".	MaPPED	Nexis
27/06/2013	Basel III / CRD IV	Publication in the official journal of the EU of the CRD IV regulation.	MaPPED	EUR-Lex
12/08/2013	GBSA	Publication in the German official journal of the "Trennbankengesetz".	MaPPED	Bundes-gesetzblatt-Archiv
03/09/2013	Basel III / CRD IV	Publication in the German official journal of the transposition of the CRD IV regulation in the German law.	MaPPED	Bundes-gesetzblatt-Archiv
30/07/2014	Bank levy	Publication in the official journal of the EU of the new regulation related to the Single Resolution Mechanism and a Single Resolution Fund.	iMapp	EUR-Lex
15/12/2015	CCyB	The countercyclical capital buffer (CCyB) was introduced and set at zero percent by Bafin.	iMapp	Bafin and ESRB
17/06/2016	SIFIs	The additional capital buffer requirement for other systemically important institutions (O-SIIs) was announced to take effect from January 1, 2017. O-SIIs are identified by using a method developed jointly by BaFin and Deutsche Bundesbank. As a result of the identification process, 14 institutions are designated in 2017 as O-SIIs. These institutions are allocated to one out of four buckets using a cluster analysis. The applicable buffer rates are: Deutsche Bank 2.00%; Commerzbank 1.50%; UniCredit, DZ Bank, LBBW, Helaba, BayernLB, and NordLB: 1.00%; Deka Bank, VW Financial Services, HSH Nordbank, NRW.Bank, ING DiBa AG, and Landwirtschaftliche Rentenbank: 0.50%. The buffers are phased in evenly from January 1, 2017 to January 1, 2019.	iMapp	ESRB
23/11/2016	SIFIs	It was announced—subject to further negotiations—that presumably with effect from January 1, 2021, exposures of a global systemically important buffer (G-SIB) to another G-SIB will be limited to 15% of the lending G-SIBs Tier 1 capital.	iMapp	iMapp
29/11/2016	Accounting standards	Announcement of the EU regulation No. 2016/2067 (effective January 1, 2018) implementing International Financial Reporting Standard 9 (IFRS 9) which introduced a forward-looking approach to loan loss provisions.	iMapp	EUR-Lex and iMapp

20/12/2018	SIFIs	It was announced that as of January 1, 2019, the following other systemically important institutions were required to hold additional capital buffer rates as follows: Deutsche Bank 2.0%; Commerzbank, DZ Bank, UniCredit Bank AG, LBBW, Helaba, BayernLB, and NordLB: 1.00%; NRW.Bank, ING-DiBa AG, Deka Bank, and Landwirtschaftliche Rentenbank: 0.50%; Volkswagen Bank: 0.16%.	iMapp	ESRB
14/05/2019	Leverage ratio	The Basel minimum leverage ratio (LR) requirement of 3% and the G-SIB LR buffer of the magnitude of 50% of the risk-weighted G-SIB buffer rate have been transposed into EU law. It was announced that the 3% LR will become binding two years after entry into force of the banking package, while the G-SIB leverage buffer will apply from January 1, 2023.	iMapp	EUR-Lex and iMapp
28/06/2019	CCyB	The CCyB buffer rate was increased to 0.25% from 0% (effective from from October 1, 2019).	iMapp	ESRB
13/12/2019	SIFIs	It was announced that the global systemically important institutions buffer for Deutsche Bank will decrease to 1.50% from 2% (effective from January 1, 2021).	iMapp	iMapp
Between 11/3/2020 and 12/3/2020	CCB	In response to the COVID-19 pandemic, the ECB issued enhanced communication to single supervisory mechanism banks under its direct supervision (that is, significant institutions), applicable to those in Germany, regarding temporary use of capital conservation buffers. The BaFin confirmed that the ECB's enhanced communication on the use of capital conservation buffers would also apply to banks under its supervision (less significant institutions). Both significant and less significant institutions were encouraged to use their liquidity buffers (temporarily operate below the LCR of 100%), if necessary.	iMapp	ECB and Refinitiv Eikon
20/03/2020	Accounting standards	The ECB recommended banks under its direct supervision (that is, significant institutions) to (1) opt to apply the transitional IFRS 9 provisions and (2) avoid excessively procyclical assumptions in their expected credit loss estimations, considering the extraordinary uncertainty during the COVID-19 pandemic. This guidance is applicable to significant institutions in Germany.	iMapp	ECB
24/03/2020	Accounting standards and restrictions on dividend distribution	The Bafin advised institutions to make use of the transitional arrangements for institutions that prepare their accounts in accordance with IFRS 9. It also recommended banks under its direct supervision (that is, less significant institutions) in Germany to refrain from making dividend distributions and performing share buy-backs aimed at remunerating shareholders during the period of the COVID-19-related economic shock, at least until October 1, 2020.	iMapp	Bafin

Between 26/03/2020 and 27/03/2020	Restrictions on dividend distribution	The ECB recommended banks under its direct supervision (that is, significant institutions) to refrain from making dividend distributions and performing share buy-backs aimed at remunerating shareholders during the period of the COVID-19-related economic shock, at least until October 1, 2020. This recommendation was applicable to significant institutions in Germany.	iMapp	ECB and Refinitiv Eikon
31/03/2020	CCyB	It was announced that the CCyB buffer would be reduced to 0% from 0.25%, with effect from April 1, 2020.	iMapp	ESRB
27/07/2020	Restrictions on dividend distribution	The ECB extended the dividend recommendation to significant institutions until January 1, 2021, as the level of economic uncertainty because of the COVID-19 pandemic remained elevated. This extension was applicable to significant institutions in Germany.	iMapp	EUR-Lex
08/08/2020	Restrictions on dividend distribution	It was announced that effective October 1, 2020, the Federal Financial Supervisory Authority of Germany (Bundesanstalt für Finanzdienstleistungsaufsicht) would allow institutions under its supervisors remit to distribute dividends on a case-by-case basis if the respective institute has a sustainable positive earnings forecast and the capital situation continues to show sufficient buffers, even in a persistent stress phase.	iMapp	iMapp

[a] The acronyms for the different categories mean the following: CRD (Capital Requirements Directive), SIFIs (Systemically Important Financial Institutions), GBSA (German Bank Separation Act; "Trennbankengesetz" in German), LCR (Liquidity coverage ratio), CCyB (Countercyclical capital buffer), CCB (Capital Conservation Buffer).

Chapter 2

Through Rose-Tinted or Dark Lenses: How Bank Manager Sentiment Affects Lending and Risk

Joint with Frank Brueckbauer

2.1 Introduction

Economic agents sentiment is known to have an impact on their behaviour since the seminal work of Keynes (1936). However, little is known about how bank manager sentiment is impacting bank lending and risk profile. Answering this question is important both from a financial stability and economy-financing perspective. If bank managers are over-optimistic, they may lend too much and take too many risks compared to the economic and financial fundamentals. If on the contrary bank managers are over-pessimistic, they may lend insufficiently, compared to the economic and financial fundamentals, hence not fulfilling their role of financing the economy.

In this paper, we provide evidence on how systematic over-optimism on the part of banks may affect the amount of credit that they supply to the real sector. We proceed in three steps. First, we extract a measure of the tone of bank earnings press release documents using textual analysis methods: the textual tone score. Our analysis focuses on medium-sized and large European banks at the banking group level, from the first quarter of 2006 to the second quarter of 2019.[1] We then explore the relationship of the textual tone score with bank-specific and macroeconomic variables. The results of these analyses strongly suggest that the textual tone scores are correlated with the fundamentals of banks, i.e. their perfor-

[1] To check the validity of the textual tone score, we study its distribution over time and compare it with the one we would have obtained using a machine learning approach. We find similar distributions.

mance, business models and the economic environments in which they operate. More specifically, over the sample period, the textual tone score is on average positively associated with GDP growth rates, interbank interest rates and bank-level retail deposits and negatively associated with the term spread, the OIS spread and bank-level impairments on loans and net interest income. Importantly, the textual tone score captures both bank-specific and macroeconomic fundamentals, bank managers' subjective opinions, or their expectations about future firm outcomes.

Second, we use the textual tone score to identify bank manager sentiment. Since we are interested in the informational content of the earnings press release documents orthogonal to the bank-specific and macroeconomic fundamentals, we control for the bank-specific and macroeconomic variables and include fixed effects in all our subsequent regressions. We define the variation in textual tone score orthogonal to fundamentals, as bank manager sentiment. Note that this definition of bank manager sentiment could capture over-optimism / over-pessimism of bank managers and / or some private information of the bank managers that is not yet observed in the contemporaneous fundamentals. For this reason, we implement two tests on our estimate of bank manager sentiment. In a first test, we explore whether bank manager sentiment has an extrapolative structure, i.e. whether it is associated with past realizations of economic fundamentals.[2] Expectations with an extrapolative structure imply over-optimism: if expectations depend on past realizations of economic fundamentals, the logical implication is that expectations will not be fully in line with current fundamentals. Thus, relative to current fundamentals, expectations will be too high, i.e. excessively optimistic, or too low, i.e. excessively pessimistic.[3] In our empirical investigation, we find two pieces of evidence that suggest that bank managers' expectations are backward looking. We first document that GDP growth rates have incremental predictive power for future values of bank manager sentiment. Furthermore, we find that bank manager sentiment is auto-correlated, implying that innovations in variables that were found to be correlated with bank manager sentiment are also associated with its subsequent realizations. In a second test, we check whether bank manager sentiment is associated with a better future financial performance of the banks. If our estimate of bank manager sentiment was capturing bank managers' private information, one would expect that a positive (negative) variation in the textual tone score would be associated with a better (worse) subsequent financial performance of banks. Depending on the financial performance indicator, we find that bank manager sentiment is either unrelated or negatively related with subsequent financial per-

[2] The existence of extrapolative expectation formation rules is well documented in the finance literature. Extrapolative expectations are, for example, prevalent in survey data on stock return expectations (Greenwood and Shleifer, 2014), survey data on the expectations of CFOs with respect to macroeconomic developments and the future profitability of their own firms (Gennaioli, Ma, and Shleifer, 2016) and forecasts of credit spreads (Bordalo, Gennaioli, and Shleifer, 2018).

[3] The implicit assumption here is that only the current state of the economy matters for decision making, which is a widely used assumption in economics and finance (Greenwood, Hanson, and Jin, 2016).

formance of banks, hence rejecting the hypothesis that bank manager sentiment captures private information.

Third, we study whether bank manager sentiment is associated with the investment decisions of banks and of their equity investors. On the part of banks, we explore whether bank manager sentiment has incremental predictive power for loan growth and risk-taking. We do this for two reasons. In the first place, evidence of a relationship between bank manager sentiment on the one hand and bank lending and risk taking on the other hand strengthens our case that bank manager sentiment reflects information about the expectations of bank managers. Furthermore, a positive relationship between bank manager sentiment and loan growth is a necessary condition for the existence of a link between excessively optimistic expectations of bank managers and high loan growth rates. In our empirical analysis, we find that bank manager sentiment has incremental but weak predictive power for bank-level loan growth over the subsequent six months. When using loan-level data to control for loan demand, we find that this incremental predictive power actually disappears. With respect to risk-taking, we find evidence that banks increase their lending to riskier borrowers when bank manager sentiment is higher, and conversely. Hence, this suggests that despite bank manager sentiment does not predict higher subsequent bank loan supply, bank manager sentiment is associated to subsequent credit supply reallocation on the part of banks from low- to high-risk borrowers.

On the part of bank equity investors, we explore whether bank manager sentiment influences how bank investors perceive the risk associated with loan growth. The perceived riskiness of a bank is an important determinant of its cost of capital, which in turn is an important determinant of the bank's investments in loans. Empirical evidence suggests that equity market participants are sometimes too optimistic when judging the risk associated with high bank loan growth.[4] Therefore, we hypothesize that bank manager sentiment is related to the perceived risk associated with bank loan growth and that this perceived risk is lower when bank managers are more optimistic.[5] Using *SRISK* (Brownlees and Engle, 2016) as our measure for the risk perception of market participants, we find that a higher bank manager sentiment is indeed associated with a lower perceived risk, and that the association between loan growth and risk decreases in bank manager sentiment, even though the latter is not significant.

The rest of the paper is organized as follows. In Section 2.2, we summarize the related literature and explains how we extend the respective strands of research. In Section 2.3, we introduce the textual tone score and other variables used throughout the paper. In Section

[4] See e.g. Baron and Xiong (2017) and Fahlenbrach, Prilmeier, and Stulz (2017).

[5] Baron and Xiong (2017) find that rapid credit expansions on the country level predict low and sometimes negative aggregate bank equity returns, suggesting that investors sometimes underestimate the risk associated with bank loan growth. Fahlenbrach, Prilmeier, and Stulz (2017) show that equity analysts' forecasts of profitability and growth for high loan growth banks are often too optimistic and are subsequently revised downwards.

2.4, we study the development of textual tone scores over time and their relationships with important bank-specific and macroeconomic variables. In Section 2.5, we define bank manager sentiment and explore whether it is extrapolative in past fundamentals and whether it predicts the future financial performance of banks. In Section 2.6, we examine whether bank manager sentiment is predictive for subsequent lending, both at the bank-level and at the loan-level hence controlling for credit demand. In Section 2.7, we study the implications of bank manager sentiment for banks' risk-taking behaviour and for the perceived risk associated with bank loan growth by bank equity investors. Finally, in Section 2.8, we summarize and discuss the results.

2.2 Related Literature

We contribute to three strands of research. First, we contribute to the growing finance and accounting literature that studies the informational content of the textual sentiment of voluntary corporate disclosures. Within this literature, researchers study different text sources (e.g. annual reports, press releases, conference call transcripts), use different approaches to classify the content of these text sources (e.g. dictionary-based and machine learning approaches) and use different ways to calculate an aggregate textual tone[6] score from the classified text contents (Kearney and Liu, 2014). Overall, the empirical evidence suggests that the textual tone of corporate disclosures contains incremental informational content about the future performance of the reporting firms and that market participants respond to textual tone. For example, Li (2010) applies a machine learning approach to the forward-looking statements in the Management Discussion and Analysis section of 10-K and 10-Q filings to study the incremental predictive power of textual tone for future earnings. He finds that textual tone is positively correlated with future return on assets up to three quarters ahead. Davis, Piger, and Sedor (2012) who focus on a large sample of earnings press release documents published between 1998 and 2003 reach a similar conclusion. Loughran and McDonald (2011) introduce a new dictionary that is better suited to capture the textual tone in financial texts than standard dictionaries like the widely used Harvard Dictionary. They find that the proportion of negative words, as identified by their new dictionary, is negatively associated with 10-K filing returns. Gandhi, Loughran, and McDonald (2019) specifically look at annual reports of US banks and find that the proportion of negative words is positively related to different measures of financial distress. Jiang et al. (2019) construct an aggregate manager sentiment score from firm level textual tone and by controlling for macroeconomic fundamentals. They find that aggregate manager sentiment is negatively associated with

[6] What we call "textual tone" is sometimes called "textual sentiment" in the existing literature. Given that we introduce the notion of "bank manager sentiment" later on, we prefer to use the term "textual tone" to avoid any confusion for the reader.

stock returns on the market level and in the cross-section and that it has predictive power for aggregate investment. Using a new sample of European banks, we extend the literature by extracting a textual tone score of earnings press release documents thanks to dictionary and machine learning approaches.[7] Most importantly, by focusing on the part of the textual tone score which is orthogonal to the macroeconomic and bank-specific fundamentals, we are able to identify bank manager sentiment and study its characteristics and influence.

Second, our paper is related to the literature that links credit cycles to behavioral factors, which was initiated by Minsky (1977). In this literature, a positive association between credit growth and financial fragility is explained by overly optimistic or extrapolative expectations. The extrapolative expectation formation rules imply that credit cycles in the model are more persistent than the cycles in the underlying fundamentals. Empirical research for credit market over-optimism include Greenwood and Hanson (2013) and Greenwood, Hanson, and Jin (2016) who show that lower average debt issuer quality predicts low excess corporate bond returns because corporate bond investors over-extrapolate past low corporate bond default rates. López-Salido, Stein, and Zakrajšek (2017) use the expected excess return for bearing credit risk as a proxy of credit market sentiment and present evidence that high credit market sentiment predicts low real GDP growth and a decrease of net debt issuance relative to net equity issuance. Fahlenbrach, Prilmeier, and Stulz (2017) show that high loan growth banks do not provision more for loan losses than low loan growth banks, consistent with banks being overoptimistic. Bordalo, Gennaioli, and Shleifer (2018) document that analysts expect credit spreads to be more persistent than they actually are. We contribute to this strand of literature in three ways. To the best of our knowledge, we are the first ones to use textual analysis to measure in fine banks' over-optimism. Furthermore, we provide bank-level evidence of the extrapolative structure of bank manager sentiment. Finally, we show that bank manager sentiment is related to future loan growth.

Third, we contribute to the empirical literature focusing on the relationship between credit growth and bank stability. Both country-level evidence as well as firm-level evidence suggest that high bank loan growth is positively associated with financial fragility and negatively associated with subsequent bank performance. At the country level, Schularick and Taylor (2012) and Aikman, Haldane, and Nelson (2014) find that the occurrence of a financial crisis is more likely after a credit boom. Jordà, Schularick, and Taylor (2013) show that the severity of recessions increases in the build-up of bank credit during the preceding boom. Baron and Xiong (2017) document that large increases in bank lending predict an increase in bank equity crash risk and that holders of bank equity have not been compensated for this crash risk in terms of higher bank equity returns. At the bank level, Foos, Norden, and Weber (2010) find that high loan growth predicts high subsequent loan loss provisions and lower

[7] By construction, the textual tone score could be related to either bank-specific and macroeconomic fundamentals, or bank managers' subjective opinions (Jiang et al., 2019), or their expectations about future firm outcomes (Li, 2010; Davis, Piger, and Sedor, 2012) or a combination of both.

returns on assets. Fahlenbrach, Prilmeier, and Stulz (2017) confirms this result and show in addition that high loan growth banks significantly underperform low loan growth banks in terms of stock market returns. Our contribution to this strand of literature is twofold. As we show that decisions on the volume of new loans partially depend on past realizations of economic fundamentals, a potential financial stability implication is that banks extend too much credit in a scenario where recent economic fundamentals were good, but where these fundamentals have already started to deteriorate. As a result, banks will be overly exposed to loan default risk, which threatens their solvency and adversely affects their ability to extend new loans. Furthermore, we show that higher bank manager sentiment is associated with both a higher subsequent loan growth and a lower risk of the banks as perceived by the financial markets. This suggests that bank managers' over-optimism also spills over to their equity investors, who then underestimate the actual riskiness of the banks.

2.3 Data

In this section, we introduce the textual tone score as well as bank-specific and macroeconomic control variables, loan-level variables and bank risk-taking proxy variables used below.

2.3.1 Textual Tone Score

Our textual tone score is based on the bank earnings press releases. Our sample comprises all English language press releases of banks from developed European markets that are available in the database of data provider S&P Global Market Intelligence (SNL, hereafter).[8] Bank earnings press releases in the SNL database are available starting from the first quarter of the year 2005. Our sample ends in the second quarter of the year 2019.

It takes three steps to transform earnings press release documents into final textual tone scores. The first step is to calculate textual tone scores for all earnings press release documents. To process the documents, we use the bag-of-words approach, i.e. for each document, we create a list of all words contained in the document and count how often they appear.[9] Based on the document-specific word lists, we then classify the words as having a positive connotation, having a negative connotation, or as being neutral. The classification is done via the financial dictionary of Loughran and McDonald (2011). We follow Davis, Piger, and Sedor (2012), Huang, Teoh, and Zhang (2013) and Jiang et al. (2019) and calculate the textual tone score, $tone_{i,p,d}$, of the earnings press release document d of bank i for the reporting period p as the difference between the share of words that have a positive connotation,

[8] The Developed Europe category in the S&P Global Market Intelligence database comprises Austria, Belgium, Cyprus, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Luxembourg, Malta, Netherlands, Norway, Portugal, Slovakia, Slovenia, Spain, Sweden, Switzerland and the United Kingdom.

[9] See e.g. Gentzkow, Kelly, and Taddy (2019) for a description of the bag-of-words approach.

$pos_{i,p,d}$, and the share of words that have a negative connotation, $neg_{i,p,d}$, i.e.

$$tone_{i,p,d} = pos_{i,p,d} - neg_{i,p,d}, \quad \text{with} \quad pos_{i,p,d} = \frac{N^{pos}_{i,p,d}}{N_{i,p,d}} \quad \text{and} \quad neg_{i,p,d} = \frac{N^{neg}_{i,p,d}}{N_{i,p,d}}. \tag{2.1}$$

The variables $N^{pos}_{i,p,d}$, $N^{neg}_{i,p,d}$ and $N_{i,p,d}$ count the occurrences of words with a positive connotation, the occurrences of words with negative connotation and the total number of words in document d, respectively. The reporting period p thereby refers to a quarter. If the bank's reporting frequency is semi-annually, press textual tone scores are only available for the second and fourth quarter of any year. In addition, we take negations into account by following Das and Chen (2007) and Renganathan and Low (2010): In the presence of negations ("no", "not", "none",...), we invert the polarity of the sentence (ex: "not good" would be considered as negative). To take care of complex negations, we identify conjunctions („and", "or", "but") and use the following rule: whenever there is a negation in a sentence, we check all the words following this negation, until there is either a punctuation mark or a conjunction. For the words between a negation and a punctuation mark or a conjunction, we then reverse the polarity of any word initially identified as positive or negative.

The second step is to deal with the existence of multiple, possibly differing earnings press release documents from the same bank and for the same reporting period. For simplicity, we solve this issue by combining all textual tone scores by calculating the average, i.e.

$$S_{i,p} = D^{-1}_{i,p} \sum_{d=1}^{D_{i,p}} S_{i,p,d}, \tag{2.2}$$

where S refers to *tone*, *pos* or *neg* and $D_{i,p}$ is the number of earnings press release documents released by bank i at the end of reporting period p.

The third and final step is to align the frequency of all bank-level textual tone score time-series. About one third of the banks in the sample report their earnings on a semi-annual frequency, the remaining banks in the sample report quarterly. We therefore transform all time-series with a quarterly frequency into time-series with a semi-annual frequency. As in the second step, we combine the textual tone scores of banks with a quarterly reporting frequency by calculating a simple average, i.e. $S_{i,t} = 0.5(S_{i,p1} + S_{i,p2})$, where t refers to the first or second half of a given year (e.g. 2006H1), S refers to *tone*, *pos* or *neg* and $p1$ and $p2$ refer to the first and second quarter, respectively, within t. A detailed analysis of the final textual tone scores is presented in Section 2.4.

Our approach to extract textual tone scores from earnings press release documents has one weakness. We are currently not able to determine to which reporting period a specific part of an earnings press release document relates to. As the main purpose of the document is to inform about the performance of the bank during the last reporting period, we treat the whole document as if it relates only to the reporting period that ends at time t. However, earnings press release documents usually also contain forward looking passages and might also contain passages that relate to previous reporting periods. If the latter is the case, the document's textual tone score will be correlated with past fundamentals, which could be a problem for our analysis in Section 2.7. More specifically, our result that the GDP growth rate has incremental predictive power for subsequent realizations of bank manager sentiment could be partially or fully driven by occurrences of passages relating to past reporting periods. Section 2.8 outlines how this weakness could be addressed in order to increase the robustness of our results.

2.3.2 Accounting Data

We merge the textual tone score dataset with a dataset containing semi-annual accounting data of European banks from SNL.[10] To ensure that the accounting data aligns with the content of the press releases documents, we download all variables as they have been originally reported at the end of the respective reporting period. However, if the originally reported values are not available, we use restated accounting values, i.e. accounting values that were changed retrospectively by the bank. The accounting data is available for the reporting periods 2006H1 to 2019H2. Some banks only report key balance sheet variables at the end of the fiscal year. To avoid losing those interim observations in our empirical analysis, we impute these missing values with the average of the value reported at the end of the previous year and the value reported in the same year. The dummy variable *imputed*, which indicates whether the value of at least one variable was imputed, is included in all regressions. Table 2.1 allows to get an overview over the accounting variables used in this paper.

On Table 2.2, we report summary statistics for the intersection of the textual tone score dataset and the accounting dataset as well as for the banks, for which no textual tone scores are available. The summary statistics provided in columns 2–7 of Panel A of Table 2.2 show a considerable variation in the size of the banks in the intersection of the two datasets. Our sample includes both very small (the fifth percentile is €1.45 billion) and also very large banks (the ninety-fifth percentile is €1,275.13 billion), as measured by their total assets (*totalassets*)[11]. The average bank has assets of 228.26 billion, invests the majority of its assets in loans (*loans*), funds about half of its balance sheet via deposits (*deposits*) and is highly reliant on net interest income (*netinterestincome*)[12]. With an average of 2.32 % and a standard deviation of 13.06 %, semi-annual loan growth rates (*loangrowth*) have been on average positive but extremely volatile. The relatively high standard deviation statistic of *loangrowth* indicates

[10] Accounting data with a semi-annual frequency is readily available in SNL. No transformations were necessary on our side.

[11] In our analysis, we only use the log of *totalassets*, which we refer to as *logta*.

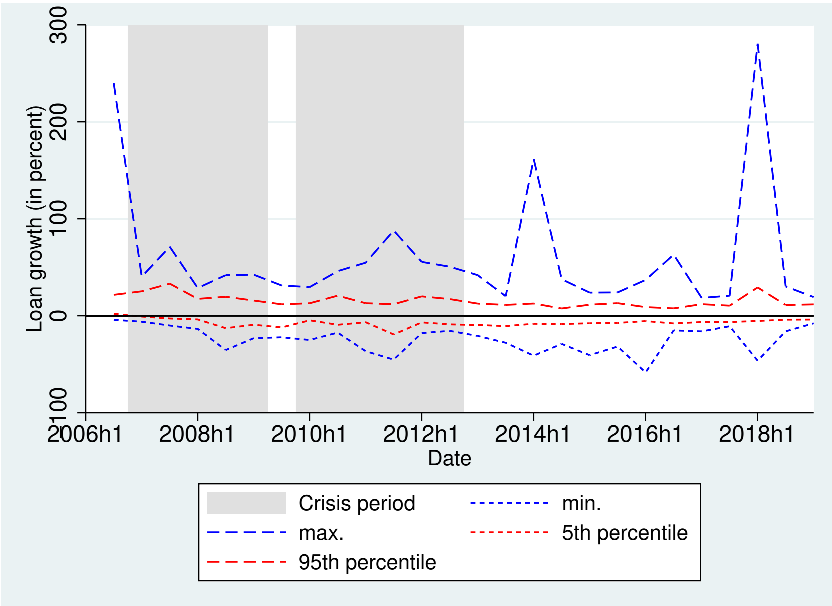
[12] We have winsorized the variable *netinterestincome* so that it lies between 0 and 1. Trading losses, which are a component of net operating income, can lead to values below 0 or above 1, which we set to 0 and 1, respectively.

Table 2.1. List of macroeconomic and financial covariates

Variable	Abbreviation	Source	Comments
Total assets	*totalassets*	SNL	SNL Code: 132264
Net loans to total assets	*loans*	SNL	SNL Codes: 132214 (loans), 132264 (total assets)
Cash to total assets	*cash*	SNL	SNL Codes: 246025 (cash), 132264 (total assets)
Total securities to total assets	*securities*	SNL	SNL Codes: 132191 (cash), 132264 (total assets)
Deposits to total assets	*deposits*	SNL	SNL Codes: 132288 (deposits), 132264 (total assets)
Equity to total assets	*equity*	SNL	SNL Codes: 132385 (equity), 132264 (total assets)
Total debt	*debt*	SNL	SNL Codes: 132319 (total debt), 132264 (total assets)
Operating income to total assets	*operatingincome*	SNL	SNL Codes: 225155 (operating income), 132264 (total assets)
Net interest income to net operating income	*netinterestincome*	SNL	SNL Codes: 132553 (net interest income), 225155 (operating income)
Operating expenses to total assets	*operatingexpenses*	SNL	SNL Codes: 225159 (operating expenses), 132264 (total assets)
Total impairments to total assets	*impairments*	SNL	SNL Codes: 225181 (impairments), 132264 (total assets)
Loan loss reserves to total assets	*reserves*	SNL	SNL Codes: 248860
GDP growth	*gdp*	Eikon Datastream	nominal, seasonally adjusted
Consumer price inflation	*inflation*	Eikon Datastream	–
Three month interbank rate	*interbank*	Eikon Datastream	EURIBOR for Eurozone countries, country-specific LIBOR rates for non-Eurozone countries
Term spread	*term*	Eikon Datastream	yield on benchmark 10-year government bonds - 3-month interbank rates
OIS spread	*ois*	Eikon Datastream	3-month interbank rates - OIS rates
Market capitalization	W	Eikon Datastream	–
Bank stock returns	R_i	Eikon Datastream	total return
Market return	R_m	Eikon Datastream	Return on the MSCI Europe Index

the presence of outliers. An inspection of the distribution of *loangrowth* over the sample period depicted in Figure 2.1 confirms this. To limit the effect that these outliers have on our regression results, we winsorize *loangrowth* by replacing its values below the 5th percentile by the its 5th percentile and values above the 95th percentile by its 95th percentile. The percentiles are thereby calculated from the distribution of *loangrowth* specific to period *t*, i.e. only the distribution of *loangrowth* observed in period *t* is used to winsorize the observations from period *t*. We choose the 5th and the 95th percentiles because these quantiles are both very stable over the sample period and have a sensible magnitude. Finally, bank profitability has been particularly weak during the sample period, which includes the financial crisis of 2007–2009 and the European debt crisis of 2010–2012. On average, operating income (*operatingincome*) was barely sufficient to cover operating expenses (*operatingexpenses*) and impairments on loans and securities (*impairments*).

Figure 2.1. The distribution of loan growth rates over the sample period



In columns 8–13 in Panel A of Table 2.2, one can see that banks that release earnings press release documents systematically differ from banks that do not. The former are on average larger, invest less in loans and are therefore less reliant on net interest income and have lower equity ratios (see also column 14). Our results thus may not necessarily generalize to all European banks. However, since the banks in our textual tone score sample account for a large majority of outstanding loans, our results may nevertheless contribute to our understanding of aggregate credit cycles.

Table 2.2. Summary statistics

Panel A: Bank-level variables	textual tone score sample						No textual tone score available						
Variable	N	mean	std	p5	p50	p95	N	mean	std	p5	p50	p95	*Δmean*
Balance sheet and income variables													
totalassets (in billion Euros)	3,033	228.26	428.94	1.45	45.33	1275.13	3,922	48.06	155.43	0.37	10.71	176.67	180.20***
loans (in %)	3,022	59.38	18.21	23.71	62.03	84.17	3,896	65.22	20.11	19.44	69.80	87.40	-5.84***
cash (in %)	3,027	4.45	5.59	0.09	2.35	15.391	3,841	5.41	9.54	0.13	1.92	18.71	-0.97*
securities (in %)	3,006	22.29	14.15	4.93	19.33	51.40	3,867	17.70	13.48	1.24	14.88	40.73	4.59***
deposits (in%)	3,021	51.16	19.39	18.55	51.84	81.96	3,892	50.72	24.16	0.00	55.95	82.27	0.44
equity (in %)	3,031	7.05	3.89	2.60	6.46	14.08	3,908	8.53	6.15	2.12	7.71	16.47	-1.47***
netinterestincome (in %)	3,033	60.54	21.96	21.14	60.42	100.00	3,922	66.44	21.10	27.03	67.58	100.00	-5.90***
loangrowth (in %)	2,792	2.32	13.06	-7.82	1.39	15.19	3,393	2.63	16.79	-8.22	1.65	13.47	-0.31
Profitability variables													
operatingincome (in %)	3,016	1.33	0.88	0.34	1.23	2.64	3,815	1.45	1.44	0.15	1.19	3.21	-0.12
operatingexpenses (in %)	3,020	0.85	0.55	0.21	0.76	1.71	3,812	0.92	1.20	0.07	0.70	2.06	-0.07
impairments (in %)	3,006	0.30	0.75	-0.02	0.11	1.15	3,839	0.27	0.67	-0.04	0.11	1.04	0.02

Panel B: Macro-level variables	textual tone score sample						No textual tone score available						
Variable	N	mean	std	p5	p50	p95	N	mean	std	p5	p50	p95	*Δmean*
gdp (in %)	3,033	1.22	1.92	-2.08	1.33	3.77	3,886	1.28	1.93	-2.04	1.39	3.82	-0,06
inflation (in %)	3,033	0.71	0.80	-0.40	0.61	2.08	3,886	0.75	0.79	-0.39	0.65	2.21	-0.04
interbank (in %)	3,033	1.07	1.65	-0.33	0.53	4.67	3,886	1.05	1.61	-0.50	0.52	4.67	0.02
term (in %)	3,031	1.71	2.22	-0.46	1.18	4.96	3,884	1.30	1.66	-0.37	0.92	4.08	0.40***
ois (in %)	2,852	0.26	0.30	0.02	0.14	0.76	3,753	0.27	0.30	0.01	0.20	0.84	-0.01

Note: On this table, we present summary statistics for the bank-specific and macroeconomic variables used throughout this paper. The summary statistics are reported for two samples. The summary statistics for the research sample, i.e. banks, for which textual tone score is available, are reported in columns 2–7. Columns 8–13 report the summary statistics for European banks, for which no textual tone scores are available. Column 14 reports the differences in means between both samples, as well as whether the differences are statistically significant at the 10%(*), 5%(**) or 1%(***) level, respectively. The statistical tests are based on standard errors clustered on the bank level.

2.3.3 Macroeconomic Data

We merge macro-level variables downloaded from Refinitiv Datastream and the website of the European Central Bank to the dataset containing the textual tone scores and accounting data. All macro-level variables are country-specific and relate to the same reporting period as the textual tone score and the accounting data.[13] The macro-level variables are GDP growth (nominal, seasonally adjusted; *gdp*), the consumer price inflation rate (*inflation*), the three month interbank rate (*interbank*), the OIS swap rate (*ois*) and the term spread (*term*) (see Table 2.1). The variables *gdp* and *inflation* have publication lags of between 1 and 2 months, i.e. the values of their realizations for period t become only known in the first half of period $t+1$. However, we do not account for publication lags in our main analyses, because we consider these variables as proxies for the economic conditions observed by bank managers during period t.[14] All interest rate variables are semi-annual averages calculated from daily data. The OIS spread is a proxy for the degree of counterparty risk in the interbank market and is calculated as the difference between the three month interbank rate and the three month OIS swap rate (see e.g. Gorton and Metrick, 2012). The term spread is the difference between the ten years government bond yield and the three months interbank rate and proxies for the slope of the yield curve. Given that our sample contains the periods of the European Sovereign Debt Crisis, *term* also captures stress in sovereign debt markets.

In Panel B of Table 2.2, we provide summary statistics for these variables. The sample period includes both boom periods and recessions, as well as periods with very low, even negative interest rates. As column 14 reveals, *term* is on average higher in our research sample than in the sample, for which textual tone scores are not available. This is the result of an over-representation of banks from countries that were affected by the sovereign debt crisis in our textual tone score sample.

2.3.4 Systemic Risk

For the listed banks in our sample, we calculate the systemic risk measure *SRISK* introduced in Brownlees and Engle (2016). *SRISK* is the dependent variable in Section 2.7.2. It is the conditional expectation of the capital shortfall of the bank under a systemic event. The capital shortfall is defined as the difference between required market equity, e.g. due to microprudential regulations, and actual market equity. The systemic event is defined as a multi-period

[13] Given that earnings press release documents and the accounting data are published 1–2 months after the end of a reporting period, at the time of the release, bank managers already have partial information about the macroeconomic environment during the next period. The textual tone score for period t might thus also be related to the realizations of macroeconomic variables between the end of t and the release of the press release document.

[14] Not accounting for publication lags does not seem to pose a problem. Robustness checks (available from the authors upon request), in which we account for these publication lags, yield very similar results.

return of the total equity market that is smaller than a threshold value c. The formula for *SRISK* Brownlees and Engle (2016, p. 52) is

$$SRISK_{i,t} = W_{i,t}\left[kLVG_{i,t} + (1-k)LRMES_{i,t} - 1\right], \tag{2.3}$$

where $W_{i,t}$, $LVG_{i,t}$ and $LRMES_{i,t}$ are the market value of equity, the market leverage ratio (market equity plus the book value of debt (*debt*, hereafter) over market equity) and the Long Run Marginal Expected Shortfall (LRMES), respectively, of bank i in period t. The parameter k represents the leverage ratio requirement. While $W_{i,t}$ and $LRMES_{i,t}$ can in principal be observed daily on the stock market, $LVG_{i,t}$ depends on *debt*, which can only be observed quarterly or semi-annualy.[15] Since the frequency chosen in this paper is semi-annual, $SRISK_{i,t}$ also has a semi-annual frequency. Given that the accounting data used in this study either relates to the six months ending in June or December of a given year, we use market values from the end of June and December, respectively, for all variables that are based on market prices, i.e. $W_{i,t}$ and $LRMES_{i,t}$. LRMES is defined as Brownlees and Engle (2016, p. 53)

$$LRMES_{i,t} = -E_t\left(R_{i,t+1:t+h}|R_{m,t+1:t+h} < c\right). \tag{2.4}$$

The variables $R_{i,t+1:t+h}$ and $R_{m,t+1:t+h}$ are the multi-period returns of bank i and the stock market, respectively, where the parameter h defines the horizon over which the returns are calculated. To obtain $W_{i,t}$ and $LVG_{i,t}$, we download market values from Datastream and *debt* from SNL. We use Datastream to obtain bank stock returns and the return on the stock market, which are the inputs to the calculation of the LRMES. As a proxy for the European stock market, we use the MSCI Europe Index.

To calculate the LRMES of a bank, we assume that its stock return and that of the market are generated by a bivariate normal distribution with mean zero. The bivariate normal model has the advantage that it has an (approximate) closed-form solution (Brownlees and Engle, 2016). The parameters to be estimated are the standard deviation of the market return ($\sigma_{m,t}$), the standard deviation of the stock return of the bank ($\sigma_{i,t}$) and their coefficient of correlation ($\rho_{i,t}$). Given $\sigma_{i,t}$, $\sigma_{m,t}$ and $\rho_{i,t}$, the LRMES of bank i at time t can be approximated by Brownlees and Engle (2016, p. 55)

$$LRMES_{i,t} \approx \sqrt{h}\rho_{i,t}\sigma_{i,t}\frac{\phi(\frac{c}{\sigma_{m,t}})}{\Phi(\frac{c}{\sigma_{m,t}})}, \tag{2.5}$$

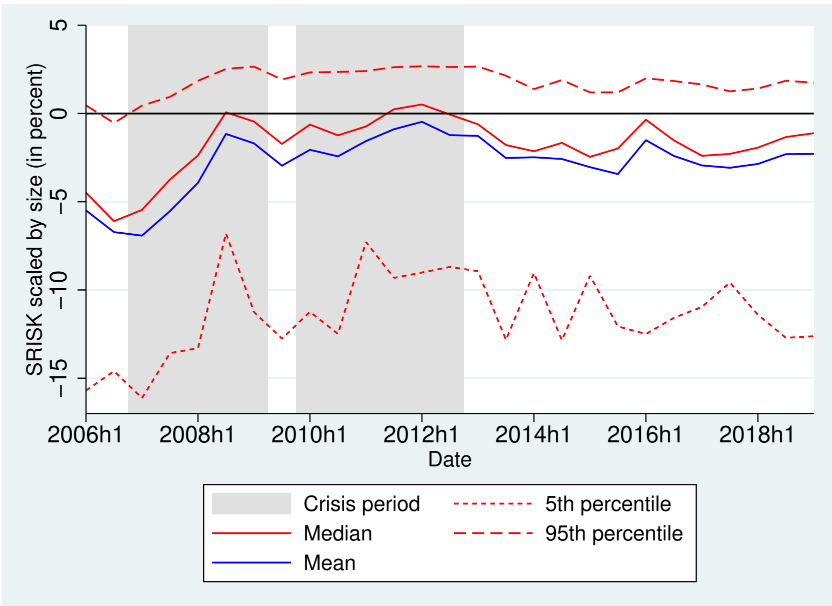
where $\phi(\cdot)$ and $\Phi(\cdot)$ are the normal distributions' density and distribution function, respectively. Since these values are likely to be dynamic, we estimate $\sigma_{i,t}$, $\sigma_{m,t}$ and $\rho_{i,t}$ with a

[15] Due to the publication lag of *debt*, the realization of $LVG_{i,t}$ becomes known only after the end of period t. We implicitly assume that the market participants can forecast *debt*.

rolling window of 60 months of stock return data, i.e. each parameter is estimated with the monthly returns between $t-59$ and t. With regard to the parameters h and c, we adopt the values chosen by Brownlees and Engle (2016) and set them to 1 month and 10 %, respectively. We set the parameter k to 3 %, which corresponds to the current Basel III leverage ratio requirement. Since it is measured in Euros, we scale *SRISK* by the enterprise value of the bank, i.e. we divide it by the sum of its market equity and the book value of its debt $(W_{i,t} + debt_{i,t})$.[16]

In Figure 2.2, we plot the distribution of scaled *SRISK* over the sample period. *SRISK* has been negative on average in the large majority of periods, meaning that the banks in our sample had capital surpluses on average. Periods with particular high levels of risk have been the second half of 2008 (the global financial crisis), the first half of 2012 (the European sovereign debt crisis) and the first half of 2016 (the Brexit referendum). In the cross-section, the dispersion between banks remains relatively stable over time. While the 25 % most risky banks had a conditional expected capital shortfall in the majority of periods, the 25 % least risky banks had conditional expected capital surpluses. With the exception of the year 2012, median *SRISK* has been negative over the sample period.

Figure 2.2. The distribution of SRISK over the sample period



[16] We scale by enterprise value and not by the size of the balance sheet, because *SRISK* is based on market equity.

2.3.5 Loan-level data

As shown by the literature, the use of bank-level data may suffer from an omitted-variable bias (Kashyap and Stein, 2000; Khwaja and Mian, 2008), in particular due to loan demand. To control for loan demand, we use the loan-level data provided by Dealscan. Dealscan is a database that contains detailed information for syndicated loan transactions (amount lent, transaction date, list of participating banks, shares of each participating bank in the loan, borrower's name and Legal Entity Identifier, covenants, etc). Syndicated loans can be structured in several tranches, which is more likely for larger loans. Even though the participants, the structure of the syndicate and general pricing terms are typically determined at the deal level, tranches differ by their active date, maturity, amount and loan type (term loan vs. revolver line). For this reason, we define the loan shares of a bank within a syndicated loan as the share of this bank within each tranche. We also drop tranche amendments as those could be related to the borrower's loan demand.

On Table 2.3, we present the summary statistics for those tranches. In Panel A, we look at the individual tranches held partly or fully by at least one of the banks with a bank manager sentiment in our sample. We find around 12,000 individual tranches. The average tranche amount is EUR 407 millions, but with a lot of variation (the standard deviation is more than EUR 1 billion). The average tranche maturity is 5.9 years, but again with a lot of dispersion (5 years of standard deviation).

In Panel B, we focus on the average share and amount of an individual tranche acquired by each bank in our sample of banks with a bank manager sentiment. In terms of share, on average, a bank acquires 18.0% of a of tranche, or equivalently EUR 46.4 millions. In both cases, the dispersion is quite high, the acquired share ranging between 1.9% (5th percentile) and 50.0% (95th percentile) of an individual tranche. Similarly, the acquired amount ranges between less than EUR 1 million (5th percentile) and EUR 156.8 million (95th percentile) of an individual tranche.

In Panel C, we aggregate the individual tranche data at the bank-semester-level. Out of the 3,000 banks for which we were able to calculate bank manager sentiment, we manage to find around one third in the Dealscan database. Among the banks with bank manager sentiment, the banks present in the Dealscan database are the biggest ones (with EUR 469.3 billion of total assets including EUR 204.5 billions of loans on average, first and second rows of Panel C), even though a few smaller banks are also present (5th percentile is EUR 21 billions of total assets). Those banks acquire on average 24 tranche shares each semester (third row), but this number varies a lot (5th and 95th percentiles are 1 and 99 shares respectively). As indicated by the fourth row of Panel C, the use of Dealscan allows us to control for loan demand, but comes at the cost of the representativeness of the European total loan market. On average, a bank acquires EUR 1.14 billion of syndicate loan tranche shares every semester. Given that the average maturity of an individual tranche is 5.9 years [17] and that a bank has EUR 204.5 billions of loans in total, the syndicated loan data only correspond to around 6.6% of total bank lending in our sample.

Table 2.3. Dealscan summary statistics

Panel A: Tranches summary statistics						
Variable	N	mean	std	p5	p50	p95
trancheamount (in million Euros)	12,057	406.92	1,140.60	3.95	126.74	1,532.09
tranchematurity (in years)	11,695	5.93	5.10	1.00	5.00	18.01
Panel B: Bank-tranche summary statistics						
Variable	N	mean	std	p5	p50	p95
loanshare (in %)	26,209	18.01	20.72	1.85	10.25	50.00
loanshare ∗ *trancheamount* (in million Euros)	26,201	46.44	111.76	0.84	20.64	156.78
Panel C: Summary statistics of the aggregated tranches at the bank-semester-level						
Variable	N	mean	std	p5	p50	p95
totalassets (in billion Euros)	1072	469.25	551.24	21.08	229.87	1770.66
loans (in billion Euros)	1,049	204.52	205.09	14.31	128.18	682.96
numberofshares	1072	24.45	33.24	1	9	99
totalshareamount (in billion Euros)	1,072	1.14	1.92	0.01	0.29	5.57

Note: In Panel A, we present tranche-level summary statistics for the following variables: *trancheamount* which represents the individual tranche amount in EUR millions and *tranchematurity* which represents the maturity in years of the individual tranches present in our sample. In Panel B, we present bank-tranche-level statistics for the following variables: *loanshare* which represents the share in % that a bank in our samples acquires in a given tranche and *loanshare* ∗ *trancheamount* which represents the corresponding amount in million Euros that a bank in our samples acquires in a given tranche. In Panel C, we present summary statistics of the aggregated tranches at the bank-semester-level for the following variables: *totalassets* and *loans* which represent the total assets and loans (in EUR billions Euros) respectively, indicated in a bank's balance sheet for the banks in our sample with a manager sentiment and present in the Dealscan database, *numberofshares* the number of tranche shares acquired by a given bank each semester and *totalshareamount* the equivalent amount of tranche shares acquired by a given bank each semester in EUR billions.

[17] Weighing the tranche maturity by its amount only slightly changed the maturity to 4.2 years.

2.3.6 Bank risk-taking proxy variables

To study the risk-taking behaviour of banks, we follow Heider, Saidi, and Schepens (2019) and build proxy variables for the risk profile of each borrower present in our loan-level sample. To do so, we use Bureau van Dijk's Orbis database to have some balance sheet information about each of those borrowers.[18] Orbis database is an extensive database containing detailed information about private and public companies worldwide. In particular, Orbis database provides indidvidual financial statements, ratios and valuation data. We exploit this data to proxy the risk profile of each borrower by following Heider, Saidi, and Schepens (2019). Heider, Saidi, and Schepens (2019) use the log-volatility of the return on asset over the last 5 years or of monthly stock returns over the last 3 years. We adopt a similar approach and use alternatively the 3-year and 5-year log-volatilities of the following financial variables for the borrowers: return on equity (*ROE*), return on assets (*ROA*), net income over assets (*netincome*) and profit margin (*profitmargin*). We present statistics for the financial variables themselves and for their corresponding 3-year and 5-year log-volatilities.

On Table 2.4, we present summary statistics for the borrowers' financial variables as well as for the 3-year and 5-year log-volatilities of those financial variables.[19] We start with the summary statistics for the financial variables (Panel A). The median borrower is profitable, with a return on equity of 10.6%, a return on assets of 3.0%, a net income over assets of 13.9% and a profit margin of 7.0%. However, there is a very high dispersion across the different borrowers as indicated by the large standard deviations and the strongly negative (positive) 5th (95th) percentiles. In particular, the return on equity and the profit margin have a standard deviation of 63.6 percentage points and 23.5 percentage points respectively.

In Panel B and C, we present summary statistics for the 3-year and the 5-year log-volatilities of the borrowers' financial variables respectively. As shown by Panel B, the log-volatilities are the highest for return on equity and profit margin. Compared with Panel B, the 5-year log-volatilities shown in Panel C allow to capture longer dynamics, but also reduce the number of observations by one third. The conclusions are similar to the ones of Panel B, but with higher average log-volatilities and slightly lower dispersion (as indicated by the smaller standard deviation and difference between the 5th and the 95th percentiles).

[18] We follow Sebnem et al. (2015) in preparing the raw Orbis data.
[19] The statistics shown in Table 2.4 and then used in the subsequent regressions of the paper are winsorized at the 1st and the 99th percentiles to remove the influence of outliers.

Table 2.4. Summary statistics of the borrowers' financial variables and of their log-volatilities

Panel A: Borrowers' financial variables						
Variable	N	mean	std	p5	p50	p95
ROE (in %)	102,846	10.44	63.55	-37.70	10.58	59.27
ROA (in %)	107,614	3.49	8.76	-9.38	2.96	17.58
netincome (in %)	107,098	2.35	7.70	-9.39	2.24	13.86
profitmargin (in %)	99,468	9.63	23.59	-25.60	6.99	50.38
Panel B: 3-year log-volatility of each borrowers' financial variables						
Variable	N	mean	std	p5	p50	p95
ROE (in %)	76435	1.60	1.34	-0.51	1.56	3.89
ROA (in %)	80,248	0.35	1.30	-1.93	0.46	2.26
netincome (in %)	79,660	0.23	1.35	-2.13	0.35	2.21
profitmargin (in %)	73,080	1.09	1.33	-1.14	1.12	3.19
Panel C: 5-year log-volatility of each borrowers' financial variables						
Variable	N	mean	std	p5	p50	p95
ROE (in %)	54,290	2.00	1.17	0.21	1.93	4.08
ROA (in %)	57,005	0.74	1.13	-1.27	0.86	2.37
netincome (in %)	56,504	0.62	1.18	-1.48	0.73	2.32
profitmargin (in %)	51,676	1.47	1.15	-0.47	1.51	3.29

Note: In Panel A of this table, we present summary statistics for the following borrowers' financial variables used throughout this paper (*ROE*, *ROA*, *netincome* and *profitmargin*). In Panel B and C, we present summary statistics for the 3-year and 5-year log-volatilities of those financial variables respectively. In the rest of the paper, we use those log-volatilities to define the riskiness profile of a given borrower and study bank risk-taking behaviour.

2.4 The Properties of Textual Tone Scores

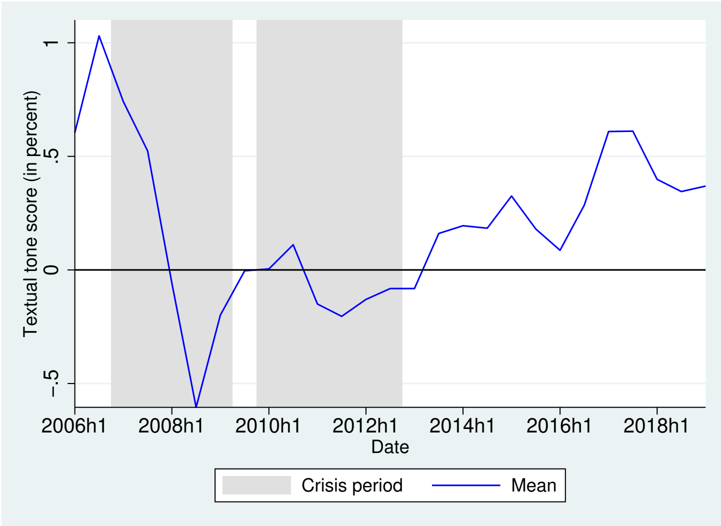
The aim of this section is to verify the validity of our textual tone scores. We first study the developments of the textual tone scores and the shares of positive and negative words, respectively, over time from the dictionary approach. We also compare the textual tone score using the dictionary approach with the one obtained using the machine learning approach. We then explore the relationship between the textual tone score obtained from the dictionary approach and its two components (i.e. *tone*, *pos* and *neg*) and important bank-specific and macroeconomic variables.

2.4.1 Textual Tone Scores over Time

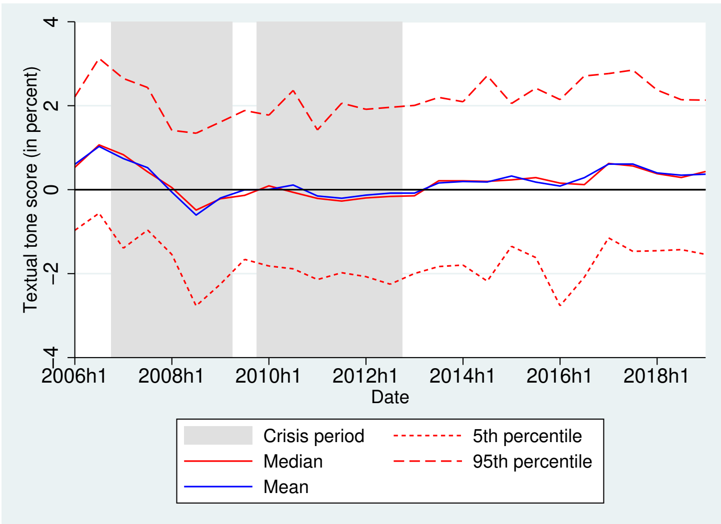
In Figures 2.3a and 2.3b, we plot the evolution of the textual tone score using the dictionary approach over the sample period. As can be seen on Figure 2.3a, the average textual tone score is pro-cyclical. Consistent with global events, the average of *tone* is negative in the crisis years 2008 and 2009 (i.e. during the global financial crisis) and 2011 to 2013 (i.e. during the European sovereign debt crisis) and positive in boom periods, i.e. before the year 2008 and after the year 2013. Average *tone* starts to decrease in 2007, remains around zero between the end of 2009 and 2013 and recovers afterwards. As can be seen on Figure 2.3b, this pro-cyclicality is an aspect which is consistent across the distribution of banks. In Figure 2.3c, one can see that the decrease in average *tone* before the financial crisis is predominantly driven by an increase in the average of *neg*. While the average of *neg* doubles between 2007H1 and 2008H2 (from 0.98 % to 1.99 %), the average of *pos* only decreases by about 19.17 % (from 1.71 % to 1.39 %). The upward trend in the average of *tone*, which has its start in the year 2013, is driven by opposing trends in *pos* and *neg*.

The dictionary approach has however some limitations (to take into account complex negations, sentences formulations, conjunctions, irony, etc). To tackle this issue, we do a robustness check by using a machine learning approach as an alternative method to compute our textual tone score. More specifically, we use FinBERT, a financial domain specific BERT (Bidirectional Encoder Representation from Transformers) model created by Yang, Uy, and Huang (2020). As for the dictionary approach, we compute the average textual tone score over time and its distribution across banks. We also estimate the micro-level correlation and rank correlation of both approaches. As we show in Appendix 2.A, the textual tone scores we obtain from the dictionary and the machine learning approaches have a very similar evolution over time (both on average and in terms of distribution), have a significant and positive correlation (both with and without bank and time fixed effects) and have a significant and positive Spearman's rank correlation (both for the whole sample period and for each semester taken separately, independently of the economic environment).
Given the similarities of the textual tone scores obtained from both approaches, we choose to focus on the textual tone score obtained from the dictionary approach (*tone*) in the rest of the paper.

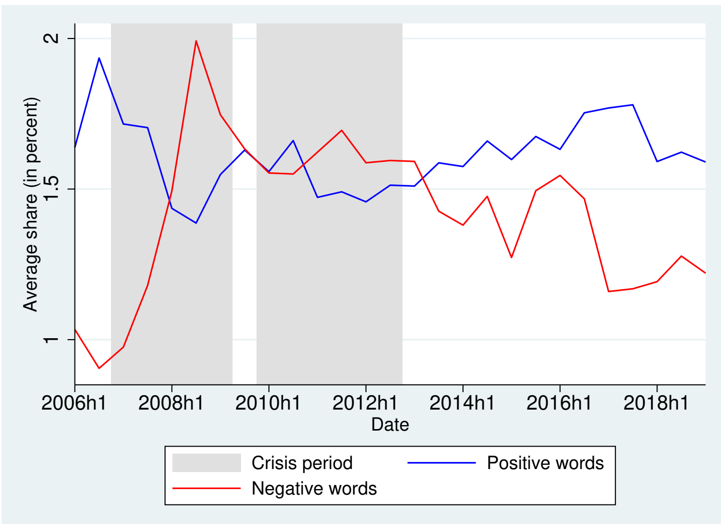
Figure 2.3. Textual tone score (dictionary approach)



(a) Average textual tone score over time



(b) The distribution of the textual tone score over time



(c) The averages of *pos* and *neg*

Note: In these figures, we plot properties of the average textual tone score using the dictionary approach (Figure 2.3a), the distributions of *tone* (Figure 2.3b), *pos* and *neg* (Figure 2.3c) over the sample period. The vertical lines indicate the start of the global financial crisis, the end of the global financial crisis and the end of the European sovereign debt crisis, respectively.

2.4.2 Textual Tone Scores at the Bank Level

To shed some light on the informational content of the textual tone scores, we run separate regressions of *tone*, *pos* and *neg* on a set of bank characteristics, macroeconomic state variables, country fixed effects and bank fixed effects. The bank-specific and country-specific variables come from three categories: profitability measures, bank business model indicators and macroeconomic state variables. The profitability variables are *operatingincome*, *operatingexpenses* and *impairments*. Given that textual tone scores are extracted from earnings press release documents, we expect that the profitability variables are directly related to *tone*. The business model indicators include *loans*, *deposits*, *equity*, *netinterestincome* and the logarithm of *totalassets*. The motivation for the inclusion of the business model proxy variables is that some bank business models may have been more successful than others since 2006, which we expect to be reflected in *tone*. Finally, the set of country-specific macroeconomic state variables encompasses *gdp*, *inflation*, *interbank*, *term* and *ois*. Since a more favorable macroeconomic environment, i.e. high values of *gdp* and *term* and low values of *ois*, is positive for the business of banks, we expect the first two variables to be positively associated with *tone* and *ois* to be negatively associated with *tone*.

2.4.2.1 Country-Specific and Bank-Specific Differences in Textual Tone Scores

Differences in culture and communication styles across countries and banks may have a significant impact on textual tone scores. Under the assumption that these differences are constant over time, we first attempt to quantify the incremental explanatory power of country and bank fixed effects. Adjusted R^2 statistics from separate regressions of *tone*, *pos* and *neg* on profitability, business model, macroeconomic, country dummy and bank dummy variables are documented in Table 2.5. The first column reports the results from our baseline regression model, which only includes the profitability, business model and macroeconomic variables. The adjusted R^2 statistics range from 8.50 % for *pos* to 18.50 % for *neg*. The majority of the variation in the textual tone score and its components thus remains unaccounted for. Next, we include country dummy variables to measure the incremental explanatory power of country fixed effects. Looking at the second column of Table 2.5, one can see that country fixed effects have sizable explanatory power for both the textual tone score and its two components. With an increase of approximately 138 %, *pos* sees the highest relative increase, suggesting that country-specific factors are an especially important determinant of the occurrence of words with a positive connotation in earnings press release documents. Finally, we replace the country dummy variables by bank dummy variables, which produces the highest increases in adjusted R^2. As we show in the third column of Table 2.5, bank fixed effects account for over 50 % of the variation in the dependent variables. The incremental explanatory power of bank fixed effects relative to the baseline specifications ranges from 35.40 to 42.40 percentage points. These results indicate that bank fixed effects are the most important determinant of *tone*, *pos* and *neg*. They also highlight the necessity to control for bank fixed effects in the following investigations.

Table 2.5. Country-specific and bank-specific differences in textual tone scores

	(1)	(2)	(3)
Adjusted R^2 (in %)	I (baseline)	II	III
tone	16.80	29.70	55.70
pos	8.50	20.20	51.10
neg	18.50	31.80	53.90

Note: In this table, we report adjusted R^2 statistics from separate regressions of *tone*, *pos* and *neg* on bank-specific and country-specific macroeconomic variables, country fixed effects and bank fixed effects. The baseline model (I) only includes the profitability, business model and macroeconomic variables. The second model (II) is augmented by country fixed effects. In the third model (III), country fixed effects are replaced by bank fixed effects.

2.4.2.2 The Textual Tone Score, Bank Characteristics and the Macroeconomic Environment

Next, we study the relationships between the three textual tone score variables (*tone*, *pos* and *neg*) and the profitability, business model and macroeconomic state variables in detail. The empirical model is

$$S_{i,t} = \alpha + \boldsymbol{X}_{i,t}^{profit} \boldsymbol{\beta}^{profit} + \boldsymbol{X}_{i,t}^{bm} \boldsymbol{\beta}^{bm} + \boldsymbol{X}_{c,t}^{macro} \boldsymbol{\beta}^{macro} + u_i + v_h + \epsilon_{i,t}, \tag{2.6}$$

where i indexes banks, t indexes time (e.g. 2006H1), c indexes countries and h indicates whether t relates to the first or second half of the year. The variable $S_{i,t}$ refers to $tone_{i,t}$, $pos_{i,t}$ or $neg_{i,t}$ of bank i in period t. The vectors $\boldsymbol{X}_{i,t}^{profit}$, $\boldsymbol{X}_{i,t}^{bm}$ and $\boldsymbol{X}_{i,t}^{macro}$ hold the profitability, business model and macroeconomic variables, respectively. We further include bank fixed effects u_i and season dummies (i.e. half-year fixed effects) v_h to control for time-invariant unobservables specific to each bank and to seasonal effects, respectively.[20]

The regression results are reported in Table 2.6. The variable *impairments* is the profitability variable in the regression of *tone* having the highest statistical significance (column 1). On average, higher impairments are associated with a decrease in *pos* (column 2), an increase in *neg* (column 3) and consequently a decrease in *tone*. While the variable *operatingincome* has a positive and statistically significant relationship with *tone* and *pos*, the variable *operatingexpenses* is statistically insignificant in all three regressions.

Of the business model variables, *netinterestincome* is statistically significant at the 1 % level while *deposits* and *equity* are statistically significant at the 5 % level. A more stable

[20] Time and country-time fixed effects are not included because they would absorb a large fraction of the variation in bank-specific and macroeconomic variables.

funding structure, i.e. higher ratios of deposits and equity to total assets, is on average associated with higher levels of *tone*. In terms of economic significance, *deposits* is the most important variable in the regression. Lastly, a larger dependence on net interest income is associated with lower textual tone score on average, whereby larger values of *netinterestincome* coincide with lower values of *pos* and higher values of *neg* on average.

Of the macroeconomic variables, all variables with exception of *inflation* are statistically significant at the 1 % or at the 5 % level. While *gdp* and *interbank* are on average positively associated with *tone*, the variables *term* and *ois* are on average negatively associated with *tone*. All four variables are thereby only associated with *neg*. The negative coefficient on *termspread* is unexpected, given that banks typically engage in maturity transformation, which is more profitable when the spread between long-term and short-term rates is larger. However, since the European sovereign debt crisis falls within the sample period, *term* might also measure sovereign risk, which we expect to be negatively associated with our textual tone score.

To summarize, the results of the analyses carried out in this section strongly suggest that the textual tone score captures relevant information about the fundamentals of the bank. The development of the textual tone score over the sample period is consistent with global events. Moreover, the textual tone score and its components co-vary with important profitability, business model and macroeconomic variables, whereas the directions of these relationships are, with the exception of the term spread, as expected.

2.5 Bank Manager Sentiment

Starting from this section, we introduce the notion of bank manager sentiment, i.e. bank managers' over-optimism or over-pessimism. We first show how we estimate bank manager sentiment. Then, we show that our estimate indeed captures bank managers' over-optimism or over-pessimism and not bank managers' private information via two tests: the extrapolative structure of our estimate, and whether our estimate predicts subsequent bank financial performance.

2.5.1 Estimating Bank Manager Sentiment

We estimate bank manager sentiment as the variation in the textual tone score orthogonal to contemporaneous realizations of economic and bank-specific fundamentals. We don't use a residual approach, which would be biased. The residual approach in our case would be equivalent to first estimate the bank manager sentiment by estimating the following regression:

$$S_{i,t} = \alpha + \boldsymbol{\beta} \boldsymbol{X}_{i,t} + u_i + v_h + S^*_{i,t}, \tag{2.7}$$

Table 2.6. Textual tone score, bank characteristics and the macroeconomic environment.

	(1)	(2)	(3)
	$tone_t$	pos_t	neg_t
$impairments_t$	-0.12***	-0.07***	0.11***
	(0.02)	(0.02)	(0.03)
$operatingincome_t$	0.10*	0.09**	-0.06
	(0.06)	(0.04)	(0.05)
$operatingexpenses_t$	-0.02	0.02	0.05
	(0.06)	(0.06)	(0.05)
$logta_t$	0.29	0.23	-0.21
	(0.26)	(0.28)	(0.23)
$loans_t$	0.05	-0.07	-0.15**
	(0.07)	(0.07)	(0.08)
$deposits_t$	0.22**	0.22***	-0.12
	(0.09)	(0.08)	(0.09)
$equity_t$	0.10**	0.05	-0.10**
	(0.05)	(0.04)	(0.05)
$netinterestincome_t$	-0.12***	-0.07**	0.12***
	(0.03)	(0.03)	(0.03)
gdp_t	0.07***	0.02	-0.09***
	(0.02)	(0.02)	(0.02)
$inflation_t$	-0.00	0.00	0.00
	(0.02)	(0.02)	(0.02)
$interbank_t$	0.13***	0.04	-0.17***
	(0.04)	(0.04)	(0.04)
$term_t$	-0.08**	-0.02	0.10***
	(0.03)	(0.03)	(0.04)
ois_t	-0.14***	-0.02	0.19***
	(0.02)	(0.02)	(0.03)
imputed	0.05	0.06	-0.01
	(0.06)	(0.06)	(0.06)
Constant	0.98***	0.58***	-0.93***
	(0.10)	(0.10)	(0.10)
Bank fixed effects	Yes	Yes	Yes
Season fixed effects	Yes	Yes	Yes
N	2,805	2,805	2,805
R^2	0.59	0.55	0.58
Adj. R^2	0.56	0.51	0.54

Note: In this table, we document the results of separate regressions of *tone*, *pos* and *neg* on bank-specific and macroeconomic variables. All variables are standardized. The variable *imputed* indicates whether missing values for an observation have been estimated via interpolation. The standard errors are clustered on the bank level and are reported in parentheses. Bank fixed effects are included as dummy variables. ***, ** and * refer to significance levels of 1%, 5% and 10%, respectively.

where $S_{i,t}$ refers to $tone_{i,t}$, $pos_{i,t}$ or $neg_{i,t}$ of bank i in period t, α is a constant, $\boldsymbol{X_{i,t}} = \left(X^{profit}_{i,t}, X^{bm}_{i,t}, X^{macro}_{i,t}\right)$, u_i and v_h hold for bank fixed effects and season dummies (i.e. half-year fixed effects) respectively, and $S^*_{i,t}$ is the residual. We would then extract the residual of the question above $S^*_{i,t}$ and estimate in a second step our regression of interest. Taking the example of the extrapolative structure of bank manager sentiment (i.e. whether bank manager sentiment is associated with past realizations of economic and financial fundamentals), we would estimate the following regression:

$$S^*_{i,t} = \alpha + \beta_1 S^*_{i,t-1} + \boldsymbol{\beta_2 X}_{i,t-1} + v_h + u_i + \epsilon_{i,t}, \tag{2.8}$$

Now, assume that we find that bank manager sentiment is indeed extrapolative, this would imply that β_2 is positive and significantly different from 0, i.e. that $S^*_{i,t}$ is correlated with $X_{i,t-1}$. But this in turn would imply that, for having an unbiased estimation of regression 2.7 (and hence of the bank manager sentiment), we would need to assume that $S^*_{i,t}$ is uncorrelated with $\boldsymbol{X}_{i,t}$. Given that S_i, t^* is correlated with $\boldsymbol{X}_{i,t-1}$, we hence need to assume that the vector $\boldsymbol{X}_{i,t}$ is not autocorrelated, which is a strong assumption given the macroeconomic and financial variables it represents. To avoid this bias, we boil down the first and second step regression in one single regression. This is equivalent to studying the textual tone score $tone_{i,t}$ while controlling for the contemporaneous realizations of economic and bank-specific variables and fixed effects, so that we can interpret the coefficients of interest as the influence of bank manager sentiment. As this reasoning is also valid for the other regressions in the rest of this paper, we implement the same strategy.[21]

2.5.2 Do Bank Managers Extrapolate Past Fundamentals?

Our estimate of bank manager sentiment, i.e. the variation in the textual tone score orthogonal to contemporaneous realizations of economic and bank-specific fundamentals, could capture different elements. In particular, it could either capture the over-optimism/pessimism of bank managers or some private information of the bank managers that is not yet observed in the contemporaneous fundamentals. In order to check that our estimate indeed captures over-optimism/pessimism of the bank managers rather than private information, we implement two tests. In a first test, we explore whether our estimate of bank manager sentiment has an extrapolative structure, i.e. whether it is associated with past realizations of economic and financial fundamentals. Expectations with an extrapolative structure imply over-optimism: if expectations depend on past realizations of economic fundamentals, the logical implication is that expectations will not be fully in line with current fundamentals.

[21] Note that we get very similar results when using the residual approach.

Thus, relative to current fundamentals, expectations will be too high, i.e. excessively optimistic, or too low, i.e. excessively pessimistic. We therefore estimate the model:

$$S_{i,t} = \alpha + \sum_{l=1}^{2} \beta_l S_{i,t-l} + \sum_{l=0}^{2} \gamma_l \boldsymbol{X}_{i,t-l} + \nu_h + u_i + \epsilon_{i,t} \tag{2.9}$$

where the variable $S_{i,t}$ represents either $tone_{i,t}$, $pos_{i,t}$ or $neg_{i,t}$, respectively. The bank-specific and macroeconomic state variables are represented by $\boldsymbol{X} = \left(X_{i,t}^{profit}, X_{i,t}^{bm}, X_{i,t}^{macro}\right)$. The variables u_i and ν_h hold for bank and seasonal fixed effects to control for unobserved time-invariant bank heterogeneity and seasonal effects, respectively. Importantly, controlling for the contemporaneous realizations of the bank-specific, macroeconomic and business-model variables, and for the bank and seasonal fixed effects allows us to interpret the coefficients on the variables of interest ($\boldsymbol{\gamma}_1$ and $\boldsymbol{\gamma}_2$, i.e. the coefficients on $\boldsymbol{X}_{i,t-1}$ and $\boldsymbol{X}_{i,t-2}$, the bank-specific and macroeconomic state variables lagged by one and two semesters, respectively) as the relation between past bank-specific and macroeconomic state variables on the one hand, and contemporaneous bank manager sentiment on the other hand. We also control for lagged bank textual tone scores variables ($S_{i,t-1}$ and $S_{i,t-2}$) to control for autocorrelation.

In table 2.7, we document the regression results.[22] We begin by estimating Equation (2.9) without controlling for auto-correlation, i.e. we drop $S_{i,t-1}$ and $S_{i,t-2}$. The results of these regressions are shown in columns 1 to 3. These columns reveal that there is a statistically significant relationship between the first lag of *gdp* and the one of *ois* on the one hand and *tone* on the other hand (column 1), as well as both components of the latter, except between *neg* and *ois* (columns 2 and 3), while controlling for contemporaneous bank-specific and economic fundamentals. A one standard deviation increase in the first lag of *gdp* is associated with an average increase in bank manager sentiment of approximately 0.08 standard deviation. While lagged *gdp* is positively associated with *pos*, it is negatively associated with *neg*. Conversely, a one standard deviation increase in the first lag of *ois* is associated with an average decrease in *tone* of approximately 0.11 standard deviation. Lagged *ois* is negatively associated with *pos*, and positively associated with *neg* (even though coefficient on the latter is not statistically significant). When focusing on the second lags of *gdp* and *ois*, the significance of the association with bank manager sentiment and its components fades out.

Next, we estimate Equation (2.9), i.e. we do not drop the lagged textual tone score variables. In Columns 4 to 6 of Table 2.7, we document the regression results. The coefficients on the first and second lagged values of *tone* (i.e. β_1 and β_2, respectively) are all positive

[22] For results readability and as we are not interested in interpreting the coefficients of the contemporaneous and lagged values of bank business model (which rather depend on the long-term strategy of banks), we control for $X_{i,t}^{bm}$, $X_{i,t-1}^{bm}$ and $X_{i,t-2}^{bm}$, but we don't include their coefficient values in table 2.7. Those coefficient values are available from the authors upon request

and statistically significant at the 1% level, suggesting a strong and persistent autocorrelation of those variables. With respect to *gdp*, controlling for lagged sentiment has virtually no impact on the interpretation of its coefficients in the regressions of *tone*, *pos* and *neg*, but reduces their significance. In contrast, *ois* is now not significant anymore albeit the sign of the coefficients stays the same. The interpretation of the results for the second lag of *gdp* and of *ois* are the same as without controlling for autocorrelation, i.e. the coefficients are insignificant. The result that bank managers seem to extrapolate past realizations of *gdp* remains valid when we use the Arellano–Bover/Blundell–Bond system estimator to estimate Equation (2.9) (columns 7–9 of Table 2.7).[23] The result is significant for the first lag of *gdp* at the 1% level for both *tone* and *pos*, but insignificant for *neg*. As in the previous specifications, the second lag of *gdp* is insignificant for both *tone*, *pos* and *neg*. The strong autocorrelation is also still present in this last specification where both first and second lags of *tone* and its components are positive and significant at the 1% or at the 5% level (with the exception of the first lag of *pos*).

In summary, the evidence reported in Table 2.7 is consistent with the hypothesis that bank managers extrapolate economic fundamentals into the future. Past realizations of *gdp* have incremental predictive power for subsequent realizations of bank manager sentiment. Furthermore, the results suggest that bank manager sentiment is strongly auto-correlated, implying that innovations in variables that were found to be correlated with *tone* are also associated with subsequent realizations of *tone*, even after controlling for contemporaneous realizations of bank-specific and macroeconomic fundamentals.

[23] The Arellano–Bover/Blundell–Bond system estimator produces consistent estimates of the coefficients of interest in a dynamic panel setting (Arellano and Bond, 1991; Blundell and Bond, 1998). In a dynamic panel setting, a bias may arise because the first lag of the dependent variable and the error term are correlated (see e.g. Baltagi, 2008). Although this bias decreases with the number of periods (Nickell, 1981), Judson and Owen (1999) show that it can be still quite large when the panel length is as large as 30.

Table 2.7. Is bank manager sentiment extrapolative in economic fundamentals?

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$tone_{i,t}$	$pos_{i,t}$	$neg_{i,t}$	$tone_{i,t}$	$pos_{i,t}$	$neg_{i,t}$	$tone_{i,t}$	$pos_{i,t}$	$neg_{i,t}$
$impairments_{i,t}$	-0.15***	-0.09***	0.14***	-0.14***	-0.08***	0.14***	-0.14***	-0.05**	0.15***
	(0.03)	(0.02)	(0.04)	(0.03)	(0.02)	(0.04)	(0.04)	(0.03)	(0.05)
$operatingincome_{i,t}$	0.24***	0.22***	-0.16**	0.24***	0.22***	-0.16**	0.22***	0.18**	-0.12
	(0.07)	(0.07)	(0.07)	(0.07)	(0.06)	(0.07)	(0.08)	(0.08)	(0.08)
$operatingexpenses_{i,t}$	-0.03	-0.04	0.01	-0.06	-0.05	0.05	-0.21**	-0.11	0.16
	(0.08)	(0.07)	(0.09)	(0.08)	(0.07)	(0.09)	(0.09)	(0.08)	(0.10)
gdp_t	0.08***	0.02	-0.11***	0.07**	0.01	-0.11***	0.06**	-0.00	-0.11***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
$interbank_t$	-0.22**	-0.19*	0.15	-0.23***	-0.18*	0.19*	-0.22**	-0.09	0.30**
	(0.09)	(0.10)	(0.11)	(0.09)	(0.09)	(0.11)	(0.11)	(0.12)	(0.14)
$term_t$	0.12*	0.09	-0.10	0.15**	0.10	-0.13**	0.14**	0.14**	-0.11*
	(0.07)	(0.07)	(0.07)	(0.07)	(0.06)	(0.06)	(0.06)	(0.07)	(0.07)
ois_t	-0.08**	0.04	0.16***	-0.09**	0.01	0.15***	-0.14***	-0.02	0.21***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)
$impairments_{i,t-1}$	-0.01	-0.01	0.00	0.01	-0.01	-0.03	0.00	0.00	-0.01
	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)	(0.02)
$operatingincome_{i,t-1}$	-0.01	-0.02	-0.01	-0.02	-0.03	-0.01	-0.06	-0.04	0.02
	(0.03)	(0.03)	(0.04)	(0.03)	(0.02)	(0.04)	(0.05)	(0.03)	(0.07)
$operatingexpenses_{i,t-1}$	0.02	0.09	0.05	-0.00	0.07	0.07	-0.04	0.09	0.18**
	(0.08)	(0.09)	(0.07)	(0.07)	(0.08)	(0.07)	(0.08)	(0.09)	(0.08)
gdp_{t-1}	0.08***	0.06*	-0.07***	0.07**	0.04	-0.06**	0.09***	0.09***	-0.04
	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)
$interbank_{t-1}$	0.33***	0.21	-0.30**	0.30**	0.20	-0.28*	0.33***	0.11	-0.48***
	(0.12)	(0.14)	(0.14)	(0.12)	(0.14)	(0.15)	(0.12)	(0.13)	(0.17)
$term_{t-1}$	-0.06	-0.02	0.08	-0.10	-0.03	0.11	-0.03	0.01	0.04
	(0.06)	(0.07)	(0.07)	(0.07)	(0.07)	(0.08)	(0.08)	(0.09)	(0.09)
ois_{t-1}	-0.11**	-0.10*	0.07	-0.08	-0.09	0.04	-0.09	-0.06	0.11
	(0.05)	(0.06)	(0.06)	(0.05)	(0.05)	(0.06)	(0.06)	(0.06)	(0.07)
$tone_{i,t-1}$				0.17***			0.10**		
				(0.03)			(0.05)		
$pos_{i,t-1}$					0.08**			0.02	
					(0.03)			(0.04)	
$neg_{i,t-1}$						0.21***			0.15***
						(0.03)			(0.04)
$impairments_{i,t-2}$	-0.06***	-0.04*	0.06*	-0.04**	-0.03	0.04	-0.03**	-0.01	0.04
	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)
$operatingincome_{i,t-2}$	0.08	0.05	-0.08	0.06	0.03	-0.07	0.04	0.01	-0.06
	(0.05)	(0.04)	(0.05)	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)	(0.05)
$operatingexpenses_{i,t-2}$	-0.07	-0.06	0.06	-0.05	-0.06	0.01	-0.06	-0.05	0.07
	(0.06)	(0.06)	(0.08)	(0.05)	(0.06)	(0.08)	(0.07)	(0.08)	(0.08)
gdp_{t-2}	0.03	0.00	-0.04*	0.01	0.01	-0.02	0.04	0.04	-0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)
$interbank_{t-2}$	0.00	0.01	0.01	-0.01	0.01	0.04	-0.04	0.12	0.07
	(0.11)	(0.10)	(0.12)	(0.10)	(0.10)	(0.12)	(0.11)	(0.10)	(0.14)
$term_{t-2}$	0.04	0.02	-0.05	0.06	0.02	-0.07	0.02	0.02	-0.03
	(0.05)	(0.04)	(0.06)	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)
ois_{t-2}	0.02	0.03	0.00	0.03	0.03	-0.02	0.05	0.05	-0.03
	(0.04)	(0.04)	(0.03)	(0.04)	(0.05)	(0.03)	(0.04)	(0.04)	(0.03)
$tone_{i,t-2}$				0.19***			0.13***		
				(0.04)			(0.04)		
$pos_{i,t-2}$					0.22***			0.18***	
					(0.04)			(0.05)	
$neg_{i,t-2}$						0.14***			0.10**
						(0.04)			(0.04)
Constant	0.92***	0.50***	-0.93***	0.52***	0.21*	-0.61***	-0.05	-0.12	0.04
	(0.14)	(0.13)	(0.14)	(0.12)	(0.11)	(0.11)	(0.07)	(0.09)	(0.07)
N	1933	1933	1933	1933	1933	1933	1933	1933	1933
R^2	0.65	0.59	0.64	0.68	0.61	0.67	NA	NA	NA
Adj. R^2	0.61	0.54	0.59	0.64	0.56	0.63	NA	NA	NA

Note: In this table, we document the results of separate regressions of *tone*, *pos* and *neg* on lagged bank-specific and macroeconomic variables. All specifications include the lagged version of the business model variables specified in Section 2.4.2 as control variables. All specifications also include the variable *imputed*, which indicates whether missing values for an observation have been estimated via interpolation. All variables are standardized. Specifications 1–3 and 4–6 are estimated with the fixed effects estimator. The standard errors are clustered on the bank level and are reported in parentheses. Specifications 7–9 are estimated with the Arellano–Bover/Blundell–Bond system estimator with robust standard errors. ***, ** and * refer to significance levels of 1%, 5% and 10%, respectively.

2.5.3 Bank Manager Sentiment and the Subsequent Financial Performance of Banks

As a second test, we check whether future financial performance of banks is positively related with contemporaneous and past realizations of our estimate of bank manager sentiment. If our estimate of bank manager sentiment was capturing bank managers' private information, one would expect that a positive (negative) variation in the textual tone score would be associated with a better (worse) subsequent financial performance of banks. In order to have a broad view of the financial performance of banks, we study several indicators: loan loss reserves over gross loans (*reserves*), interest income over assets (*interestincome*), interest expenses over assets (*interestexpense*), return on average assets (*ROAA*), earnings per share (*EPS*) and non-performing loans ratio (*NPL*). As we are interested in the component of the textual tone score orthogonal to bank-specific and economic fundamentals, we regress the future financial performance indicators over the contemporaneous and past realizations of the textual tone score, while controlling for the realizations of the bank-specific and macroeconomic controls defined previously. Therefore, we estimate the following model:

$$\begin{aligned} finperf_{i,t+2} = &\ \alpha + \beta_1 tone_{i,t+1} + \beta_2 tone_{i,t} + \\ &\ \boldsymbol{\gamma}_1 \boldsymbol{X}_{i,t+1} + \boldsymbol{\gamma}_2 \boldsymbol{X}_{i,t} + \boldsymbol{\lambda}_1 X^{bk}_{i,t+1} + \boldsymbol{\lambda}_2 X^{bk}_{i,t} + \\ &\ u_i + w_{c(i),t+2} + \epsilon_{i,t+2} \end{aligned} \tag{2.10}$$

where $finperf_{i,t}$ contains alternatively $reserves_{i,t}$, $interestincome_{i,t}$, $interestexpenses_{i,t}$, $ROAA_{i,t}$, $EPS_{i,t}$ and $NPL_{i,t}$. $\boldsymbol{X}^{bk}_{i,t}$ is a vector holding for the control variables *cash*, *securities* and *reserves*. The variables u_i and $w_{c,t}$ capture bank and country-time fixed effects, respectively.[24] The coefficients of interest are β_1 and β_2. As we control for $X_{i,t+1}, X^{bk}_{i,t+1}, X_{i,t}, X^{bk}_{i,t}$, u_i and $w_{c,t+2}$, we can interpret the remaining variation in the textual tone score, which identifies β_1 and β_2, as bank manager sentiment. All variables are standardized, which enables a better assessment of economic significance.

The regression results documented in Table 2.8 suggest that bank manager sentiment is not predictive of subsequent realizations of *interestexpenses* (column 3), *ROAA* (column 4), *EPS* (column 5) or *NPL* (column 6), as their respective coefficients are all non significant. Interestingly, a one standard deviation increase in bank manager sentiment is on average associated with a 0.02 standard deviations decrease in *reserves* in the next six months (column 1), and with a 0.02 standard deviations decrease in *interestincome* in the next year (column 2), both coefficients being significant at the 10% level.

[24] The inclusion of country-time fixed effects absorbs the effect of the country-specific macroeconomic variables contained in $\boldsymbol{X}_{i,t}$ but also allows to control for any unobserved country-time specific developments.

As robustness test, we include the autocorrelation terms $finperf_{i,t+1}$ and $finperf_{i,t}$ in model 2.10 and use the Arellano–Bover/Blundell–Bond system estimator. The results are presented in Table 2.9.[25] Bank manager sentiment is not predictive anymore of *reserves* (column 1). Interestingly, a one standard deviation increase in bank manager sentiment is on average associated with a 0.02 standard deviations increase in *interestincome* in the next six months (column 2), but also a 0.03 standard deviations increase in *interestexpenses* (column 3), and with an increase in *NPL* of 0.08 standard deviations in the next six month, and of 0.05 standard deviations in the next year, respectively (column 6), all coefficients being significant at the 1% or the 5% level.

In summary, a higher bank manager sentiment is not associated with a better subsequent financial performance for banks, we actually observe the contrary for some indicators. Combined with our finding that our bank manager estimate has an extrapolative structure, we therefore confirm that this estimate indeed captures over-optimism/pessimism of the bank managers rather than their private information.

[25] As there is not enough heterogeneity between the different country-time fixed effects for regressions in columns 2, 4 and 5, we remove country-time pairs having 1, 4 and 2 observations or less respectively. This allows us to estimate the standard errors of the coefficients.

Table 2.8. Is bank manager sentiment predictive of banks' financial performance?

	(1)	(2)	(3)	(4)	(5)	(6)
	$reserves_{i,t+2}$	$interestincome_{i,t+2}$	$interestexpenses_{i,t+2}$	$ROAA_{i,t+2}$	$EPS_{i,t+2}$	$NPL_{i,t+2}$
$tone_{i,t+1}$	-0.0204*	0.0139	0.0037	0.0000	-0.0210	-0.0168
	(0.0116)	(0.0137)	(0.0159)	(0.0000)	(0.0427)	(0.0202)
$tone_{i,t}$	0.0071	-0.0211*	-0.0131	-0.0000	-0.1252	-0.0123
	(0.0108)	(0.0123)	(0.0138)	(0.0000)	(0.0814)	(0.0220)
imputed	0.0060	0.0593	0.0410	-0.0000	0.0240	0.0446
	(0.0270)	(0.0384)	(0.0454)	(0.0000)	(0.1009)	(0.0478)
Constant	10.8417	-8.6801	18.7439	-0.0922	-33.5003	-4.1548
	(11.8348)	(15.8382)	(16.5434)	(.)	(28.1969)	(10.0696)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Additional controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	1877	1817	1815	1894	1458	391
R^2	0.8972	0.8787	0.8923	0.7184	0.4808	0.8146
Adj. R^2	0.866	0.840	0.858	0.634	0.270	0.712

Note: In this table, we report the results of separate regressions of financial performance on *tone*. All variables are standardized. The controls include *impairments*, *operatingincome*, *operatingexpenses*, *logta*, *loans*, *deposits*, *equity*, *netinterestincome*, *gdp*, *inflation*, *interbank*, *term*, *ois*. The additional controls refer to the vector $X_{i,t}^{bk}$ and include *cash*, *securities*, and *reserves*. The variable *imputed* indicates whether missing values for an observation have been estimated via interpolation. The standard errors are clustered on the bank level and are reported in parentheses. ***, ** and * refer to significance levels of 1%, 5% and 10%, respectively.

Table 2.9. Is bank manager sentiment predictive of banks' financial performance, while controlling for autocorrelation?

	(1)	(2)	(3)	(4)	(5)	(6)
	$reserves_{i,t+2}$	$interestincome_{i,t+2}$	$interestexpenses_{i,t+2}$	$ROAA_{i,t+2}$	$EPS_{i,t+2}$	$NPL_{i,t+2}$
$tone_{i,t+1}$	-0.0036	0.0247**	0.0281***	-0.0305	-0.0000	0.0819***
	(0.0063)	(0.0098)	(0.0098)	(0.0592)	(0.0000)	(0.0309)
$tone_{i,t}$	0.0053	-0.0004	0.0080	-0.0645	-0.0000	0.0531***
	(0.0099)	(0.0121)	(0.0083)	(0.0478)	(0.0000)	(0.0198)
imputed	-0.0086	-0.0114	-0.0012	-0.0686	-0.0000	-0.0477
	(0.0172)	(0.0226)	(0.0201)	(0.0588)	(0.0000)	(0.0483)
Constant	-1.6730	1.0780	3.0467	-433.2950	-0.0921***	-2.1460
	(202.7757)	(19.4246)	(10.2963)	(1244.7535)	(0.0000)	(4.3052)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Additional controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	1877	1668	1665	1058	1354	262
r2	NA	NA	NA	NA	NA	NA
ar2	NA	NA	NA	NA	NA	NA

Note: In this table, we report the results of separate regressions of financial performance on *tone*. The controls include *impairments*, *operatingincome*, *operatingexpenses*, *logta*, *loans*, *deposits*, *equity*, *netinterestincome*, *gdp*, *inflation*, *interbank*, *term*, *ois*. The additional controls refer to the vector $X_{i,t}^{bk}$ and include *cash*, *securities*, and *reserves*. The variable *imputed* indicates whether missing values for an observation have been estimated via interpolation. All variables are standardized. All the specifications of this table include two lags in order to take into account autocorrelation and are estimated with the Arellano–Bover/Blundell–Bond system estimator with robust standard errors, which are reported in parentheses. ***, ** and * refer to significance levels of 1%, 5% and 10%, respectively.

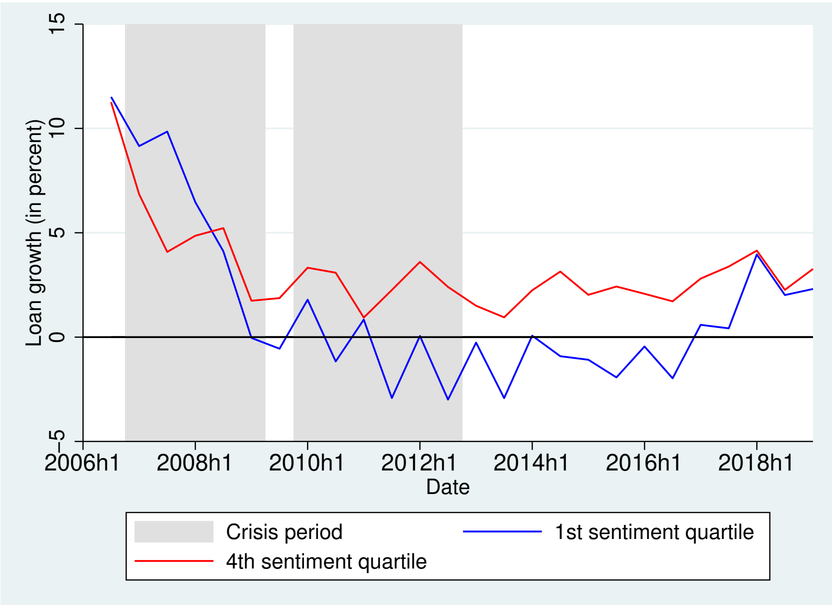
2.6 Bank Manager Sentiment and Bank Lending

In this section, we study whether bank manager sentiment is associated with the bank lending. In Section 2.6.1, we explore whether bank manager sentiment has incremental predictive power for the bank's loan growth over the subsequent six months. In Section 2.6.2, we use loan-level data to isolate loan supply from loan demand.

2.6.1 Is Bank Manager Sentiment Predictive for Loan Growth?

A first look at the average loan growth rates of the banks with the highest textual tone score and the banks with the lowest textual tone score (Figure 2.4) suggests that the textual tone score is positively associated with loan growth rates.

Figure 2.4. Average loan growth rates for high and low textual tone score banks



Note: In this figure, we compare the development of loan growth rates for high textual tone score banks and low textual tone score banks. It has been constructed as follows: every six months, banks have been sorted into quartiles based on the textual tone score. The depicted loan growth rates are then calculated as the average of the seasonally-adjusted growth rates over the next six months within the quartiles. Loan growth rates are winsorized at the 5th and 95th percentile.

To test whether there is indeed a difference between the loan growth rates of the two groups, we run regressions of loan growth rates on *tone* and control variables. As we are interested in the component of the textual tone score orthogonal to bank-specific and economic fundamentals, we include the contemporaneous realizations of the bank-specific and macroeconomic controls defined previously. Therefore, we estimate the following model:

$$loan\ growth_{i,t+1} = \alpha + \beta S_{i,t} + \boldsymbol{\gamma} \boldsymbol{X}_{i,t} + \boldsymbol{\lambda} X_{i,t}^{bk} + u_i + w_{c,t} + \epsilon_{i,t} \tag{2.11}$$

where $\boldsymbol{X}_{i,t}^{bk}$ is a vector holding for the control variables *cash*, *securities* and *reserves*. The variables u_i and $w_{c,t}$ capture bank and country-time fixed effects, respectively.[26] The coefficient of interest is β. As we control for $X_{i,t}$, $X_{i,t}^{bk}$, u_i and $w_{c,t}$, we can interpret the remaining variation in textual tone score, which identifies β, as bank manager sentiment. All variables are standardized, which enables a better assessment of economic significance.

We first estimate model (2.11) without $X_{i,t}^{bk}$ and without country-time fixed effects. The regression results documented in the first column of Table 2.10 suggest that bank manager sentiment on its own is predictive of subsequent loan growth, with a statistical significance at the 1% level. A one standard deviation increase in bank manager sentiment is associated with an average increase in the loan growth rate of 0.16 standard deviations. When distinguishing between the positive and the negative components of *tone*, most of the variation in loan growth rates seems to be driven by *neg*. While both coefficients on *pos* and *neg* are significant at the 1% level, the magnitude of the coefficient of *neg* is three times larger than the one of *pos* (column 2 and 3 of Table 2.10).

As robustness tests, we include additional control variables and estimate model (2.11) with country-time fixed effects. When we include the control variables contained in the vector $X_{i,t}^{bk}$ into the model, we find that the coefficients on *tone* and *neg* (columns 4 and 6 of Table 2.10) are smaller in magnitude than those from the model without those variables (columns 1 and 3), but remain statistically significant at the 1% level. The value of the coefficient on *pos* is mostly unchanged and now only statistically significant at the 5% level. The introduction of country-time fixed effects further reduces the magnitude of the coefficients on *tone* and *neg*, the former being statistically significant at the 5% level as a result (columns 7 and 9). Compared with the previous estimations, the coefficient on *pos* in column 8 of Table 2.10 is still positive but has a much lower value and is not significant anymore. Even if bank manager sentiment on its own is predictive of subsequent loan growth (given the significance at the 1% level of the coefficient of *tone*), it has only weak incremental explanatory power. When we run the same model, but without the textual tone score or each of its components as regressor[27], we indeed find an adjusted R^2 of 0.305, compared to an adjusted R^2 of 0.307 for the fully specified model (column 7), where most of the variation seems to be driven by the negative component with an adjusted R-squared of 0.309 (column 9).

[26] The inclusion of country-time fixed effects absorbs the effect of the country-specific macroeconomic variables contained in $\boldsymbol{X}_{i,t}$ but also allows to control for any unobserved country-time specific developments.
[27] The results are available from the authors upon request.

Table 2.10. Is bank manager sentiment predictive of loan growth?

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$loangrowth_{t+1}$	$loangrowth_{t+1}$	$loangrowth_{t+1}$	$loangrowth_{t+1}$	$loangrowth_{t+1}$	$loangrowth_{t+1}$	$loangrowth_{t+1}$	$loangrowth_{t+1}$	$loangrowth_{t+1}$
$tone_t$	0.1569***			0.1321***			0.0803**		
	(0.0330)			(0.0312)			(0.0319)		
pos_t		0.0591***			0 .0570**			0.0179	
		(0.0279)			(0. 0272)			(0.0294)	
neg_t			-0.1724***			-0.1375***			-0.0995***
			(0.0336)			(0.0330)			(0.0340)
imputed	0.1572*	0.1324	0.1520*	0.0555	0 .0439	0.0502	-0.0315	-0.0397	-0.0311
	(0.0813)	(0.0815)	(0.0799)	(0.0755)	(0. 0750)	(0.0755)	(0.0845)	(0.0840)	(0.0841)
Constant	-0.0204***	-0.0136*	-0.0203***	0.2047***	0 .2078***	0.2063***	-5.0900	-4.1922	-5.0283
	(0.0077)	(0.0076)	(0.0075)	(0.0425)	(0. 0435)	(0.0427)	(9.0336)	(9.1226)	(8.7695)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Additional controls	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-time fixed effects	No	No	No	No	No	No	Yes	Yes	Yes
N	2417	2417	2417	2208	2208	2208	2208	2208	2208
R^2	0.0419	0.0072	0.0550	0.1991	0 .1922	0.2002	0.4508	0.4488	0.4521
Adj. R^2	0.0411	0.0064	0.0543	0.1925	0 .1855	0.1936	0.3070	0.3045	0.3086

Note: In this table, we report the results of separate regressions of loan growth on *tone*, *pos*, *neg*. All variables are standardized. The controls include *impairments*, *operatingincome*, *operatingexpenses*, *logta*, *loans*, *deposits*, *equity*, *netinterestincome*, *gdp*, *inflation*, *interbank*, *term*, *ois*. The additional controls refer to the vector $X_{i,t}^{bk}$ and include *cash*, *securities*, and *reserves*. The variable *imputed* indicates whether missing values for an observation have been estimated via interpolation. The standard errors are clustered on the bank level and are reported in parentheses. ***, ** and * refer to significance levels of 1%, 5% and 10%, respectively.

2.6.2 Bank Manager Sentiment and Bank Lending Supply (Controlling for Loan Demand)

As shown by the literature, the use of bank-level data may suffer from an omitted-variable bias (Kashyap and Stein, 2000; Khwaja and Mian, 2008). In our case, assume that a given bank is specialized in lending to some specific sector. Then an idiosyncratic shock affecting this sector would likely affect both the loan demand to this bank as well as the sentiment of this bank compared to other banks lending to other sectors. In order to isolate loan supply from loan demand, we merge our bank manager sentiment dataset with Dealscan over the bank-time dimension. Focusing on a within syndicated loan analysis by including a loan fixed effect offers an ideal setting for controlling loan demand. Within a syndicated loan, the loans conditions are negotiated by the lead arranger and the borrower before the participating banks are offered to take some shares in the syndicated loan, making those shares unlikely to be affected by the borrower's loan demand (Dennis and Mullineaux, 2000; Sufi, 2007; Ivashina, 2009; Ongena, Benincasa, and Kabas, 2021). Syndicated loans can be structured in several tranches, which is more likely for larger loans. Even though the participants, the structure of the syndicate and general pricing terms are typically determined at the deal level, tranches differ by their active date, maturity, amount and loan type (term loan vs. revolver line). For this reason, we define the loan shares of a bank within a syndicated loan as the share of this bank within each tranche. We also drop tranche amendments as those could be related to the borrower's loan demand. We then estimate the following model:

$$\textit{loan share}_{i,l,f,t+1} = \alpha + \beta S_{i,t} + \boldsymbol{\gamma}\boldsymbol{X}_{i,t} + \boldsymbol{\lambda} X^{bk}_{i,t} + u_i + w_{c,t} + \gamma_l + \epsilon_{i,l,f,t} \tag{2.12}$$

where *loan share*$_{i,l,f,t}$ is the share of bank i in syndicated loan l to borrowing firm f at semester t. $\boldsymbol{X}^{bk}_{i,t}$ is a vector holding for the control variables *cash*, *securities* and *reserves*. The variables u_i and $w_{c,t}$ capture bank and country-time fixed effects, respectively.[28] Importantly, γ_l is a loan fixed effect that allows to control for loan demand. The coefficient of interest is β. As we control for $X_{i,t}$, $X^{bm}_{i,t}$, $X^{bk}_{i,t}$, u_i and $w_{c,t}$, we can interpret the remaining variation in textual tone score, which identifies β, as bank manager sentiment. We cluster the standard errors at the bank's level as it is the unit of treatment (Abadie et al., 2023).

We first estimate model (2.12) without $X^{bk}_{i,t}$ and without bank and country-time fixed effects. The regression results documented in the first column of Table 2.11 suggest that a

[28] The inclusion of country-time fixed effects absorbs the effect of the country-specific macroeconomic variables contained in $\boldsymbol{X}_{i,t}$ but also allows to control for any unobserved country-time specific developments.

higher bank manager sentiment predicts a higher subsequent loan supply when controlling for loan demand, but the effect is not statistically significant. A one standard deviation increase in bank manager sentiment is associated with an average increase in the loan share of 0.09 percentage points (no statistical significance). When distinguishing between the positive and the negative components of *tone*, both coefficients are surprisingly positive, but the coefficient of *pos* is larger and has a stronger statistical significance (0.23, statistically significant at the 1% level) than the coefficient of *neg* (0.14, statistically significant at the 10% level, column 2 and 3 of Table 2.11).

As robustness tests, we estimate model (2.12) with bank and country-time fixed effects. When we include bank fixed effects into the model, we find that the coefficients on *tone* has a smaller magnitude (0.04) and is still statistically insignificant (column 4 of Table 2.11). When decomposing bank manager sentiment between its positive and negative components, most of the effect seems to be driven by *neg*. While both coefficients on *pos* and *neg* are negative, the coefficient on *neg* has a larger magnitude and a stronger statistical significance (-0.19, significant at the 10% level) than the coefficient on *pos* (-0.09, no statistical significance, columns 5 and 6 of Table 2.11). When we introduce country-time fixed effects (columns 7, 8 and 9 of Table 2.11) all the magnitude on the coefficient on *sent* is absorbed (-0.00, no statistical significance). When decomposing bank manager sentiment between its positive and negative components, the conclusions are very similar to the case when we included only bank fixed effects. Both coefficients on *pos* and *neg* are negative, with the coefficient on *neg* having a larger magnitude than the coefficient on *pos* (-0.26 and -0.12 respectively). However, none of the coefficients are statistically significant anymore.

In summary, our empirical results suggest that bank manager sentiment is significantly and positively associated with subsequent loan growth. However, bank manager sentiment overall has limited explanatory power that is derived from its component *neg*. Also, bank manager sentiment does not have anymore a statistically significant relationship with subsequent bank lending supply once we control for loan demand. One potential explanation for this absence of relation when controlling for loan demand is that we only study syndicated loans that represents around 6.6% of the total lending in our sample of banks. Other types of loans that we don’t observe may be more affected by bank manager sentiment.

Table 2.11. Is bank manager sentiment predictive of loan supply (controlling for loan demand)?

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$loanshare_{i,l,f,t+1}$	$loanshare_{i,l,f,t+1}$	$loanshare_{i,l,f,t+1}$	$loanshare_{i,l,f,t+1}$	$loanshare_{i,l,f,t+1}$	$loanshare_{i,l,f,t+1}$	$loanshare_{i,l,f,t+1}$	$loanshare_{i,l,f,t+1}$	$loanshare_{i,l,f,t+1}$
$tone_{t-1}$	0.0943			0.0408			-0.0013		
	(0.0787)			(0.1010)			(0.1683)		
pos_{t-1}		0.2315***			-0.0870			-0.1190	
		(0.0713)			(0.0933)			(0.1315)	
neg_{t-1}			0.1363*			-0.1854*			-0.2596
			(0.0772)			(0.0993)			(0.1790)
Constant	12.8802***	12.8854***	12.8480***	12.8836***	12.8863***	12.8577***	13.1514***	13.1572***	13.1395***
	(0.0635)	(0.0631)	(0.0629)	(0.1030)	(0.1025)	(0.1032)	(0.0846)	(0.0845)	(0.0843)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank fixed effects	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Country-time fixed effects	No	No	No	No	No	No	Yes	Yes	Yes
N	15663	15663	15663	15652	15652	15652	15620	15620	15620
R^2	0.7966	0.7968	0.7966	0.8073	0.8073	0.8073	0.8137	0.8137	0.8137
Adj. R^2	0.7016	0.7019	0.7017	0.7152	0.7152	0.7153	0.7184	0.7184	0.7184

Note: In this table, we report the results of separate regressions of loan shares on *tone*, *pos*, *neg*. The controls include *impairments*, *operatingincome*, *operatingexpenses*, *logta*, *loans*, *deposits*, *equity*, *netinterestincome*, *gdp*, *inflation*, *interbank*, *term*, *ois*. The standard errors are clustered on the bank level and are reported in parentheses. ***, ** and * refer to significance levels of 1%, 5% and 10%, respectively.

2.7 Bank Manager Sentiment and the Riskiness of Banks

In the previous section, we have studied the influence of bank manager sentiment on bank lending decisions. Now, we turn to the question of whether bank manager sentiment is associated with the subsequent riskiness of the bank from two perspectives. First, we focus on the risk-taking behavior of banks, and second, we look at how bank manager sentiment spills over to their equity investors.

2.7.1 Bank Manager Sentiment and the Risk-Taking Behavior of Banks

In this subsection, we study whether over-optimistic bank managers increase their lending towards riskier borrowers. We answer this question by exploiting the information available in Dealscan, in particular about the corporate borrower of each syndicated loan. We merge Dealscan with the Orbis database to have some balance sheet information about the borrowers.[29] We then use this information to proxy the risk profile of each borrower by following Heider, Saidi, and Schepens (2019). Heider, Saidi, and Schepens (2019) use the log-volatility of the return on asset over the last 5 years or of monthly stock returns over the last 3 years. We adopt a similar approach and use the 3-year log-volatility of the following financial variables for the borrowers: return on equity (*ROE*), return on assets (*ROA*), net income over assets (*netincome*) and profit margin (*profitmargin*). We estimate model (2.12) again but this time by interacting $S_{i,t}$ with the log-volatility of the different financial variables mentioned above:

$$loan\ share_{i,l,f,t+1} = \alpha + \beta \times S_{i,t} \times log[volatility(variable_f)^{Y}_{y(t)-1}] + z_{i,t} + \gamma_l + \epsilon_{i,l,f,t} \quad (2.13)$$

where $volatility(variable_f)^{Y}_{y(t)-1}$ is the Y-year standard deviation of each of the borrower f's four alternative financial variables (*ROE*, *ROA*, *netincome* or *profitmargin*) from accounting year $y(t)-Y$ to $y(t)-1$, both years included, where $y(t)$ is the year of the semester t. Y is alternatively 3 or 5 years.[30] Importantly, we strengthen our identification by including bank-time fixed effects $z_{i,t}$ instead of controlling only for bank-specific variables ($X_{i,t}$) and for country-time fixed effects ($w_{c,t}$) since our variables of interest is bank-time-borrower variant. As for the previous section, we include some loan fixed effects γ_l to control for loan demand.

We first estimate model (2.13) using the 3-year log-volatility of the borrower's *ROE*, *ROA*, *netincome* and *profitmargin* (table 2.12). A higher bank manager sentiment is associated with

[29] We exploit the Legal Entity Identifier (LEI) of the different corporate borrowers in Dealscan, which is available for around half of those borrowers. We are currently working on an additional strategy to complete merge for the corporate borrowers with missing LEI.

[30] For instance, regarding the sentiment calculated for the reporting period 2017H1 or 2017H2, we calculated the 3-year and the 5-year volatility over the accounting years 2014-2016 and 2012-2016 respectively.

a higher log-volatility of each of the borrower's financial variables (first row of 2.12). A one standard deviation increase in bank manager sentiment increases bank loan share by 0.15 percentage points when the 3-year volatility of the borrower's *ROE* is higher by 1%, the effect being statistically significant at the 10% level (column 1). Similarly, a one standard deviation increase in bank manager sentiment increases bank loan share by 0.16, 0.15 and 0.24 percentage points when the 3-year volatility of the borrower's *ROA*, *netincome* and *profitmargin* is higher by 1% respectively. The effect is statistically significant at the 10% level for *ROA*, and *netincome*, and at the 5% level for *profitmargin* (columns 4, 7 and 10). When decomposing bank manager sentiment between its two components, most of the effect is driven by *neg*. Depending on the chosen borrower's financial variable chosen, a one standard deviation increase in the negative component of bank manager sentiment decreases bank loan share by 0.14 to 0.25 percentage points when the 3-year volatility of the borrower's financial variable is higher by 1%, the effect being statistically significant at the 10%, 5% or 1% level (columns 3, 6, 9 and 12). In comparison, the coefficient on the interaction between the 3-year log-volatility of the different financial variables and the positive component of bank manager sentiment is not statistically significant and has a magnitude 1.4 to 14 times smaller.

As robustness test, we estimate model (2.13) using the 5-year log-volatility of the borrower's *ROE*, *ROA*, *netincome* and *profitmargin* (table 2.B.1 in Appendix 2.B). Despite losing almost one third of our observations, we still find similar conclusions for most financial variables. A one standard deviation increase in bank manager sentiment increases bank loan share by 0.26 and 0.20 percentage points when the 5-year volatility of the borrower's *ROE* and *profitmargin* is higher by 1% respectively (statistically significant at the 5% level for both variables). The coefficients for *ROA* and *netincome* are still positive, but not statistically significant anymore. Regarding the decomposition of bank manager sentiment between its positive and negative components, all the coefficients of the positive component interacted with each of the 5-year log-volatilities are positive, suggesting that a more positive bank manager sentiment is associated with an increase in the loan share towards borrowers whose financial variables are more volatile. Conversely, all the coefficients of the negative component interacted with each of the 5-year log-volatilities are negative, suggesting that a more negative bank manager sentiment is associated with a decrease in the loan share towards borrowers whose financial variables are more volatile. However, none of those coefficients are statistically significant.

In summary, we find that a higher bank manager sentiment is positively related with the subsequent risk-taking behaviour of banks. This result holds when studying the volatility of different financial variables of the borrowers, and when taking different time length for the volatility calculation.

Table 2.12. Is bank manager sentiment predictive of bank risk-taking behaviour (based on the 3-year log-volatility of the borrower's *ROE*, *ROA*, *netincome* or *profitmargin*)?

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	ROE_f	ROE_f	ROE_f	ROA_f	ROA_f	ROA_f	$netincome_f$	$netincome_f$	$netincome_f$	$profitmargin_f$	$profitmargin_f$	$profitmargin_f$
$tone_{i,t} * log[volatility(variable_f)^{3y}_{y(t)-1}$	0.1465*			0.1587*			0.1483*			0.2407**		
	(0.0795)			(0.0811)			(0.0743)			(0.1090)		
$pos_{i,t} * log[volatility(variable_f)^{3y}_{y(t)-1}$		-0.0176			0.0480			0.0981			0.1378	
		(0.0806)			(0.0844)			(0.0866)			(0.1292)	
$neg_{i,t} * log[volatility(variable_f)^{3y}_{y(t)-1}$			-0.2465***			-0.2165**			-0.1366*			-0.2381***
			(0.0860)			(0.0833)			(0.0699)			(0.0863)
Constant	12.4481***	12.5385***	12.3993***	12.6366***	12.6541***	12.6302***	12.5477***	12.5547***	12.5491***	12.5064***	12.5693***	12.5171***
	(0.0457)	(0.0289)	(0.0463)	(0.0109)	(0.0069)	(0.0107)	(0.0059)	(0.0042)	(0.0053)	(0.0460)	(0.0364)	(0.0330)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank-time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	6493	6493	6493	6736	6736	6736	6696	6696	6696	6293	6293	6293
R^2	0.8046	0.8044	0.8048	0.7989	0.7988	0.7990	0.7963	0.7963	0.7963	0.7938	0.7936	0.7938
Adj. R^2	0.7008	0.7006	0.7011	0.6919	0.6917	0.6920	0.6884	0.6883	0.6883	0.6826	0.6823	0.6825

Note: In this table, we report the results of separate regressions of loan shares on *tone*, *pos*, *neg* interacted with the 3-year log-volatility of one of the following borrower's financial variables indicated in the columns of this table: *ROE*, *ROA*, *netincome* or *profitmargin*. The controls include *impairments*, *operatingincome*, *operatingexpenses*, *logta*, *loans*, *deposits*, *equity*, *netinterestincome*, *gdp*, *inflation*, *interbank*, *term*, *ois*. The standard errors are clustered on the bank level and are reported in parentheses. ***, ** and * refer to significance levels of 1%, 5% and 10%, respectively.

2.7.2 Bank Manager Sentiment and the Risk Associated with Loan Growth

As has been shown empirically, equity investors and analysts are sometimes too optimistic when assessing the risk–return profile of high growth banks (see e.g. Baron and Xiong, 2017; Fahlenbrach, Prilmeier, and Stulz, 2017). Fahlenbrach, Prilmeier, and Stulz (2017), in particular, show that equity analysts systematically underestimate the risk associated with high loan growth rates.

Motivated by this empirical evidence, we ask whether equity investors' assessments of the risk associated with bank loan growth is influenced by the sentiment of bank managers. More specifically, we explore whether bank equity investors interpret the combination of a high loan growth rate and high bank manager sentiment as a signal for "healthy" loan growth, i.e. loan growth that creates value for the bank and its investors. We measure the equity market participants' assessment of bank risk by *SRISK* scaled by the enterprise value of the respective banks (see Section 2.3.4). Since it is based on equity market prices, *SRISK* is a forward-looking measure that is driven by market participants' assessments for the outlooks for cash flows and exposures to equity market risk. This leads us to the following predictions: Investors interpret high bank manager sentiment as a positive signal for the risk associated with bank loan growth. Higher values of bank manager sentiment are negatively associated with the relationship between *SRISK* and loan growth. To test these predictions, we estimate the following model:

$$\begin{aligned} SRISK_{i,t} \;=\; & \alpha + SRISK_{i,t-1} + \beta_1 \times loangrowth_{i,t-1} \\ & + \beta_2 \times tone_{i,t-1} + \beta_3 \times tone_{i,t-1} \times loangrowth_{i,t-1} \\ & + \boldsymbol{\gamma X}_{i,t-1} + u_i + w_{c,t} + \epsilon_{i,t} \end{aligned} \tag{2.14}$$

where the variables u_i and $w_{c,t}$ are bank and country-time fixed effects, respectively.[31] Using the same logic as before, as we control for contemporaneous bank-specific and macroeconomic fundamentals, the coefficient of interest, β_3, can be interpreted as how the relationship between *SRISK* and loan growth depends on bank manager sentiment.

We lag the explanatory variables by one period for two reasons. First, financial results and the corresponding press releases are typically released a few weeks after the end of the reporting period. Because the book value of total debt is an input in the calculation of *SRISK*, $SRISK_{i,t}$ is thus also observable only after the release of the financial statement. Second, to

[31] The inclusion of country-time fixed effects absorbs the effect of the country-specific macroeconomic variables contained in $\boldsymbol{X}_{i,t-1}$ but also allows to control for any unobserved country-time specific developments.

avoid that our results suffer from both hindsight bias and endogeneity problems, we use the next observable realization, $SRISK_{i,t+1}$ as our dependent variable. We also include the first lag of *SRISK* as a control variable, given that it is highly persistent.

The regression results are documented in Table 2.13. All variables are standardized. In Columns 1 and 2 of Table 2.13, we report the results from nested versions of the model specified in Equation (2.14). These nested versions only include $loangrowth_{t-1}$ (column 1) and $loangrowth_{t-1}$ and $tone_{t-1}$ (column 2), respectively. The results reported in both columns suggest that the two variables are negatively associated with *SRISK*, but the relationship is not significant. When we distinguish by bank manager sentiment (column 3), we are also able to detect a negative but statistically insignificant relationship between bank loan growth and bank risk for banks with the most optimistic bank managers.

Since we include the first lag of the dependent variable as a control variable in our regressions, a concern with the results in columns 1–3 is dynamic panel bias (see also Section 2.5). To increase the robustness of our results, we re-estimate the specifications in columns 1–3 using the Arellano–Bover/Blundell–Bond system estimator. The results are reported in columns 4–6 of Table 2.13 and suggest that dynamic panel bias is an issue with the OLS results. Notable differences between the results from the Arellano–Bover/Blundell–Bond system estimator and that from the OLS estimator are that the coefficient on $tone_{t-1}$ in column 5 is statistically significant at the 5% level. The results in column 5 suggest that a one standard deviation increase in $tone_{t-1}$ is on average associated with an 0.0272 standard deviations decrease in $SRISK_t$. The results in column 6 suggest that the Arellano–Bover/Blundell–Bond system only changes the statistical significance of the coefficient of $tone_{t-1}$ (at the 10% level) but not its economic interpretation and does not change the conclusion for the coefficient of the interaction between $tone_{t-1}$ and $loangrowth_{t-1}$ (still negative but insignificant).

The results documented in columns 3 and 6 of Table 2.13 support that the sentiment of bank managers has a negative influence on how equity investors perceive the riskiness of a bank, but does not support the hypothesis that it has a statistically significant negative influence on the association between the sentiment of bank managers and loan growth.[32] In both cases, the coefficients on $tone_{t-1}$ are negative (and statistically significant at the 10% level in the case of the Arellano–Bover/Blundell–Bond system estimation), respectively. The coefficients on the interaction between $loangrowth_{t-1}$ and $tone_{t-1}$ are negative but statistically insignificant for both the OLS and Arellano–Bover/Blundell–Bond estimations, respectively. Given that dynamic panel bias might be an issue when estimating Equation (2.14), the estimates from the Arellano–Bover/Blundell–Bond system estimator are likely to have the lowest

[32] In this context, a negative influence means lower risk.

bias. We therefore consider the estimates reported in column 6 of Table 2.13 as the best estimate of the effect of bank manager sentiment and of the interaction between loan growth and bank manager sentiment.

Table 2.13. Does bank manager sentiment spill over to equity investors?

	(1)	(2)	(3)	(4)	(5)	(6)
	$SRISK_t$	$SRISK_t$	$SRISK_t$	$SRISK_t$	$SRISK_t$	$SRISK_t$
$loangrowth_{t-1}$	-0.0204*	-0.0197	-0.0195	0.0013	0.0019	0.0040
	(0.0122)	(0.0120)	(0.0119)	(0.0101)	(0.0101)	(0.0099)
$tone_{t-1}$		-0.0208	-0.0208		-0.0272**	-0.0204*
		(0.0160)	(0.0159)		(0.0132)	(0.0119)
$loangrowth_{t-1} \times tone_{t-1}$			-0.0053			-0.0254
			(0.0174)			(0.0185)
$SRISK_{t-1}$	0.6686***	0.6678***	0.6677***	0.4229***	0.4207***	0.4214***
	(0.0547)	(0.0546)	(0.0549)	(0.0596)	(0.0587)	(0.0560)
Constant	5.0103*	4.8347*	4.6930	21.0017	20.7769	21.2870
	(2.7924)	(2.8090)	(2.8718)	(29.3188)	(30.0985)	(29.2500)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	1169	1169	1169	1169	1169	1169
R^2	0.8685	0.8689	0.8690	NA	NA	NA
Adj. R^2	0.8100	0.8110	0.8110	NA	NA	NA

Note: In this table, we report the results from regressions of scaled *SRISK* on *loangrowth*, *tone* and bank-specific and macroeconomic control variables. The control variables include *impairments*, *operatingincome*, *operatingexpenses*, *logta*, *loans*, *deposits*, *equity*, *netinterestincome*, *gdp*, *inflation*, *interbank*, *term*, *ois* and a dummy for whether missing values for an observation have been estimated via interpolation. All variables are standardized. Specifications 1–3 are estimated with the fixed-effects estimator (OLS). The standard errors are clustered on the bank level and are reported in parentheses. Specifications 4–6 are estimated with the Arellano–Bover/Blundell–Bond system estimator with robust standard errors. ***, ** and * refer to significance levels of 1%, 5% and 10%, respectively.

In summary, we find that a higher bank manager sentiment affects both the risk-taking behaviour of banks and the risk perception from equity investors about banks. While, banks with a higher bank manager sentiment increase their lending supply for riskier borrowers rather than for safer borrowers, we also find that banks with a higher bank manager sentiment are perceived as being less risky by their equity investors, even though this is not associated with bank-level loan growth.

2.8 Summary and Discussion

We provide evidence on how systematic over-optimism on the part of bank managers directly or indirectly affects the amount of credit that they supply to the real sector. Based on a textual tone score extracted from earnings press release documents and identifying bank manager sentiment as the variation of the score orthogonal to current realizations of bank-specific and macroeconomic fundamentals, we have documented four main findings. First, bank manager sentiment is partially backward-looking, i.e. it depends positively on past realizations of economic fundamentals, implying that it is on average too high relative to current fundamentals. Second, a higher bank manager sentiment is associated with a higher bank-level loan growth, but not with bank lending supply when using loan-level data and when controlling for credit demand. One potential explanation for this absence of relation when controlling for loan demand is that we focus on syndicated loans which only represent a small share of bank total lending in our sample, and that other types of loans may be more affected by bank manager sentiment. Third, a higher bank manager sentiment predicts more risk-taking on the part of banks. Fourth, bank manager sentiment influences equity investors' assessments of the bank's systemic risk in that, the banks with the most over-optimistic managers are perceived as less risky than the banks with the most over-pessimistic managers.

Taken together, some of these findings suggest that systematic over-optimism on the part of banks and their investors affect credit market outcomes. More specifically, findings one and three suggest that decisions on the lending supply to risky borrowers partially depend on past realizations of economic fundamentals. If this is the case, a financial stability implication will be that banks extend too much credit to risky borrowers in a scenario where recent economic fundamentals were good, but where these fundamentals have already started to deteriorate. As a result, banks will be overly exposed to loan default risk, which threatens their solvency and adversely affects their ability to extend new loans. Findings one and four suggest that over-optimism on the part of bank managers also spills over to their equity investors, who then underestimate their perceived risk of the banks.

An interesting question for future research is whether bank managers are aware of investors' increasing use of textual analysis tools and have started to strategically alter their language in their corporate disclosures so that they appear more optimistic than they actually are (see e.g. Huang, Teoh, and Zhang (2013) and Cao et al. (2020)). One possible implication of such a behavior in the context of this paper is that textual tone scores are biased upwards, whereas the biases are likely to be specific to each bank, depending on whether and when European bank managers have started to strategically manage the textual tone score of their corporate disclosures. Moreover, our decision to define bank manager sentiment as the part of textual tone scores orthogonal to a set of bank-specific and macroeconomic variables might introduce additional biases as the decision to begin managing the content of corporate disclosures might alter the relationships between the resulting textual tone score and economic fundamentals.

In relation to whether and to what extend bank managers strategically manage the content of their corporate disclosures, another question for future research is whether investors eventually recognize such a behavior. In general, it would be very interesting to explore whether there is a feedback loop between how optimistic bank managers choose to appear and how investors assess current and future bank performance and risk.

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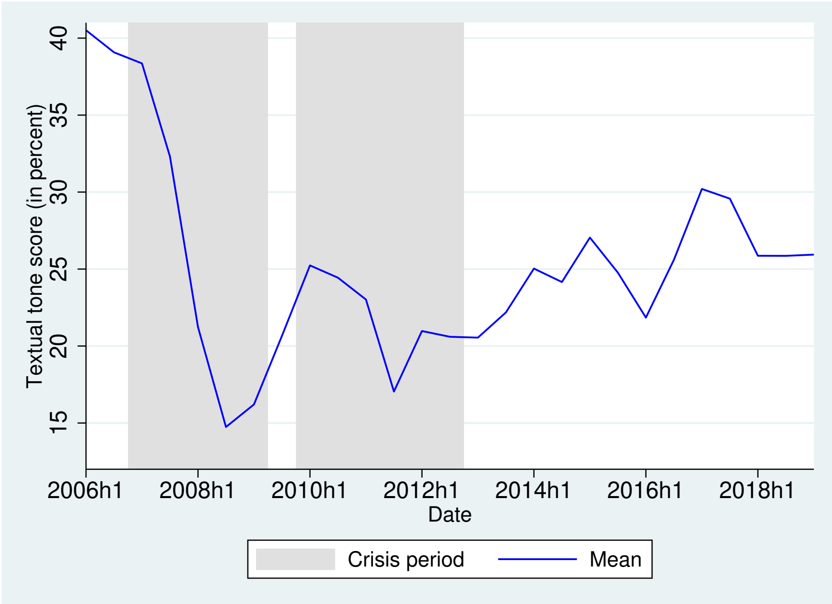
Appendices to Chapter 2

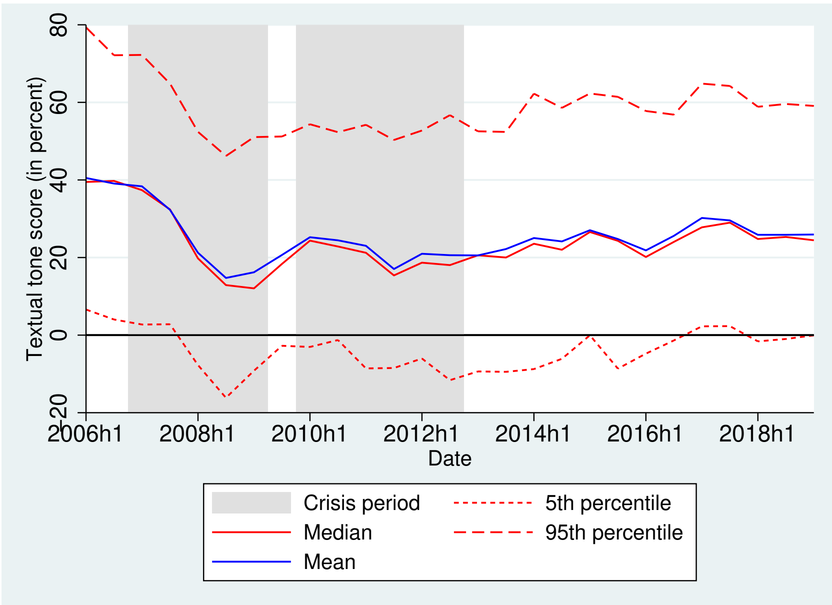
Appendix 2.A Textual tone score computation using the machine learning approach

In this appendix, we present the computation of the textual tone score we obtain by using the machine learning approach and the results of the comparison with the textual score from the dictionary approach (robustness check mentioned in Section 2.4.1). In contrast to the dictionary approach, in which we had to specify ourselves the rules for the handling of negations and long-range connections between words, machine learning algorithms are able to learn these rules from large amounts of existing text data. Among those models, we use FinBERT, a financial domain specific BERT (Bidirectional Encoder Representation from Transformers) model created by Yang, Uy, and Huang (2020). In practice, both BERT and FinBERT require a high memory and computational power for the pre-training step. Because of these costs and because the financial sentiment classification task we would like to perform is similar to the one of Yang, Uy, and Huang (2020), we do not fine-tune FinBERT to our earnings press release documents. Instead, we use the pre-trained and fine-tuned version provided by Yang, Uy, and Huang (2020) to predict the tone of each of the financial statements in our dataset. As FinBERT is fine-tuned at the sentence level, we compute a textual tone score for each sentence of our press releases. We then aggregate those scores at the press release level by summing the sentences' scores and by dividing this sum by the number of sentences in the press release. We refer to the textual tone score obtained from the machine learning approach and aggregated at the press release level as *tone_ML*. The average textual tone score over time and its distribution across banks are shown in Figures 2.A.1a and 2.A.1b. The evolution of both the average textual tone score and of its distribution are very similar to the ones we obtained in the dictionary approach. The levels are however very different, due to the different approaches used. In order to check that both approaches are also similar at the micro level, we compute two additional exercises. First, we regress the textual tone score obtained from the machine learning approach (*tone_ML*) on the textual tone score obtained from the dictionary approach (*tone*) at the bank-time level. Including bank fixed effects has the advantage of taking into account the specificity of each bank when computing our textual tone score. However, if the rank of the textual tone score is different between the two approaches, this would also be captured by the bank fixed effect. Similarly, time fixed effects would allow to take into account the influence of being in a specific time period, although time fixed effects would also capture any change of relationship between the textual tone score of the two approaches. For this reason, we estimate the regression both with and without bank and time fixed effects. The results are presented in Table 2.A.1. The textual tone scores obtained from each approach have a strong and positive relation, with or without fixed effects. As a further check, we also compute the Spearman's rank correlation between the textual tone scores obtained from each approach. We implement this exercise both for the full sample period (2006H1-2019H1) and for each semester to check that the correlation is stable over the business cycle. The results are presented in Table 2.A.2. The Spearman's rank correlation is strongly positive and significant at the 1% level, not only for the full sample period (0.72), but also for each semester taken separately, independently of the economic environment.

Figure 2.A.1. Textual tone score (machine learning approach)



(a) Average textual tone score over time



(b) The distribution of the textual tone score over time

Note: On those figures, we plot properties of the average textual tone score using the machine learning approach (Figure 2.A.1a) and the distributions of *tone_ML* (Figure 2.A.1b) over the sample period. The vertical lines indicate the start of the global financial crisis, the end of the global financial crisis and the end of the European sovereign debt crisis, respectively.

Table 2.A.2. Spearman's rank correlation (ρ) between the textual tone score of the dictionary approach ($tone_{i,t}$) and the textual tone score of the machine learning approach ($tone\_ML_{i,t}$)

Time window	ρ	N
Full period	0.7242***	3316
2006h1	0.5971***	83
2006h2	0.7447***	97
2007h1	0.6444***	101
2007h2	0.7465***	112
2008h1	0.6541***	112
2008h2	0.6613***	123
2009h1	0.7641***	122
2009h2	0.6742***	141
2010h1	0.5848***	127
2010h2	0.7345***	144
2011h1	0.6301***	133
2011h2	0.6090***	142
2012h1	0.6964***	117
2012h2	0.7228***	129
2013h1	0.6862***	127
2013h2	0.7281***	137
2014h1	0.7713***	131
2014h2	0.7510***	131
2015h1	0.6739***	114
2015h2	0.6948***	131
2016h1	0.7757***	127
2016h2	0.7454***	123
2017h1	0.7781***	128
2017h2	0.7124***	129
2018h1	0.7077***	129
2018h2	0.8184***	115
2019h1	0.6265***	109

Note: ***, ** and * refer to significance levels of 1%, 5% and 10%, respectively.

Table 2.A.1. Regression of the textual tone score from the machine learning approach ($tone\_ML_{i,t}$) on the textual tone score from the dictionary approach ($tone_{i,t}$)

	$tone\_ML_{i,t}$	$tone\_ML_{i,t}$	$tone\_ML_{i,t}$
$tone_{i,t}$	11.19***	10.23***	8.96***
	(0.20)	(0.24)	(0.25)
Constant	0.23***	0.38***	0.53***
	(0.00)	(0.09)	(0.09)
Bank fixed effects	No	Yes	Yes
Time fixed effects	No	No	Yes
N	3316	3316	3316
R^2	0.50	0.64	0.67
Adjusted R^2	0.49	0.61	0.64

Note: The standard errors are reported in parentheses. ***, ** and * refer to significance levels of 1%, 5% and 10%, respectively.

Appendix 2.B Bank manager sentiment and subsequent bank risk-taking behavior using the 5-year log-volatility

Table 2.B.1. Is bank manager sentiment predictive of bank risk-taking behaviour (based on the 5-year log-volatility of the borrower's *ROE*, *ROA*, *netincome* or *profitmargin*)?

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	ROE_f	ROE_f	ROE_f	ROA_f	ROA_f	ROA_f	$netincome_f$	$netincome_f$	$netincome_f$	$profitmargin_f$	$profitmargin_f$	$profitmargin_f$
$tone_{i,t} \times log[volatility(variable_f)_{y(t)-1}^{5y}$	0.2553**			0.0702			0.1021			0.2030**		
	(0.1113)			(0.1091)			(0.0948)			(0.0971)		
$pos_{i,t} \times log[volatility(variable_f)_{y(t)-1}^{5y}$		0.2183			0.0908			0.1049			0.2055	
		(0.1400)			(0.1122)			(0.1154)			(0.1582)	
$neg_{i,t} \times log[volatility(variable_f)_{y(t)-1}^{5y}$			-0.1477			0.0011			-0.0387			-0.0796
			(0.1255)			(0.1040)			(0.0913)			(0.1168)
Constant	12.1416***	12.2527***	12.2610***	12.5939***	12.5979***	12.6207***	12.4361***	12.4452***	12.4559***	12.4080***	12.4603***	12.4958***
	(0.1102)	(0.0910)	(0.1135)	(0.0410)	(0.0277)	(0.0357)	(0.0279)	(0.0230)	(0.0241)	(0.0666)	(0.0671)	(0.0757)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank-time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	4510	4510	4510	4650	4650	4650	4665	4665	4665	4221	4221	4221
R^2	0.8133	0.8133	0.8132	0.8017	0.8017	0.8016	0.7999	0.7999	0.7999	0.8002	0.8003	0.8000
Adj. R^2	0.7120	0.7120	0.7117	0.6943	0.6943	0.6942	0.6916	0.6916	0.6915	0.6876	0.6877	0.6873

Note: In this table, we report the results of separate regressions of loan shares on *tone*, *pos*, *neg* interacted with the 5-year log-volatility of one of the following borrower's financial variables indicated in the columns of this table: *ROE*, *ROA*, *netincome* or *profitmargin*. The controls include *impairments*, *operatingincome*, *operatingexpenses*, *logta*, *loans*, *deposits*, *equity*, *netinterestincome*, *gdp*, *inflation*, *interbank*, *term*, *ois*. The standard errors are clustered on the bank level and are reported in parentheses. ***, ** and * refer to significance levels of 1%, 5% and 10%, respectively.

Chapter 3

The Green Bond Market Elasticity

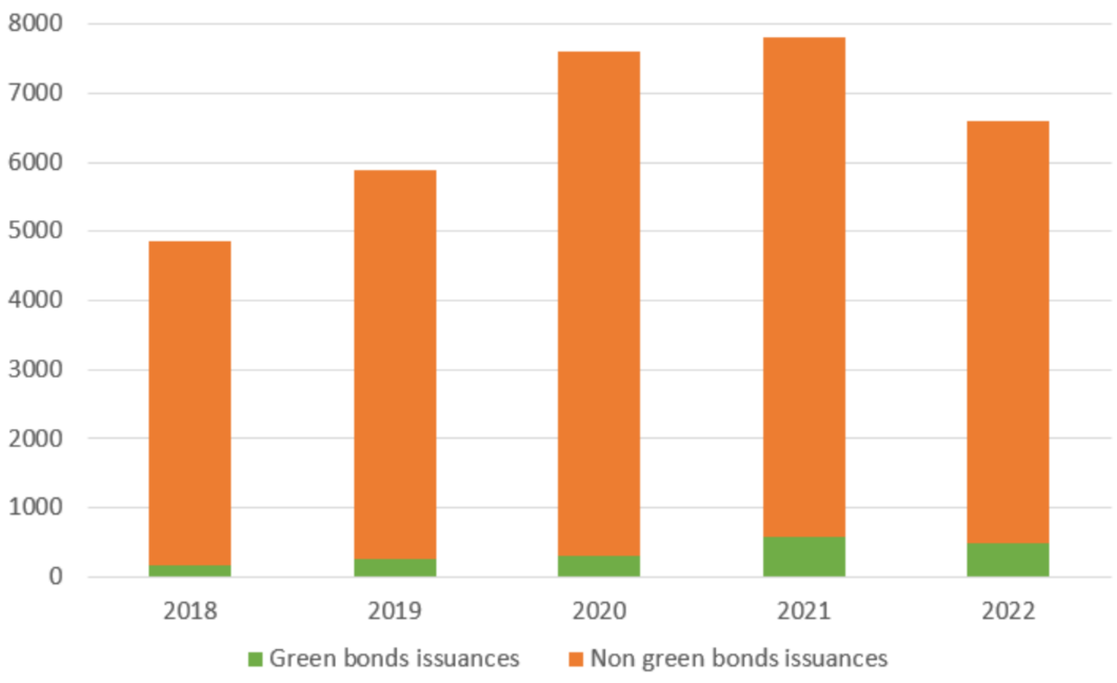
Joint with Maurice Bun

3.1 Introduction

The green bond market has been booming over the past decade. According to the Climate Bonds Initiative, global green bond issuances rose from a cumulated amount of around USD 120 billions until 2015 to USD 487 billions for the single year 2022[1]. Green bonds, dedicated to financing projects with positive environmental impacts, are increasingly viewed as a key instrument in supporting the ecological transition. However, despite this growth, the green bond market remains small relative to the broader bond market (Figure 3.1) and is characterized by unique features, including investor preferences for environmental attributes and potential differences in liquidity and pricing dynamics. These characteristics suggest that green bond prices could be particularly sensitive to fluctuations in supply and demand. In markets with limited depth and strong non-financial motivations among investors, shocks to issuance volumes or to investor demand may have outsized effects on relative pricing. Understanding how supply and demand shocks affect the green spread—the yield differential between green and otherwise equivalent conventional bonds[2]—is therefore crucial both for assessing the maturity of the green bond market and for evaluating the potential effectiveness of policy initiatives aimed at promoting green finance.

This paper addresses this question by studying how exogenous green bond supply and demand shocks impact the green spread, and what are the main factors driving this impact.

Figure 3.1. Green and non green bond issuances per year (World, USD bns)



Source: S&P Global Ratings

[1] More details can be found here: https://www.climatebonds.net/market/data/ and https://www.climatebonds.net/files/reports/cbi_sotm_2022_03e.pdf .

[2] The green spread we are referring to here is sometimes called greenium in the existing literature. To avoid any confusion between green spread and greenium, we follow D'Amico, Klausmann, and Pancost (2023) who distinguish the green spread (defined as the yield spread observed between a green bond and its equivalent conventional bond) and the greenium (defined as the component of the green spread related to investors' environmental preferences).

We proceed in four steps. First, we construct a daily measure of the green spread at the bond-level. To do so, we follow Zerbib (2019) and build a synthetic conventional (i.e. non-green) bond match for each green bond of our sample sharing the same key characteristics (issuer, currency, seniority, coupon type and maturity). We then obtain the green spread by computing the difference between the daily yield of each green bond of our sample and of its synthetic conventional bond match. Our analysis focuses on green bonds issued by European entities.

Second, we identify shocks to the supply and demand of green bonds and study their effect on the green spread. As supply, demand and prices are endogenous, we use high-frequency (daily) public announcements of new green bond issuances to identify supply shocks. As those announcements precede actual issuance and are likely to reflect shifts in expected supply rather than concurrent changes in market conditions, we exploit those announcements as exogenous supply shocks. To identify exogenous demand shocks, we focus on announcements from the European Central Bank (ECB) related to the incorporation of climate considerations in its different policy tools, namely its asset purchase programmes, of its collateral framework, of its market operations, or of its non-monetary policy portfolio. Using a narrative approach à la Christina D Romer and David H Romer (1989, 2023), we construct an indicator capturing the stance of the ECB with respect to the incorporation of climate considerations in its policy tools.

Third, we estimate the dynamic response of the green spread to these shocks using bond pair-panel local projections with fixed effects (Jordà, 2005). This econometric setup allows us to study the persistence of the effect of the supply and demand shocks on the green spread, while taking into account the autocorrelation of the variables. If the green bond market is separated from the conventional bond market, then one would expect the yield of green bonds to react more to both the supply and demand shocks than the yield of conventional bonds. This is what we find: supply shocks — proxied by public announcements of new green bond issuances — increase the green spread of already existing green bonds, even though the effect is economically limited (with a peak of 0.06 basis points for a one-standard deviation supply shock, or equivalently USD 1.17bns after 13 business days) and short-lived. Conversely, demand shocks — proxied by ECB's announcements related to the incorporation of climate considerations in its different policy tools — reduce the green spread. The effect is more persistent and larger but still rather limited (with a maximum effect of -0.5 basis points for a one-unit positive demand shock 11 business days).

Fourth, we explore the heterogeneity of these effects to better understanding their underlying factors and the extent of the green bond market segmentation. On the supply side, we examine whether the effect differs by type of issuer, country of issuance, and size of the shock. We find that larger supply shocks and those originating from the same country as the affected bonds exert stronger green spread responses, while issuer type appears to play a minimal role. On the demand side, we explore heterogeneity by policy type and find that announcements related to either asset purchase programs or collateral frameworks, or those that signal a general climate commitment without specifying instruments have the strongest impact, even though this impact tends to be again limited and/or transitory.

The rest of the paper is organized as follows. In Section 3.2, we summarize the related literature and lay out our contributions. In Section 3.3, we describe how we compute the green spread, the supply and the demand shocks used for the empirical analysis. In Section 3.4, we present the main empirical strategy we implement to study the overall effect of supply and demand shocks on the green spread. In Section 3.5, we show the results for this main empirical strategy. In Section 3.6, we present the heterogeneity analysis we implement and the corresponding results. In Section 3.7, we present the next steps we want to implement in the paper. Finally, in Section 3.8, we conclude.

3.2 Literature Review

We contribute to three strands of literature. First, we contribute to a growing literature examining how supply and demand shocks influence asset prices. Recent work emphasizes that financial markets may be "inelastic," in the sense that asset flows can have large and persistent effects on prices and risk premia (Charoenwong, Morck, and Wiwattanakantang, 2021; Gabaix and Koijen, 2021). This perspective contrasts with the traditional view of elastic, arbitrage-free markets and has important implications for both asset pricing and financial regulation. While the inelastic markets hypothesis has been explored in the context of equities and broader bond markets, its relevance for green bonds—an asset class with limited depth and unique investor preferences—remains largely unexplored. A small number of studies focus on the demand side of the green bond market using central bank interventions. For example, Bremus, Schütze, and Zaklan (2021), Macaire and Naef (2021) and Giovanardi et al. (2023) show that the eligibility of green bonds in central bank collateral frameworks reduces their yields relative to comparable securities. Eliet-Doillet and Maino (2022) show that the ECB's climate strategy announcement on July 8, 2021 mentioning the incorporation of climate change considerations in its collateral framework and corporate sector asset purchases led to a significant decrease in the green spread. A last paper close to ours which highlights supply-demand imbalances on the green bond market is Amel-Zadeh et al. (2024). The authors investigate whether green bonds trade differently from conventional bonds in secondary markets using intraday trading data between 2017 and 2023. They provide evidence of strong asymmetries between the effect of buy and sell trades for green bonds suggesting strong demand-supply imbalances, with a demand for green bonds higher than supply. Our contribution to this strand of literature is twofold. To the best of our knowledge, our paper is the first to provide high-frequency evidence on the supply side of the green bond market and to test for its elasticity using daily exogenous variation. Furthermore, our results complement the analysis of Amel-Zadeh et al. (2024) by providing causal evidence on how exogenous supply and demand shocks affect the relative pricing of green versus conventional bonds, and confirms the presence of strong demand-supply imbalances with demand shocks having a stronger and more persistent impact than supply shocks on the green spread.

Second, we contribute to the literature on the segmentation of the green bond market. Many papers have focused on how the green bond market is a specific segment of the overall bond market, either because of its limited depth (Deschryver and De Mariz, 2020) or specific investor preferences (Fama and French, 2007; Baker et al., 2018; Zerbib, 2019; Wang and Wu, 2022). This segmentation may be exacerbated by institutional features—such as issuer type or country of origin—or by policy interventions. By showing that green bonds overreact to supply and demand shocks compared to equivalent synthetic conventional bonds, our paper confirms the segmentation of the green bond market compared to the rest of bond market. Furthermore, our findings that the green spread reacts more strongly to larger supply shocks, supply shocks originating from the same country, or to certain types of ECB announcements, offer novel evidence of geographic and policy-driven segmentation within the green bond market.

Third, we contribute to the literature focusing on the factors explaining the existence of non-zero green spread. On the one hand, some factors make green bonds less attractive than conventional bonds, and hence imply a positive green spread. Companies issuing green bonds are committed to realize green projects, which hence restricts their investment policies. Also, getting a green bond certification requires a third-party verification, which increases administrative and compliance costs. Finally, green bonds generally have a lower liquidity and a higher volatility compared to conventional bonds. On the other hand, other factors make the green spread negative. Some investors are ready to sacrifice some return in order to satisfy their environmental preferences (Fama and French, 2007; Baker et al., 2018; Zerbib, 2019; Wang and Wu, 2022). This sacrifice in return related to environmental preferences is the greenium. Also, as shown by the existing literature, ESG assets have a positive relationship with financial performance (Guenster et al., 2011; Flammer, 2013; Eccles, Ioannou, and Serafeim, 2014) and a negative relationship with risk (Godfrey, Merrill, and Hansen, 2009; Hoepner et al., 2018). By studying the effect of supply shocks on the green spread, we may elicit a new factor influencing the green spread, related to the fact that green bonds react more than conventional bonds to supply shocks both in terms of yield, making them less predictable, more volatile and hence less attractive.

3.3 Data

In this Section we discuss the key variables used in our empirical analysis. Subsequently we describe the bond yields of green and conventional bonds, the supply shocks and the demand shocks.

3.3.1 The green spread

We collect the yields of green and conventional bonds from Refinitiv Eikon. We focus on all the bonds issued by European entities[3] between 2007 and 2022[4]. Based on this sample, we estimate the green spread by following the method of Zerbib (2019). This method allows to find a synthetic equivalent conventional bond for each green bond present in our sample. The method is composed of two steps. In a first step, a green bond is matched with all the conventional bonds having similar characteristics (same issuer, rating, currency, seniority and coupon type). While restrictive, imposing same issuer and same seniority ensures that any event affecting the issuer's default risk is not affecting the yield spread between a green bond and its comparable conventional bonds. Since the maturity and the liquidity cannot be matched perfectly between a green bond and a conventional bond, we also use the criteria defined by Zerbib (2019): we restrict the comparable conventional bonds to have a maturity that is neither two years shorter nor two years longer than the green bond's maturity. Similarly we restrict the eligible conventional bonds to those with an issue amount of less than four times the green bond's issue amount and greater than one-quarter of this amount and with an issue date that is, at most, six years earlier or six years later[5] than the green bond's issue date. The second step allows to neutralize the effect of maturity mismatch, which could otherwise strongly bias our estimates (Nyborg and Woschitz, 2024). Here, we focus only on

[3] We take all issuers type, i.e., corporates, central and local governments, agencies (in particular public banks such as Kreditanstalt für Wiederaufbau in Germany or Société de financement local in France) and other supranational entities (e.g. the European Investment Bank, the European Bank for Reconstruction and Development, etc) between 2007 and 2022.

[4] Starting in 2007 allows us to study the whole development of the green bond market as the first green existing bond was issued in 2007 by the European Investment Bank (ISIN XS0301665310).

[5] By taking six years, we simply follow Zerbib (2019). However, given that we have a much longer time window for our sample (and hence more observations), we may be able to make the issue date constraint of the matching method stricter in the future.

those green bonds which have at least two conventional bond matches. Then, for each triplet (i.e. for each green bond and its two conventional bonds matches), we interpolate (or extrapolate) the two conventional bonds' yields linearly at the green bond maturity date to obtain a synthetic conventional bond yield, which thus shows the same properties as the green bond. The green spread is then obtained as the difference between the daily yield of each green bond and of its synthetic conventional bond.

Figure 3.2 presents the time series of average yields on green bonds and their synthetic non-green counterparts, alongside the 10-year German and Italian sovereign yields. Both green and conventional bond yields exhibit strong co-movement with sovereign yields, underscoring their sensitivity to broader market conditions. At the beginning of the sample period, the average yields on green and conventional bonds are closely aligned with the German 10-year yield, reflecting the dominance of low-risk issuers such as supranational entities (in particular the EIB and EBRD) and public agencies. From late 2015 onward, the strong increase of green bond issuances from corporations —characterized by higher credit and liquidity risk premia — into the green bond market introduces a notable composition effect, progressively aligning both green and non-green average yields with the Italian 10-year yield. Figure 3.3 plots the average green spread. The green spread remains small over most of the sample, mostly ranging between -10 and +18 basis points. The average green spread is positive until the end of 2015 (around 7 basis points) before turning negative during the rest of the sample period and remaining reasonably stable between 0 and -10 basis points, which is consistent with prior literature. In particular, D'Amico, Klausmann, and Pancost (2023), who focus on German sovereign twin bonds [6] and show that their green spread varies between 0 and -9 basis points from September 2020 to August 2022, depending on the maturity considered. Interestingly, the shift of the green spread from positive to negative values at the end of 2015 also corresponds to the moment when more green bonds started to be issued, in particular by the corporate sector. Substantial short-term fluctuations are observed, however, primarily driven by composition effects. To mitigate the composition effects and isolate time-variation in the green spread, we standardize the green spread at the bond level before computing the average (Figure 3.4). While this normalization renders the sign of the spread less interpretable in absolute terms, it allows us to abstract from level differences across bonds and focus on relative trends. The standardization highlights a constant decrease of the green spread between the beginning of 2014 until the end of 2017 before its stabilization.

[6] German sovereign twin bonds are defined as green bonds issued by the German government based on an existing conventional Federal security with identical coupons and maturity dates, but usually smaller issuance volumes. More information about the German sovereign twin bonds can be found in this link.

Figure 3.2. Average green vs synthetic conventional bond yield over time, compared to the 10-year German and Italian sovereign yields (in basis points)

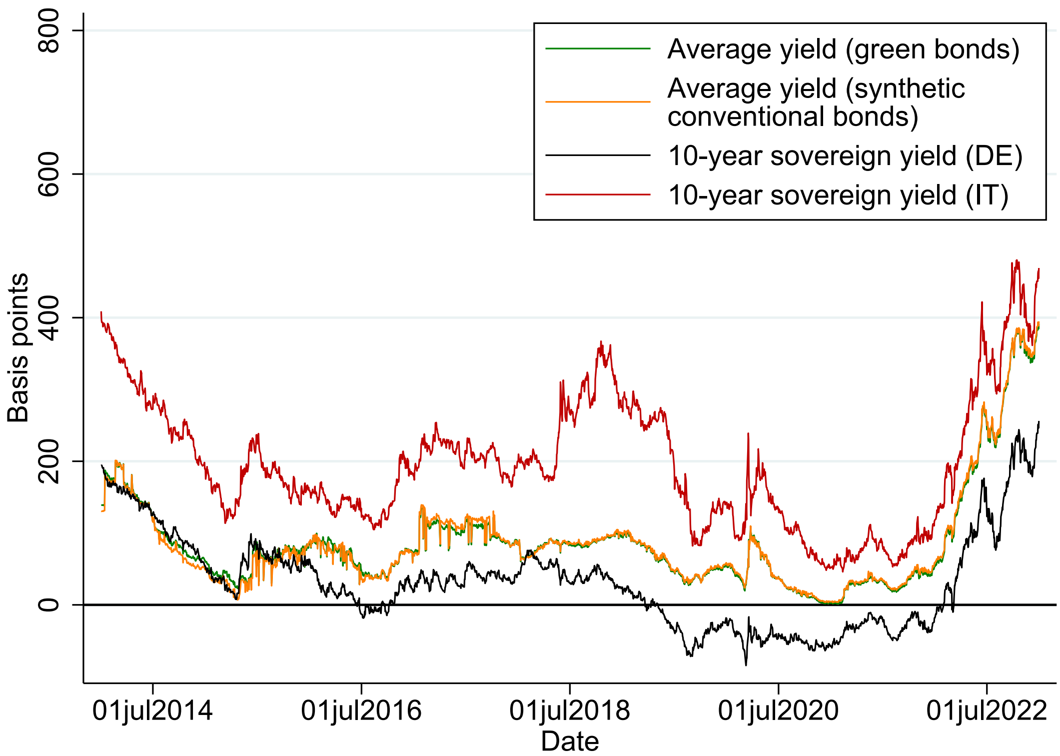


Figure 3.3. Average green spread over time (in basis points)

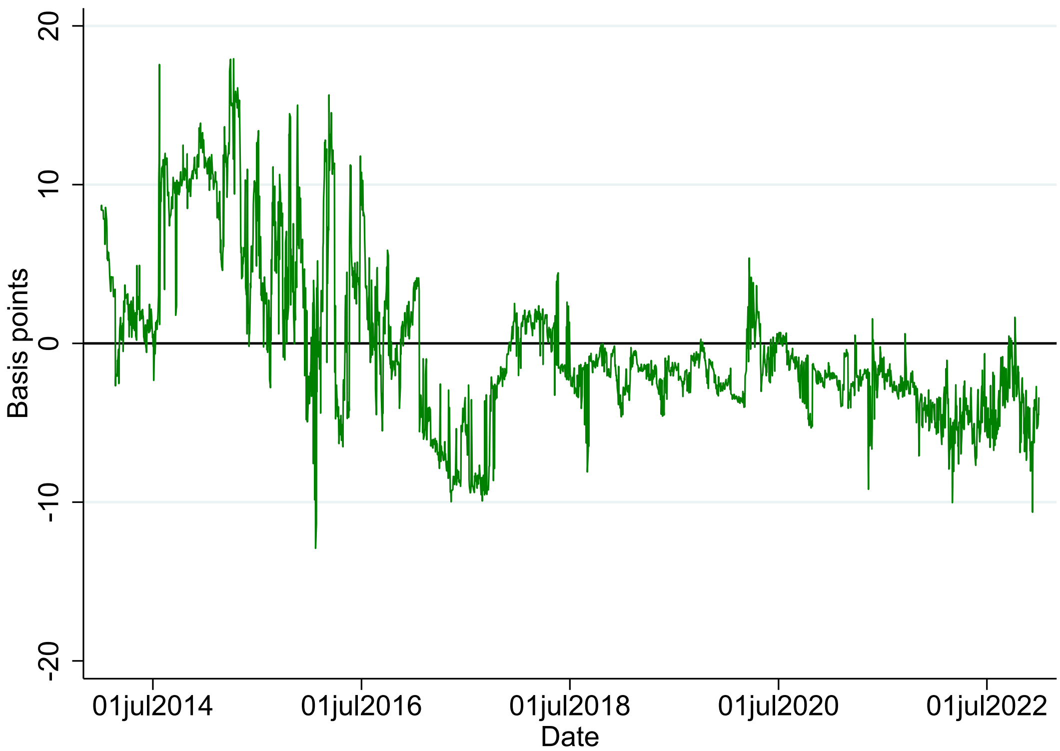
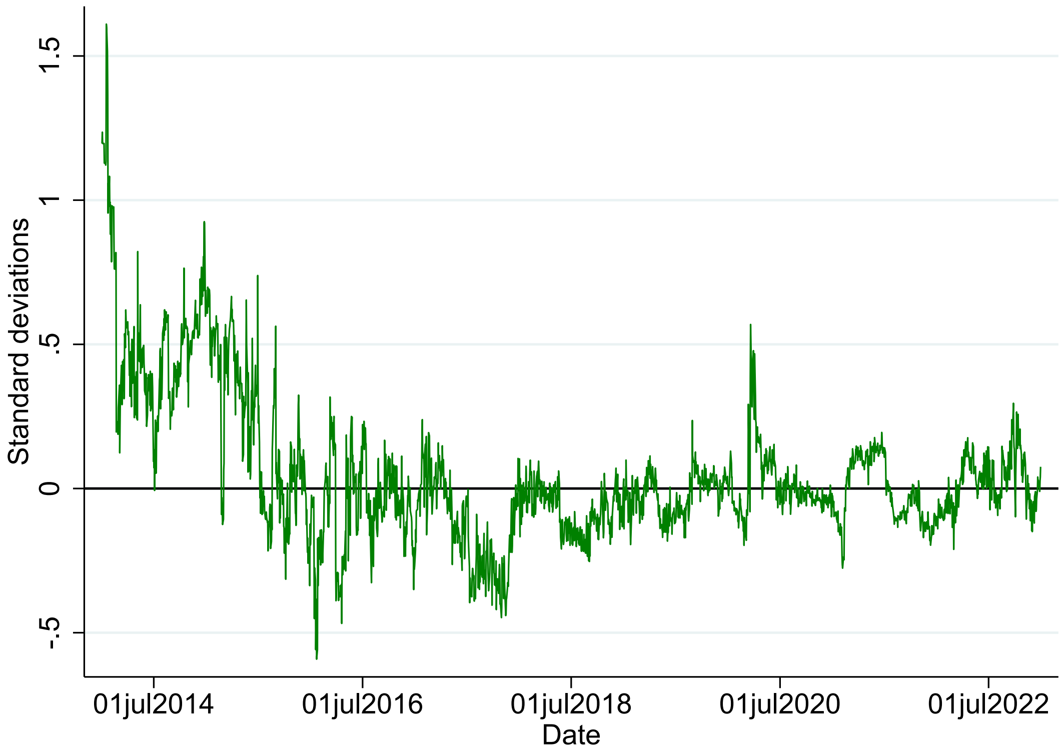


Figure 3.4. Average green spread over time, after having standardized the observations at the bond-level



We next analyze the distribution of the green spread and of the green and synthetic conventional bond yields. In Table 3.1, we show some summary statistics for those variables. For comparison purposes, we present the statistics for the sample in which both the green and synthetic conventional bond yields are observed. We manage to build a synthetic conventional bond for 649 green bonds. On average, we observe the green spread between a given green bond and its synthetic conventional bond match for 412 business days. The green spread is on average negative but modest (-1.46 basis points), indicating a small yield discount for green bonds relative to comparable conventional instruments. This result aligns with the literature focusing on the greenium and on the green spread, finding that both are negative by only a few basis points. However, the distribution is wide and skewed, with a standard deviation of 24.06 basis points and extreme values ranging from –256.14 to +185.92 basis points. This variation highlights the influence of bond-level heterogeneity as well as market factors. When looking at the decomposition of the green spread, both green and synthetic conventional bond yields exhibit similar central tendencies (averaging 122.44 and

123.90 basis points, respectively), and display comparable dispersion (standard deviations of 140.94 and 143.53 basis points, respectively). The similarity in their yield distributions across percentiles suggests that the synthetic matching procedure performs well in constructing a credible counterfactual for the yield of each green bond.

Just like its components, the green spread is autocorrelated. To quantify the autocorrelation, we estimate the following AR(p) regression:

$$GS_{b,t} = \alpha_b + \sum_{1}^{p} \beta_p * GS_{b,t-p} + FE_{my(t)} + \varepsilon_{b,t}$$

where $GS_{b,t}$ represents the green spread on day t of the green bond b and of its synthetic conventional bond, α_b represents bond-pair fixed effects to capture the time-invariant and bond pair-specific component of the green spread, and $FE_{my(t)}$ represents month-year fixed effects to control for macroeconomic and market-wide shocks, and p represents the number of lags chosen for estimating the AR(p) model. Table 3.2 presents estimates from the autoregressive (AR) model of the green spread described above, ranging from an AR(1) specification in column (1) to an AR(5) specification in column (5). The results reveal that the green spread is highly persistent. In the AR(1) model, the coefficient on the first lag is 0.90 and statistically significant at the 1% level, suggesting that most of the variation in the green spread can be attributed to its own past value. As additional lags are introduced, the magnitude of the first lag decreases—falling to 0.65 in the AR(5) specification—but the sum of the autoregressive coefficients remains high. Although highly persistent, the pattern of the autoregressive estimates is consistent with mean-reverting dynamics. All five lags are statistically significant in the AR(5) model, underscoring the presence of short-term dynamics in the green spread. Across all specifications, both the R-squared and adjusted R-squared remain high-all above 0.90—highlighting the strong explanatory power of past green spreads in capturing their current level. Together, these results emphasize the importance of accounting for serial correlation when studying the impact of shocks on the green spread.

Table 3.1. Green spread and yields summary statistics

	Green spread (basis points)	Green bond yield (basis points)	Synthetic conventional bond yield (basis points)
mean	-1.46	122.44	123.90
sd	24.06	140.94	143.53
min	-256.14	-56.53	-96.29
p1	-88.78	-50.30	-50.89
p5	-31.88	-32.23	-32.06
p25	-4.45	15.62	15.46
p50	-0.12	65.14	66.40
p75	3.17	217.96	218.63
p95	25.02	396.45	402.40
p99	64.72	502.59	528.91
max	185.92	786.39	891.26
N*T (in days)	267,321	267,321	267,321
N	649	649	649

Note: In this table, we report summary statistics for the green spread and for the green and synthetic conventional bond yields. For comparison purposes, we present the statistics when both the green spreads, the green and synthetic conventional bond yields are observed simultaneously. All the statistics above (except N and N*T) are expressed in basis points.

Table 3.2. Autoregressive coefficients of the green spread

	(1) $GS_{b,t}$	(2) $GS_{b,t}$	(3) $GS_{b,t}$	(4) $GS_{b,t}$	(5) $GS_{b,t}$
$GS_{b,t-1}$	0.90^{***}	0.69^{***}	0.66^{***}	0.65^{***}	0.65^{***}
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$GS_{b,t-2}$		0.24^{***}	0.14^{***}	0.12^{***}	0.11^{***}
		(0.00)	(0.00)	(0.00)	(0.00)
$GS_{b,t-3}$			0.14^{***}	0.08^{***}	0.07^{***}
			(0.00)	(0.00)	(0.00)
$GS_{b,t-4}$				0.10^{***}	0.06^{***}
				(0.00)	(0.00)
$GS_{b,t-5}$					0.06^{***}
					(0.00)
Constant	-0.15^{***}	-0.11^{***}	-0.09^{***}	-0.08^{***}	-0.08^{***}
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Bond-pair fixed effects	Yes	Yes	Yes	Yes	Yes
Month-year fixed effects	Yes	Yes	Yes	Yes	Yes
N	280699	279848	279037	278254	277490
R^2	0.910	0.917	0.920	0.922	0.922
Adj. R^2	0.910	0.916	0.920	0.921	0.922

Note: In this table, we report the results from the AR(p) model for the green spread. Specifications 1–5 report the results for the AR model with p = 1,...,5 lags respectively . The standard errors are reported in parentheses. ***, ** and * refer to significance levels of 1%, 5% and 10%, respectively.

3.3.2 The supply shocks

Regarding supply shocks, we use the amount of green bonds announced to be issued at each daily date of our sample. We retrieve this variable for all the green bonds contained from Refinitiv Eikon. For each green bond, this variable contains the date of the first time such issuance has been made public and the amount to be issued in USD[7] . Given that this is the first time such issuances are made public, and that their announcements are in general spontaneous and made independently of more regular publications (such as financial statements), we argue that those announcements are unexpected by the financial markets. Importantly, given that we observe those announcements at a daily frequency, we also believe that they are exogenous to both the pricing of already existing bonds, and any confounding demand shocks. Finally, as asset prices should react quickly to important announcements, exploiting daily supply shocks should be sufficient to capture the main effect of those announcements. In Figure 3.5, we show the evolution of green bond issuance announcements over time. As indicated in Figure 3.5, there is a lot of variation in the issued amount as daily announced over time, which varies from USD 0 to USD 36 bns. Also, consistent with the fast but recent expansion of the green bond market, we observe very small amounts announced daily until 2014 before a rapid increase.

We also check the number of green bonds by time lag between their announcement date and their issuance date (Figure 3.6). One concern for the immediate effect of the announced issued amount on the green spread would be that the announcement date precedes too much the actual issuance date. However, this does not seem to be the case, as 90% of the announcements are done at most 10 days before the actual issuance date.

In Figure 3.7, we split the supply shocks by type of issuer[8] As shown in Figure 3.7, we observe a lot of heterogeneity both in terms of daily announcements frequency and in terms of announced amount. In particular agencies[9] and companies announce green bond issuances very frequently, but for medium-size amounts (at most USD 8 bns, see Figures 3.7a and 3.7b, respectively). On the contrary, central governments announce green bond issuances irregularly, but for very high amounts (up to USD 36 bns, see Figure 3.7c). Municipalities announce green bond issuances for very low amounts (less than USD 1 bn, see Figure 3.7d). Interestingly, other governmental or supranational entities were the first type of issuer to announce green bond issuances (already in 2007), did those announcements very frequently, but for low amounts (less than USD 5 bns) until the end of 2021 when they started to announce large amounts of green bond issuances (up to USD 20 bns, see Figure 3.7e).

In the rest of the paper, we standardize the supply shocks, i.e. the announced amount to be issued. Expressing supply shocks in units of standard deviations facilitates the interpretation of the estimated coefficients and improves comparability with the demand shocks, which are captured using an indicator equal to (-1), 0 or +1 (see Subsection 3.3.3 below).

[7] The different amounts we retrieve from Refinitiv Eikon are all expressed in USD, independently on their currency of issuance.

[8] We follow the classification from Refinitiv Eikon, which assigns 5 different alternative issuer types: agencies, corporates, central governments, municipalities, and other governmental or supranational entities.

[9] Agencies are defined as public organization with a specific mission. Most of the agencies in our sample are public banks such as Kreditanstalt für Wiederaufbau in Germany or Société de financement local in France.

Figure 3.5. Issued amount of green bonds (in USD bns) by announcement date

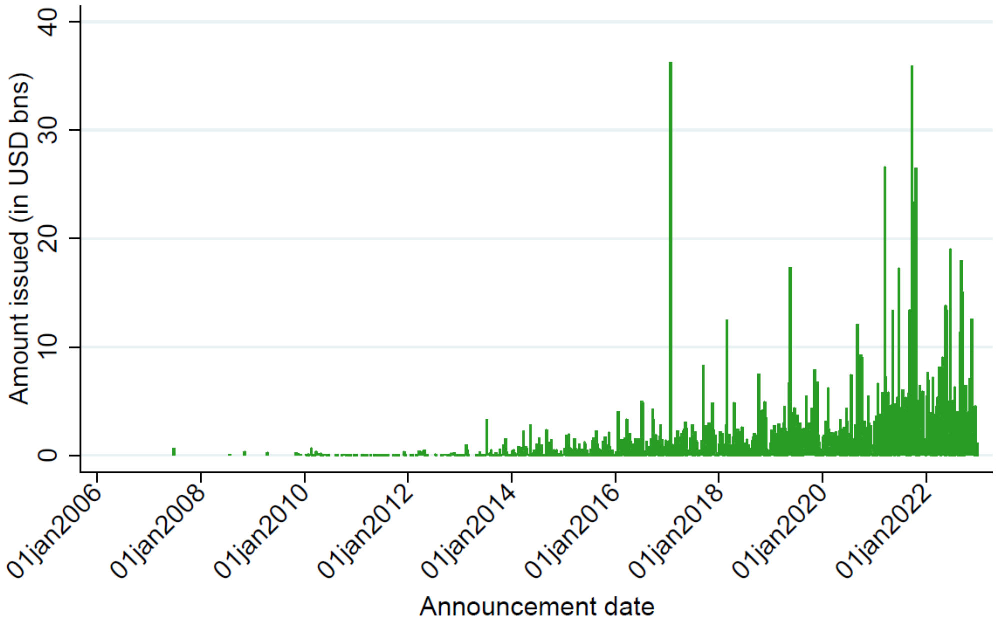


Figure 3.6. Number of green bonds by time lag between their announcement date and their issuance date

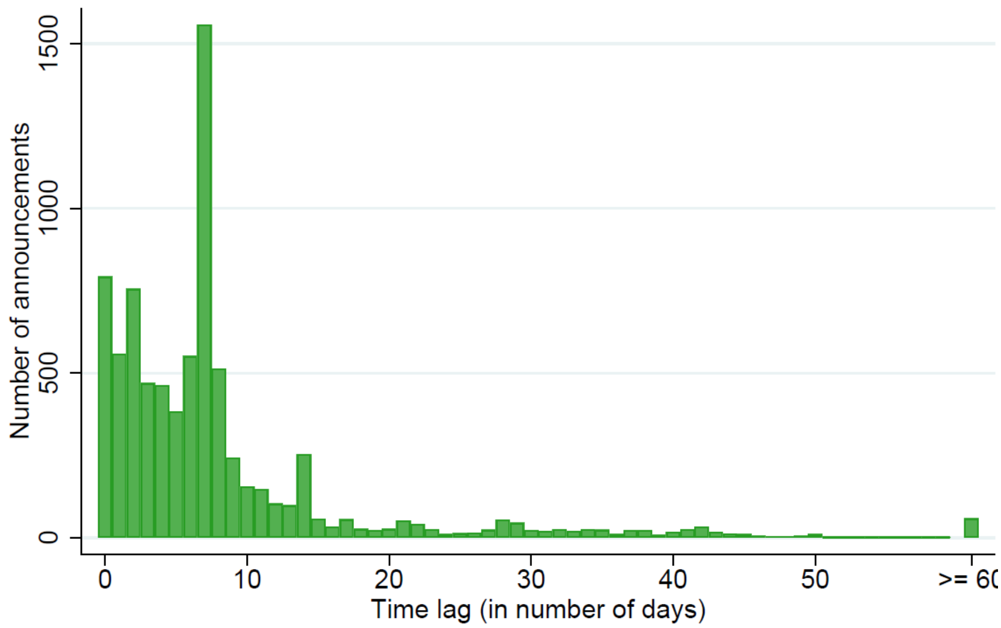
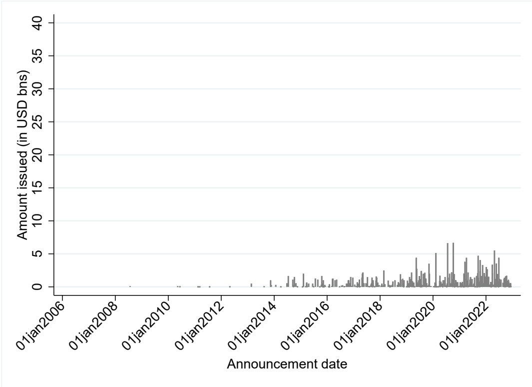
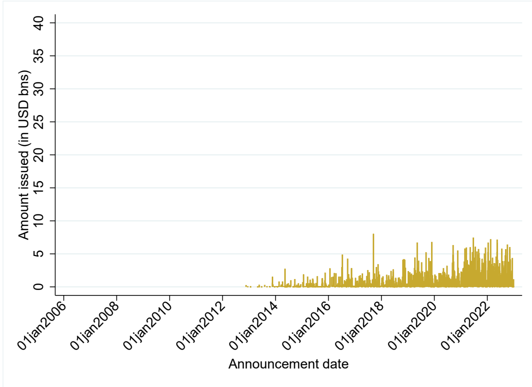


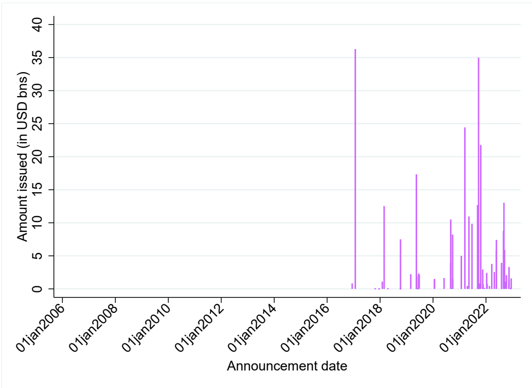
Figure 3.7. Issued amount of green bonds (in USD bns) by announcement date and issuer type



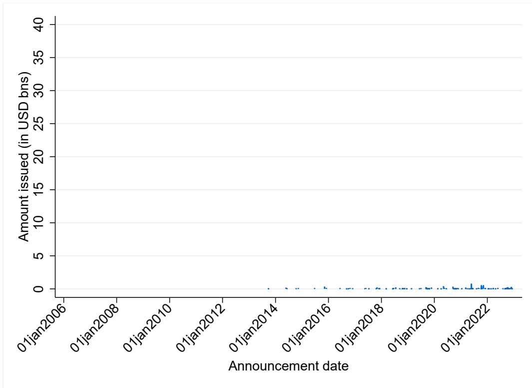
(a) Agencies



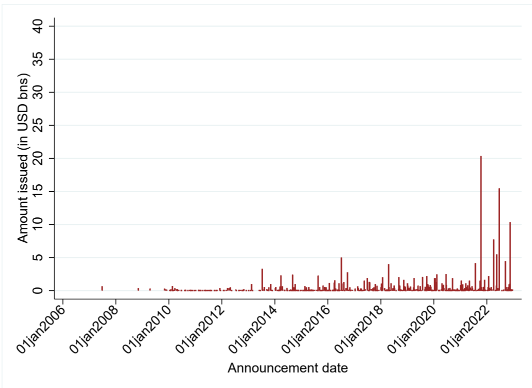
(b) Companies



(c) Central governments



(d) Municipalities



(e) Other governmental or supranational entities

Note: In this figure, we plot the issued amount of green bonds (in USD bns) by announcement date. The sample is split by issuer type: in Figure 3.7a), we only consider announcements made by agencies, in Figure 3.7b), we only consider announcements made by companies, in Figure 3.7c), we only consider announcements made by central governments, in Figure 3.7d), we only consider announcements made by other governmental or supranational entities, and in Figure 3.7e), we only consider announcements made by municipalities.

3.3.3 The demand shocks

In order to identify demand shocks for green bonds, we focus on 69 announcements from the European Central Bank (ECB) on climate change, from the beginning of 2018 to the end of 2022. Those announcements are either press releases from the ECB or speeches made by ECB board members [10]. Among those 69 announcements, we only keep 29 of them, which are related to the incorporation of climate considerations in the different ECB's policy tools, either through the greening of its asset purchase programmes, of its collateral framework, of its market operations, or of its non-monetary policy portfolio. We then adopt a narrative approach similar to Christina D Romer and David H Romer (1989, 2023) to classify those announcements according to their stance and create an indicator reflecting this classification: (+1) if the announcement is in favor of incorporating climate considerations in the ECB's policy tools, (-1) of it is against this incorporation, and 0 if no clear stance appears.

In Figure 3.8, we show examples of announcements for each stance, and in Table 3.A.1 of Appendix 3.A, we summarize the content of each announcement and give the value of the narrative indicator we just described. Overall, we classify 24 announcements as being in favor of incorporating climate considerations (indicator equal to +1), 2 announcements as being against (-1), and 3 as having no clear stance (0). Most of the announcements against the incorporation of climate considerations, or having no clear stance are concentrated at the beginning of our sample, i.e. when this incorporation was still debated, i.e. before the ECB officially started to effectively incorporate them in different ways (in particular the press releases of the 22/09/2020, 25/01/2021, 08/07/2021 and 04/07/2022, see Table 3.A.1 of Appendix 3.A).

[10] Those can be found in this link and in this link, respectively.

Figure 3.8. Examples of announcements from the ECB and their classification using the narrative approach

Positive demand shock (indicator = +1):

"And we will adjust the framework guiding the allocation of corporate bond purchases to incorporate climate change criteria, in line with our mandate.“ (Christine Lagarde, 11/07/2021)

Neutral demand shock (indicator = 0):

“The third, and most controversial, way in which we can contribute is by taking climate considerations into account when designing and implementing our monetary policy operations. […]These and other questions will feature prominently in our monetary policy strategy review. Without pre-empting the discussion, there are two opposing views regarding the debate on greening asset purchases.” (Isabel Schnabel, 17/07/2020)

Negative demand shock (indicator = -1):

“Moreover, focusing purchases on green bonds would run counter to the requirement to respect the workings of an open market economy and be tantamount to industrial policy. The APP is a tool for macroeconomic stabilisation, not for microeconomic reallocation. Deviating from market neutrality and interfering with economic policy risks exposing the ECB to litigation. It is not up to the central bank but to elected governments to decide which industry is to be closed and when. As central bankers, we have to respect and implement legitimate decisions in this context. And the effectiveness of monetary policy has been bolstered by abstaining from normative judgments on the morality of markets and industries.“ (Yves Mersch, 27/11/2018)

3.4 Methodology

We use a panel local projection framework with fixed effects (Jordà, 2005). In this framework, the dependent variable is the green spread, i.e. the difference between the green bond yield and matched conventional bond yield, measured at the daily frequency. For this dependent variable, we estimate the impulse response functions to the supply and demand shocks as described in Section 3.3. This framework allows us to study the dynamics of the effect of the supply and demand shocks on the green spread, controlling for a set of other factors affecting the green spread as well as taking into account the serial correlation in the data. Specifically, we estimate the following specification:

$$GS_{b,t+h} \;=\; \alpha_{b,h} + \beta_h^S * Supply_t + \beta_h^D * Demand_t + \gamma_h' * W_{b,t} + \varepsilon_{b,t+h} \tag{3.1}$$

where $GS_{b,t}$ represents the green spread on day t of the green bond b and of its synthetic conventional bond. The supply shock occurring on day t, i.e. a one-standard deviation increase in green bond issuances announced on day t, is represented by the variable $Supply_t$. The demand shock occurring on day t, i.e. the indicator variable capturing the stance of the announcements made by the ECB on day t, is represented by the variable $Demand_t$. The bond pair fixed effects $\alpha_{b,h}$ capture the time-invariant and bond pair-specific component of the green spread. Given that we estimate the local projection for each horizon h separately, the bond pair fixed effects also vary across horizon h. The vector $W_{b,t}$ contains daily market control variables, namely the spread between the Italian and the German 10-year sovereign yields, the 3-month OIS rate, the VIX, the EuroStoxx 600, the difference of bid-ask spread between green bond b and its synthetic conventional bond, and the total amount (standardized) of conventional green bond issuances announced on day t to control for conventional bond supply shocks. We also include 5 lagged values of $GS_{b,t}$, $Supply_t$, $Demand_t$ and of the different controls we just described to take into account serial correlation as well as daily seasonality within a given week. We finally saturate the model with month-year fixed effects ($FE_{my(t)}$, subsumed in the vector $W_{b,t}$) to capture any unobserved developments that affect the green spread of all the bond pairs in our sample within the month and year of the day t of occurrence of the demand and supply shocks, including monthly seasonality. Given that we include the one period lagged green spread $GS_{b,t-1}$ in the vector of control variables, the dependent variable can also be rewritten as $GS_{b,t+h}\breve{}GS_{b,t-1}$ without changing the results (Olea et al., 2025). From that perspective, the coefficients of interest β_h^S and β_h^D are interpreted as the effect of supply and demand shocks, respectively, that occur on day t on the green spread observed on day $(t+h)$ compared to day $(t-1)$, i.e. the day before the demand or supply shock occurred. Regarding the horizon of the local projection, we choose $h = 0, 1, 2, ..., 20$ days, which corresponds to four business weeks. Finally, we supplement the OLS coefficient estimates with standard errors robust to arbitrary heteroscedasticity and serial correlation within a bond-pair time series.

3.5 Empirical Results

Figures 3.9 and 3.10 summarize the estimation results of equation 3.1. Specifically, Figures 3.9 and 3.10 plot the impulse response functions of the supply and demand shocks, respectively.

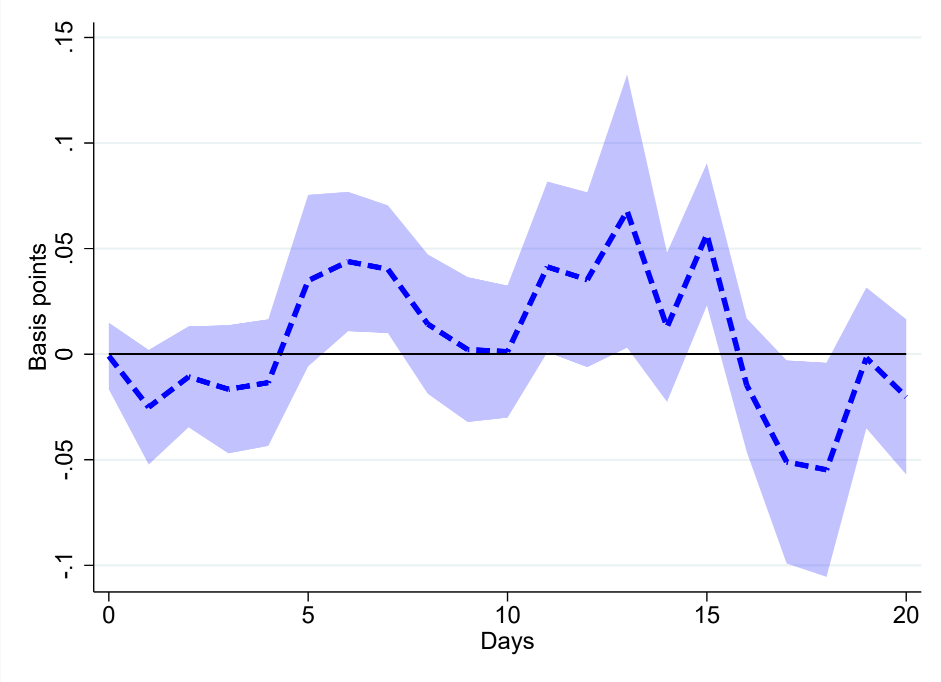
As shown by Figure 3.9, supply shocks have a very small and temporary effect on the green spread. The effect reaches its peak after 13 business days: a one-standard deviation increase in green bond issuances increases the green spread by around 0.06 basis points (significant at the 10% level). Given that a one-standard deviation increase in green bond issuances equals around USD 1.17bns, this result implies that the green spread increases by up to 0.05 basis points following the announcement of USD 1bn green bond issuances. Interestingly, the effect takes a few days to occur and only persists a few days.

As shown by Figure 3.10, demand shocks have a significantly negative and persistent but rather small effect on the green spread. The effect is significant starting from the day when the demand shock occurs, reaches its peak after 11 business days before slowly converging back to 0. Overall, an increase in the demand shock indicator by one decreases the green spread by around 0.5 basis points (significant at the 5% level). In other words, when the ECB makes an announcement in favor of the incorporation of climate considerations in its different policy tools, the green spread decreases immediately by around 0.3 basis points, continues to decrease in the following business days until reaching a total decrease of 0.5 basis points, and finally converges back to zero in the next business days.

Several existing papers document larger effects of central bank announcements on green bond spreads. Eliet-Doillet and Maino (2022) find that the ECB's July 8, 2021 climate strategy announcement led to a 3-to-4 basis point decrease in the green spread of eligible green vs eligible conventional bonds. Macaire and Naef (2021) find that the People's Bank of China's 2018 collateral policy shift towards green bonds led to a 46 basis point drop in the green spread of ten eligible green compared to equivalent conventional bonds. Giovanardi et al. (2023) use a calibrated model to quantify the effect on the green spread of central bank news shocks related to the future preferential treatment of green bonds in its collateral framework. They find that a negative effect that lies between 8.3 basis points (if the preferential treatment is implemented two years after the announcement) and 3.7 basis points (if implemented five years after the announcement). Bremus, Schütze, and Zaklan (2021) focus on the reaction of the yield spread between eligible vs non-eligible green bonds to the announcement of the ECB's Corporate Sector Purchase Programme (CSPP) in 2016, and Pandemic Emergency Purchase Programme (PEPP) in 2020. They find heterogenous effects, depending on the asset purchase programme considered, on the control group used, on the focus on green bond issued by financial or non-financial firms, and on the specification. When using their most general specification (which includes bond, week, and country-month fixed effects), they find that the effect ranges from an increase by 7 basis points (not significant) for the CSPP to a decrease by 135 basis points (significant at the 1% level) for the PEPP.

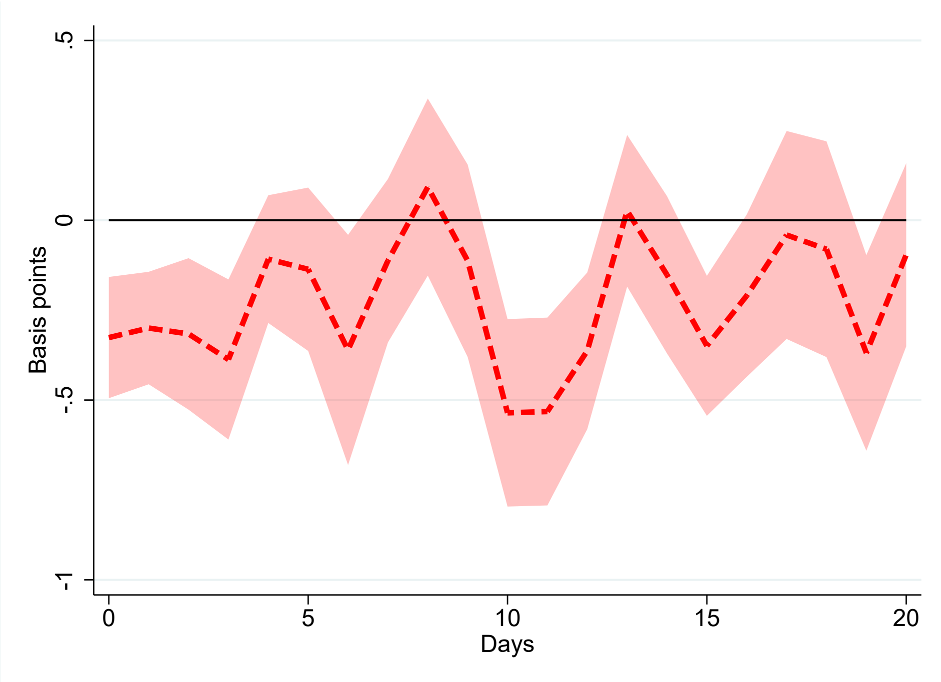
Compared to those papers, our results belong to the lower bound in terms of economic magnitude. This could be explained by the fact that our paper differs in scope, specification, and sample coverage. First, we consider a broad set of 29 ECB announcements including more recent ones than the ones used in the existing literature. Second, we include all European green and non-green bonds, regardless of eligibility to the ECB's asset purchase programme or collateral framework. Third, we compare green to conventional bonds rather than comparing eligible to non-eligible green bonds. Fourth, we neutralize any maturity difference between green and conventional bonds, we control for daily market variables, we take into account for serial correlation in a local projection framework, and we include bond and month-year fixed effects. In order to improve the comparability of our results with the rest of the literature, we distinguish by type of ECB policy announcement in the next Section 3.6. Even though our results have a larger magnitude and get closer to the ones of the existing papers mentioned above, in particular Eliet-Doillet and Maino (2022) and Giovanardi et al. (2023), they stay smaller.

Figure 3.9. Response of the green spread (bps) to a one-standard deviation positive green bond supply shock



Note: In this figure, we plot the effect of a one-standard deviation positive supply shock occurring on day t on the green spread over different time horizons h where $h = 0, 1, ..., 20$ business days. The blue dashed line represents the coefficient for the supply shock in day t (i.e. β_h^S) for each horizon h. The light blue area represents the 90 percent confidence bands of each coefficient β_h^S.

Figure 3.10. Response of the green spread (bps) to a one-unit positive green bond demand shock



Note: In this figure, we plot the effect of a one-unit positive green bond demand shock occurring on day t on the green spread over different time horizons h where $h = 0, 1, ..., 20$ business days. The red dashed line represents the coefficient for the demand shock in day t (i.e. β_h^D) for each horizon h. The light red area represents the 90 percent confidence bands of each coefficient β_h^D.

3.6 Understanding the underlying dynamics of the green spread reaction to demand and supply shocks

The overall effect of demand and supply shocks on the green spread seems to be economically limited as shown in the results presented above. These results assume a common or pooled impulse response function, however, and therefore may hide parameter heterogeneity. In particular, for the supply shock, the dynamic effects as estimated by the local projections in equation 3.1 may differ by type of issuer, country of issuance, and size of the shock, hence reflecting different dimensions of segmentation of the green bond market. For the demand shocks, the estimated impulse responses may differ by type of policy announced by the ECB to incorporate climate considerations. In this section, we explore each of those types of heterogeneity. We first present how we refine specification 3.1, and then present the results.

3.6.1 Empirical specifications

In order to explore this potential heterogeneity, study whether or not the green bond market is segmented, and better understand the main drivers of our results, we refine our main specification in alternative ways.

In order to study the heterogeneous effects of the supply shocks, we first focus on the issuer-type segmentation of the green bond market. To do so, we check whether the issuance announcements have a stronger effect on the green spread of bonds that have been issued by the same type of issuer. Specifically, we split the green bond issuance announcements between the ones made by the same type of issuer i as the one of the issuer of bond pair b, and the ones made by other types of issuer $\bar{i}$ than the one of the issuer of bond pair b:

$$GS_{b,t+h} \ = \ \alpha_{b,h} + \beta_h^{S,i} * Supply_{i,t} + \beta_h^{S,\bar{i}} * Supply_{\bar{i},t} + \beta_h^D * Demand_t + \gamma_h' * W_{b,t} + \varepsilon_{b,t+h} \quad (3.2)$$

We then adopt a similar approach to look at country-segmentation of the green bond market, i.e. we check whether the issuance announcements have a stronger effect on the green spread of bonds that have been issued in the same country. In the same spirit, we split the green bond issuance announcements between the ones made in the same country c as the one of the issuer of bond pair b, and the ones made by issuers based in other countries $\bar{c}$ than the one of the issuer of bond pair b:

$$GS_{b,t+h} \ = \ \alpha_{b,h} + \beta_h^{S,c} * Supply_{c,t} + \beta_h^{S,\bar{c}} * Supply_{\bar{c},t} + \beta_h^D * Demand_t + \gamma_h' * W_{b,t} + \varepsilon_{b,t+h} \quad (3.3)$$

Finally, to check whether the size of the supply shocks matters, we split the green bond issuance announcements by size and distinguish between small, medium and large announcements:

$$\begin{aligned} GS_{b,t+h} \ = \ & \alpha_{b,h} + \beta_h^{S,small} * Supply_{small,t} + \beta_h^{S,medium} * Supply_{medium,t} \\ & + \beta_h^{S,large} * Supply_{large,t} + \beta_h^D * Demand_t + \gamma_h' * W_{b,t} + \varepsilon_{b,t+h} \end{aligned} \tag{3.4}$$

where $Supply_{small,t}$, $Supply_{medium,t}$ and $Supply_{large,t}$ represent the (standardized) announced issued amount of green bonds if the announced issued amount is below USD 1bn, between USD 1bn and USD 5bns and above USD 5bns respectively, and 0 otherwise. Those announced issued amount buckets represent respectively 2,558 distinct dates (or equivalently 92.4% of the sample), 221 distinct dates (or equivalently 7.9% of the sample) and 19 distinct dates (or equivalently 0.7% of the sample).

In order to study the heterogeneity of the demand shocks, we check whether the different policy tools at the disposal of the ECB have different effects on the green spread. Concretely, we split the demand shocks by the following 5 different policy tools: (1) asset purchase programmes, (2) non-monetary policy portfolio, (3) collateral framework, (4) market operations, or (5) no clear instrument[11] . We adapt our main specification as follows:

$$GS_{b,t+h} \ = \ \alpha_{b,h} + \beta_h^S * Supply_t + \beta_h^{D,a} * Demand_{a,t} + \gamma_h' * W_{b,t} + \varepsilon_{b,t+h} \tag{3.5}$$

where $Demand_{a,t}$ is the demand shock indicator if announcement made by the ECB on day t is of related to tool a, and 0 otherwise, with $a = 1, ..., 5$ representing one of the five ECB policy instruments listed above.

3.6.2 Results

We start by presenting the heterogeneity analysis for the supply shocks, i.e. the issuer-type and country segmentation, and the split by size of announcements. In Figure 3.11, we show the results for the issuer-type segmentation (equation 3.2). Even though the green spread seems to react somewhat more strongly to green bond issuance announcements when those are made by a similar type of issuer, there is no clear sign of issuer-type segmentation. On the one hand, a one-standard deviation increase in announced green bond issuances has a

[11] One example of announcement without specifying a clear instrument is the speech from Christine Lagarde made on the 12th of October 2021 when she said the following: "And climate change is definitely part of our considerations for setting monetary policy and implementing it. The Governing Council has decided on a comprehensive action plan to further incorporate climate change considerations throughout our policy framework.".

stronger positive effect on the green spread when the announcement is made by the same type of issuer (a maximum of around 0.17 basis points after 8 business days, Figure 3.11a) than when it is made by a different type of issuer (a maximum of around 0.11 basis points after 5 business days, Figure 3.11b). On the other hand, the positive effect of the announcements made by a similar type of issuer is much less persistent than when those announcements are made by a different type of issuer (significant 7 and 8 business days vs 3 to 5 days and 11 to 15 days after the supply shock occurred, respectively). Hence, there is no clear evidence of issuer-type segmentation on the green bond market for supply shocks.

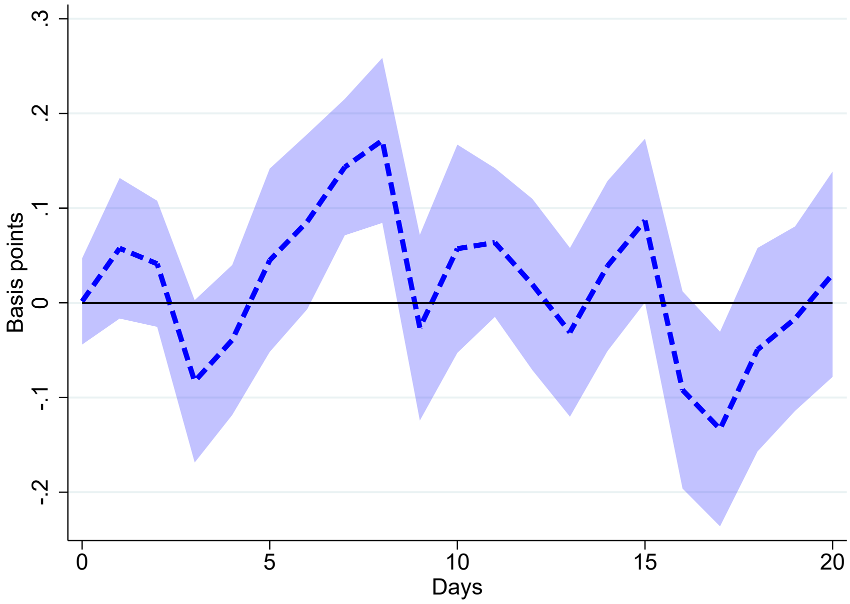
We next analyze the extent of country segmentation in the effect of supply shocks on the green bond market (equation 3.3) and show the results in Figure 3.12. The effect of green bond issuance announcements on the green spread appears to be much larger and persistent when the announcements are made by an issuer from the same country than from another country. A one-standard deviation increase in announced green bond issuances by entities of a given country has a peak effect of around 0.31 basis points on the green spread of bond pairs that have been issued by entities from the same country (Figure 3.12a). Given that a one-standard deviation increase in green bond issuances equals around USD 1.17bns, this result implies that a USD 10bns green bond issuance announcement by an entity of a given country increases the green spread of bond pairs that have been issued by entities from the same country by around 2.6 basis points. The effect is also quite persistent, 4 to 7 business days, and 13 to 16 business days after the supply shock occurred. On the contrary, the effect of green bond issuance announcements by entities of a given country have a much smaller effect on the green spread of bond pairs that have been issued by entities from different countries: a one-standard deviation increase in announced green bond issuances by entities of a given country has a peak effect of around 0.1 basis points on the green spread of bond pairs that have been issued by entities from other countries, and is only slightly significant temporarily and sporadically (Figure 3.12b). Hence, there seems to be a country segmentation on the green bond market for supply shocks.

We next estimate equation 3.4 to analyze whether the size of the green bond issuance announcements matter. Figure 3.13 reports the shock size specific impulse response functions of the green spread. We find strong nonlinearities, with only the large announcements having a significantly positive effect on the green spread. Small announcements (less than USD 1bn) have a completely insignificant effect on the green spread, at impact and up 20 business days afterwards (Figure 3.13a). Surprisingly, medium announcements (between USD 1bn and USD 5bns) have a negative effect on the green spread: a one-standard deviation increase in announced green bond issuances decreases the green spread by around 0.1 basis points, conditional on this announcement being between USD 1bn and USD 5bns, the effect being significant 1 to 4 days and 18 to 19 days after the announcement (Figure 3.13b). On the contrary, large announcements (more than USD 5bns) have a strongly positive and significant effect on the green spread (Figure 3.13c). The effect reaches its peak 15 days after the shock (0.1 basis points) and is significant 2 to 7 business days and 15 business days after the announcement. Given those strong nonlinearities, we conclude that the size of the announcement matters, with larger announcements having a stronger effect per standard deviation on the green spread than smaller announcements.

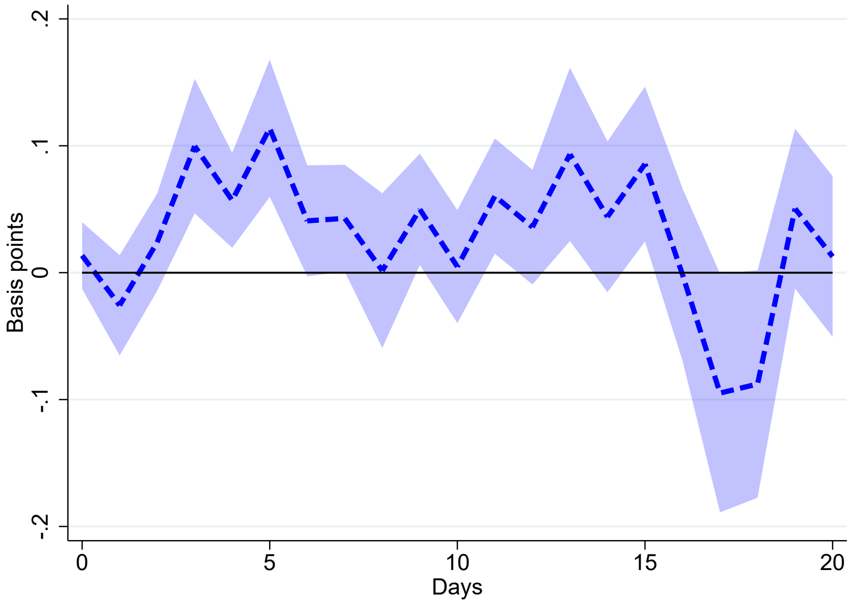
Finally, we address the heterogeneous responses of the green spread to demand shocks (equation 3.5). Figure 3.14 reports the impulse responses differentiating between the various policy tools at the disposal of the ECB. As shown by Figure 3.14, the ECB's announcements with the strongest effect on the green spread are the ones mentioning no clear instrument, the asset purchase programmes, and the collateral framework. As shown by Figure 3.14e, the announcements from the ECB in favor of incorporating climate change but without mentioning a clear instrument are the announcements with the strongest effect on the green spread. Such a type of announcements has a negative effect on the green spread of about 2.5 basis points, 2 business days after the announcement. The effect is immediate (-0.7 basis points at impact), but is short-lived (significant up to 3 business days after the announcement). As shown by Figures 3.14a and 3.14c, an announcement from the ECB in favor of incorporating climate change in its asset purchase programmes or its collateral framework has a similar effect in terms of magnitude (up to -0.6 basis points after 10 business days and -0.7 basis points after 6 business days, respectively). The persistence of the two tools seems to be however different, with the announcements related to collateral framework having a significant effect on the green spread at impact and during most of the subsequent periods, including 20 business days afterwards. Conversely, the announcements related to asset purchase programmes have a significant impact on the green spread 6 business days, 10 to 11 business days and 19 business days after the announcement. On the contrary, the ECB's announcements related to the incorporation of climate considerations in its non-monetary policy portfolio and its market operations don't have a strong effect on the green spread (Figures 3.14b and 3.14d). An ECB's announcement related to its non-monetary policy portfolio has a negative effect on the green spread of about 0.8 basis points, but the effect is almost never significant (Figure 3.14b). Regarding the ECB's announcements related to the incorporation of climate considerations in its market operations, the effect is actually slightly positive (+0.9 basis points) but barely significant, before being significantly negative only 16 business days after the announcement (-1.0 basis points, Figure 3.14d).

Figure 3.11. Response of the green spread (bps) to a one-standard deviation green bond supply shock by splitting the sample between announcements made by issuers of the same type as vs different types from the issuer of the green spread

(a) Same type of issuer



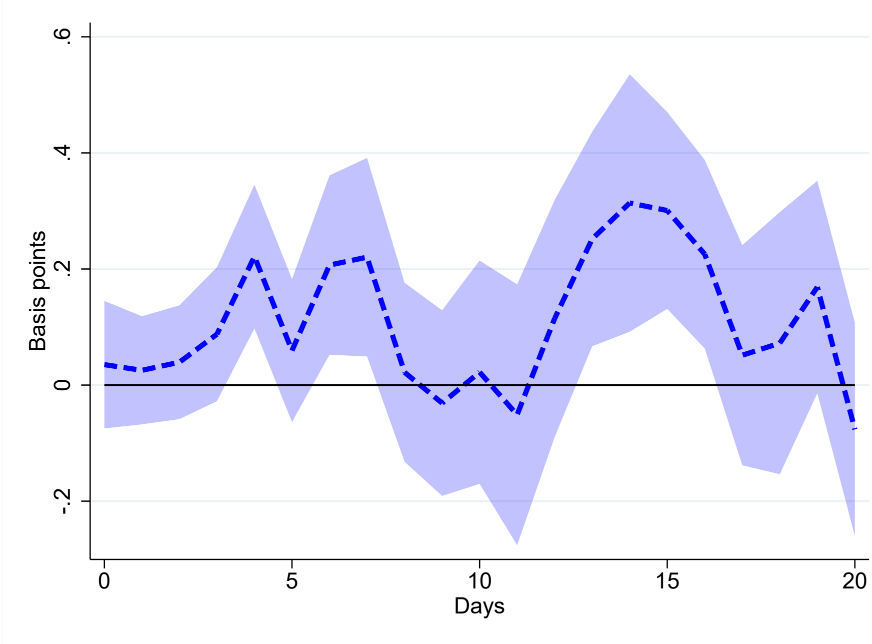
(b) Different type of issuer



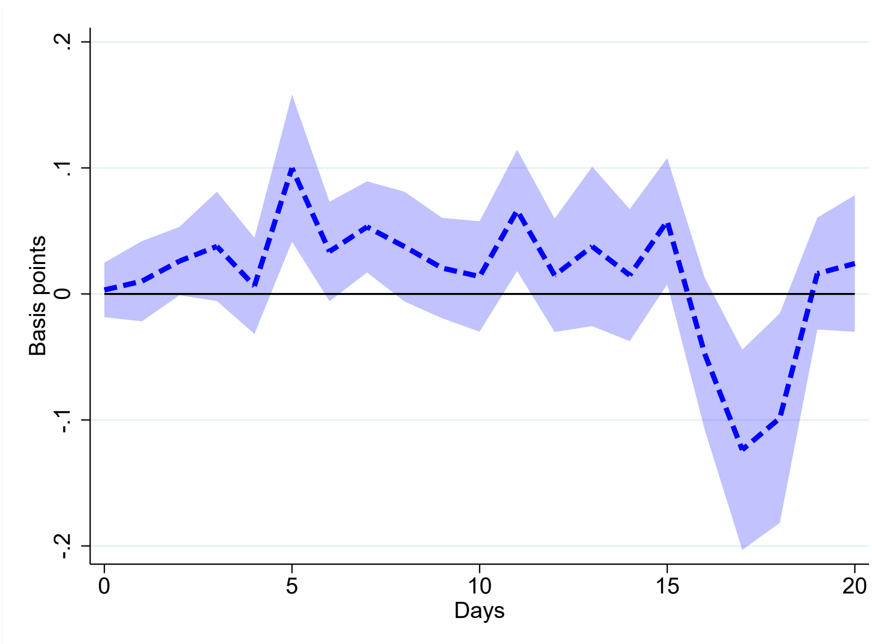
Note: In this figure, we plot the effect of a one-standard deviation positive supply shock occurring on day t on the green spread over different time horizons h where $h = 0, 1, ..., 20$ business days. The sample of green bond issuance announcements is split between the ones made by the same type of issuer (Figure 3.11a) as the one of the issuer of bond pair b used to calculate the green spread $GS_{b,t+h}$, and the ones made by other types of issuer (Figure 3.11b) than the one of the issuer of bond pair b. In each figure, the blue dashed line represents the coefficient for the supply shock in day t (i.e. $\beta_h^{S,i}$ in Figure 3.11a and $\beta_h^{S,\bar{i}}$ in Figure 3.11b) for each horizon h. The light blue area represents the 90 percent confidence bands of each coefficient $\beta_h^{S,i}$ in Figure 3.11a and $\beta_h^{S,\bar{i}}$ in Figure 3.11b.

Figure 3.12. Response of the green spread (bps) to a one-standard deviation green bond supply shock by splitting the sample between announcements made by issuers of the same country as vs different countries from the issuer of the green spread

(a) Same country



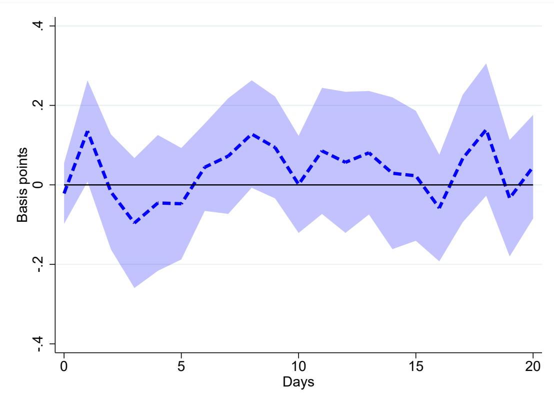
(b) Different country



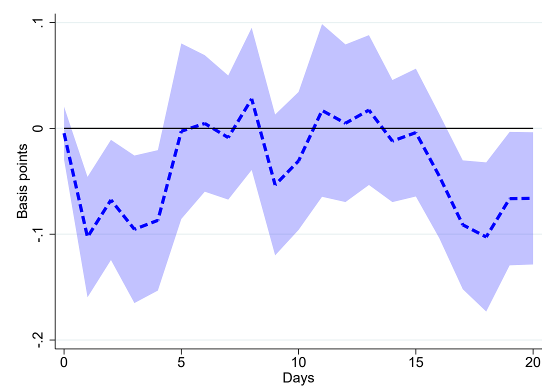
Note: In this figure, we plot the effect of a one-standard deviation positive supply shock occurring on day t on the green spread over different time horizons h where $h = 0, 1, ..., 20$ business days. The sample of green bond issuance announcements is split between the ones made by the same country (Figure 3.12a) as the one of the issuer of bond pair b used to calculate the green spread $GS_{b,t+h}$, and the ones made by issuers located in other countries (Figure 3.12b) than the one of the issuer of bond pair b. In each figure, the blue dashed line represents the coefficient for the supply shock in day t (i.e. $\beta_h^{S,c}$ in Figure 3.12a and $\beta_h^{S,\bar{c}}$ in Figure 3.12b) for each horizon h. The light blue area represents the 90 percent confidence bands of each coefficient $\beta_h^{S,c}$ in Figure 3.12a and $\beta_h^{S,\bar{c}}$ in Figure 3.12b.

Figure 3.13. Response of the green spread (bps) to a one-standard deviation green bond supply shock by splitting the sample between small, medium and large announcements

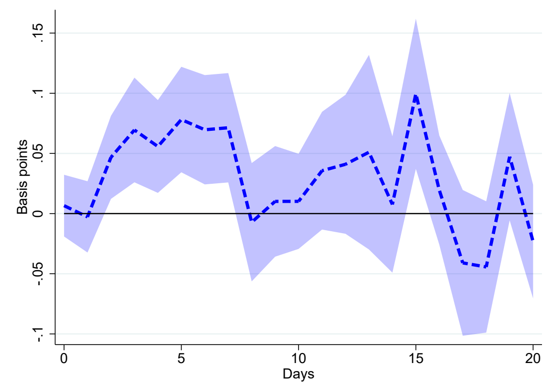
(a) Small announcements



(b) Medium announcements

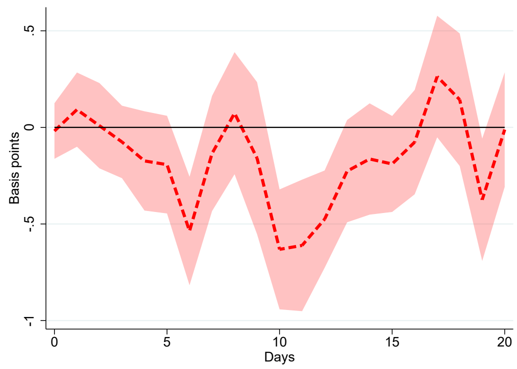


(c) Large announcements

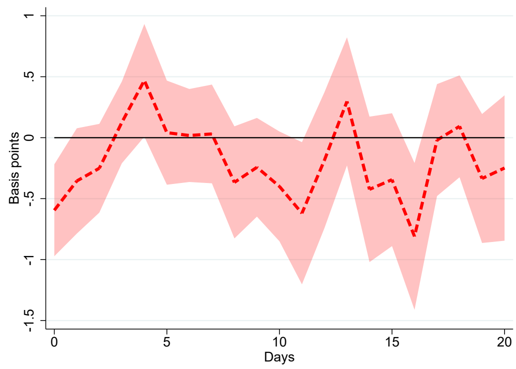


Note: In this figure, we plot the effect of a one-standard deviation positive supply shock occurring on day t on the green spread over different time horizons h where $h = 0, 1, ..., 20$ business days. The sample of green bond issuance announcements is split by size: in Figure 3.13a), we only consider announcements below USD 1bn, in Figure 3.13b), we only consider announcements between USD 1bn and USD 5bns, and in Figure 3.13c), we only consider announcements above USD 5bns. In each figure, the blue dashed line represents the coefficient for the supply shock in day t (i.e. $\beta_h^{S,small}$ in Figure 3.13a, $\beta_h^{S,medium}$ in Figure 3.13b, and $\beta_h^{S,large}$ in Figure 3.13c) for each horizon h. The light blue area represents the 90 percent confidence bands of each coefficient $\beta_h^{S,small}$ in Figure 3.13a, $\beta_h^{S,medium}$ in Figure 3.13b, and $\beta_h^{S,large}$ in Figure 3.13c.

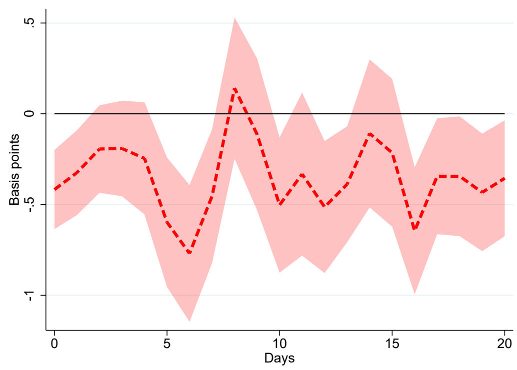
Figure 3.14. Response of the green spread (bps) to a one-unit positive green bond demand shock by splitting the demand shocks by policy tool



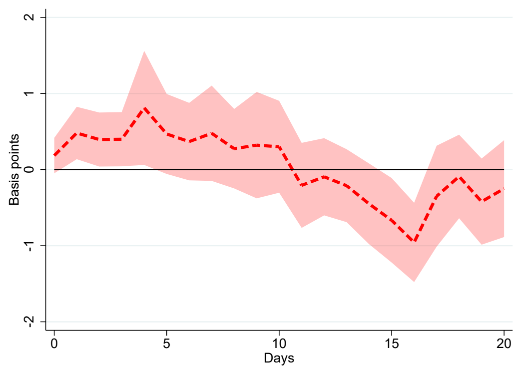
(a) Asset purchase programmes



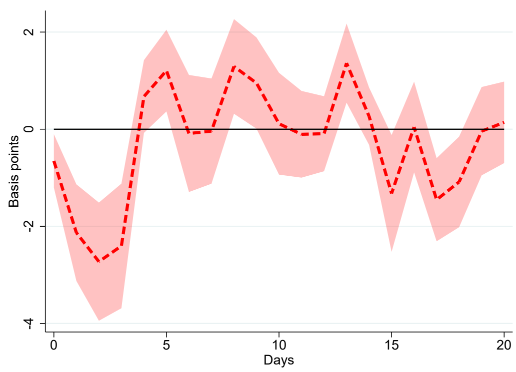
(b) Non-monetary policy portfolio



(c) Collateral framework



(d) Market operations



(e) No clear instrument

Note: In this figure, we plot the effect of a one-unit positive green bond demand shock occurring on day t on the green spread over different time horizons h where $h = 0, 1, ..., 20$ business days. The sample of ECB announcements is split by policy tool: in Figure 3.14a), we only consider announcements related to the ECB's asset purchase programmes, in Figure 3.14b), we only consider announcements related to its non-monetary portfolio, in Figure 3.14c), we only consider announcements related to its collateral framework, in Figure 3.14d), we only consider announcements related to its market operations, and in Figure 3.14e), we only consider announcements not mentioning any clear instrument. In each figure, the red dashed line represents the coefficient for the demand shock in day t (i.e. $\beta_h^{D,a}$ where a represents alternatively one of the ECB's tools mentioned above) for each horizon h. The light red area represents the 90 percent confidence bands of each coefficient $\beta_h^{D,a}$ in each of the figures above.

3.7 Extension(s)

We consider a number of extensions to further substantiate the current empirical findings. First, we are currently identifying demand shocks for green bonds. We are doing so by analysing Refinitiv Eikon News about green bonds and isolating the ones related to demand, i.e. if the news story is about a private company or a central bank announcing it will buy green bonds in the near future.

Second, we are working on studying the longer term effects of demand and supply shocks on the green spread. The currently exploited event study framework is especially useful to analyse the short-term impact of demand and supply shocks. Extending the time window too much, however, would enlarge the threat of confounding factors in the analysis. It also requires a more structural modeling of the demand and supply mechanisms of the green bond market. In the remaining of this section we discuss the recent advances in structural modeling of bond markets, which we then propose to adapt to the green bond market.

There is a growing literature that emphasizes the role of demand in explaining asset prices across various financial markets, including bond markets. Koijen and Yogo (2019) formulate a demand-based asset-pricing model with flexible heterogeneity in asset demand across investor types. To estimate the price elasticity of bond demand, apart from bond yields also bond holdings data are needed. Koijen et al. (2021) apply this framework to directly estimate the price elasticity of government bonds, while Bretscher et al. (2022) adapt the methodology to the corporate bond market.

The resulting empirical bond demand function is a linear regression in which bond holdings are determined by bond yields and other important bond or macro characteristics measuring key sources of risk, e.g. maturity, credit rating and macroeconomic conditions. A key element in the empirical model is parameter slope heterogeneity. Notably, the price elasticity of demand can differ between investor sectors reflecting the different responses of preferred habitat investors and arbitrageurs to price changes. Classical simultaneity is absent in this set up as the bond supply is assumed to be exogenous. Nevertheless, the bond yield is still considered an endogenous regressor due to correlated demand shocks and, hence, instrumental variables estimation is performed. The instrumental variables used by Koijen and Yogo (2019) and Bretscher et al. (2022) rely on institution-specific investment mandates, which restricts the type of assets in which the institution can invest. Koijen et al. (2021) construct as instrumental variable for government bond yields the predicted government bond purchases following from the capital key of the public sector purchase program.

For their sample of euro area government bonds, Koijen et al. (2021) find that mutual funds have a relatively elastic (downward sloping) demand compared to banks and insurance companies, while pension funds actually have upward sloping demand. Regarding a global sample of corporate bonds, Bretscher et al. (2022) also find that mutual funds are the most price elastic, while insurers and exchange rate funds have relatively low elasticities. The results in both studies furthermore confirm a large heterogeneity in estimated elasticities across investors.

Regarding the green bond market, Boermans (2023) estimates the demand for green bonds by different investor types using quarterly data for the period 2016Q4-2022Q4. The empirical specification for bond holdings in this study is a panel gravity model, in which bond holdings are explained by bond, issuer, and investor characteristics. The preference for green bonds is modeled by an interaction of the green bond label with the investor sector indicator. It represents the excess demand for green bonds, controlling for all other determinants. Adding the bond's quarterly price change, it is furthermore tested whether preferred habitat investors are less price sensitive. The main finding is that mutual funds and pension funds have a preference for green bonds, while at the same time those investor sectors are not sensitive to price changes. Note that in this study mutual funds have a relatively low price elasticity, which is markedly different from the empirical results of Koijen et al. (2021) and Bretscher et al. (2022). Note that Boermans (2023) assumes exogeneity of bond prices to latent demand shocks, hence results are obtained from OLS estimation rather than applying IV estimation. The key empirical finding from Boermans (2023) is consistent with the empirical results in this study. If the investors who have excess demand for green bonds also have a low price elasticity, no large changes in bond yields are seen as supply and demand shocks occur. To verify this, we need to extend the analysis and explicitly estimate the demand for green bonds.

These results from bond demand estimation have been obtained exploiting a critical assumption of an exogenous supply side. In other words, firms (and governments) do not react to investor flows arising from heterogeneous investor demand. After some time, however, both demand and supply would probably adjust to each other leading to simultaneity bias. To solve this issue, we will use the granular instrumental variables (GIV) setup developed by Gabaix and Koijen (2020). The GIV framework can be implemented to measure elasticities, including for financial assets. In particular, Gabaix and Koijen (2021) use the GIV framework to measure the price elasticity of demand for stocks. Zhang (2024) applies the GIV methodology to a structural asset pricing model in which supply is endogenized, i.e. corporate financing and investment policies interact with heterogeneous investor demand. We propose to adapt this methodology by focusing on the green bond holdings of European institutional investors from the Securities Holdings Statistics (SHS) data. We will proceed in two steps. First, we will extract the idiosyncratic shocks from factor models estimated on the changes in green bond holdings. Second, we will regress those changes on the factors identified in the first step as well as on the green bonds return instrumented by the GIVs (i.e. the size-weighted sums of the idiosyncratic shocks extracted in the first step).

3.8 Conclusion

We use daily announcements about future green bond issuances and from the European Central Bank about the incorporation of climate considerations into its different policy tools to identify exogenous supply and demand shocks for green bonds. We then study how these shocks affect the green spread, i.e. the yield differential between existing green and equivalent conventional bonds. Our results show that supply shocks increase the green spread, though the effects are economically limited and short-lived. In contrast, demand shocks significantly and persistently reduce the green spread, albeit with modest economic magnitude. We also document that supply shocks exert stronger effects on bonds issued in the same country as the origin of the shock, and that large supply shocks have a stronger impact. Regarding demand shocks, we show that the ECB's announcements not mentioning any clear instrument, or mentioning asset purchase programmes or collateral framework have the strongest impact, even though the effect is limited and/or transitory. These findings carry direct implications for the design of green fiscal and monetary policies. They suggest that large green bond issuance programs may induce localized distortions in green bond markets, whereas demand-side central bank interventions, in particular general announcements, greening asset purchase programmes or collateral framework, can affect the pricing of green relative to conventional bonds.

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Appendices to Chapter 3

Appendix 3.A Complete list of ECB announcements related to the incorporation of climate considerations in its different policy tools

Table 3.A.1. Complete list of ECB announcements related to the incorporation of climate considerations in its different policy tools

Announcement Date	Speech / Press Release	Summary	Demand shock indicator value
08/11/2018	Speech	Benoît Cœuré's speech explores the impact of climate change on monetary policy, arguing that it can influence inflation dynamics, financial stability, and central banks' ability to respond to economic shocks. He highlights how climate-related disruptions, such as extreme weather events and the transition to a low-carbon economy, can create inflation-output trade-offs and complicate monetary policy decisions. He also emphasizes that while central banks cannot lead climate policy, they can support the transition by integrating climate risks into financial regulations and monetary policy frameworks, particularly through sustainable finance initiatives.	0
27/11/2018	Speech	Yves Mersch argues that while climate change is a significant economic and social issue, central banks should not take on a primary role in addressing it. He emphasizes that monetary policy is focused on price stability and that climate-related risks, while relevant to financial stability, do not justify a shift in the ECB's mandate. Mersch warns against politicizing central banking, highlighting the potential risks of asset price distortions and speculative bubbles in green finance. He acknowledges the role of public policy in mitigating climate change but insists that elected governments, not independent central banks, should lead these efforts.	-1
30/10/2019	Speech	In her speech, Sabine Lautenschläger emphasized the importance of European unity in addressing global challenges like increasing competition, climate change, and technological progress. She argued that individual countries, including Germany, cannot effectively tackle these issues alone, and that the EU's collective strength is necessary for prosperity, social stability, and global influence. Lautenschläger highlighted the EU's role in combating climate change through coordinated policies, its need for a more integrated payment system, and the significance of advancing the banking union, especially with a shared European deposit insurance scheme. She concluded by advocating for deeper European integration and more inclusive political processes, such as citizens' assemblies, to strengthen the EU's connection with its people and enhance trust in its institutions. Regarding greening the asset purchase programmes of the ECB, she insists on making sure the ECB would not create market distortions.	-1

05/02/2020	Speech	In her speech upon receiving the Grand Prix de l'Économie, Christine Lagarde highlights two key challenges and opportunities for Europe: building "European autonomy" and addressing climate change. She emphasizes the importance of strengthening the euro's global role and deepening European financial integration, particularly through capital markets. She also underscores the need for Europe to lead in climate risk disclosure and green finance. Lagarde calls for cooperation between policymakers, businesses, and citizens to address these challenges, improve Europe's resilience, and secure its global standing. She mentions the current examination about the incorporation of climate issues into the risk assessment of the ECB's collateral framework.	1	
11/02/2020	Speech	Christine Lagarde, President of the ECB, emphasized the importance of the ECB's independence and accountability, particularly through its relationship with the European Parliament. She discussed the ECB's response to the euro area's slowing growth, highlighting the role of its monetary policy in supporting job creation and economic resilience, while acknowledging the risks of prolonged accommodative measures. Lagarde also addressed the structural challenges of digitalization, climate change, and the need for a more complete Economic and Monetary Union (EMU), including a full banking union and capital markets union. She stressed that these challenges require coordinated action from all parties, including the ECB and the European Parliament, to ensure Europe's future prosperity. Regarding climate change, she emphasizes that the ECB is investigating what can be done in its market operations to align them better with the objectives of the Paris Agreement.	1	
27/02/2020	Speech	Christine Lagarde highlighted the significant risks climate change poses to the financial sector, including risks from ignoring, delaying, and insufficiently addressing the transition to a carbon-neutral economy. Disregarding climate change can lead to increased insurance and economic losses, while delaying action could result in a disruptive transition with asset re-pricing and stranded assets. The financial sector must enhance disclosures on climate risks and provide sufficient finance for the transition, with the European Union leading the way in green bonds and sustainable finance initiatives. Lagarde emphasized that the financial sector can play a vital role in fostering a sustainable economic future, turning climate risks into opportunities. She also mentions the ongoing review of the ECB's monetary policy strategy that creates an opportunity to reflect on how to address sustainability considerations within its monetary policy framework.	1	
17/07/2020	Speech	In her speech, Isabel Schnabel highlights the dual crises of COVID-19 and climate change, arguing that the pandemic underscores the urgent need for structural change in the global economy. She stresses that while the pandemic temporarily reduced CO_2 emissions, it also revealed the risks of inadequate prevention and collective action. To tackle climate change, Schnabel proposes three key pillars: global carbon pricing, green investments, and a greener financial market. She also highlights that central banks, including the ECB, have a role in mitigating climate risks, ensuring price stability, and potentially greening their asset purchases while recognizing both pros and cons of such policy.	0	
22/09/2020	Press Release	The ECB announced that, from 1 January 2021, bonds with coupons tied to sustainability performance targets will be eligible as collateral for Eurosystem credit operations and potentially for asset purchases under the APP and PEPP. These bonds must align with environmental objectives in the EU Taxonomy Regulation or the UN Sustainable Development Goals related to climate change. This move expands the pool of eligible assets and supports sustainable finance innovation, aligning marketable bonds with the existing treatment of non-marketable assets with similar structures.	1	

28/09/2020	Speech	Isabel Schnabel, in her speech at the European Sustainable Finance Summit, highlights the urgent need for collective action to tackle climate change and its economic risks. She argues that despite growing efforts, climate policies are insufficient and market failures persist, especially in the mispricing of climate risks. Schnabel stresses the importance of a global carbon price and substantial investment in green technologies, with central banks, including the ECB, playing a key role. She advocates for proactive measures, including adjusting monetary policy to address climate risks and support the transition to a carbon-neutral economy.	1
25/01/2021	Speech + Press Release	Two speeches and two press releases: - In his keynote speech, Fabio Panetta highlights the growing importance of sustainable finance in addressing climate-related risks and fostering long-term economic stability. He discusses the need to transition towards sustainable development, especially in the wake of the COVID-19 pandemic, which has exacerbated social and environmental vulnerabilities. Panetta emphasizes the role of financial institutions in promoting responsible growth through ESG (Environmental, Social, and Governance) investments and calls for stronger regulation and data transparency in sustainable finance. He also outlines the European Central Bank's efforts to integrate climate risks into its policies, stressing that responsible finance is essential for reconciling economic development with environmental and social values. - Christine Lagarde's speech highlights the urgent need for action on climate change and the role central banks, particularly the European Central Bank (ECB), can play in supporting this transition. She stresses that while central banks are not the primary actors in climate policy, they must acknowledge the risks climate change poses to financial stability, price stability, and their own balance sheets. Lagarde outlines three key areas for progress: pricing carbon accurately, improving climate risk disclosures, and fostering green innovation and investment. The ECB is actively engaging in these areas, enhancing its policy framework to address climate-related risks and supporting the EU's green transition. Ultimately, Lagarde calls for collaborative, multifaceted efforts to combat climate change, warning that inaction could lead to dire consequences. She also emphasizes the plan of the ECB to raise the share of green bonds in its own funds portfolio. - The ECB has established a climate change centre, operational from early 2021, to coordinate and strengthen its work on climate-related issues across different policy areas. Reporting directly to President Christine Lagarde, the unit will guide the ECB's climate agenda, integrating climate considerations into monetary policy and prudential functions. This move reflects the growing importance of climate change for the economy and the ECB's strategy. The centre's structure will be reviewed after three years, with the goal of embedding climate considerations into the ECB's routine operations.	1

		- The ECB has decided to invest part of its own funds portfolio in the BIS's euro-denominated green bond fund, which supports renewable energy and energy efficiency projects. This move aligns with the ECB's sustainable investment strategy and contributes to EU climate goals. The ECB already holds green bonds amounting to 3.5% of its €20.8 billion own funds portfolio and aims to increase this share. Additionally, the ECB is integrating sustainability into its staff pension fund by adopting low-carbon benchmark indices. This investment reinforces the ECB's commitment to environmental responsibility and its role in the Network for Greening the Financial System.		
04/02/2021	Press Release	The Eurosystem central banks, including the ECB, have agreed on a common stance to apply sustainable and responsible investment principles in their euro-denominated non-monetary policy portfolios. This initiative aims to enhance climate-related disclosures, increase awareness of climate risks, and support the transition to a low-carbon economy. The Eurosystem plans to begin annual climate-related disclosures within two years, following the Task Force on Climate-related Financial Disclosures (TCFD) framework. While each central bank remains responsible for its own portfolio, they will continue collaborating to harmonize approaches.	1	
08/02/2021	Speech	Christine Lagarde's speech at the European Parliament focused on the ECB's response to the COVID-19 crisis and its role in Europe's recovery. She emphasized the ECB's proactive measures, such as the Pandemic Emergency Purchase Programme (PEPP) and targeted longer-term refinancing operations (TLTROs), which aimed to stabilize the economy and support lending. Lagarde highlighted the importance of maintaining accommodative monetary policies while also urging continued fiscal support to ensure a robust recovery. She stressed the need for investments in green and digital transitions, and discussed the ECB's ongoing work on a digital euro and sustainable finance. Finally, she affirmed the ECB's commitment to transparent communication and its dialogue with the European Parliament, ans insisted on the ECB's plan to increase the share of green bonds in its own funds portfolio over the coming years.	1	
03/03/2021	Speech	In her speech, Isabel Schnabel emphasized the urgent need to address climate change and its risks to price stability and economic functioning, particularly due to both physical and transition risks. She outlined the European Central Bank's (ECB) obligation to integrate climate change considerations into its monetary policy, while remaining focused on its primary mandate of maintaining price stability. Schnabel acknowledged the limitations of the ECB's role, stressing that it cannot replace government policies but can contribute by adjusting its asset purchase strategies to mitigate environmental risks. She discussed the challenges posed by the ECB's current "market neutrality" principle, which may inadvertently support emission-heavy sectors, and proposed reevaluating this approach to better align with climate objectives without compromising the ECB's core mandate.	1	
27/05/2021	Speech	In her speech, Isabel Schnabel discusses the evolving role of central banks, particularly the ECB, in addressing societal concerns beyond traditional price stability. She highlights the shift in public expectations, especially among younger generations, who prioritize issues like climate change and job uncertainty. While central banks, including the ECB, remain primarily focused on maintaining price stability, Schnabel acknowledges the need for responsiveness to public concerns and the potential role central banks could play in supporting broader societal goals, such as environmental sustainability, without compromising their independence or mandate. She emphasizes the importance of balancing these responsibilities to maintain public trust and effective policy.	0	

08/07/2021	Press Release	The ECB has announced an action plan to integrate climate change considerations into its monetary policy strategy, reinforcing its commitment to environmental sustainability. The plan includes enhancing macroeconomic modeling, improving climate-related statistical data, and incorporating climate risk into monetary policy operations, such as asset purchases and collateral frameworks. The ECB will also introduce disclosure requirements for private sector assets, conduct climate stress tests on its balance sheet, and adjust corporate bond purchases to align with EU climate goals. Implementation will align with EU sustainability policies, ensuring a structured transition to a greener economy while maintaining price stability.	1
11/07/2021	Speech	In her speech, Christine Lagarde outlines the ECB's approach to addressing climate change, emphasizing the risks it poses to the economy, financial system, and the Eurosystem's balance sheet. She explains the ECB's strategy in three areas: analyzing climate risks, advising on policies, and taking action. The ECB is conducting climate-related stress tests, urging stronger climate disclosures, and advocating for an effective carbon price. The ECB has started integrating sustainability into its monetary policy operations, including accepting sustainability-linked bonds and considering climate risks in asset purchases. Lagarde stresses the importance of continued analysis and action within the ECB's mandate to mitigate climate-related risks, in particular adjusting the framework guiding the allocation of corporate bond purchases to incorporate climate change criteria.	1
23/09/2021	Speech	In his speech, Frank Elderson, a member of the ECB's Executive Board, discusses the importance of integrating climate and environmental challenges into the missions of central banks and supervisors. He emphasizes that climate change poses significant physical and transition risks, which could greatly impact the financial system. The ECB has taken steps to incorporate these risks into its operations, including banking supervision, monetary policy, and asset management. Elderson highlights the need for urgent, large-scale action to mitigate climate change and stresses that the ECB is committed to developing models, frameworks, and strategies to address these challenges, working alongside other central banks and institutions.	1
12/10/2021	Speech	Christine Lagarde highlights the urgent need for action on climate change and the critical role of the financial sector in supporting the transition to a carbon-neutral economy. She outlines three key contributions finance can make: disseminating reliable information to combat greenwashing and improve transparency, accelerating innovation by channeling investment into green technologies, and bolstering adaptation through improved risk management and insurance coverage. While early action may entail short-term costs, the long-term benefits far outweigh them. The ECB is integrating climate considerations into its policy framework and emphasizes that all sectors, including finance and central banks, must actively contribute to climate action. In particular, she insists on the fact that climate change is part of the ECB's considerations for setting monetary policy and implementing it.	1

19/10/2021	Speech	Frank Elderson emphasizes the urgent role of central banks and supervisors in addressing the climate crisis by incorporating climate risks into financial regulation and monetary policy. He highlights the financial risks posed by climate change—both physical (extreme weather events) and transition-related (shifts to a low-carbon economy). The ECB has taken steps to integrate climate considerations into its activities, including stress tests and supervision of banks' climate risk management. Elderson also promotes the Network for Greening the Financial System (NGFS) as a key initiative for collaboration and knowledge-sharing among financial institutions worldwide, urging central banks in Portuguese-speaking countries to join efforts in mitigating climate-related financial risks.	1	
17/03/2022	Speech	In her speech, Isabel Schnabel outlines the challenges and opportunities presented by energy inflation in the context of climate change. She identifies three main inflationary shocks: "climateflation," driven by the costs of climate change; "fossilflation," stemming from the high costs of fossil fuels; and "greenflation," the price pressure caused by the increased demand for minerals necessary for green technologies. Schnabel emphasizes that while the transition to a greener economy may lead to higher short-term costs, it is essential for energy independence and long-term sustainability. She advocates for a balanced monetary policy approach that considers both price stability and the green transition, emphasizing the importance of fiscal policies in driving investments in green infrastructure. The European Central Bank (ECB) is also focusing on aligning its financial instruments with climate goals and supporting the growth of green financial markets.	1	
21/04/2022	Speech	Christine Lagarde's statement at the IMF Spring Meetings (April 2022) highlights the economic impact of the Russian invasion of Ukraine, which has heightened inflationary pressures and created uncertainty for global growth. While the euro area had recovered to pre-pandemic levels by late 2021, the war, energy price hikes, and supply bottlenecks have constrained growth. Inflation, mainly driven by energy and food costs, has surged to 7.5%, prompting the ECB to adjust its monetary policy with a planned end to asset purchases in Q3 2022. The ECB remains committed to price stability and financial stability, extending liquidity support measures where needed. Fiscal policy, including EU-level initiatives, aims to shield vulnerable groups while supporting economic resilience. The euro area banking sector remains robust but faces risks from higher credit exposures. On a global scale, coordinated financial support for Ukraine and other affected countries is emphasized, alongside efforts to accelerate the energy transition, climate-related financial policies, and digital euro development. She also emphasizes that the ECB will continue to work with the IMF, central banks and other partners to advance the global response to climate change.	1	
27/04/2022	Speech	Philip R. Lane's keynote speech highlights two key statistical implications from the ECB's 2021 monetary policy strategy review. First, he discusses the need for a more comprehensive inclusion of owner-occupied housing costs in the Harmonised Index of Consumer Prices (HICP) to better reflect household inflation experiences. The ECB prefers the "net acquisition" method but acknowledges challenges in capturing housing's dual investment-consumption nature. Second, he emphasizes the ECB's commitment to integrating climate change into its monetary policy framework, in relation to disclosures, risk assessment, corporate sector asset purchases and the collateral framework.	1	

04/07/2022	Press Release	The ECB is strengthening its efforts to incorporate climate change into its monetary policy operations by adjusting corporate bond purchases, collateral frameworks, disclosure requirements, and risk management. These measures aim to reduce climate-related financial risks, promote transparency, and support the green transition in line with the Paris Agreement and EU climate goals. The ECB will tilt corporate bond holdings toward issuers with better climate performance, limit high-carbon assets as collateral, and require firms to comply with sustainability reporting standards. It will also enhance risk assessment by urging rating agencies to improve transparency on climate risks. These actions will be regularly reviewed to ensure they remain effective and aligned with evolving regulations.	1
19/09/2022	Press Release	The ECB has detailed its strategy to decarbonize its corporate bond holdings by tilting purchases toward issuers with better climate performance, starting October 2022. This will be determined by a climate score based on past emissions, future decarbonization targets, and the quality of climate disclosures. Companies with higher scores will receive greater bond purchases, while lower-scoring issuers will face maturity limits and reduced purchases. The ECB will regularly review and update its methodology and begin publishing climate-related data on its corporate bond holdings in early 2023. These measures align with the Paris Agreement and the ECB's broader climate action plan.	1
29/09/2022	Speech	Frank Elderson's speech emphasizes the urgent need for financial institutions and regulators to integrate nature-related risks—such as biodiversity loss and ecosystem degradation—into their frameworks, just as they have begun doing with climate risks. He highlights that nature underpins over half of global GDP, making its deterioration a direct financial stability concern. While progress on climate risk integration has advanced, nature-related risks remain underexplored due to challenges in measurement and complexity. The ECB is pushing banks to assess and manage these risks, with expectations for full compliance by 2024. Elderson calls on central banks, regulators, and policymakers to embed nature considerations into financial decision-making, as nature is not just an asset but a fundamental driver of economic and financial stability. He also ensured that the ECB will adapt the measures proposed in its action plan if necessary to address other environmental risks within our mandate."	1
14/10/2022	Speech	Christine Lagarde's IMFC statement highlights the global economic slowdown due to high energy prices, geopolitical tensions, and inflationary pressures, exacerbated by Russia's war on Ukraine. The ECB remains committed to monetary policy normalization, having raised interest rates significantly to combat inflation, which is expected to remain above target through 2023-24. Fiscal policy should be targeted and temporary to support vulnerable groups without fueling inflation. Financial stability risks have risen, though euro area banks remain resilient. The ECB continues to integrate climate risks into its monetary policy and supervisory frameworks, and will adjust the corporate bond holdings in the Eurosystem's monetary policy portfolios and collateral framework, introduce climate-related disclosure requirements and enhance risk management practices as already said in its action plan.	1

04/11/2022	Speech	Luis de Guindos' speech discusses the euro area economy, inflation, and the energy transition. He highlights that economic growth has slowed due to high inflation, weaker global demand, and rising energy prices, largely driven by supply disruptions and geopolitical events. The ECB has responded by raising interest rates to curb inflation and adjusting monetary policy tools to reinforce price stability. He also emphasizes the ECB's commitment to addressing climate change, including integrating climate considerations into monetary policy operations and corporate bond holdings. The energy crisis presents both challenges and opportunities for the green transition, requiring targeted fiscal policies to support vulnerable groups while ensuring a shift towards renewable energy.	1
09/11/2022	Speech	Frank Elderson highlights the ECB's commitment to integrating climate and environmental risks into its monetary policy, banking supervision, and financial stability efforts. The ECB has begun tilting corporate bond purchases towards issuers with better climate performance and expects banks to fully align their risk management with climate goals. Despite progress, he stresses the urgency of further action to ensure a Paris-compatible transition path. He calls on financial institutions and regulators to assess their remaining distance to meeting climate targets and to take immediate, concrete steps toward achieving them.	1
01/12/2022	Speech	In his speech, Frank Elderson discusses the European Climate Law and its potential implications for the European Central Bank (ECB). He highlights the EU's ambitious climate goals, such as reducing greenhouse gas emissions by 55% by 2030 and achieving climate neutrality by 2050, as set out in the European Climate Law. While the ECB is not directly bound by the law, Elderson emphasizes that it must still consider climate objectives in its monetary and supervisory policies, in line with the Treaty on the Functioning of the European Union. He outlines actions the ECB has taken, such as "tilting" its corporate bond purchases toward greener companies, and stresses that banks must manage climate-related risks. Ultimately, Elderson underscores the importance of the ECB's role in supporting the transition to a sustainable economy while remaining within its mandate.	1

Declaration

This dissertation is the result of my own work, and no other sources or means, except the ones listed, have been employed.

19. May 2025

Thibault Cézanne

Curriculum Vitae

Education

2019-2025	University of Mannheim
	Ph.D. in Economics
2016-2017	ENSAE ParisTech
	Master's Degree in Applied Economics
2014-2016	Paris-Dauphine University
	M.Sc. in Economic and Financial Engineering
2011-2014	Paris-Dauphine University
	B.Sc. in Applied Economics