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Bank Funding, SME lending and Risk Taking

Does a bank's financing structure matter for its risk taking? We show that a bank's financing structure relates to the riskiness of lending to European SMEs. Banks using a higher share of market funding, money obtained on capital markets, in their funding mix lend to firms of lower creditworthiness. The riskiness of SME lending is unaffected by a bank's level of capitalization.

We have built a comprehensive micro dataset, in which European SMEs were matched to banks, allowing us to analyze in detail how different funding elements by banks are transmitted to firms.

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Bank Funding, SME Lending and Risk Taking

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Abstract

In this paper, we explore how a bank's funding composition affects the risk profile of its lending to small and medium-sized enterprises (SMEs). By analyzing SME loan growth across Europe, we find that banks under the Single Supervisory Mechanism (SSM) that rely more on non-equity funding, tend to lend to SMEs with lower creditworthiness. Our analysis reveals significant variation in the relationship between different funding sources and both the volume and riskiness of lending. Notably, we find that banks with a higher proportion of market funding lend to riskier firms. Interestingly, the level of bank capitalization does not appear to influence the riskiness of SME lending, suggesting that while equity provides a cushion against losses, it does not affect lending risk. Our results are robust across different sample variations, timing adjustments, and alternative measures of creditworthiness.

Keywords: Capital structure, Banks, Lending practices, SMEs, Risk taking.

JEL codes: G21, G32, E52.

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1 Introduction

Firm financing through bank lending is key for private sector investment and economic growth. This especially concerns European small and medium-sized enterprises (SMEs), as they rely heavily on bank debt other than internal financing or bond issuance to finance operations and investments (Adalid et al., 2020; Bending et al., 2014; Claessens and Laeven, 2005; De Haan and Hinloopen, 2003; Giannetti and Ongena, 2012). Moreover, SMEs constitute the vast majority of all firms in the European Union (EU) and account for more than half of the EU's GDP (EC, 2023a). As such, bank lending to SMEs in Europe has received substantial attention from academia and policy makers. The existing empirical literature typically studies the determinants of the *quantity* of bank credit supply to firms, see for instance Jiménez et al. (2012), Jiménez et al. (2014) and Kishan and Opiela (2000). However, it is not only the quantity of credit supply that matters, but also its *quality*. In this regard, it is essential that firms have access to sufficient bank credit and that banks lend and take risks. Bank lending to firms has stagnated in several European countries over the past decade (ECB, 2023). This stagnation in lending has adverse effects on the real economy.

Contemporaneous with the stagnation of bank lending to firms, the funding composition (i.e. the relative proportion of its different funding elements which include equity, market debt, interbank lending and customer deposits) of banks has changed substantially. This is partly a consequence of changes in banking regulation and unprecedented monetary policy. Bank capital requirements have increased following the introduction of the European Single Supervisory Mechanism (SSM) in 2014, and direct refinancing in significant amounts by the ECB to commercial banks has been largely adopted by commercial banks in Europe, altering their funding composition. While capital requirements were raised to enhance banks' resilience to credit losses (*ex-post* risk), it is unclear to what extent higher bank capitalization, i.e., a higher proportion of equity, relates to a bank's lending volume and riskiness (*ex-ante* risk).

This paper aims at filling this gap in the literature by estimating how a bank's funding composition is related to the riskiness of SME lending. This is a banking activity where banks are less constrained to take risks, compared to (for instance) mortgage origination. By showing how a bank's riskiness of lending relates to its funding composition, we also document how the composition relates to the volume of lending. We do so by measuring how the individual funding components are related to lending to SMEs of different *ex-ante* creditworthiness. To the best of our knowledge, the academic literature to date has not yet shown how a bank's individual funding components relate to risk. Although we cannot determine whether risk taking is also excessive (as we do not observe *ex-post* creditworthiness or firm defaults after the lending decision), our findings provide insights into how the changing funding structures are related to risk taking. Our findings can be used to explore how policies that could change a bank's funding composition (such as increases in capital requirements or a taxation of a bank's use of market funding) could affect lending behaviour.[1]

There is considerable ambiguity in the economic literature on this topic. Theory provides conflicting predictions on the direction and magnitude of different funding elements, while empirical literature is scarce and suffers from shortcomings (particularly on how a bank's risk taking is measured). Moreover, the operating environment as well as funding conditions for banks in Europe have changed significantly as a result of unprecedented accommodative monetary policy. This adds complexity to the equation and may compromise the external

[1] Several European countries have imposed a 'bank tax' after the global financial crisis where the tax base is typically a bank's level of market funding (OECD, 2023).

validity of existing studies. The traditional view is that accommodative monetary policy unambiguously induces bank risk taking through a 'search for yield'. However, this view is contested by DellAriccia et al. (2014) who argue that risk taking in such an environment depends on the funding composition of the bank.

We study the period 2014-2019, a period with unprecedented accommodative monetary policy. We use a novel and comprehensive dataset covering SMEs from ten European countries, matched to their primary credit-supplying banks. Our analysis focuses on banks supervised by the SSM, as these banks are subject to the same monetary policy and supervisory policy regime. We measure the creditworthiness of firms via the Altman Z-score, a widely-used proxy to predict the probability of default of a firm, and analyze how the different funding elements are associated with loan growth to firms of different creditworthiness. We find that a bank's proportion of equity is not related to the riskiness of SME lending, while banks relying on market funding are most strongly inclined to lend to firms of lower creditworthiness. These firms have a higher bankrupcy risk. When adding granularity by accounting for market funding instruments of different initial maturity, we find that this association is driven by banks relying more on longer-term market funding. This finding seems consistent with earlier literature (Martinez-Miera and Repullo, 2017) and may be a result of a 'search for yield'. Our findings are largely robust to sample changes, different timing of variables, and an alternative measure of firms' creditworthiness which we construct by applying principle components analysis to a set of firms' financial ratios.

This paper makes several contributions to the literature. Given the scarcity of empirical studies in this area, and the conflicting theoretical predictions, our results should be viewed as exploratory. Firstly, we investigate firm-level risk using a novel dataset that matches firms with their main credit-supplying banks. This firm-bank pairing enables a more detailed examination of the relationship between a bank's funding composition and risk-taking than achieved in previous studies. More specifically, unlike existing literature that typically employs a single measure of risk at the bank level, we utilize *ex-ante* credit-risk measures at the firm level. Secondly, we exploit greater granularity and model the role of the individual funding elements (e.g. equity, market debt, interbank lending and customer deposits) in the same specification. Lastly, our study focuses on European data (both firms and banks), whereas some related empirical research relies mainly on US data.

The remainder of this paper is structured as follows. Section 2 reviews the theoretical and empirical literature. Section 3 describes the dataset and presents our empirical strategy. Section 4 shows and discusses the baseline results. Section 5 presents a battery of robustness checks. Section 6 concludes, presents policy implications, discusses limitations, and identifies areas for future research.

2 Literature Review

This paper is linked to an established body of research on how a bank's funding composition, monetary policy, the regulatory environment, and risk taking are connected. We first review the predictions from the theoretical literature on how individual funding components relate to risk taking. The main finding from this review is that economic theory provides conflicting predictions, consistent with what Demirgüç-Kunt and Huizinga (2010) and Bitar et al. (2018) conclude. Next, we review empirical studies that are, to a varying degree, related to this paper.

2.1 Theoretical Literature

There is an abundance of theoretical models on how a bank's level of equity relates to its risk taking. However, these models come with equivocal predictions. The seminal papers of Diamond (1984) and Stiglitz and Weiss (1981) demonstrate that financing, while requiring a higher share of equity, reduces risk taking. This is a result of reducing moral hazard by providing bankers with incentives to monitor project quality. Later models postulate that the relationship between a bank's capitalization and risk taking is not uniform. Saunders et al. (1990), for instance, show that the effects of a bank's equity on risk taking depend on who holds the equity: banks where the equity is predominantly held by its managers have stronger incentives to reduce risk than those that are owned by external stockholders. A similar conditionality is analyzed by Rochet (1992) and Diamond and Rajan (2000). They find that the relationship between the level of equity and risk taking depends, for instance, on the bank's business model: higher levels of equity lower incentives to take risk when a bank is *utility maximizing* whereas there is no effect when banks are *value maximizing*. More recent theory by Hellmann et al. (2000) and Repullo (2002) shows that the relationship between a bank's equity and risk taking is not straightforward. In these models, equity indeed provides bankers with incentives to monitor project quality, since adverse consequences of gambling (i.e. taking excessive risk) are internalized. However, higher equity levels do not necessarily reduce a bank's risk taking. Higher capitalization could also reduce a bank's franchise value, which in turn encourages gambling. Moreover, they show that the effect on risk taking also depends on the level of competition. More recent work by DellAriccia et al. (2014) shows that, in an environment where interest rates are low (as is the case during our observation window), highly capitalized banks monitor their project quality less, encouraging risk taking.

Higher bank capitalization implies a lower proportion of other bank liabilities. Largely overlooked by the previously reviewed studies, these liabilities comprise very different funding elements that are shown to affect a bank's risk taking through various channels. Calomiris and Kahn (1991) and Calomiris (1999) postulate that banks relying more on *demandable debt*, and thus having higher leverage, have an incentive to operate more prudently, i.e. take less excessive risks. This is a result of monitoring by sophisticated debt-holders, which disciplines banks. This relationship need not be linear, as shown by Blum (2002) and Inderst and Mueller (2008). Others argue that there exists an optimal level of leverage that is welfare maximizing (DeAngelo and Stulz, 2015). Other scholars argue that not just the level, but also the composition of such debt matters. Demandable debt in itself comprises funding elements (e.g. deposits, market debt) exhibiting very different characteristics. Building on the framework by Calomiris and Kahn (1991), Huang and Ratnovski (2011) account for the maturity structure of demandable debt. They distinguish short-term (typically 1-year maturity) market debt from its longer term counterpart and deposits. They show that short-term financiers have a lower incentive to engage in costly monitoring of the bank's project quality (a result of relatively high fixed costs incurred with monitoring), therefore lowering incentives for the bank to operate prudently or finance smaller firms.[2] On the other hand, banks relying on short-term market debt would need to replenish ('roll over') such debt more frequently, which increases the number of occasions on which the bank is potentially monitored. The expected sign of long-term debt on risk taking is also ambiguous: although long-term financiers may have a stronger incentive to monitor the bank's project quality,[3] the longer maturity comes with a higher cost of debt, which can incentivize the bank to raise expected returns by increasing risk. A similar result is presented in more recent theoretical work by Martinez-Miera and

[2]A claim similar to Holmstrom and Tirole (1997).

[3]Because of the higher uncertainty given the longer maturity, resulting in more information assymetry between the bank and the provider of funds.

Repullo (2017), who find that banks monitored by external investors (as is thus the case with long-term debt) have an incentive to engage in 'search for yield' and lend to riskier projects (or, firms) when interest rates are low.

Demandable debt also comprises customer deposits, typically demandable at once, and they tend to have fundamentally different characteristics from market debt. As such, they also have different implications for a bank's risk taking. Deposits typically do not expire and does not have to be regularly refinanced, like market debt, and deposit holders generally lack resources and incentives for sophisticated monitoring of the bank. This may partially explain the sticky nature of deposits. Banks relying more on customer deposits may therefore have a stronger incentive to take risk and raise the expected return for their equity holders. Since the seminal paper by Diamond and Dybvig (1983), theoretical literature has traditionally focused on the implications of deposit guarantee schemes (or *deposit insurance*) on liquidity risks (bank runs) and not on the implications of a bank's proportion of deposit financing on lending risk. Following an extensive review of theoretical literature, Boyd and De Nicolo (2005) conclude that theoretical predictions on the effects on risk taking of the proportion of deposit financing used by banks as well as deposit insurance schemes are mixed and fragile, as they highly depend on environmental circumstances such as deposit market competition.

Finally, we consider interbank lending and risk taking, on which economic theory is less abundant. Rochet and Tirole (1996) argue that lending banks may disciplinize borrowing banks, therefore reducing excessive risk taking, because banks are particularly skilled at identifying risks at other banks. However, the composition of interbank funding of borrowing banks itself has changed significantly since the Global Financial Crisis (GFC). In Europe, the ECB has - as a form of interbank lending - provided a substantial amount of direct funds to banks (e.g. via its refinancing operations) after the GFC, unconditional on a bank's project quality. ECB-financing may as such lack the disciplining implication that commercial banks exert. This compromises the predictions by Rochet and Tirole (1996) and therefore the expected implication of interbank lending on a bank's risk taking is ambiguous.

2.2 Empirical Literature

We review a number of empirical studies that are related to this paper. Empirical research on the topic can be charterized by two main observations. First, the empirical literature has to a large extent focused on the relationship between capitalization and risk taking, leaving the role of other funding elements relatively underexplored. Second, there are various ways to calculate a bank's risk and those commonly applied in the literature, the Z-score[4] or a bank's loan loss reserve policy, may not reflect risk taken on specific banking activites.

As pointed out in the previous subsection, the relationship between a bank's level of capitalization and lending practices has been a topic of debate. Empirical evidence of the relationship between capitalization and lending practices, both volume and risk, is also mixed. We highlight a few studies that are, to varying degrees, related to this paper. For a more extensive overview, we refer to Bitar et al. (2018), who provide a recent and more comprehensive summary of empirical studies on the effects of capitalization.

Using a sample of banks from 15 European countries over the period 1992-2000, Altunbas et al. (2007) find that the effect of a bank's proportion of equity on a bank's risk depends

[4] The Z-score denotes the number of standard deviations that a bank's return on assets has to fall for the bank to become insolvent. A higher Z-score therefore implies lower risk.

on the business model of the bank.[5] The effect is found to be positive for commercial banks and negative for cooperative as well as efficiently operating banks. They proxy a bank's risk through the level of loan loss reserves. Relatedly, Laeven and Levine (2009) study how a bank's shareholder structure is associated with a bank's risk, using a sample of 279 listed banks in 48 countries over the period 1996-2001. They include the minimum regulatory capital requirement in their regression models and show that it is positively related to an individual bank's Z-score, thus lowering risk. Studying a sample of banks from 39 OECD countries in the period 1999-2013 and accounting for different ways of calculating capital ratios, Bitar et al. (2018) find that risk-based capital ratios[6] have no impact on a bank's risk, while non-risk based capital ratios increase bank risk. The authors proxy bank risk via loan loss reserves.

Proxying a bank's lending risk via the bank's Z-score or loan loss reserves merits some discussion. The Z-score is an *ex-post* measure of risk for the bank as a whole. As such, it may not reveal *ex-ante* risk taking, and diversification among different bank activities (e.g. mortgages business versus SME lending) may cancel out risks. For instance, it is possible that a bank increases its risk on loans to firms, whereas risks on its mortgages business decreases due to macroeconomic developments. Loan loss reserves as a proxy for risk has similar drawbacks: although reserves are an *ex-ante* measure of risk, increasing reserves does not necessarily imply higher risk taking as the increase could also reflect forecasted macroeconomic developments.

To overcome the shortcomings of proxying risk via the Z-score, Klomp and De Haan (2012) employ principle component analysis to identify two single risk measures from a set of bank-level financial ratios: *'capital and assets risks'* and *'liquidity and market risk'*. They examine the relationship between a bank's regulatory capital level and the constructed risk measures, using a sample of banks from 21 OECD countries over the period 2002-2008, and find that regulatory capital levels do not affect these risks in a uniform way. Although their risk measures reflect banks' risks more granularly, the authors do not observe actual lending.

When it comes to empirical studies that focus on non-equity funding instruments, closest to our study is Demirgüç-Kunt and Huizinga (2010). They study the association between a bank's short-term funding strategy, activity mix and a bank's risk (proxied via a bank's Z-score). They find that low levels of short-term market funding and deposits funding, observed in a sample of listed US banks in 1995-2007, lower a bank's risk and that higher levels of short-term market funding increase a bank's risk. Demirgüç-Kunt and Huizinga (2010) measure short-term funding by the so-called *nondeposit funding share*, i.e. the share of short-term market funding in total deposits and short-term market funding, which in itself comprises different funding elements. We exploit considerably more granularity in different funding elements compared to Demirgüç-Kunt and Huizinga (2010).

Using a comprehensive empirical strategy and a sample of US banks over the period 1997-2006, Craig and Dinger (2013) examine the effect of deposit market competition and market funding rates on bank risk, which is proxied via ROA-volatility, non-performing loans ratio and stock price volatility. They conclude that deposit market competition increases bank risk, while the effects of market funding rates are ambiguous. Although the authors provide

[5]In our paper, we account for the business model of the bank by including bank-fixed effects in our models, as described in the following sections. We do not distinguish banks according to their business models (e.g. retail lenders or specialized lenders), and do not explicitely run separate analyses regarding the business model of the bank, as it is not the focus of this study. We do, however, consider only lending banks, and filter from our dataset non-lending banks such as custodians.

[6]That is, where the required regulatory capital ratio is calculated using a risk-weighting of a bank's exposures.

valuable insights into the interplay between deposit market competition, market funding conditions and bank risk, the authors do not reveal how the relative sizes of deposit and market funding relate to risk taking. Another paper examining the role of market funding is Vazquez and Federico (2015). Using a sample of US banks over the period 2001-2009, they find that banks having lower *net stable funding ratios*[7] (NSFR) and higher leverage had a higher likelihood of default during the financial crisis of 2008-9. A high NSFR and low leverage are thus found to be associated with a lower likelihood of default. Although defaults and bank risk are likely correlated, this needs not be the case. Therefore, the authors do not explicitly measure how a bank's funding composition affects *risk taking*. Moreover, the precise composition of the NSFR is unspecified, thus making it unclear what market funding elements precisely contribute to bank defaults. Moreover, the authors examine defaulting banks during the global financial crisis, which may not generalize to more normal conditions.

Finally, a growing strand of the empirical literature investigates interbank lending and specifically the effect of quantitative easing (QE) on banks' risk taking. A number of studies focus on central-bank refinancing operations to commercial banks. Although the aim of our paper is not to study whether these operations induce risk taking, the average bank in our sample uses central-bank funding extensively, following QE by the ECB. An average of 70% of interbank lending in our sample period comprises central-bank funding. Recently, studies have investigated how different rounds of quantitative easing or, more specifically, the ECB's bank refinancing operations have affected the riskiness of bank lending to firms. Chen et al. (2022) show that during the 2008 quantitative easing by the Federal Reserve, when substantial liquidity was injected in both US firms and banks, banks lowered lending standards to firms. Using data from the Italian credit registry, Benetton and Fantino (2021) and Esposito et al. (2020) found weak evidence that refinancing operations induced risk taking. Using cross-sectional data of banks in multiple European countries and focusing on different rounds of refinancing operations by the ECB, Andreeva and García-Posada (2021) and Barbiero et al. (2022) found no evidence for excessive risk taking. Our sample period covers multiple rounds of different refinancing operations by the ECB (LTROs, TLTROs, etc). As such, we indirectly document how the various rounds of the ECB's refinancing operations are associated with the riskiness of lending to SMEs.

3 Data and Empirical Strategy

This section presents our dataset, the empirical strategy and the sample used in the baseline specification. In short, to investigate how a bank's funding composition affects lending to SMEs, we construct a unique panel dataset that allows us to observe 'firm-bank pairs'. Our empirical strategy relies on matching firms with their primary credit-supplying banks. We built the dataset by first constructing a sample containing financial statements of European firms, and subsequently matching these firms to financial characteristics of their credit-supplying banks, using reported bank relations by firms.

3.1 Database Construction

3.1.1 Firm financial data

We obtained financial statements of firms incorporated in Europe from Bureau van Dijk's Orbis dataset. Orbis contains standardized financial statements and other detailed firm char-

[7]The NSFR is a regulatory metric indicating the proportion of liabilities considered to be relatively stable, such deposits and longer term market funding.

acteristics of approximately 20 million European firms and is a widely used source for firms' microdata, the lion's share comprising unlisted SMEs. SMEs are defined as firms with total assets below 43 million EUR (EC, 2023b). We use annual historical vintages of Orbis and year-end data from balance sheets, and profit and loss accounts of firms in ten EU member states (Austria, Germany, Spain, France, Ireland, Latvia, Luxembourg, the Netherlands, Portugal, and Slovenia).[8] Our focus on European firms has also practical reasons, as bank-firm relations for non-European advanced economies, such as the United States, are unavailable.

We extract data for the financial reporting years 2010 up to and including 2019. We thus exclude the Covid-19 pandemic as it may have distorted firms' financial performance, creditworthiness and banks' funding conditions (Barbiero et al., 2022). Subsequently, we prepared this financial data for analysis and a few elements of this process are highlighted here. First, we followed guidelines as presented in Kalemli-Ozcan et al. (2015) to clean the data and create a nationally representative panel of firms. Second, we keep only data from non-financial firms, thus excluding firms operating in the financial sector. Third, we keep only data for firms at the highest available level of financial consolidation.[9] Fourth, and this only concerns items extracted from firms' balance sheets, we exclude observations if we observe unlikely values on variables as well as substantial yearly changes in the item's value. This concerns a firm's total assets (i.e. balance sheet size), fixed assets, debt, and equity, as these balance sheet items are unlikely to show significant yearly volatility. If the year-on-year change in an item's value exceeds the 99th percentile of the distribution of the corresponding annual change in the item's value over the period 2010-2019, we treat the value as missing. In this way, we exclude potentially erroneous entries from the sample. Finally, all firm-level variables are winsorized at 1% to exclude extreme outliers from our sample.

3.1.2 Matching firms to bank-level data

Information on which banks provide credit to firms (henceforth referred to as 'firm-bank relations') is scarce because European credit registries are incomplete and confidential. For example, the recently developed credit registry by the ECB, 'AnaCredit', is confidential and has data availability limitations. We therefore resort to Orbis as the only publicly available source of firm-bank relations: firms in Orbis can report up to seven individual bank names with whom they maintain a relation. Using firms' reported bank relations as a source for firms' credit-supplying banks is consistent with related literature (Ferrando et al., 2019; Giannetti and Ongena, 2012; Ongena et al., 2015). As Orbis does not specify the nature of the bank relation (e.g. lending vs. checking accounts), nor provides information on the relative importance of every single relation, we follow Ongena et al. (2015) and Beck et al. (2018) in classifying the bank which is reported first in Orbis as the primary, most significant, bank of each firm.

We obtain firm-bank relations as reported in the year 2018 and match firm-level data to that of their primary bank. Giannetti and Ongena (2012) and Kalemli-Özcan et al. (2022) have investigated firm-bank relations over time and have found them to be strongly persistent. Firms do not change their primary bank often, illustrating the sticky nature of relationship

[8]Member states as of January 2022. We excluded firms incorporated in countries where none of the firms have reported bank relations. Important to note is that we do not exclude banks from these countries in our sample. For instance, a Spanish firm could report a relation with a Finish bank and the pair could be included in our dataset.

[9]More specifically, we keep records with the following consolidation codes in Orbis: C1 (consolidated account of a company where no unconsolidated account is available), and U1 (unconsolidated account of a company with no consolidated account available).

banking in which banks have long-lasting relations with SMEs (Beck et al., 2018). We, therefore, assume that the reported firm-bank relations in 2018 do not differ systematically from the non-observed firm-bank relations in other years in our sample. As such, we map the firm-bank relations observed in the year 2018 to the entire period in a similar fashion as in Storz et al. (2017) and Faccia et al. (2020).

As mentioned, Orbis does not specify the nature of the firm-bank relations. Ongena et al. (2015), Giannetti and Ongena (2012) as well as Wang et al. (2020) have asserted, however, that the reported firm-bank relations in Orbis mostly concern lending relations. Moreover, we omit banks from our sample if we can manually ascertain that the bank concerned is primarily engaging services other than lending. For instance, we exclude firm-bank relations if a bank's business model is clearly not lending (e.g. custody banks, pure investment banks, or brokers), which we determine by investigating a bank's annual reports and websites.

We subsequently match the name of each bank involved in a firm-bank relation in Orbis with the name of a bank entity in another Bureau van Dijk database: Bankfocus (formerly known as 'Bankscope'). This database provides annual financial statements for the banks in our sample. Detailed information on the matching procedure can be found in the Appendix. A few elements of our matching procedure merit explanation in this section. Some entries on bank relations are potentially erroneous, which may be the case for bank relations obtained by Orbis prior to 2018 (but still in the data for 2018). We reduce this potential measurement error by hand-checking all bank relations and excluding those potentially erroneous bank relations from our sample. Specifically, in case we can establish that a reported bank was merged with another bank, has been taken, or has been liquidated, we exclude the firm-bank relation.

Subsequently, we rely on Bankfocus to establish in which country the bank is incorporated, which can be another country than the country in which the firm is operating (in that case the bank is foreign). Next, we determine whether a bank is officially classified as a 'significant institution' and therefore a bank that is subject to the SSM. This procedure is described in detail in the Appendix. In case a bank is categorized as a subsidiary of a significant credit institution[10], we also obtain the financial data of the parent institution. This allows us to analyze the effects of a bank's funding composition at the level of the parent institution as well as at the subsidiary level, in case the subsidiary is part of a significant credit institution. Finally, we complete our dataset with a limited set of macroeconomic variables from the ECB's Statistical Data Warehouse. Data sources for all variables in our dataset are listed in Table A.1 of the Appendix.

[10]It is important to restrict the sample of banks to banks that are formally classified as a credit institution, as these are banks that take funding for lending.

3.2 Empirical Strategy

We study how a bank's funding composition affects the volume and riskiness of SME lending by modelling loan growth at the firm level as a function of the bank's funding composition and the firm's creditworthiness. Specifically, we estimate the following baseline specification:

$$\text{Firm loan growth}_{i,b,c,t} = \alpha + \beta(\text{Firm creditworthiness})_{i,t-1} +$$
$$\textstyle\sum_{j=1}^{N} \gamma_j(\text{Bank funding component})_{b,t-1} +$$
$$\textstyle\sum_{j=1}^{N} \delta_j[(\text{Bank funding component})_{b,t-1} * (\text{Firm creditworthiness})_{i,t-1}] +$$
$$\zeta(\text{Firm controls})_{i,t-1} + \psi(\text{Bank controls})_{b,t-1} + \phi(\text{Macro controls})_{c,t-1} +$$
$$\mu_i + \eta_b + \rho_c + \theta_t + \epsilon_{i,b,c,t}$$

Subscript i refers to the individual firm, b to the individual bank, t to the financial reporting year of both the firm and the bank, and c indicates the country in which the firm is incorporated. In addition, we include time-varying control variables at firm, bank, and country level, as well as firm-, bank- and country-fixed effects μ_i, η_b, and ρ_c, respectively. Finally, θ_t represents time-fixed effects and ϵ denotes the error term.[11] The specification is estimated using the fixed-effects estimator for the sample period 2014-2019. During this period, the ECB's monetary policy was especially accommodative and the SSM came into effect as of 2014. Since our 'treatment' is at the bank level, following current best practices for robust inference (MacKinnon et al., 2023), we cluster standard errors at the bank level in all models.[12] The next subsection describes how a firm's creditworthiness is calculated.

3.2.1 Calculating a firm's creditworthiness

To measure a firm's creditworthiness, we calculate the firm's Altman Z-score for every single year (Altman, 1968). Initially developed as a measure to predict a firm's likelihood of default in the following two years, the score indicates the financial health and, as such, the creditworthiness of a firm. Despite its age, the original Altman Z-score is still a widely used proxy for a firm's creditworthiness in academia and practice (Altman et al., 2017). The Altman Z-score is calculated as a linear combination of five firm-level financial ratios: 1.2×(working capital/total assets) + 1.4×(retained earnings/total assets) + 3.3×(earnings before interest and tax (EBIT)/total assets) + 0.6×(market value of equity/total liabilities) + 1.0×(sales/total assets). Following its original definition, three zones of discrimination are distinguished: (1) a firm with a score exceeding 2.99 is considered to be in the 'safe zone' (high creditworthiness); (2) a score between 1.81 and 2.99 reflects the 'grey zone' (moderate creditworthiness), and (3) a score below 1.81 indicates a firm in 'distress zone'. These three zones are included as categorical variables (dummies) in our model.

3.2.2 Dependent variable, interaction terms and control variables

Consistent with related literature (Ongena et al., 2015), our dependent variable, loan growth, is the annual percentage change of a firm's bank loans. It is calculated as the difference

[11] Technically, note that the firm-fixed effect μ captures the bank-fixed effect η and the firm-country fixed effect ρ by construction, since the firm-bank relation is observed as constant over time. We depart from notating the model above in the most parsimonious manner to preserve clarity.

[12] Clustering standard errors at the bank level is the most conservative (from a statistical significance viewpoint) option in this case.

between a log-transformed firm's outstanding loans in year t minus its log-transformed outstanding loans in year *t-1*. An increase in this item's value reflects additional credit and thus net lending by a firm's credit-supplying bank.

The different elements of a bank's funding composition are included in the model altogether, and are all scaled by a bank's total assets (i.e. the size of its balance sheet): a bank's equity, customer deposits, bank deposits (interbank lending), and total market funding. The funding elements are therefore both our main variables, while they also serve as control variables. Section 3.3 reports descriptive statistics of the different funding components. We use equity rather than regulatory capital, such as the bank's CET1-ratio, because it can be consistently measured over time (the definition of regulatory capital ratios has changed during the sample period as a result of changes in the bank regulatory framework). Moreover, regulatory capital measures are potentially endogenous, as they are calculated based on the risk of a bank's activities (i.e. risk weighting). Total market funding equals the sum of short-term and long-term debt instruments issued by the bank, among which certificates of deposit (CDs) and repos. Short-term is defined as a bank's debt securities with an initial maturity of up to a year, and long-term as debt securities with a maturity exceeding a year. As short-term and long-term debt instruments could have different implications for a bank's risk taking (Huang and Ratnovski, 2011), we split market funding into these separate elements in one specification. In total, the different funding elements account for an average of 81% of the total liabilities of banks included in the sample. This mitigates concerns of multicollinearity among the different funding elements in the model. The remaining share comprises, amongst others, trading liabilities, deferred and current tax liabilities, and provisions.

Importantly, the effect of a bank's funding composition on the riskiness of its lending to firms is captured by the interaction terms, which are therefore the key coefficients of interest in this paper. We interact the individual elements of a bank's funding composition with the Altman zones to measure to which extent a bank provides credit to the firm (hence we observe positive loan growth), depending on the different elements of its funding structure, and the creditworthiness of the firm. Note that a positive and statistically significant sign on one of the interaction terms implies that banks relying more on a particular funding element, provide credit to firms of higher creditworthiness firms. Hence, a negative coefficient on the interaction terms implies higher risk taking by the bank, as this indicates that fewer credit is provided to firms of higher creditworthiness (negative loan growth). While we use the original Altman zones in our baseline model, below we will also evaluate the robustness of our results by using different cutoff values of the Altman score.

The nature of our dataset does not allow us to determine precisely *when* changes in a bank's funding composition are transmitted to SME lending. We assume that banks observe the creditworthiness of a firm from its financial performance (from at least) a year earlier. All firm-level variables are therefore lagged by one year, corresponding with the previous accounting year. To account for potential endogeneity, specifically the simultaneity between a firm's loan growth and a bank's funding composition, we follow related empirical literature (Altunbas et al., 2007; Bitar et al., 2018; Demirgüç-Kunt and Huizinga, 2010), by lagging bank-level variables by one year. The endogeneity problem may also be limited because we measure bank lending at the firm level and funding at the bank level. Moreover, we observe only a fraction of a bank's total lending portfolio, as banks also lend to households and engage in other activities. Thus, it is unlikely that an individual firm's lending alone would directly affect the total funding composition of a bank. Lagging variables of interest is a common practice in the banking literature whenever a quasi-experimental setting cannot be created. Lagging our bank-level variables presumably also matches the timing of lending decisions:

banks take on funding in year t and may lend those funds the year after, *t+1*. In our robustness analysis, we experiment how our results are affected by allowing for lending and funding decisions to occur in the same year.

In all specifications, we control for firm-level, bank-level, and macroeconomic characteristics that are expected to affect loan growth of a firm. For our set of controls, we follow Demirgüç-Kunt and Huizinga (2010) and Barbiero et al. (2022). At the firm level, we control for factors that are supposed to affect the demand for credit. Apart from including the Altman Z-score (not interacted) as a regressor, we also add the firm's size, proxied by the log-transformed amount of total assets, and its availability of collateral, proxied by the tangible assets to total asset ratio. Arguably, larger and therefore more established firms may grow slower and therefore demand less credit. In a similar fashion, firms having more potential for posting collateral may be more eligible for getting additional credit from a bank, but may on the other hand also be more established and grow slower. Firm-fixed effects account for all time-invariant characteristics, such as a firm's reputation or the quality of its management, which tends to be sticky over time (Ang and Wight, 2009). At the bank level, we control for the bank's size, return on assets (ROA) and efficiency ratio, as suggested by Altunbas et al. (2007). Larger banks, proxied by log-transformed total assets, may have more potential to diversify risk among different activities and therefore could have higher risk appetite with respect to firm lending. Banks with a higher ROA could have less incentive to take on additional risk on business loans. In a similar fashion, banks operating more efficiently, as proxied by the ratio of overhead expenses over total expenses, could have a lower incentive to raise expected returns through a higher risk appetite on firm lending. Bank-fixed effects account for all time-invariant characteristics, such as its reputation. Finally, we include three control variables at the level of the country of the firm: the annual change in aggregate credit demand conditions, the change in the level of competition among banks, and the extent to which an economy is dependent on credit. Credit demand conditions are included to further isolate credit supply, and are taken from the ECB's Bank Lending Survey, depicting the net change[13] in demand for credit on three dimensions.[14] The annual change in the country's Herfindahl index is expected to affect loan supply and risk taking (Boyd and De Nicolo, 2005; Jiménez et al., 2013), and is taken from the ECB's Statistical Data Warehouse. Country-level fixed effects capture time-invariant conditions (such as having a deposit guarantee scheme) and year dummies capture additional common factors.

We restrict our baseline sample to firms reporting a relationship with an SSM parent and their subsidiary banks for two reasons.[15] First, SSM banks form a more homogeneous set of banks as they are subject to the same banking regulation, supervisory regime, reporting requirements, and access to monetary funding by the ECB. Second, SSM banks are larger and economically significant. We include both parent and subsidiary banks in the baseline model. This means that we regress a firm's loan growth on both funding variables of the parent bank, if the firm reports a parent bank (ING N.V., for example), and regress loan growth on funding variables of the subsidiary bank, if the firm reports a relation with a subsidiary (ING Belgium N.V., for instance). In our robustness section, we examine how results change if we only include firms reporting a relation with an SSM parent bank ('lead institution'). This is because subsidiary banks may be partially funded and monitored by the parent bank, which may affect their funding composition and hence risk taking. Since the SSM has been in effect since 2014 (ECB, 2014), we restrict the sample period to 2014-2019. But we will show below that our results are robust to longer (2010-2019) and shorter (2017-2019) estimation samples.

[13]Specifically, we choose the net percentage and the 'backward-looking three months' indices.
[14]'Debt refinancing', 'large enterprises' and 'small medium enterprises'.
[15]Example: ING Bank N.V. (parent bank) and ING Belgium N.V. (subsidiary bank).

Furthermore exclude observations from countries if there are fewer than 100 observations in that country to reduce overrepresentation of countries with few observations.

Importantly, our specification is reduced form. While we observe the quantity of loans, and hence the annual loan growth, we cannot extract the exact pricing of these loans, i.e. the interest rate charged by banks to firms. We have no data on interest rates on individual loans.[16] As such, we cannot precisely disentangle supply-side factors from demand-side factors. However, to the best of our knowledge, our specification is the closest one could get to measuring the transmission of bank-level factors with microdata in a broader European context. Credit registries, which typically do contain information on interest rates on individual loans to firms, are often incomplete or cover a single country. Jiménez et al. (2014) and Benetton and Fantino (2021), for instance, exploit Spanish and Italian credit registries. Measuring loan growth without controlling for its pricing is consistent with related literature (Barbiero et al., 2022; Ongena et al., 2015).

Table 1: Summary Statistics

Variable	**Mean**	**SD**	**Median**	**Min.**	**Max.**
Firm loan growth	0.04	1.04	-0.02	-16.05	16.06
Firm age	25.61	15.01	23.00	1.00	640.00
Firm debt	2,237,367	5,179,755	219,095	2	39,240,264
Firm Altman Z-score	2.67	1.54	2.57	-4.95	19.96
Firm total assets	5,787,017	10,134,969	1,473,122	268	39,240,264
Firm fixed assets ratio	0.35	0.27	0.29	0.00	1.09
Bank ROA	0.00	0.00	0.00	-0.03	0.04
Bank efficiency ratio	0.58	0.11	0.54	0.18	1.30
Bank total assets	615,082	656,434	347,927	829	2,077,759
Bank equity ratio	0.08	0.02	0.07	0.02	0.25
Customer deposits ratio	0.54	0.12	0.54	0.01	0.87
Deposits from banks ratio	0.14	0.11	0.12	0.00	0.77
Bank total market funding ratio	0.09	0.05	0.08	0.00	0.75
Bank short-term funding ratio	0.02	0.02	0.01	0.00	0.22
Bank long-term funding ratio	0.07	0.04	0.06	0.00	0.62

Notes. Firm debt and firm total assets are displayed in Euros. Bank assets are displayed in millions of Euros.

3.3 Descriptive Statistics

Table A.2 in the Appendix reports frequency statistics. It shows the number of firms and banks in the baseline model by country in the baseline model. Both the number of banks and the number of firms vary substantially by country of origin, which is a result of data availability. Some banks are reported more frequent than others because bank-firm pairs are more available in some countries than others. Although the number of firms in our sample varies per country and our sample is clearly a subset of all SMEs in a country, our selection of firms (and hence, also banks) follows a data cleaning procedure, which results in nationally representative subsets (Kalemli-Ozcan et al., 2015). Table 1 reports summary statistics of the firm-level and bank-level variables in the baseline model. The model clearly relies on SMEs, constituting the vast majority of firms in Europe. The firms included in the model represent a diverse set in terms of age, bank debt and the Altman Z-score. With an average age of about 25 years, we observe relatively established firms. On average, firms in the sample are of moderate creditworthiness (referred to as the 'grey zone') and the sample is not skewed towards one end of the creditworthiness distribution. Importantly, for only 16% of firms in

[16] In our dataset, we have the total interest amount paid at the firm level, rather than at the individual loan level. We tested the robustness of the baseline model by controlling for the interest paid, scaled by a firm's revenues. The baseline model remained highly robust. However, we chose not to include this variable in the baseline model because it significantly reduced the sample size due to data availability constraints.

the sample, there is no change in the Altman zone over the entire sample period [17], thus 84% of firms show variation in the Altman zone. Table 1 also shows the variety in the funding composition of banks in the model. On average, the most significant funding element is customer deposits (54% of total funding), followed by deposits from banks. Finally, it is worth noting that our panel is unbalanced and that a firm is in the sample for an average of 3.1 years.

4 Empirical Results

In this section, we report and evaluate regression results for the baseline specification as presented in Section 3.2. In column (1) of Table 2, we start by analyzing results of a model that excludes the interaction terms that capture risk taking. This specification serves as a starting point. We find that the equity ratio of a bank enters with a negative and statistically significant coefficient. This coefficient indicates that a bank's capitalization, for the average firm in the sample, is negatively related to loan growth at the firm level.[18] Bank's relying more on equity funding, on average, provide less credit to firms. This could be a consequence of how the equity is used: European banking regulation requires banks to hold part of the equity in liquid assets such as highly rated government bonds (i.e. not corporate loans), which could reduce illiquid firm lending when a bank relies more on equity funding. Column (1) also shows that all non-equity funding elements are positively associated with higher firm lending and, in most cases, this association is statistically significant, indicating that, as expected, these elements increase firm lending.[19]

The negative association between equity funding and firm lending as reported in column (1), however, is not robust across different specifications when accounted for differences in the creditworthiness of a firm. In column (2), we include the interaction terms in the model and find that the associations between firm lending and the individual funding elements are highly nonlinear, depending on the creditworthiness of a firm, as indicated by the statistically significant coefficients of the interaction terms. Recall that a negative and significant coefficient on the interaction term indicates an increase in risk taking on firm lending. Only the grey and safe zones are reported, given that the distess zone (i.e. the lowest creditworthiness category) is the 'base' in the model and the three categorical variables cannot be jointly included in the model as a firm always belongs to one of the categories. In column (2) we find that banks relying more on market funding most strongly exhibit a lower lending volume to firms of higher creditworthiness, as captured by the increasingly negative coefficient on the interaction term. In other words, banks relying more on market funding reduce lending to firms of higher creditworthiness. This result implies that banks relying more on market funding take higher *ex-ante* risks on their lending to SMEs. This finding is consistent across all specifications where a bank's market funding ratio is interacted with a firm's zone of creditworthiness, both in this section as well as in robustness analyses in the next section. Column (2) also shows that the customer deposit and the deposits from banks ratios have both a positive direct effect on lending, but not for firms of higher creditworthiness. More precisely, banks relying more on customer deposits and deposits from banks exhibit a lower volume of lending to safe firms.

In column (3), we decompose market funding into its short- and long-term components.

[17]Note that the underlying Altman Z-score could change, however, while a firm could remain in the same zone.
[18]This result is consistent with the findings of Jiménez et al. (2012), although their sample is different, containing larger firms and Spanish firms only.
[19]Also this finding is consistent with the empirical literature, and in particular Jiménez et al. (2012).

Recall that market funding comprises debt that is traded on international capital markets and this debt can have a short, typically less than a year, and longer term to maturity, and could have distinctive effects on a bank's risk taking (Huang and Ratnovski, 2011). We find that the elevated risk taking following reliance on market funding is explained by longer-term market funding. The association of market funding is economically the most significant among the funding components. As can be calculated from column (2) in Table 2, a 10%-point increase in the use of market funding, implies a 5.4% decrease in lending to firms of the highest creditworthiness. Although our data restricts us from identifying the precise mechanism at play, mostly since we do not observe the interest rate on lending to SMEs, we hypothesize that the 'search-for-yield' mechanism described by Martinez-Miera and Repullo (2017) could play a role here. Their model shows that banks that are monitored by external investors (as is the case with longer-term market funding as illustrated by Huang and Ratnovski (2011)), have a stronger incentive to finance riskier firms in a low-interest-rate environment.

The observed nonlinearity in the transmission of a bank's funding composition to the riskiness of SME lending is plausible from a practical perspective. From the perspective of the bank, the decision to provide credit depends on the probability of being repaid. In other words, the probability that a loan becomes non-performing is the risk that banks face. Based on European Banking Federation data (EBF, 2023), non-performing loans peaked at 7.5% of all outstanding firm loans in Europe in 2012. To the bank, all above-average creditworthiness firms likely have a similar negligible level of ending up in this bottom 7.5% of loans. Banks therefore would have an incentive to lend to the non-marginal firm (i.e. those skewed towards the lower ends of the creditworthiness distribution) in order to raise expected returns on the loan by charging a higher interest rate to compensate for the lower creditworthiness, without compromising the default risk of the loan. This is also consistent with corporate credit standards reported on bank lending surveys (DNB, 2023).

Common to all specifications are the positive, relatively constant and statistically significant coefficients that are increasing in the Altman zones. This implies that SMEs of higher creditworthiness generally exhibit higher loan growth and that loan growth is increasing with the firm's creditworthiness. In Table A.5 of the Appendix we report the estimated coefficients of the controls in the three columns of Table 2. Interestingly, we find that a firm's total assets enters all specifications with a negative and statistically significant coefficient, indicating that larger firms (even among SMEs) generally display lower annual loan growth. This could signal that larger SMEs, which also tend to be older (see Table A.3 in the Appendix), grow slower and invest less. As such, they would presumably also demand less bank credit via loans than younger firms. A firm's level of collateral, proxied by its fixed assets ratio, also enters all specifications with a negative and statistically significant coefficient. We argue that this is a result of lagging firm-level variables: higher fixed assets such as machinery could be a result of investments (hence, loans) in the past, therefore exhibiting negative loan growth in the future. Finally, the Herfindahl index enters all specifications with a statistically significant positive coefficient. Recall that an increase in the Herfindahl index indicates a decrease in competition in loan supply or an increase in a bank's market power. As such, a decrease in competition among banks is positively associated with SME lending. Recall that, inherent to using bank-firm relations that lack variability over time, we observe the existing portfolio of SMEs in a bank's lending book. Therefore, it makes sense that a higher market power of the primary credit-supplying bank is positively associated with loan growth to its existing portfolio of SMEs.

Table 2: Baseline Results

Dependent variable: Firm loan growth	**(1)**	**(2)**	**(3)**
Altman (grey zone)	0.088***	0.101***	0.101***
	(0.012)	(0.014)	(0.014)
Altman (safe zone)	0.273***	0.275***	0.275***
	(0.017)	(0.021)	(0.021)
Bank equity ratio	-1.208***	-0.459	-0.446
	(0.424)	(0.518)	(0.542)
Bank equity ratio x Altman (grey zone)		-0.295	-0.273
		(0.646)	(0.626)
Bank equity ratio x Altman (safe zone)		-0.410	-0.377
		(1.115)	(1.088)
Customer deposits ratio	0.423***	0.526***	0.447***
	(0.153)	(0.139)	(0.159)
Customer deposits ratio x Altman (grey zone)		-0.181***	-0.175**
		(0.068)	(0.070)
Customer deposits ratio x Altman (safe zone)		-0.579***	-0.573***
		(0.115)	(0.117)
Deposits from banks ratio	0.140	0.417*	0.434**
	(0.144)	(0.215)	(0.205)
Deposits from banks ratio x Altman (grey zone)		-0.223	-0.244
		(0.175)	(0.167)
Deposits from banks ratio x Altman (safe zone)		-0.744***	-0.774***
		(0.268)	(0.267)
Bank total market funding ratio	0.237*	1.248***	
	(0.141)	(0.260)	
Bank total market funding ratio x Altman (grey zone)		-0.972***	
		(0.216)	
Bank total market funding ratio x Altman (safe zone)		-1.792***	
		(0.332)	
Bank short-term funding ratio			0.518
			(0.622)
Bank short-term funding ratio x Altman (grey zone)			-0.542
			(0.364)
Bank short-term funding ratio x Altman (safe zone)			-1.201
			(1.050)
Bank long-term funding ratio			1.404***
			(0.331)
Bank long-term funding ratio x Altman (grey zone)			-1.092***
			(0.285)
Bank long-term funding ratio x Altman (safe zone)			-1.956***
			(0.471)
Constant	9.878***	9.927***	9.993***
	(0.629)	(0.605)	(0.622)
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	501,469	475,985	475,985
R-squared	0.239	0.247	0.247

Notes. The dependent variable is the log difference of firm bank debt. All regressors are specified as the first lag, with the exemption of the Herfindahl index. The Herfindahl index is the absolute first-difference. For readability, the estimated coefficients on the remaining control variables are reported in Table A.5 of the Appendix. Standard errors (clustered at bank level) in parenthesis. The conventional significance thresholds are displayed by * (0.1), ** (0.05) and *** (0.01).

5 Robustness Analysis

In this section, we evaluate the robustness of the baseline results by performing a battery of tests. First, we evaluate whether the baseline results are robust to sample and timing changes including (i) allowing bank funding to be related to SME lending contemporaneously, (ii) assessing overrepresentation of Iberian and French firms, (iii) restricting the analysis to banks with SSM-parent institutions only, (iv) extending the sample period to include the aftermath of the 2008 financial recession, the European sovereign debt crisis and the ensuing period of economic recovery, and (v) restricting the sample period closely around 2018, the year when firm-bank relationships are reported. Second, we evaluate whether results are sensitive to alternative risk measures to acknowledge that the Altman score is just one proxy of firm creditworthiness. Finally, we assess how the inclusion of fixed effects in the model affects the results. Overall, we find that the baseline results are largely robust.

5.1 Sample Changes

Tables 3 and 4 report the results of robustness tests involving alternative bank dynamics, firm overrepresentation in the baseline sample, SSM parent banks, and alternative estimation periods. In column (1) of both tables we report the baseline specification (that is column (2) of Table 2) to facilitate the comparison.

In column (2) of Table 3, we use the contemporaneous values of the bank funding elements, i.e. not lagged by one year. As theory does not guide the precise dynamics of the relationship between banks' funding composition and their SME lending behaviour, the rationale for this sensitivity analysis is based on two arguments. First, the transmission channel from banks' funding to their lending decisions may operate faster than the 1-year lag as specified in the baseline model. Thus, column (2) evaluates whether the results are robust to allowing for this flexibility. Second, even though the transmission channel from banks' realized funding structure to their lending decisions may operate with a 1-year lag as specified in the baseline specification, banks may already consider their future realized funding structure in their contemporaneous lending decisions through a forecasting exercise. For each funding component, the relationship between banks' funding structures and SME lending (loan growth) remains qualitatively and quantitatively similar to our baseline results.

Columns (3) in Table 3 addresses the overrepresentation of Spanish and Portuguese firms that are served by a relatively low number of banks (see Table A.2 in the Appendix) in the baseline sample by estimating the model excluding Iberian (i.e. Spanish and Portuguese) firms. Overall, despite the significant drop in the number of observations, the results remain qualitatively similar when Iberian firms are excluded. The same is true for a model that includes only Iberian firms (results not reported in the table). Column (4) presents a similar analysis exluding French firms and shows that the baseline results again remain largely robust. A bank's market funding ratio remains the funding element most strongly related to lending to SMEs with lower creditworthiness, as indicated by the strongly negative and statistically significant coefficient on the interaction term. Consistent with our full sample analysis, coefficients for other non-equity funding elements are less pronounced, and equity funding itself is unrelated to the riskiness of SME lending, in line with the baseline results.

Table 3: Robustness Results: Sample Changes (1)

Dependent variable: Firm loan growth	**(1)**	**(2)**	**(3)**	**(4)**
	Baseline	**Cont.**	**No ES/PT**	**No FR**
Altman grey zone	0.101***	0.099***	0.086***	0.111***
	(0.014)	(0.015)	(0.022)	(0.017)
Altman safe zone	0.275***	0.275***	0.206***	0.305***
	(0.021)	(0.021)	(0.027)	(0.019)
Bank equity ratio	-0.459	-0.945	-1.733	0.487
	(0.518)	(0.703)	(1.421)	(0.844)
Bank equity ratio x Altman (grey zone)	-0.295	0.192	-0.509	-1.573
	(0.646)	(0.608)	(1.066)	(1.024)
Bank equity ratio x Altman (safe zone)	-0.410	0.040	-0.916	-1.845
	(1.115)	(1.270)	(1.447)	(1.464)
Customer deposits ratio	0.526***	0.591***	0.713*	0.222
	(0.139)	(0.126)	(0.419)	(0.175)
Customer deposits ratio x Altman (grey zone)	-0.181***	-0.234***	-0.312***	0.020
	(0.068)	(0.064)	(0.110)	(0.104)
Customer deposits ratio x Altman (safe zone)	-0.579***	-0.653***	-0.697***	-0.297*
	(0.115)	(0.130)	(0.169)	(0.150)
Deposits from banks ratio	0.417*	0.432**	0.207	0.654***
	(0.215)	(0.174)	(0.399)	(0.149)
Deposits from banks ratio x Altman (grey zone)	-0.223	-0.312**	-0.052	-0.403**
	(0.175)	(0.148)	(0.257)	(0.178)
Deposits from banks ratio x Altman (safe zone)	-0.744***	-0.810***	-0.506	-1.247***
	(0.268)	(0.272)	(0.325)	(0.273)
Bank total market funding ratio	1.248***	1.291***	0.350**	0.973***
	(0.260)	(0.194)	(0.226)	(0.226)
Bank total market funding ratio x Altman (grey zone)	-0.972***	-1.036***	-0.156**	-1.033***
	(0.216)	(0.155)	(0.033)	(0.218)
Bank total market funding ratio x Altman (safe zone)	-1.792***	-1.746***	-0.622**	-1.859***
	(0.332)	(0.234)	(0.420)	(0.293)
Constant	9.927***	9.643***	13.325***	9.556***
	(0.605)	(0.635)	(1.092)	(0.461)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	475,985	475,985	166,308	343,606
R-squared	0.247	0.256	0.243	0.259

Notes. The dependent variable is the log difference of firm bank debt. Column (1) is the baseline (corresponding to column (2) in Table 2). In column (2), the contemporaneous value of the bank funding variables is used, while other variables are still lagged by one year (with the exemption of the Herfindahl index). Column (3) excludes Spanish and Portuguese firms, and column (4) excludes French firms. For readability, estimated coefficients on remaining control variables are reported in Table A.6 of the Appendix. Standard errors (clustered at bank level) in parenthesis. The conventional significance thresholds are displayed by * (0.1), ** (0.05) and *** (0.01).

In column (2) of Table 4, the sample is restricted to SSM-significant banks that are the leading credit institution of their group ('parent banks'), thus excluding all bank subsidiaries and their direct bank relationships. The rationale for this sample restriction is twofold. First, and most importantly, the extent to which subsidiary banks receive funding from their parent institution is not observed. In case subsidiary banks are highly dependent on their parent institution to acquire funding, then any relation between subsidiary banks' funding components and the quantity and quality of their SME lending may be spurious. Secondly, the exclusive focus on leading credit institutions implies that the set of banks used in column (2) is more homogenous than the sample of banks used in the original baseline specifications in terms of institutional characteristics and size. This may potentially limit omitted variable bias since the scope of this study is restricted to heterogeneity in banks' funding components. The results of this alternative sample specification are qualitatively similar to the baseline results, but generally feature lower statistical significance.[20]

Table 4: Robustness Results: Sample Changes (2)

Dependent variable: Firm loan growth	**(1)**	**(2)**	**(3)**	**(4)**
	Baseline	**Parent banks**	**2010-2019**	**2017-2019**
Altman grey zone	0.101***	0.110***	0.107***	0.056***
	(0.014)	(0.017)	(0.012)	(0.016)
Altman safe zone	0.275***	0.304***	0.299***	0.163***
	(0.021)	(0.020)	(0.024)	(0.025)
Bank equity ratio	-0.459	0.781	0.926	-0.415
	(0.518)	(1.011)	(0.638)	(0.999)
Bank equity ratio x Altman (grey zone)	-0.295	-1.824	-0.448	1.250
	(0.646)	(1.284)	(0.347)	(0.859)
Bank equity ratio x Altman (safe zone)	-0.410	-2.727	-1.015*	-0.125
	(1.115)	(1.695)	(0.580)	(1.142)
Customer deposits ratio	0.526***	0.314	0.310**	0.557**
	(0.139)	(0.201)	(0.142)	(0.252)
Customer deposits ratio x Altman (grey zone)	-0.181***	0.061	-0.114***	-0.416***
	(0.068)	(0.134)	(0.041)	(0.122)
Customer deposits ratio x Altman (safe zone)	-0.579***	-0.169	-0.470***	-0.735***
	(0.115)	(0.160)	(0.064)	(0.156)
Deposits from banks ratio	0.417*	0.827***	0.279**	0.552**
	(0.215)	(0.226)	(0.137)	(0.265)
Deposits from banks ratio x Altman (grey zone)	-0.223	-0.446**	-0.265***	-0.451*
	(0.175)	(0.214)	(0.082)	(0.239)
Deposits from banks ratio x Altman (safe zone)	-0.744***	-1.409***	-0.626***	-0.763**
	(0.268)	(0.315)	(0.126)	(0.310)
Bank total market funding ratio	1.248***	1.059***	0.799***	0.798**
	(0.260)	(0.298)	(0.191)	(0.392)
Bank total market funding ratio x Altman (grey zone)	-0.972***	-1.034***	-0.770***	-0.584*
	(0.216)	(0.262)	(0.098)	(0.308)
Bank total market funding ratio x Altman (safe zone)	-1.792***	-1.748***	-1.529***	-1.126**
	(0.332)	(0.338)	(0.200)	(0.531)
Constant	9.927***	9.457***	6.218***	14.689***
	(0.605)	(0.507)	(0.564)	(1.430)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	475,985	340,107	965,347	248,926
R-squared	0.247	0.253	0.183	0.343

Notes. The dependent variable is the log difference of firm bank debt. Column (1) is the baseline (corresponding to column (2) in Table 2). In column (2) we restrict the sample of banks only to SSM-parent banks. Column (3) is the baseline specification with the data range extended back to 2010, whereas column (4) is the baseline with the data range between 2017-2019. For readability, estimated coefficients on remaining control variables are reported in Table A.6 of the Appendix. Standard errors (clustered at bank level) in parenthesis. The conventional significance thresholds are displayed by * (0.1), ** (0.05) and *** (0.01).

[20] The model displayed in column (2) relies on 33 leading credit institutions (and thus fewer clusters in the regression), which is considered too low to apply least squares with clustering. Following current best practice, we apply the Wild Bootstrap algorithm with a Rademacher distribution of standard errors (Cameron et al., 2008) to correct standard errors in estimating column (2). This algorithm is recommended (Cameron et al., 2008; Djogbenou et al., 2019; MacKinnon et al., 2023) when the number of clusters is lower than 50 or when cluster sizes differ substantially (as it is the case for this specification).

In column (3), we evaluate whether the baseline results are robust over time, by extending the sample period to include the aftermath of the 2008 financial recession, the European sovereign debt crisis and the ensuing period of economic recovery in the observation period. It extends the observation period to commence in 2010 instead of 2014 and as such captures more variation, amongst others, in monetary policy. The sign and significance of the terms of interest, the standalone funding variables and the interaction terms, again remain qualitatively similar to the baseline results.[21] Finally, column (4) shows that the results remain robust when restricting the sample to the period 2017-2019, which includes one year before and one year after 2018, the year in which the firm-bank relations are reported. These last two columns provide indirect evidence of the long-lasting and persistent nature of firm-bank relations.

5.2 Alternative Firm's Risk Measures

We employ two robustness tests to assess whether the baseline results are sensitive to using Altman zones as indicators of *ex-ante* firm creditworthiness. First, we classify firm creditworthiness using the Altman Z-score in a data-driven manner, applying tertiles of its distribution instead of the original predetermined cutoff values of the Altman zones. Second, we use Principal Component Analysis (PCA) to calculate an alternative measure of *ex-ante* firm creditworthiness. In this case, we identify a single risk measure from a set of financial variables that have been identified as relevant for firm credit risk (Bonfim, 2009; Clarke et al., 2006; Impson, 2000) by employing PCA. Overall, we find that the results of both specifications remain qualitatively similar to our baseline findings.

First, we analyze the sensitivity of using the Altman zones, by deriving a firm's creditworthiness zone from the distribution of the underlying Altman Z-score in the sample. We use *tertiles* of the Altman Z-score of firms in the sample. Results of this model are reported in column (2) of Table 5 (the lowest Altman Z-score is again the base group, and hence omitted from the regression output). In column (1) we report the baseline specification (that is column (2) of Table 2) to facilitate the comparison. Again, the results of this robustness test are qualitatively similar to the baseline results.

To assess the sensitivity of the baseline results to the use of the Altman Z-score and its associated zones, we derive a novel indicator of *ex-ante* firm creditworthiness using PCA. PCA is a dimensionality reduction technique that allows us to summarize multiple firm financial metrics into a single indicator with minimal loss of explanatory power. The PCA-derived indicator has two main advantages over the Altman Z-score. First, it likely provides a more valid and consistent estimate of *ex-ante* firm creditworthiness, as firm credit default may not be captured by a single financial metric (Boguslauskas et al., 2011) or a fixed linear combination of a limited number of firm-level financial ratios. Furthermore, the PCA-derived indicator has lower distortion caused by measurement errors in the individual metrics. We obtain a set of financial ratios that are predictors for a firm's default risk from the credit risk literature and subsequently apply the PCA to a subset of these ratios. We use financial ratios that can be classified into profitability metrics, liquidity metrics and metrics displaying a firm's balance sheet strength, to identify a firm's creditworthiness from different dimensions.[22]

We employ an R-type factor analysis (Hair et al., 2009). While multicollinearity among explanatory variables is typically problematic, the R-type factor analysis can solely be em-

[21]A drawback of this longer sample period is that the assumption of the stability of the bank relations is even stronger, because we still assume the bank relation as reported in 2018 to be unchanged over time.
[22]Table A.8 in the Appendix lists the financial ratios that are obtained from the credit-risk literature.

ployed if the ratios are sufficiently correlated. We formally evaluate the appropriateness of using factor analysis through a Measure of Sampling Adequacy (*Kaiser-Meyer-Olkin, 'KMO'*) test. This test quantifies the degree to which a newly derived metric can be explained by the underlying variables (financial ratios).[23] Table A.9 in the Appendix provides the results of this test and reports a score close to or in excess of 0.5 for each metric and the overall matrix. Following Kaiser and Rice (1974) in which statistics exceeding 0.5 indicate that the underlying variable has a sufficient degree of explanatory power for the newly constructed factor (i.e. the novel indicator), we conclude that the financial metrics selected are suitable for a factor analysis. The eigenvalue of the new indicator itself equals 2.90, exceeding the recommended cutoff of 1.00 for a PCA-derived component. Table A.9 furthermore demonstrates the eigenvector, or the correlation of each financial metric with the novel indicator. The interpretation of the newly derived creditworthiness indicator is straightforward: like the Altman Z-score, a higher value of the indicator implies that a firm is of higher creditworthiness, thus exhibiting lower *ex-ante* credit risk for the credit-supplying bank. Consistent with the approach used in column (2) and to enhance comparability, we present the results of the specification where the sample of firms is divided into three tertiles based on the value of the new PCA-derived indicator,[24] and keep the sample period and other specifications similar to the baseline model. Substituting the tertiles of the Altman Z-score with PCA categories, has an important drawback. The number of observation falls to 265,141, a reduction of 44 percent relative to the baseline specification.

Column (3) of Table 5 shows that our key finding - that a bank's market funding is associated with lending to SMEs of lower *ex-ante* creditworthiness - is confirmed when using the PCA indicator. This finding also holds for the observed nonlinearity: the coefficients on the interaction term between the market funding ratio and the PCA indicator decrease strongly with a firm's creditworthiness. Although the signs are consistent across both risk measures, we emphasize the use of the Altman Z-score as an established risk measure, believing it to be a more reliable proxy for a firm's creditworthiness.

5.3 Fixed-Effects Analysis

In this final robustness section, we evaluate how the inclusion of control variables and fixed effects affects our results. Specifically, we assess whether the baseline results remain robust under several variations: by retaining only fixed effects as controls (excluding both firm- and bank-level control variables), excluding firm- (and consequently bank-) fixed effects, excluding year-fixed effects, and excluding all fixed effects. Ideally, we would also test the inclusion of bank-year fixed effects to account for potential supply-side shocks, as done in related literature (Amiti and Weinstein, 2018). However, this test is not feasible in our setup due to collinearity with funding variables. Similarly, interacted firm-year fixed effects could control for shocks in credit demand at the firm level, but this approach is also impractical as it would lead to an overidentified model (with every observation represented by a fixed effect). Additionally, we already account for credit demand conditions through macroeconomic controls from the ECB Bank Lending Survey. Table 6 presents the results of these four alternative fixed-effects specifications. Overall, the results remain qualitatively and quantitatively similar to the baseline model: banks that rely on market funding are most strongly associated with providing credit to firms of lower creditworthiness.

[23] The KMO-test is similar in scope as Bartlett's test of sphericity (Hair et al., 2009). We employ the KMO-test because the Bartlett's test of sphericity is unsuitable in large samples such as ours.

[24] Hence, we also construct three zones of creditworthiness and the PCA-derived indicator is also a categorical variable in the model.

Table 5: Robustness Results: Altman and PCA Tertiles

Dependent variable: Firm loan growth	**(1)**	**(2)**	**(3)**
	Baseline	**Alt. tertiles**	**PCA tertiles**
Altman or PCA 2nd tertile	0.101***	0.087***	-0.008
	(0.014)	(0.013)	(0.032)
Altman or PCA 3rd tertile	0.275***	0.242***	0.095
	(0.021)	(0.021)	(0.068)
Bank equity ratio	-0.459	-1.236	-1.102
	(0.518)	(0.892)	(0.797)
Bank equity ratio x Altman or PCA 2nd tertile	-0.295	-0.975*	-1.310
	(0.646)	(0.526)	(0.847)
Bank equity ratio x Altman or PCA 3rd tertile	-0.410	-1.060	-2.114*
	(1.115)	(1.431)	(1.147)
Customer deposits ratio	0.526***	0.365**	0.066
	(0.139)	(0.154)	(0.207)
Customer deposits ratio x Altman or PCA 2nd tertile	-0.181***	-0.166***	0.126
	(0.068)	(0.050)	(0.195)
Customer deposits ratio x Altman or PCA 3rd tertile	-0.579***	-0.540***	0.006
	(0.115)	(0.131)	(0.298)
Deposits from banks ratio	0.417*	-0.087	0.050
	(0.215)	(0.248)	(0.199)
Deposits from banks ratio x Altman or PCA 2nd tertile	-0.223	0.123	0.061
	(0.175)	(0.183)	(0.189)
Deposits from banks ratio x Altman or PCA 3rd tertile	-0.744***	-0.262	0.085
	(0.268)	(0.356)	(0.311)
Bank total market funding ratio	1.248***	1.315***	1.091**
	(0.260)	(0.287)	(0.458)
Bank total market funding ratio x Altman or PCA 2nd tertile	-0.972***	-1.267***	-0.683
	(0.216)	(0.203)	(0.446)
Bank total market funding ratio x Altman or PCA 3rd tertile	-1.792***	-2.361***	-1.927***
	(0.332)	(0.327)	(0.703)
Constant	9.927***	11.629***	12.679***
	(0.605)	(0.673)	(0.558)
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	475,985	475,985	265,141
R-squared	0.247	0.282	0.273

Notes. The dependent variable is the log difference of firm bank debt. Column (1) is again our baseline specification, the same as column (2) in Table 2 using the original Altman zones. Column (2) employs the Altman Z-score as an *ex-ante* firm creditworthiness metric, while column (3) employs the PCA component score. In both columns, the base group refers to the sample tertile of firms with the lowest creditworthiness. For readability, estimated coefficients on remaining control variables are reported in Table A.7 of the Appendix. Standard errors (clustered at bank level) in parenthesis. The conventional significance thresholds are displayed by * (0.1), ** (0.05) and *** (0.01).

Table 6: Robustness Results: Fixed-Effects Analysis

Dependent variable: Loan growth	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
	Baseline	**No controls**	**No f/b FE**	**No year FE**	**No FE**
Altman grey zone	0.101***	0.185***	0.202***	0.102***	0.203***
	(0.014)	(0.019)	(0.019)	(0.014)	(0.019)
Altman safe zone	0.275***	0.454***	0.510***	0.278***	0.510***
	(0.021)	(0.026)	(0.029)	(0.021)	(0.029)
Bank equity ratio	0.459	0.485	0.692	-0.095	0.702
	(0.518)	(0.566)	(0.464)	(0.484)	(0.462)
Bank equity ratio x Altman (grey zone)	-0.295	-0.425	-0.737*	-0.296	-0.754**
	(0.646)	(0.635)	(0.359)	(0.639)	(0.359)
Bank equity ratio x Altman (safe zone)	-0.410	-0.710	-1.322*	-0.417	-1,346*
	(1.115)	(0.953)	(0.684)	(1.102)	(0.684)
Customer deposits ratio	0.526***	0.835***	0.329***	0.761***	0.334***
	(0.139)	(0.217)	(0.069)	(0.219)	(0.070)
Customer deposits ratio x Altman (grey zone)	-0.181***	-0.210**	-0.190***	-0.182***	-0.188***
	(0.068)	(0.085)	(0.043)	(0.068)	(0.043)
Customer deposits ratio x Altman (safe zone)	-0.579***	-0.606***	-0.588***	-0.581***	-0.585***
	(0.115)	(0.123)	(0.080)	(0.114)	(0.080)
Deposits from banks ratio	0.417*	0.451*	0.230**	0.348	0.237*
	(0.215)	(0.245)	(0.120)	(0.236)	(0.122)
Deposits from banks ratio x Altman (grey zone)	-0.223	-0.077	-0.103	-0.225	-0.103
	(0.175)	(0.159)	(0.094)	(0.174)	(0.094)
Deposits from banks ratio x Altman (safe zone)	-0.744***	-0.479*	-0.364***	-0.746***	-0.363*
	(0.268)	(0.217)	(0.185)	(0.264)	(0.185)
Bank total market funding ratio	1.248***	1.008***	0.637***	1.196***	0.617***
	(0.260)	(0.216)	(0.110)	(0.260)	(0.105)
Bank total market funding ratio x Altman (grey zone)	-0.972***	-0.499**	-0.308***	-0.952***	-0.308***
	(0.216)	(0.202)	(0.077)	(0.218)	(0.077)
Bank total market funding ratio x Altman (safe zone)	-1.792***	-1.033***	-0.853***	-1.755***	-0.855***
	(0.332)	(0.269)	(0.169)	(0.337)	(0.168)
Constant	9.927***	-0.555***	-0.347***	8.548***	-0.348***
	(0.605)	(0.133)	(0.087)	(0.639)	(0.084)
Controls	Yes	No	Yes	Yes	Yes
Firm FE	Yes	Yes	No	Yes	No
Bank FE	Yes	Yes	No	Yes	No
Year FE	Yes	Yes	Yes	No	No
Observations	475,985	476,334	518,604	475,985	518,604
R-squared	0.247	0.230	0.020	0.247	0.020

Notes. The dependent variable is the log difference of firm bank debt. Column (1) is the baseline specification (corresponding to column (2) of Table 2). Column (2) is the baseline specification without firm and bank control variables. Column (3) is the baseline without firm (and hence also bank and country) fixed effects. Column (4) is the baseline without year fixed effect. Column (5) is the baseline without any fixed effects. Standard errors (clustered at bank level) in parenthesis. The conventional significance thresholds are displayed by * (0.1), ** (0.05) and *** (0.01).

6 Conclusions

The impact of a bank's funding composition on its risk-taking is not well understood. Theoretical predictions are ambiguous, and empirical literature is limited and often lacks granularity, with risk measurement frequently disputed. Banks obtain funding through various sources, including equity, customer deposits, market funding from international capital markets, and interbank lending (including central bank loans). In this paper, we demonstrate that the relative proportions of these funding sources significantly influence the risk a bank takes when lending to SMEs in Europe.

Analyzing loan growth among SMEs in ten European countries, we find robust evidence that SSM-supervised banks relying on non-equity funding instruments are more likely to lend to SMEs with lower creditworthiness. There is significant variation in the impact of these funding sources: market funding is most strongly associated with risky lending, followed by interbank lending and customer deposits. In our examination of market funding, we also explore how its composition affects risk-taking by considering the maturity structure of this debt. We find that both the volume of lending and risk-taking are more strongly associated with debt instruments that have longer initial maturities, rather than those with shorter terms. Our findings are economically significant: a 10% increase in a bank's market funding is associated with a 5.4% annual decline in loans provided to firms with the highest creditworthiness. We hypothesize that this result may be explained by a 'Martinez-Miera-Repullo' (2017) mechanism: in a low-interest rate environment, banks that rely on market funding may lend to lower-creditworthy firms because they have fewer incentives to monitor them. Importantly, we find that a bank's capitalization level is not consistently associated with the riskiness of SME lending, suggesting that while equity provides loss-absorbing capacity, it does not significantly impact the riskiness of a bank's lending to SMEs. Additionally, our results remain largely robust to substantial changes in the sample, variations in the timing of variables, and, to some extent, the use of alternative measures of firm creditworthiness beyond the Altman Z-score.

The results in this paper have important implications for banking policy and shed light upon how bank risk taking. Our results suggest that policies that reduce the proportion of market funding, could lead to a reduction of the risk taken on SME lending (and *vice versa*). This is an important insight for two reasons. First, bank lending to SMEs is crucial, and since SMEs rely heavily on bank debt, a decline in lending and risk taking could adversely affect economic growth. Second, policy makers in some Europan countries were considering to levy additional taxes on banks' use of market funding, in the light of substantially increased profits of European banks in 2023. Some European countries already levy taxes on their use of market funding (OECD, 2023). Some governments are considering increasing the tax levy on market funding to reduce banks' windfall profits. Our analysis suggest that such an increase could be followed by a reduction in the volume of lending as well as a reduction in risks taken on SME lending. While taxation of market funding by banks can be motivated to enhance financial stability (since market funding needs to be refinanced when it matures and thus poses a liquidity risk for banks), it comes with considerable tradeoffs for the real economy. Furthermore, while we acknowledge that a bank's level of capitalization acts as a buffer to absorb losses, we find no evidence that a bank's level of capitalization mitigates risk taking on SME lending, thus questioning the validity of further increasing regulatory capital requirements if the goal were to reduce risk taking.

We identify a number of areas for future research. First, given conflicting predictions from economic theory, research should examine the precise mechanisms behind our findings for market funding that we attribute to a search-for-yield mechanism (Martinez-Miera and Repullo, 2017). Second, although we observe a firm's *ex-ante* creditworthiness, data limitations restrict us from measuring *ex-post* creditworthiness or actual firm defaults. We suggest future research to address this limitation, such that one could judge whether risks taken ex ante also materialized into losses and are therefore also *excessive.* Third, our specification is reduced form, and we cannot precisely disentangle demand (firm) from supply-side factors (banks). Future research should also address this limitation. Finally, we suggest more granular research on the credit recipient firms to identify whether the credit provided to the riskier firms also raises investment and productivity and therefore economic growth in the longer run.

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Appendix

Additional Tables

Table A.1: Data Sources

Variables	**Subject**	**Source**
Firm age	Firm-specific	BvD Orbis
Firm Altman Z-score	Firm-specific	BvD Orbis
Firm total assets	Firm-specific	BvD Orbis
Firm fixed asset ratio	Firm-specific	BvD Orbis
Bank ROA	Bank-specific	BvD Bankfocus
Bank efficiency ratio	Bank-specific	BvD Bankfocus
Bank total assets	Bank-specific	BvD Bankfocus
Bank equity ratio	Bank-specific	BvD Bankfocus
Customer deposits ratio	Bank-specific	BvD Bankfocus
Deposits from banks	Bank-specific	BvD Bankfocus
Bank total market funding ratio	Bank-specific	BvD Bankfocus
Bank short-term funding ratio	Bank-specific	BvD Bankfocus
Bank long-term funding ratio	Bank-specific	BvD Bankfocus
Debt restructuring impact on credit demand	Macro-control	ECB Statistical Data Warehouse
SME impact on credit demand	Macro-control	ECB Statistical Data Warehouse
Large enterprise impact on credit demand	Macro-control	ECB Statistical Data Warehouse
Herfindahl index	Macro-control	ECB Statistical Data Warehouse

Notes. The Altman Z-score is not obtained directly from BvD Orbis, but calculated from a set of financial ratios.

Table A.2: Frequency Statistics

Country	**#Firms**	**#Domestic banks**	**#Total banks**
Austria	491	6	10
France	26,501	58	61
Germany	3,196	12	21
Ireland	140	1	9
Latvia	250	2	2
Luxembourg	489	3	5
The Netherlands	721	4	7
Portugal	12,849	2	4
Spain	47,710	5	8
Slovenia	2,316	2	2

Notes. This tables shows the total number of firms for each country in our sample. The number of total banks reported in the outer right column are all banks, parent and subsidiaries, serving firms in the baseline model. The centre column reports where banks are based.

Table A.3: Correlation Matrix: Firm Variables

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
(1) Bank debt	1				
(2) Altman score	-0.093	1			
(3) Total assets	0.912	-0.067	1		
(4) Fixed asset ratio	0.069	-0.435	0.083	1	
(5) Age	0.146	-0.023	0.212	0.017	1

Table A.4: Correlation Matrix: Bank Variables

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) ROA	1								
(2) Efficiency ratio	-0.489	1							
(3) Total assets	0.015	0.128	1						
(4) Equity ratio	0.381	-0.296	-0.444	1					
(5) Customer deposit ratio	-0.141	-0.218	-0.492	-0.101	1				
(6) Deposits from banks ratio	0.264	-0.161	-0.386	0.700	-0.417	1			
(7) Total market funding ratio	0.059	-0.140	0.437	-0.366	-0.067	-0.400	1		
(8) Short-term funding ratio	0.053	0.082	0.532	-0.222	-0.339	-0.040	0.502	1	
(9) Long-term funding ratio	0.042	-0.200	0.249	-0.315	0.084	-0.441	0.911	0.102	1

Table A.5: Baseline: Control Variables

Dependent variable: Loan growth	(1)	(2)	(3)
Firm total assets	-0.677***	-0.718***	-0.718***
	(0.031)	(0.031)	(0.030)
Firm fixed asset ratio	-0.549***	-0.679***	-0.679***
	(0.077)	(0.074)	(0.074)
Bank ROA	-0.191	0.161	0.016
	(0.849)	(0.947)	(0.965)
Bank efficiency ratio	-0.001	-0.001***	-0.001***
	(0.001)	(0.000)	(0.000)
Bank total assets	-0.021	0.034	0.032
	(0.032)	(0.030)	(0.032)
Herfindahl index (1st difference)	1.028**	1.054***	0.990**
	(0.451)	(0.379)	(0.389)

Notes. Columns correspond to the columns of Table 2 in the main text. Standard errors (clustered at bank level) in parenthesis. The conventional significance thresholds are displayed by * (0.1), ** (0.05) and *** (0.01).

Table A.6: Robustness (Sample Changes): Control Variables

Dependent variable: Loan growth	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Firm total assets	-0.718***	-0.697***	-0.880***	-0.673***	-0.668***	-0.466***	-1.035***
	(0.031)	(0.031)	(0.048)	(0.018)	(0.018)	(0.032)	(0.034)
Firm fixed asset ratio	-0.679***	-0.626***	-1.139***	-0.518***	-0.510***	-0.569***	-0.977***
	(0.074)	(0.065)	(0.167)	(0.049)	(0.052)	(0.072)	(0.085)
Bank ROA	0.161	0.985**	0.306	0.317	2.349	0.276	-9.272**
	(0.947)	(0.413)	(1.178)	(0.682)	(2.602)	(0.444)	(3.532)
Bank efficiency ratio	-0.001***	-0.002**	-0.001*	-0.000	-0.001	0.000	-0.007
	(0.000)	(0.001)	(0.001)	(0.036)	(0.001)	(0.000)	(0.002)
Bank total assets	0.034	0.032	-0.000	0.009	0.002	0.031	0.038
	(0.030)	(0.035)	(0.066)	(0.071)	(0.041)	(0.028)	(0.088)
Herfindahl index (1st difference)	1.054***	1.229***	0.438	0.824	0.745*	-0.154	2.019***
	(0.379)	(0.339)	(1.448)	(0.441)	(0.412)	(0.562)	(0.604)

Notes. Columns (1), (2), (3) and (4) correspond to columns (1), (2), (3) and (4) of Table 3. Columns (5), (6), and (7) correspond to columns (2), (3) and (4) of Table 4. Standard errors (clustered at bank level) in parentheses. The conventional significance thresholds are displayed by * (0.1), ** (0.05) and *** (0.01).

Table A.7: Tertiles and PCA: Control Variables

Dependent variable: Loan growth	Baseline	Alt. Tertile	PCA Tertile
Firm total assets	-0.718***	-0.834***	-0.840***
	(0.031)	(0.032)	(0.032)
Firm fixed asset ratio	-0.679***	-0.666***	-0.689***
	(0.074)	(0.065)	(0.061)
Bank ROA	0.161	-2.888	-2.275
	(0.947)	(3.039)	(2.925)
Bank effiency ratio	-0.001***	-0.000	0.001
	(0.000)	(0.001)	(0.001)
Bank total assets	0.034	0.052	-0.023
	(0.030)	(0.056)	(0.053)
Herfindahl index (1st difference)	1.054***	0.267	-0.309
	(0.379)	(0.527)	(0.568)

Notes. Columns correspond to the columns of Table 5. Standard errors (clustered at bank level) in parenthesis. The conventional significance thresholds are displayed by * (0.1), ** (0.05) and *** (0.01).

Table A.8: Selection of Variables for PCA

Variable	Dimension	Motivation
ROA	Profitability	Bonfim (2009)
ROE	Profitability	Bonfim (2009)
Quick ratio	Liquidity	Boguslauskas et al. (2011)
Free cash flow to current liabilities	Liquidity	Filipe et al. (2016)
Turnover to total liabilities	Liquidity	Filipe et al. (2016)
Working capital to total assets	Balance sheet strength	Boguslauskas et al. (2011)
Equity to total assets	Balance sheet strength	Boguslauskas et al. (2011)
Current liabilities to total assets	Balance sheet strength	Filipe et al. (2016)

Table A.9: PCA Selection Statistics

Variable	Eigenvector	KMO Statistic
ROA	0.237	0.505
ROE	0.109	0.515
Quick ratio	0.308	0.650
Free cash flow to current liabilities	0.372	0.612
Turnover to total liabilities	0.379	0.752
Working capital to total assets	0.395	0.809
Equity to total assets	0.458	0.679
Current liabilities to total assets	-0.434	0.660

Matching of Firm-Bank Relations

Hand-matching banks reported in firm-bank relations in Orbis with bank entities in Bankfocus

Orbis lists the firm-bank relations for the firms in the sample. As these reports may feature severe (spelling) inconsistencies, we employ the automatic matching algorithm in Bankfocus to match each firm-bank relation in Orbis with the corresponding bank entity in Bankfocus. Next, we verify each match manually and omit a firm-bank relation if it cannot be matched unambiguously with a bank entity in Bankfocus. Finally, we select the highest available consolidation code for each matched bank entity in Bankfocus to obtain information on the parent institution since banks are likely to obtain funding on capital markets at the highest level of consolidation. We performed this procedure for all firm-bank relations reported in our sample, although our procedure to match Spanish firms and banks is slightly different. The reason for this is that Orbis contained an extremely large variety of spelling inconsistencies for firm-bank relations in Spain and resource constraints prevented us from manually verifying each matched bank entity. Consequently, we only considered the most frequently reported spelling varieties of firm-bank relations in Spain. The majority of these frequently reported spelling varieties are trivial to recognize manually. For instance, some firms that maintain a bank relation with Banco Santander S.A. include the address of their bank office when specifying the name of their bank or use incorrect capitalization.

Classifying a bank as significant according to the Single Supervisory Mechanism (SSM)

We use the list of supervised entities from the ECB to determine whether a bank is significant according to the SSM in a step-wise fashion. First, we source the Legal Entity Identifier (LEI) code for each bank which is featured in a firm-bank relation from Bankfocus. Second, we verify if this LEI code is included in the list of supervised entities from the ECB. If and only if this is the case, we consider the bank to be classified as significant according to the SSM.