CPB Netherlands Bureau for Economic Policy Analysis

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.

CPB Discussion Paper

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Abstract

We show that a bank's funding composition is associated with the riskiness of its SME lending. Analyzing loan growth for SMEs in eleven European countries, we find that SSM-supervised banks relying more on market funding exhibit lending to SMEs of lower creditworthiness. The association is driven by debt instruments with longer initial maturity rather than its shorter-term counterpart. Our findings are economically significant. A bank's level of capitalization is not robustly associated with the riskiness of SME lending, suggesting that, while equity has a loss absorbing capacity, it does not alter the riskiness of SME lending. We show that our results are largely robust to sample changes, changes in the timing of variables, and employing different measures proxying firms' creditworthiness. We contribute by analyzing a novel and comprehensive dataset, allowing us to study the transmission of a bank's funding composition to European firms at a granular level.

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Keywords Capital structure, Banks, Lending practices, SMEs

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Data availability. We constructed a proprietary database that is not publicly accessible.

List of abbreviations

BIS	Bank for International Settlements
BvD	Bureau van Dijk
EBF	European Banking Federation
EC	European Commission
ECB	European Central Bank
ECB SDW	European Central Bank Statistical Data Warehouse
EIB	European Investment Bank
EUR	Euro
OECD	Organisation for Economic Co-operation and Development
SME	Small and medium-sized firms

1 Introduction

Firm financing through bank lending is key for private sector investment and economic growth. This is especially relevant for European small and medium-sized firms (SMEs), as they rely heavily on bank debt rather than internal financing or bond issuance to finance operations and investments (Adalid et al., 2020; Bending et al., 2014). Moreover, SMEs constitute the vast majority of all firms in the European Union (EU) and account for more than half of its GDP (EC, 2023a). As such, bank lending to SMEs in Europe has received substantial attention from academia and policy makers. The current empirical macro and monetary literature to date have typically studied determinants of the *quantity* of bank credit supply (Jiménez et al. 2012; Jiménez et al. 2014) to firms, including the effects of recent monetary policy on the quantity of credit supply (the so-called bank lending channel, see 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 that promote economic growth have access to bank credit.

Precisely because banks are so important to European SMEs, it is crucial that banks take risks. Firms could be of lower creditworthiness, and thus riskier for banks, but may still invest, innovate or enhance productivity that contributes to economic growth. When making lending decisions, banks typically evaluate a firm's *ex-ante* creditworthiness. However, *excessive* risk taking is undesirable as this could result in an increase of non-performing loans or even credit losses (i.e. ex-post creditworthiness). Therefore, it could also negatively affect financial stability. To enhance banks' resilience to credit losses, amongst others, higher bank capital requirements (comprising equity) were implemented for European banks. Apart from enhancing a bank's loss absorption capacity, it is poorly understood how this level of equity relates to (ex-ante) risk taking. Following our review of the economic literature to date, we conclude that this also holds for other bank liabilities through which banks fund themselves.

This paper fills this gap by showing how a bank's funding composition, i.e. the relative size of its different funding elements among which equity, market debt, interbank lending and customer deposits, is related to the riskiness of SME lending. We, therefore, contribute to understanding how the funding composition is related to the quality of credit supply, which is essential to economic growth as well as to financial stability. We do so by analyzing how the funding composition of a bank relates to lending to firms of different levels of ex-ante creditworthiness. 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 important insights into what induces banks to take risks. As such, we shed light on how policies targeting banks' liabilities could affect the quality of credit. This, for instance, considers capital regulation (requiring higher levels of equity), taxes on a bank's market funding[1] as well as central bank refinancing operations for commercial banks.

There is considerable ambiguity in the economic literature on how a bank's funding composition is related to risk taking. Theory provides conflicting predictions on the direction and magnitude of how different funding elements relate to risk taking, while empirical literature is scarce and provides little guidance. Moreover, the operating en-

[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)

vironment 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. Interest rates have been particularly low as a result of this policy. It is especially hard to ascertain, a priori, how under these conditions a bank's funding composition is associated with its risk taking. The traditional view is that accommodative monetary policy unambiguously induces bank risk taking through a 'search for yield'. However, this view is contested (DellAriccia et al., 2014). It has been argued that risk taking in such an environment depends on the funding composition of the bank, notably a bank's leverage. While DellAriccia et al. (2014) show that a bank's leverage is instrumental to risk taking in such an environment, this leverage in itself comprises different funding elements that could have varying implications for risk taking.

As we study the period 2014-2019, this paper documents how, given recent accommodative monetary policy in Europe, the different elements of a bank's funding composition are associated with the riskiness of lending to European SMEs. We analyze a novel and comprehensive dataset covering firms from 11 European countries, matched to their primary credit-supplying banks. Our analysis focuses on banks supervised by the Single Supervisory Mechanism (SSM), as these banks are subject to the same monetary and supervisory policy regime. We measure the creditworthiness of firms via their Altman Z-score, a widely-used proxy, and analyze how the different funding elements are associated with loan growth to firms of different creditworthiness. We find that banks relying on market funding were inclined to lend to firms of lower creditworthiness. 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 could indeed be a result of a 'search for yield'. The level of capitalization (equity over total assets) is not associated with the riskiness of SME lending. 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.

We contribute to the empirical literature in a number of ways. Since empirical literature in this field is scarce and theory provides conflicting predictions, our results are explorative. First and foremost, we study the actual risk at the firm-level with a dataset in which we matched firms to data of firms' main credit supplying banks. These firm-bank pairs allow us to study the association between a bank's funding composition and firm more granularly than existing papers to date. Previous empirical studies typically employed an overall measure of risk (such as the Z-score) at the bank level. Moreover, where existing literature typically uses one measure of risk, we use two separate measures of credit risk (the Altman Z-score in the baseline and a novel measure in our robustness analyses). Second, our focus on SMEs accounts for a more representative set of European firms than previous research. Third, we exploit more granularity in the funding composition itself.

The remainder of this paper is structured as follows. We review the theoretical and empirical literature in the next section. Section 3 describes the dataset construction and explains our empirical identification strategy. Section 4 shows and discusses the baseline results. Section 5 presents a battery of robustness checks. Section 6 concludes, presents policy implications and identifies areas for future research.

2 Literature Review

In this section, we first review predictions from economic theory on the effects of a bank's funding composition on its risk taking. We structure this section by considering economic theory of each single funding element separately. We conclude that economic theory provides conflicting predictions on how the different funding elements are associated with risk taking, consistent with previous findings by Demirgüç-Kunt and Huizinga (2010) and Bitar et al. (2018). Next, we review empirical studies on the topic, which is also structured as per funding element: a bank's equity, customer deposits, market debt and interbank lending.

2.1 Economic Theory

There is an abundance of theoretical models on the effects of a bank's level of equity (or, *capitalization*) on its risk taking. Diamond (1984) and Stiglitz and Weiss (1981) demonstrate in seminal papers that banks that use more equity-financing reduce risk taking. This is a result of a reduction in moral hazard risk by providing bankers with incentives to monitor a bank's project quality. Later models, however, demonstrate that the relation between a bank's capitalization and risk taking is not uniform. Saunders et al. (1990), for instance, show that the implications 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. Such dichotomy in the effect of a bank's equity level on risk taking is also shown by Rochet (1992). He finds that the expected sign of a bank's level of equity on risk taking crucially depends on a bank's business model: higher levels of equity reduce incentives to take risk when a bank is *utility maximizing* and has no effect on risk taking when banks are *value maximizing*. Diamond and Rajan (2000) also show that the effect of a bank's capitalization on its risk taking depends on the bank's business model. Models are further nuanced by Hellmann et al. (2000) and Repullo (2002). They show that equity indeed provides bankers with incentives to monitor project quality, since adverse consequences of gambling (i.e. taking excessive risk) are internalized, but that higher equity levels do not necessarily reduce a bank's risk taking. In their model, higher capitalization also reduces a bank's franchise value, which in turn encourages gambling. Moreover, they show that the effect also depends on the level of (deposit market) competition. More recent work by DellAriccia et al. (2014) shows that, in an environment where interest rates are low, highly capitalized banks monitor their project quality less, and as a result take more risk.

Higher bank capitalization implies a lower share 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) show that banks relying more heavily on *demandable debt* (which is withdrawable and comprises deposits and market debt traded on international capital markets) have an incentive to operate more prudently (i.e. take less excessive risks), since monitoring by sophisticated debt-holders disciplines banks. With demandable debt too, the implications for a bank's risk taking may not be uniform, as demandable debt in itself comprises funding elements with very different characteristics. The aforementioned papers do not discern demandable debt into its separate elements. Huang and Ratnovski (2011), however, distinguish short-term market debt[2] 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, therefore arguably lowering incentives for the bank to operate prudently. 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. This may reduce incentives to take risk. 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, the longer maturity comes with a higher cost of debt, which can incentivize the bank to raise expected returns by increasing risk. This finding is consistent with more recent theoretical work by Martinez-Miera and 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' on firm lending when interest rates are low.

Inderst and Mueller (2008) study the effect of leverage on a bank's risk taking on loans and also how that demandable debt does not invariably incentivize banks to reduce (excessive) risk taking. They show that the effect is non-linear, as it depends on whether such debt is comprised of market debt (secured or unsecured) or customer deposits as well as whether such deposits are secured by a deposit guarantee scheme.

Consumer deposits tend to have fundamentally different characteristics from market debt and as such, also different implications for a bank's risk taking. Deposits typically do not expire, like market debt, and customers (typically households) generally lack resources 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 to a lesser extent on bank risk taking. Following a review of theoretical literature, Boyd and De Nicolo (2005) contest that deposit financing induces risk taking, as they conclude that deposit insurance incentivizes risk taking, but deposit financing in itself does not.

Next, consider another funding element, interbank lending[3], on which economic theory is less abundant. Rochet and Tirole (1996) argue that lending banks may have a disciplining effect on borrowing banks, therefore reducing excessive risk taking, because banks are particularly strong at identifying risks at other banks. However, the composition of interbank funding of borrowing banks has changed significantly since the Global Financial Crisis (GFC). In Europe, the ECB has 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 and such funds are also classified as interbank lending. ECB-financing may as such lack the disciplining implication that commercial banks exert. Therefore, also the expected implication of interbank lending on a bank's risk taking is theoretically ambiguous.

[2] I.e., debt which has a relatively short maturity.

[3] Accounting-wise, banks formally report interbank lending as 'deposits from banks' in financial statements.

2.2 Empirical Literature and Contribution

Considering the fact that bank's funding compositions have received substantial attention from policy makers over the past decade, resulting in higher bank regulatory capital requirements or taxes on market funding, empirical studies on how the funding composition is associated with risk are surprisingly scarce. Moreover, empirical papers in this field tend to focus on the implications of a bank's capitalization. Bitar et al. (2018) provide an extensive overview of this empirical literature rather than that of other funding elements. More recently, a small but growing literature examines the effect of central bank refinancing operations on a bank's risk taking.

We review a number of empirical studies that are, to varying degrees, related to this paper. We focus on studies that examine banks from Europe or the United States. Closest to our study is Demirgüç-Kunt and Huizinga (2010), who study the association between a bank's short-term funding strategy, activity mix and risk. 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. Risk is proxied via a bank's Z-score, i.e. the distance to default score, or the number of standard deviations that a bank's return on assets needs to fall for the bank to become insolvent. It is questionable whether the Z-score truly reflects risk taking (Klomp and De Haan, 2012). The Z-score reflects solvency risk of the bank (i.e. an ex-post measure reflecting risks that actually materialized), not necessarily risk taking on lending (an ex-ante measure). The Z-score reflects the aggregate default risk of the bank as a whole, while banks may increase risk on one banking activity, such as firm lending, and decrease it at other activities, such as mortgage lending. Our focus on the riskiness of firm lending by analyzing actual lending to firms overcomes this drawback and measures risk taking more directly. Demirgüç-Kunt and Huizinga (2010) measure short-term funding by the *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.

A number of empirical studies focus on the implications of a bank's equity on its risk. 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 capital requirement, i.e. the same minimum capital requirement for all banks in the same country, in their regression models and show that it is positively related to an individual bank's Z-score. While using the Z-score as a proxy for a bank's risk has drawbacks as discussed previously, another shortcoming is that the capital requirement at the country level does not capture within-country differences in the level of capitalization among banks. Our paper addresses these drawbacks.

Using a sample of banks from 15 European countries over the period 1992-2000, Altunbas et al. (2007) find that the effect that the level of equity (over total assets) exerts a bank's risk depends on the business model of the bank [4]. 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. This measure may not fully reflect the actual risk taking of the bank, as loan loss provisioning

[4] In our paper, we account for the business model of the bank by including bank fixed effects in our models.

is fundamentally different from actual materializing risks, and loss provisioning and risk taking are not necessarily correlated. Furthermore, the operating environment for banks in the 1990s is fundamentally different from the recent (low-interest rate) environment, reducing the external validity of the results.

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 relation 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 study still does not observe actual lending, nor does it use data from a credit registry. Our empirical strategy overcomes this drawback by observing the actual credit provided.

Next, consider Bitar et al. (2018), who study a sample of banks from 39 OECD countries in the period 1999-2013. Distinguishing different ways of calculating regulatory capital ratios, they find that risk-based capital ratios[5] have no impact on a bank's risk while non-risk based capital ratios increase bank risk. Similar to previously reviewed studies, this study also demonstrates shortcomings in the way that bank risk is proxied (also through loan loss reserves) and in their identification, as they do not consider actual lending.

Next, consider empirical papers studying the effects of deposit and market funding on a bank's risk. 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 valuable insights into the interplay between deposit market competition, market funding conditions and bank risk, the authors shed no light on how the relative sizes of deposit and market funding attribute 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 possessing lower *net stable funding ratios* [6] (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 need not be the case. Therefore, we believe the authors do not 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. At last, the authors examine defaulting banks during the global financial crisis.

Finally, a growing strand of empirical literature investigates interbank lending, of which central bank refinancing operations (i.e. central bank funding) in particular. Al-

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

[6]The NSFR is a regulatory metric indicating the share of liabilities comprising stable funding elements (the inverse of short term market funding) which includes deposits and market funding with a relatively long initial maturity.

though 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. An average of 70% of interbank lending in our sample period comprises central bank funding. Recently, studies have investigated how different rounds of the ECB's refinancing operations have affected the riskiness of bank lending 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 counties 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 (2014-2019) covers multiple rounds of different refinancing operations by the ECB (TLTROs, LTROs). Therefore, we arguably also 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

In this section we describe our dataset, present the empirical strategy, describe the sample used in the baseline specification and analyze potential sample selection bias. 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 compiled the dataset by first creating a sample containing financial information of European firms and subsequently matching these firms to financial characteristics of their credit-supplying bank(s), using reported bank relations by firms. We finally merge this dataset with (macroeconomic) variables at the country level.

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 characteristics of about 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 (offline) historical vintages of Orbis and year-end data from balance sheets, and profit and loss accounts of firms in EU member states[7] (Austria, Germany, Estonia, Spain, France, Ireland, Latvia, Luxembourg, the Netherlands, Portugal, Slovenia). Our focus on European firms has two reasons: i) we lack bank-firm relations for non-European advanced economies, such as the United States, ii) European firms, and especially SMEs, are heavily dependent on bank loans for their financing needs (Claessens and Laeven, 2005; De Haan and Hinloopen, 2003; Giannetti and Ongena, 2012).

We extract data for the financial reporting years 2010 up to and including 2019. We thus exclude the recent Covid-19 pandemic (years 2020 and 2021) as it may have

[7] Member states as of January 2022. A priori we excluded firms incorporated in countries where none of the firms have reported bank relations. This applies to all firms in: Italy, Slovakia, Romania and Finland. Important to note is that we do not exclude banks from these countries from our sample. For instance, a Spanish firm could report a relation with an Italian bank and thus could be included in our dataset.

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 merit attention here. First, we followed guidelines as presented in Kalemli-Ozcan et al. (2015) to clean the data and create a reliable and representative yearly 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.[8] 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. These items comprise 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. Fourth, 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 as European credit registries are incomplete and confidential. For example, a recently developed credit registry by the ECB 'Anacredit', is confidential and only covers data starting in 2019. We therefore also 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, credit-supplying 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. The absence of variation over time in a firm's reported bank relations should not be a major constraint. Giannetti and Ongena (2012) and Kalemli-Özcan et al. (2022) have investigated variation in firm-bank relations over time and have found firm-bank relations to be strongly persistent. Firms do not change their (primary) bank often, illustrating the sticky nature of relationship 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).

Orbis does not specify the nature of the firm-bank relations. Hence, a reported firm-bank relation does not necessarily imply that the bank provides credit to the firm and it could also represent a deposit-taking relation or checking account, for instance.

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

Ongena et al. (2015), Giannetti and Ongena (2012) as well as Wang et al. (2020) have asserted, however, that the reported firm-bank relations mostly concern lending relations. Moreover, we omit banks from our analysis 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 website.

We 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 this 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 bank was merged with another bank, has been taken over during the sample period or has been liquidated in advance of the period, 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 incorporated (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, using the list of supervised entities by 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[9] on this list, we expand our dataset by matching the relevant variables from the balance sheet and income statement information of the parent credit institution leading the subsidiary to the corresponding firm-bank relation as well. 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 by including macroeconomic variables (i.e. at the country level of the firm). This data is sourced from the ECB's Statistical Data Warehouse as well as the World Bank. Data sources for all variables in our dataset are listed in Table 10 of the Appendix. Section 3.3 describes the variables in our specification as well as their transformation in more detail.

3.2 Calculating a Firm's Creditworthiness

To measure a firm's creditworthiness (or vice versa, its credit risk) we calculate the firm's Altman Z-score for every single year. Initially developed as a measure to predict a firm's likelihood of default, the score indicates the financial health and as such the creditworthiness of a firm. The Altman Z-score (Altman, 1968) is a composite and continuous measure, a linear combination of five firm-level financial ratios and is calculated as follows: 1.2*(working capital/total assets) + 1.4*(retained earnings/total

[9] 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.

assets) + 3.3*(EBIT/total assets) + 0.6*(market value of equity/total liabilities) + 1.0*(sales/total assets). A firm can be categorized into three zones of discrimination: a firm with a score exceeding 2.99 is considered 'safe' (high creditworthiness), 1.81-2.99 reflects the 'grey zone' (moderate creditworthiness) whereas a score below 1.81 indicates a firm 'in distress'. Despite its age, The Altman Z-score is still a widely used, reliable and valid proxy for a firm's creditworthiness, both in academia and practice (Altman et al., 2017). A higher Altman Z-score implies that a firm is of higher creditworthiness, thus having a lower default risk and exhibiting lower credit risk for the credit-supplying bank. We furthermore define a dummy variable ('Altman dummy') assuming a value of 1 if a firm's Altman Z-score, in a given year, exceeds the median Altman score of firms in the sample period and a value of 0 if the score is below the median.

3.3 Empirical Strategy

We study how a bank's funding composition affects the riskiness of lending by observing loan growth at the firm-level, as a function of a firm's creditworthiness and a bank's funding composition. The following baseline specification is estimated:

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

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, c indicates the country in which the firm is incorporated and j the country where the bank is incorporated. In addition, control variables are included at the firm-level, bank-level, and the macroeconomic (country) level, while fixed effects respectively at these levels are included by μ, η, and ρ. ζ, ψ and ϕ denote vectors containing individual coefficients. Finally, θ represents time fixed effects and ϵ denotes the error term[10]. The specification is estimated using the fixed effects (first difference) estimator for the sample period 2014-2019. During this period, ECB's monetary policy was especially accommodative and the SSM came into effect as of 2014. Since our 'treatment' is at the bank level and following current best practices for robust inference (MacKinnon et al., 2023), we cluster standard errors at the bank level in all models, unless stated otherwise.

Importantly, our specification is arguably reduced form. While we observe the quantity of loans, and hence annual loan growth, we cannot extract the pricing of these loans, i.e. the interest rate charged by banks to firms. We have no data on interest rates on individual loans. 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 micro-

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

data in a European context. Credit registries, which typically contain information on interest rates on individual loans, only cover a short time period (such as the ECB's 'Anacredit') or 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 (e.g. Barbiero et al. (2022); Ongena et al. (2015)). While not a perfect proxy for individual firm-level demand, we disentangle supply and demand as much as possible by controlling for credit demand conditions at the macroeconomic level.[11]

Our dependent variable, loan growth, proxies the annual percentage change of a firm's bank loans and is calculated as the difference 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 lending from a firm's credit-supplying bank, whereas a decrease implies loan repayment. Measuring lending by calculating loan growth is consistent with previous literature (see for instance Ongena et al. (2015)).

The different elements of a bank's funding composition are separately included in the model 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. Section 3.5 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 conditional on the risk of a bank's lending (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 include short and long-term funding as separate variables 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, which mitigates the concern of potential multicollinearity among the different funding elements in the model. The remaining share comprises highly volatile liabilities such as, 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 separate interaction terms, which are therefore the key coefficients of interest in this paper. We interact the different elements of a bank's funding composition with the Altman dummy to capture whether a bank provides credit to the firm (hence we observe positive loan growth), conditional 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 if the share of the funding element is also higher. Obviously, a negative coefficient on the interaction term implies higher risk taking by the bank, as this indicates that less

[11] i.e. at the country where the firm is incorporated.

credit is provided to firms of higher creditworthiness. While we use the Altman dummy (i.e. based on the median of the continuous Altman Z-score) in our baseline model, we evaluate additional nonlinearity in our robustness analyses by replacing the Altman dummies with its quartiles, the 'original' Altman-cutoffs and its continuous score.

With our dataset, we cannot determine precisely when the different elements of the 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. Firm-level variables are therefore lagged by one year, corresponding with the previous accounting year. To account for potential endogeneity, specifically 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 also lagging bank-level variables by one year. Lagging variables of interest is common practice in the banking literature where 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 lend those funds the year after, *t+1*. In our robustness analyses, we experiment how results are affected by changing the timing of variables.

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 (non-interacted) Altman Z-score as a regressor, we include: a 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 a 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 country level 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[12] in demand for credit on three dimensions.[13] 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 also taken from

[12]Specifically, we choose the net percentage and the 'backward-looking three months' indices
[13]'Debt refinancing', 'large enterprises' and 'small medium enterprises'.

the ECB's Statistical Data Warehouse. The national credit to GDP ratio captures a country's capital abundance and is sourced from the World Bank. County-level fixed effects capture time-invariant conditions (such as having a deposit guarantee scheme) and year dummies capture additional common trends.

We restrict our sample to firms reporting a relation with SSM parent and their subsidiary banks[14] only, for two reasons. 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. In our robustness analyses, 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 alter their funding composition and hence risk taking. Since the SSM is in effect since 2014 (ECB, 2014), we restrict the sample period to 2014-2019. We furthermore exclude observations from countries if there are fewer than 100 complete observations.

3.4 Sample Selecion Analysis

Whether an observation is ultimately included in the baseline model, depends on data coverage on all variables in the model as well as whether the firm has reported a bank relation. As the inclusion of those observations in the model could be a result of non-random selection, we evaluate potential sample selection bias. Firms reporting a bank relation may possess significantly different characteristics than those that do not. We do so by estimating four probit models in a similar fashion as Giannetti and Ongena (2012), where the dependent variable either indicates a firm reporting a bank relation or a firm showing up in the sample of the baseline model. Appendix 8.4 provides more detail on the analysis and shows regression results for the probit models. We conclude that sample selection bias is unlikely, promoting the external validity of our results.

3.5 Descriptives

Table 11 and 12 (Appendix) report frequency statistics. Table 11 reports the number of banks and firms in the baseline model by the eleven Eurozone countries in which a firm is registered. Note that, for example, a German firm can be related to a French bank. As data coverage varies per variable in our dataset, our baseline model includes a total of 475,985 firm-year observations and 96 unique banks. The number of banks and firms varies per country, reflecting data availability. Table 11 (Appendix) shows that firms included in the baseline model represent a diverse set of industries with the majority operating in wholesale, retail and repair services, manufacturing, and construction. Table 12 (Appendix) furthermore reports the number of banks by country of origin, which also differs per country because reported bank relations vary substantially per country (some banks are reported more 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, external validity should not be compromised. Our selection of firms follows a data cleaning procedure, which has been shown to result in nationally representative subsets (Kalemli-Ozcan et al., 2015). Table 1 in this section reports summary statistics of the firm-level and bank-level variables in the baseline model. Clearly, the model

[14]Example: ING Bank N.V. (parent bank), ING Belgium N.V. (subsidiary bank).

relies on small and medium-sized enterprises (SMEs) that constitute the vast majority of firms in Europe. The firms included in the model are diverse in terms of age, bank debt and the Altman Z-score. With an average age of about 25 years, we observe relatively established firms rather than startups. On average, firms in the sample are of moderate creditworthiness (referred to as the 'grey zone' where the Z-score lies between 1.81 and 2.99, according to Altman, 1968) and the sample is not skewed towards one end of the distribution. Furthermore, Table 1 displays the large variety in the funding composition of banks in the model. This holds both for banks' equity ratio as well as the different types of liabilities: deposits, short-term market debt, and long-term market debt. On average, the most significant funding component is customer deposits (54% of total funding). This is followed by deposits from banks.

Table 1: Summary Statistics

Variable	**N**	**Mean**	**SD**	**Median**	**Min.**	**Max.**
Loan growth	475985	0.004	1.04	-0.02	-16.05	16.06
Firm age	475962	25.61	15.01	23.00	1.00	640.00
Firm debt	475985	2237367	5179755	219095	2	39240264
Firm Altman Z-score	475985	2.67	1.54	2.57	-4.95	19.96
Firm total assets	475985	5787017	10134969	1473122	268	39240264
Firm fixed assets ratio	475985	0.35	0.27	0.29	0.00	1.09
Bank ROA	475985	0.00	0.00	0.00	-0.03	0.04
Bank efficiency ratio	475985	0.58	0.11	0.54	0.18	1.30
Bank total assets	475985	615082	656434	347927	829	2077759
Bank equity ratio	475985	0.08	0.02	0.07	0.02	0.25
Customer deposits ratio	475985	0.54	0.12	0.54	0.01	0.87
Deposits from banks ratio	475985	0.14	0.11	0.12	0.00	0.77
Bank total market funding ratio	475985	0.09	0.05	0.08	0.00	0.75
Bank short-term funding ratio	475985	0.02	0.02	0.01	0.00	0.22
Bank long-term funding ratio	475985	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. Loan growth is a ratio, 1.00 thus indicates a 100% increase.

4 Results

In this section, we examine regression results for our baseline specification as presented in section 3.3. Table 2 reports regression results for the baseline model. We start by describing coefficients on our variables of interest, followed by common denominators across specifications.

Since our dependent variable in all models captures annual loan growth, we not only document risk taking (as captured by the interaction terms) but also to what extent the individual variables in our regressions relate to the quantity of credit supply (SME lending). Starting with column (1) which excludes interaction terms, it is noteworthy that this is the only model in which the equity ratio of a bank enters with a negative and statistically significant coefficient. This coefficient would suggest that a bank's capitalization is negatively related to credit supply, which is consistent with earlier literature (see for instance Jiménez et al. (2012)[15]). However, we do not find this result to be

[15]Note that Jiminez et al. use a different sample, containing larger firms and firms from Spain only.

robust across different specifications, which leads us to conclude that higher capitalization is not negatively associated with the quantity (as captured by loan growth) of SME lending in our sample.

Across models, all non-equity funding elements are positively and statistically significantly associated with loan growth. These results suggest that a bank's leverage (which is based on the sum of all non-equity funding elements) is positively associated with SME lending. This finding is consistent with empirical literature (Jiménez et al., 2012). Yet, the associations between loan growth and the individual funding elements are found to be highly nonlinear as they depend on the creditworthiness of a firm. This is indicated by the statistically significant coefficients and negative signs on the individual interaction terms in the next columns. Recall that a value of 1 on the 'Altman dummy' indicates a firm of relatively high creditworthiness (the Altman score exceeds the median of the sample), such that a negative coefficient on the interaction term signals an increase in risk taking.

Column (2) reports regression results for a specification in which market funding is not decomposed into its short and longer-term components. Here, we observe that a bank's market funding is positively associated with lending (loan growth), as captured by the positive and statistically significant coefficient of the standalone market funding ratio. The association between the market funding ratio and lending is highly nonlinear, as captured by the negative and statistically significant coefficient when the market funding is interacted with the Altman dummy. Banks relying more on market funding instruments exhibit a lower volume of lending to firms of higher creditworthiness or, in other words, lend less to firms of higher creditworthiness. Banks relying more on market funding, relative to the size of the balance sheet, take higher ex-ante risks on SME lending. For market funding, a 10 percentage point increase in the market funding ratio thus implies almost a 8.6% annual loan growth (i.e. approximately 8.4 standard deviations) to firms of low creditworthiness and a 2.3% annual loan *decline* to firms of high creditworthiness. This result is robust across specifications, both in this section as well as in our robustness analyses.

In column (3), we decompose market funding into its short and longer-term components. We find that the elevated risk taking following reliance on market funding is explained by longer-term market funding (0.947 vs. -0.261 interacted). The association of this funding component is economically the most significant among the funding components: a 10 percent increase in a bank's long-term market funding implies a 9.5% annual growth rate of loans provided to firms of low creditworthiness and 2.6% *decline* for firms of high 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 'Martinez-Miera and Repullo (2017)' search for yield dynamics may 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.

Common to all specifications is the positive, relatively constant and statistically significant coefficient for the Altman Z-score. SMEs of higher creditworthiness thus generally exhibit higher loan growth. 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 indicate that larger SMEs, which also tend to be older (see correlation table), grow slower and invest less. As such, they would require less bank credit via loans. 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[16] in the past, therefore exhibiting negative loan growth in the future[17]. Finally, the Herfindahl index[18] 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 higher market power of the primary credit-supplying bank is positively associated with loan growth to its existing portfolio of SMEs.

Table 3 reports estimation results for alternative samples. First, column (1) and column (2) address the overrepresentation of Spanish and Portuguese firms (see frequency table in the Appendix) in the baseline sample by estimating the model using exclusively Iberian (i.e. Spanish and Portuguese) and non-Iberian firms, respectively. Overall, the results remain similar when Iberian firms are excluded. A bank's market funding ratio is still the funding element that is most strongly related to lending to SMEs of lower creditworthiness, as captured by the negative and statistically significant coefficient on the interaction term. Similar to results from our full sample analysis, this association is of lower magnitude for other non-equity funding elements while equity itself is not related to the riskiness of SME lending.

Lastly, column (3) restricts our sample to SSM-significant banks that are the leading credit institution of their group ('parent banks'), thus excluding all (smaller) bank subsidiaries. The rationale for this sample restriction is twofold. Primarily, 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 rather than economically insightful. In addition, the exclusive focus on leading credit institutions implies that the set of banks used in column (3) 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 reported in Table 2, but generally feature lower statistical significance. The model displayed in column (3) relies on 33 leading credit institutions (and thus clusters in the regression), which is considered too few 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. This algorithm is recommended

[16] And hence, loans.

[17] Following loan repayment with the investment's dividends.

[18] To be precise, its first difference denoting the annual change in the index.

(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 is the case).

Table 2: Baseline Results

Dependent variable: Loan growth	**(1)**	**(2)**	**(3)**
Firm Altman score	0.129***	0.133***	0.136***
	(0.007)	(0.008)	(0.007)
Firm total assets	-0.639***	-0.651***	-0.663***
	(0.029)	(0.027)	(0.028)
Firm fixed asset ratio	-0.441***	-0.527***	-0.514***
	(0.061)	(0.062)	(0.057)
Bank ROA	-0.280	-0.128	-0.251
	(0.954)	(0.925)	(0.954)
Bank effiency ratio	-0.001	-0.001***	-0.001**
	(0.001)	(0.000)	(0.000)
Bank total assets	-0.039	0.013	-0.008
	(0.031)	(0.031)	(0.030)
Bank equity ratio	-1.030**	-0.444	-0.420
	(0.478)	(0.344)	(0.440)
Bank equity ratio x Altman dummy		-0.478	-0.498
		(0.714)	(0.755)
Customer deposits ratio	0.422***	0.507***	0.341**
		(0.136)	(0.138)
Customer deposits ratio x Altman dummy		-0.366***	-0.367***
		(0.067)	(0.067)
Deposits from banks ratio	0.228*	0.288*	0.279*
	(0.134)	(0.159)	(0.165)
Deposits from banks ratio x Altman dummy		-0.349*	-0.377*
		(0.182)	(0.209)
Bank total market funding ratio	0.353***	0.858***	
	(0.122)	(0.203)	
Bank total market funding ratio x Altman dummy		-1.088***	
		(0.255)	
Bank short-term funding ratio			0.199
			(0.557)
Bank short-term funding ratio x Altman dummy			-0.579
			(0.925)
Bank long-term funding ratio			0.947***
			(0.193)
Bank long-term funding ratio x Altman dummy			-1.208***
			(0.338)
Herfindahl index	0.869*	1.361***	1.033***
	(0.479)	(0.369)	(0.376)
Constant	9.297***	8.905***	9.452***
	(0.618)	(0.552)	(0.596)
Macroeconomic credit demand controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Clustering of standard errors	Bank	Bank	Bank
Observations	475.985	475.985	475.985
R-squared	0.241	0.246	0.247

Notes. The dependent variable is the log difference of firm bank debt. All explanatory variables are specified as the first lag, with the exemption of the Herfindahl index. The Herfindahl is the absolute first-difference. Bank ratios are standardized by absolute bank total assets. The separate bank total assets control variable is specified as the natural log. The Altman dummy assumes the value of 1 if the firm has an Altman Z-score exceeding the sample median and 0 otherwise. The conventional significance thresholds are displayed by * (0.1), ** (0.05) and *** (0.01).

Table 3: Analysing Overrepresentation of Firms

Dependent variable: Loan growth	Excl. Ib.	Only Ib.	SSM parents
Firm Altman score	0.128***	0.132***	0.124***
	(0.019)	(0.007)	(0.010)
Firm total assets	-0.796***	-0.604***	-0.611***
	(0.046)	(0.015)	(0.015)
Firm fixed asset ratio	-0.948***	-0.406***	-0.383***
	(0.145)	(0.042)	(0.045)
Bank ROA	0.151	2,268	2,341
	-1,188	-2,955	-2,456
Bank effiency ratio	-0.001*	-0.001	-0.001
	(0.001)	(0.002)	(0.001)
Bank total assets	-0.008	0.004	-0.023
	(0.067)	(0.069)	(0.042)
Bank equity ratio	-2.162*	0.554	-0.134
	-1,210	(0.676)	(0.571)
Bank equity ratio x Altman dummy	-0.406	-0.797	-1,445
	(0.641)	(0.640)	(0.905)
Customer deposits ratio	0.437	0.483*	0.431*
	(0.386)	(0.250)	(0.172)
Customer deposits ratio x Altman dummy	-0.404***	-0.201***	-0.126
	(0.089)	(0.055)	(0.069)
Deposits from banks ratio	0.165	0.619***	0.585*
	(0.321)	(0.175)	(0.181)
Deposits from banks ratio x Altman dummy	-0.468***	-0.503**	-0.700**
	(0.145)	(0.212)	(0.206)
Bank total market funding ratio	0.243	0.895***	0.769*
	(0.397)	(0.241)	(0.234)
Banks total market funding x Altman dummy	-0.544**	-1.362***	-1.126**
	(0.235)	(0.199)	(0.241)
Herfindahl index	0.612	1,742	0.937**
	-1,288	-1,252	(0.413)
Constant	11.868***	8.106***	8.698***
	-1,099	(0.721)	(0.475)
Macroeconomic credit demand controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Significance corrected using bootstrapping algorithm (Cameron, 2008)	No	No	Yes
Observations	166.308	309.677	340.107
R-squared	0.244	0.249	0.249

Notes. In column (1) and column (2), only Iberian and only non-Iberian firms are considered, respectively. In column (3), only observations involving a leading SSM credit institution are considered. The dependent variable is the log difference of firm bank debt. All explanatory variables are specified as the first lag, with the exemption of the Herfindahl index. The Herfindahl is the absolute first-difference. Bank ratios are standardized by absolute bank total assets. The separate bank total assets control variable is specified as the natural log. The Altman dummy assumes the value of 1 if the firm has an Altman Z-score in excess of the sample median and 0 otherwise. The conventional significance thresholds are displayed by * (0.1), ** (0.05) and *** (0.01).

5 Robustness

We evaluate the robustness of the baseline results by performing a battery of sensitivity tests adjusting three model specification categories. First, we evaluate whether the results are robust when allowing bank funding to be related to bank lending instantaneously and when 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. Second, we evaluate how the results are affected by the inclusion of fixed effects. Lastly, we evaluate whether the results are sensitive to alternative risk measures to acknowledge that the Altman sample median dummy is just one proxy of ex-ante firm creditworthiness. Overall, we find that the baseline results are largely robust.

5.1 Alternative Dynamics and Period

Table 4 reports the results of two categories of robustness tests involving alternative bank dynamics and a longer observation period. In particular, the model specification in column (1) deviates from the baseline by using the contemporaneous values (hence not lagged) of the bank funding elements. As theory does not guide the precise dynamics of the relation between banks' funding composition and their SME lending, 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 (1) 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 relation between banks' funding structures and SME lending (loan growth) remains qualitatively similar to our baseline results.

Column (2) and column (3) evaluate whether the baseline results are robust to including the aftermath of the 2008 financial recession, the European sovereign debt crisis, and the ensuing period of economic recovery in the observation period. Specifically, both columns extend the observation period to commence in 2010 instead of 2014 while column 3 adds the interaction of country and year fixed effects to account for country-specific trends which are more likely to affect results when the sample period is longer. In both columns, the sign and significance of the interacted terms of interest remain similar to the baseline results.

5.2 Fixed Effects Analyses

Next, we perform an econometric exercise by evaluating how fixed effects in our models affect results. We evaluate if the baseline results are robust to maintaining only fixed effects as controls (thus excluding firm and bank control variables), to keeping only firm fixed effects, to exclude all fixed effects and to include interacted fixed effects. The latter controls for potential supply-side shocks, which is consistent with insights from recent literature on firm investment (Amiti and Weinstein, 2018). In a similar fashion, interacted firm-year fixed effects could be included to control for demand shocks. However, this is impossible in our case as it would result in an overidentified model (every single observation would then be represented by a fixed effect). Moreover, we already control for credit demand (conditions) via our macroeconomic controls taken from the ECB Bank Lending Survey. Table 5 reports the results of the analyses. Overall, results from the baseline model remain qualitatively similar to column (2) of the baseline model: banks relying on market funding are most strongly associated with providing credit to firms of lower creditworthiness. The association is again not statistically robust for equity, while the interaction terms capturing customer deposits and interbank lending feature lower magnitudes.

Table 4: Dynamics and Longer Sample Period

Dependent variable: Loan growth	**Funding not lagged**	**Sample 2010-2019**	**Sample 2010-2019**
Firm Altman score	0.132***	0.123***	0.123***
	(0.008)	(0.006)	(0.006)
Firm total assets	-0.632***	-0.421***	-0.420***
	(0.027)	(0.028)	(0.028)
Firm fixed asset ratio	-0.476***	-0.431***	-0.431***
	(0.053)	(0.060)	(0.060)
Bank ROA	0.841*	0.225	-0.231**
	(0.434)	(0.455)	(0.107)
Bank efficiency ratio	-0.002**	0.000	0.000
	(0.001)	(0.000)	(0.000)
Bank total assets	0.003	0.025	0.035*
	(0.037)	(0.026)	(0.019)
Bank equity ratio	-0.966*	0.754	0.949**
	(0.542)	(0.554)	(0.374)
Bank equity ratio x Altman dummy	0.156	-0.618	-0.583
	(0.818)	(0.410)	(0.406)
Customer deposits ratio	0.567***	0.296**	0.492***
	(0.122)	(0.136)	(0.086)
Customer deposits ratio x Altman dummy	-0.450***	-0.295***	-0.285***
	(0.076)	(0.046)	(0.045)
Deposits from banks ratio	0.328**	0.195	0.289***
	(0.144)	(0.120)	(0.087)
Deposits from banks ratio x Altman dummy	-0.455**	-0.323***	-0.326***
	(0.203)	(0.092)	(0.091)
Bank total market funding ratio	0.882***	0.567***	0.879***
	(0.185)	(0.159)	(0.144)
Banks total market funding x Altman dummy	-0.987***	-1.020***	-1.103***
	(0.216)	(0.149)	(0.145)
Herfindahl index		0.203	33.585***
		(0.529)	-7,038
Constant	8.759***	5.381***	4.687***
	(0.653)	(0.490)	(0.479)
Macroeconomic credit demand controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Country x Year FE	No	No	Yes
Observations	453.321	965.347	965.347
R-squared	0.255	0.182	0.182

Notes. The dependent variable is the log difference of firm bank debt. In column 1, the contemporaneous value of the bank funding variables is considered, while other variables are specified as the first lag (with the exemption of the Herfindahl index). In column 2 and column 3, all explanatory variables are specified as the first lag (with the exemption of the Herfindahl index). The Herfindahl is the absolute first-difference. Bank ratios are standardized by absolute bank total assets. The separate bank total assets control variable is log-transformed. The Altman dummy assumes the value of 1 if the firm has an Altman Z-score in excess of the sample median and 0 otherwise. In column 1, the sample period remains 2014-2019, whereas the results in columns 2 and 3 are based on a substantially longer sample period (2010-2019). The conventional significance thresholds are displayed by * (0.1), ** (0.05) and *** (0.01).

Table 5: Sensitivity to Including Fixed Effects

Dependent variable: Loan growth	No bank/firm controls	Only firm FE	No FE	Bank*year FE
Firm Altman score		0.134***	0.079***	0.134***
		(0.008)	(0.005)	(0.008)
Firm total assets		-0.646***	0.007***	-0.651***
		(0.026)	(0.002)	(0.027)
Firm fixed asset ratio		-0.525***	-0.155***	-0.526***
		(0.060)	(0.017)	(0.062)
Bank ROA		0.417	0.941	
		(1.025)	(1.271)	
Bank efficiency ratio		-0.001***	0.000	
		(0.000)	(0.000)	
Bank total assets		0.069**	0.000	
		(0.033)	(0.000)	
Bank equity ratio	0.012	-0.200	0.252	
	(0.319)	(0.248)	(0.273)	
Bank equity ratio x Altman dummy	-0.338***	-0.482	-0.760*	-0.425
	(0.502)	(0.711)	(0.393)	(0.730)
Customer deposits ratio	0.656***	0.640***	0.148***	
	(0.188)	(0.183)	(0.053)	
Customer deposits ratio x Altman dummy	-0.338***	-0.367***	-0.277***	-0.370***
	(0.066)	(0.046)	(0.039)	(0.068)
Deposits from banks ratio	0.409**	0.241	0.081	
	(0.184)	(0.158)	(0.080)	
Deposits from banks ratio x Altman dummy	-0.314**	-0.349*	-0.117	-0.343*
	(0.138)	(0.181)	(0.097)	(0.187)
Bank total market funding ratio	0.719***	0.828***	0.331***	
	(0.185)	(0.199)	(0.071)	
Banks total market funding x Altman dummy	-0.693***	-1.074***	-0.473***	-1.099***
	(0.221)	(0.258)	(0.145)	(0.259)
Herfindahl index		1.850***	2.067***	5.460*
		(0.279)	(0.261)	(3.179)
Constant	0.309**	8.045***	-0.271***	9.335***
	(0.124)	(0.498)	(0.479)	(0.402)
Macroeconomic credit demand controls	No	Yes	Yes	
Firm FE	Yes	Yes	No	Yes
Bank FE	Yes	No	No	Yes
Year FE	Yes	No	No	Yes
Country x Year FE	No	No	No	No
Bank x Year FE	No	No	No	Yes
Observations	475.985	475.985	518.604	475,985
R-squared	0.222	0.246	0.02	0.247

Notes. The dependent variable is the log difference of firm bank debt. In columns, all explanatory variables are specified as the first lag (with the exemption of the Herfindahl index). The Herfindahl is the absolute first-difference. Bank ratios are standardized by absolute bank total assets. The separate bank total assets control variable is log-transformed. The Altman dummy assumes the value of 1 if the firm has an Altman Z-score in excess of the sample median and 0 otherwise. The sample period remains 2014-2019. The last column excludes bank-level controls because of collinearity with interacted fixed effects. The conventional significance thresholds are displayed by * (0.1), ** (0.05) and *** (0.01).

5.3 Alternative Risk Measures

We employ two types of robustness tests to evaluate whether the baseline results are sensitive to the use of the Altman sample median dummy as an indicator of firm ex-ante creditworthiness. First, we use the Altman Z-score to classify firm creditworthiness more granularly, by using quartiles of its distribution and 'original' zones of discrimination as cutoff values, instead of considering the score in a strictly binary manner. While the use of a sample median dummy is consistent with earlier literature (Clarke et al., 2006; Impson, 2000), ranking ex-ante firm creditworthiness strictly dichotomously may not be fully reflective of a bank's practice. Second, we use principle component analysis (PCA) to calculate an alternative measure of ex-ante firm creditworthiness. PCA summarizes a set of variables, in this case variables that have been identified as relevant for firm credit risk, in a single risk measure (Bonfim, 2009; Clarke et al., 2006; Impson, 2000). Overall, we find that the results of both tests remain qualitatively similar to our baseline findings.

Table 6: Robustness Results: Exploring Alternative Cutoffs

Dependent variable: Loan growth	**Altman distress/grey/safe**
Firm Altman score	0.137***
	(0.008)
Firm total assets	-0.661***
	(0.027)
Firm fixed asset ratio	-0.570***
	(0.063)
Bank ROA	-0.091
	(0.919)
Bank effiency ratio	-0.001***
	(0.000)
Bank total assets	0.026
	(0.030)
Bank equity ratio	-0.334
	(0.539)
Bank equity ratio x Altman grey	-0.327
	(0.646)
Bank equity ratio x Altman safe	-0.432
	-1,120
Customer deposits ratio	0.579***
	(0.142)
Customer deposits ratio x Altman grey	-0.190***
	(0.070)
Customer deposits ratio x Altman safe	-0.605***
	(0.117)
Deposits from banks ratio	0.459**
	(0.218)
Deposits from banks ratio x Altman grey	-0.218
	(0.174)
Deposits from banks ratio x Altman safe	-0.763***
	(0.270)
Bank total market funding ratio	1.339***
	(0.267)
Bank total market funding x Altman grey	-0.989***
	(0.218)
Bank total market funding x Altman safe	-1.834***
	(0.345)
Herfindahl index	1.314***
	(0.365)
Constant	8.940***
	(0.547)
Macroeconomic credit demand controls	Yes
Firm FE	Yes
Bank FE	Yes
Year FE	Yes
Observations	475.985
R-squared	0.250

Notes. The dependent variable is the log difference of firm bank debt. All explanatory variables are specified as the first lag, with the exemption of the Herfindahl index. The Herfindahl is the absolute first-difference. Bank ratios are standardized by absolute bank total assets. The separate bank total assets control variable is specified as the natural log. The base group are *distressed* firms according to the original Altman zones of discrimination, while *grey* and *safe* firms feature in the interaction terms of interest. The conventional significance thresholds are displayed by * (0.1), ** (0.05) and *** (0.01).

Table 6 employs the original zones of discrimination of the Altman Z-score to distinguish so-called *safe*, *grey*, and *distressed* firms. *Safe* firms with an Altman Z-score above 2.99 generally feature low default risk, *grey* firms with an Altman Z-score between 1.80 and 2.99 experience heightened default risk, and finally, *distressed* firms with an Altman Z-score below 1.80 are exposed to the highest default risk. In Table 6, *distressed* firms represent the base group, thus firms with the lowest Altman Z-score (below 1.80) while the bank funding variables of interest are interacted with *grey* firms and *safe* firms.

The results of this analysis are again similar to the baseline results, in terms of sign and statistical significance. Most importantly, Table 6 confirms that a higher bank total market funding ratio is positively and statistically significantly associated with credit provision to *distressed* and grey firms relative to lending to *safe* firms. Its magnitude is again the strongest among non-equity funding elements, which is consistent with baseline results. Next, we again find no statistically significant relation between a bank's equity ratio and SME lending - both in terms of the quantity (captured by the standalone equity ratio) as well as the riskiness of credit.

Next, we introduce an additional degree of granularity of the creditworthiness measure by interacting the bank funding elements with sample *quartile* dummies of the Altman Z-score instead of the yearly sample median as a cutoff value. The result of this robustness model is reported in the first column of Table 7 in which the sample quartile of firms with the lowest Altman Z-score constitutes the base group and the fourth quartile refers to the sample quartile of firms exhibiting the highest Altman Z-score. Again, the results of this robustness test are qualitatively similar to the baseline results. Importantly, we note that the interactions between bank funding elements and firm ex-ante creditworthiness do typically not resemble obvious linearity. In fact, we find results to be strongly nonlinear. Except for a bank's equity, the reported coefficients on the interaction terms are strongly decreasing in a firm's creditworthiness score, while maintaining statistical significance. In other words, the associations are highly skewed towards the higher end of the creditworthiness distribution. This indicates that banks relying on either type of non-equity funding have a stronger incentive to provide less credit to firms of higher creditworthiness (or vice versa: to provide more credit to firms of lower creditworthiness, i.e. take more risk).

The observed nonlinearity in the transmission of bank funding 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 mechanism would explain why our quartile results are more pronounced at the bottom half of the creditworthiness distribution only. This is also consistent with corporate credit standards reported on bank lending surveys (DNB, 2023).

To further assess the sensitivity of the baseline results to the use of the Altman Z-score, we use principle component analysis (PCA) to create a novel indicator of ex-ante firm creditworthiness. Essentially, PCA is a dimension reduction technique that we employ to summarize several firm financial metrics into a single indicator, without considerable loss of variation. The advantages of employing the PCA indicator instead of substituting the Altman Z-score with an individual firm metric (e.g. a financial ratio such as ROA) are twofold. Primarily, the indicator identified via PCA likely provides a more valid and consistent estimate of ex-ante firm creditworthiness as firm credit default is generally not well explained by a single financial metric (Boguslauskas et al., 2011). Furthermore, the PCA indicator mitigates potential distortion caused by measurement errors in one of 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 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.

Table 8 lists the financial ratios that are obtained from the credit risk literature. We employ R-type factor analysis (Hair et al., 2009). Whereas multicollinearity among explanatory variables is typically problematic, R-type factor analysis can solely be employed if the financial metrics involving firms' profitability, liquidity position and balance sheet strength are sufficiently related. We formally evaluate the appropriateness of using factor analysis through a Measure of Sampling Adequacy (*Kaiser-Meyer-Olkin*) test. This test quantifies the degree to which a financial metric can be explained by the remaining five metrics [19]. Table 9 provides the results of this test and reports a score close to or in excess of 0.6 for each metric and the overall matrix. Following the seminal paper of Kaiser and Rice (1974) in which statistics above 0.6 are recommended for this test, we conclude that the financial metrics selected are suitable for factor analysis. Table 9 furthermore demonstrates the eigenvector, or the correlation of each financial metric with the novel indicator. It should be noted that the negative sign corresponding to *Current liabilities to total assets* is intuitive: firms with a higher ratio of this metric are generally considered of lower creditworthiness. The interpretation of the newly derived indicator is straightforward: a higher value of the indicator implies that an individual firm operates more profitably, features a better liquidity position or has a stronger balance sheet. Therefore, a higher score on the indicator reflects higher creditworthiness, similar to the Altman Z-score. In a similar fashion as the Altman Z-score, we directly exploit more granularity in the new indicator by interacting the funding elements with the quartiles of the new indicator (rather than using a median dummy). We keep the sample period the same as in the baseline model: 2014-2019.

Substituting the quartiles dummies of the Altman Z-score with PCA quartiles dummies, the robustness of the results is mixed as reported in Table 7. Primarily, we find that the signs of each standalone and interacted bank funding element are consistent across Altman Z-score and PCA sample median quartiles. Importantly, our main result that a bank's market funding is associated with lending to SMEs of lower ex-ante creditworthiness is confirmed by the specification where we use the PCA indicator. The same holds for the nonlinearity of our finding: the coefficients on the interaction term where a market funding ratio is interacted with the PCA-indicator is strongly decreasing in a firm's measure of creditworthiness. However, evidence of the associations being non-spurious as indicated by statistical significance is lower when using the PCA relative to the Altman Z-score as risk measure. Thus, although the signs are consistent across both risk measures, we emphasize the use of the Altman Z-score as an established risk measure.

[19] 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.

Table 7: Robustness Results Quartiles and PCA

Dependent variable: Loan growth	**Altman Quart.**	**PCA Quart.**
Firm Altman score	0.140***	
	(0.008)	
Firm PCA score		0.064***
		(0.020)
Firm total assets	-0.668***	-0.712***
	(0.027)	(0.030)
Firm fixed asset ratio	-0.600***	-0.686***
	(0.067)	(0.074)
Bank ROA	-0.073	-0.319
	(0.877)	(0.773)
Bank efficiency ratio	-0.002***	-0.001***
	(0.000)	(0.000)
Bank total assets	0.028	0.026
	(0.031)	(0.024)
Bank equity ratio	-0.300	-0.495
	(0.541)	(0.608)
Bank equity ratio x Q2 Cred.w.	-0.045	0.134
	(0.641)	(0.598)
Bank equity ratio x Q3 Cred.w.	-0.615	-0.374
	(0.847)	(0.936)
Bank equity ratio x Q4 Cred.w.	-0.490	-0.803
	-1,265	-1,052
Customer deposits ratio	0.645***	0.361*
	(0.144)	(0.193)
Customer deposits ratio x Q2 Cred.w.	-0.194***	-0.044
	(0.069)	(0.117)
Customer deposits ratio x Q3 Cred.w.	-0.474***	-0.084
	(0.092)	(0.219)
Customer deposits ratio x Q4 Cred.w.	-0.874***	-0.313
	(0.130)	(0.290)
Deposits from banks ratio	0.539**	0.251
	(0.227)	(0.181)
Deposits from banks ratio x Q2 Cred.w.	-0.275	-0.040
	(0.177)	(0.104)
Deposits from banks ratio x Q3 Cred.w.	-0.466**	-0.033
	(0.233)	(0.183)
Deposits from banks ratio x Q4 Cred.w.	-1.073***	-0.341*
	(0.327)	(0.197)
Bank total market funding ratio	1.360***	0.827***
	(0.306)	(0.293)
Bank total market funding x Q2 Cred.w.	-0.717***	-0.185
	(0.170)	(0.230)
Bank total market funding x Q3 Cred.w.	-1.393***	-0.699*
	(0.327)	(0.369)
Bank total market funding x Q4 Cred.w.	-2.174***	-1.428**
	(0.482)	(0.593)
Herfindahl index	1.360***	1.174***
	(0.364)	(0.330)
Constant	9.013***	10.068***
	(0.555)	(0.537)
Macroeconomic credit demand controls	Yes	Yes
Firm FE	Yes	Yes
Bank FE	Yes	Yes
Year FE	Yes	Yes
Observations	475.985	464.669
R-squared	0.254	0.240

Notes. The dependent variable is the log difference of firm bank debt. All explanatory variables are specified as the first lag, with the exemption of the Herfindahl index. The Herfindahl is the absolute first-difference. Bank ratios are standardized by absolute bank total assets. The separate bank total assets control variable is specified as the natural log. Column 1 employs the Altman Z-score as an ex-ante firm creditworthiness metric while column 2 employs the PCA component score. In both columns, the base group refers to the sample quartile of firms with the lowest creditworthiness, while the remaining quartiles feature in the interaction terms of interest. The conventional significance thresholds are displayed by * (0.1), ** (0.05) and *** (0.01).

Table 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 9: PCA Selection Statistics

Variable	**Eigenvector**	**KMO**
ROA	0.2373	0.5053
ROE	0.1089	0.5153
Quick ratio	0.3078	0.6498
Free cash flow to current liabilities	0.3723	0.6120
Turnover to total liabilities	0.3789	0.7523
Working capital to total assets	0.3954	0.8088
Equity to total assets	0.4581	0.6795
Current liabilities to total assets	-0.4344	0.6599

6 Conclusion

The role of a bank's funding composition on this risk taking is poorly understood, as theoretical predictions are ambiguous and empirical literature is scarce. We show that a bank's funding composition is associated with a bank's SME lending behavior. Analyzing loan growth for SMEs in eleven European countries, we find that SSM-supervised banks relying on market funding robustly exhibit lending to SMEs of lower creditworthiness. We proxy the creditworthiness of a firm, in our baseline model, via a firm's Altman Z-score. The association between a bank's funding use of market funding and lending to SMEs is highly nonlinear and is strongest for firms displaying the lowest creditworthiness.

The association between market funding and the riskiness of SME lending is driven by debt instruments with longer initial maturity rather than their shorter-term counterpart. Our findings are economically significant: a 10 percent increase in a bank's long-term market funding implies a 9.5 percent annual growth rate of loans provided to firms of low creditworthiness and 2.6 percent decline for high-creditworthiness firms. We hypothesize that this result is driven by a 'Martinez-Miera-Repullo' (2017) search for yield mechanism: following reliance on (long-term) market funding and in a low-interest rate environment, banks that are monitored by external investors lend to firms of lower creditworthiness. A bank's level of capitalization is not robustly associated with the riskiness of SME lending, suggesting that, while equity has loss-absorbing capacity, it does not alter the riskiness of a bank's credit supply to SMEs. We show that our results are largely robust to sample changes, changes in the timing of variables and, to some extent, to employing an alternative measure of a firm's creditworthiness other than the Altman Z-score.

From a policy perspective, our findings highlight which funding elements are related to a bank's risk taking. Our results suggest that policies that reduce the level of (long-term) market funding, could (notwithstanding second-order effects) potentially lead to a lower risk of SME lending (and vice versa). While we acknowledge that a bank's level of capitalization functions 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 increasing regulatory capital requirements to reduce a bank's risk taking. Interestingly, many European countries have imposed bank taxes over recent years, whose tax base is typically the sum of market funding and interbank lending ("non-equity and non-deposit funding") (OECD, 2023). Discouraging banks to use this non-equity funding could thus result in lower risk taking, which may promote financial stability, but not economic growth when it blocks productive firms from obtaining financing.

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 that we (for market funding) attribute to the 'Martinez-Miera-Repullo' search for yield mechanism. Secondly, although we observe a firm's ex-ante creditworthiness, data limitations restrict us from measuring ex-post creditworthiness or actual firm defaults. We suggest research to address this limitation, such that one could judge whether risks are also *excessive*. Thirdly, our specification is reduced form and we cannot precisely disentangle demand (firm) from supply-side factors (banks). Future research should 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 productivity and therefore economic growth in the longer run.

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Appendices

Additional Descriptives

Table 10: Data Sources

Variables	**Subject**	**Source**
Firm age	Firm-specific	BvD Orbis
Firm Altman 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 score is not obtained directly from BvD Orbis, but calculated from a set of financial ratios.

Table 11: Frequency Statistics

Country (firm)	**Number of banks**	**Number of firms**
Austria	12	658
Germany	23	3888
Estonia	1	2
Spain	9	54716
France	68	38947
Ireland	11	1242
Luxembourg	6	639
Latvia	2	312
The Netherlands	7	1085
Portugal	5	21410
Slovenia	2	2376

Table 12: Banks per Bank Country

Country (bank)	**Number of banks**
Austria	6
Belgium	1
Germany	12
Spain	5
Finland	2
France	58
Ireland	1
Luxembourg	3
The Netherlands	4
Portugal	2
Slovenia	2

Table 13: Correlation Matrix: Firm Variables

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
(1) Bank debt	1				
(2) Altman score	-0.0932***	1			
(3) Total assets	0.912***	-0.0668***	1		
(4) Fixed asset ratio	0.0688***	-0.435***	0.0825***	1	
(5) Age	0.146***	-0.0234***	0.212***	0.0171***	1

Table 14: 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	0.0147***	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	0.0585***	-0.140***	0.437***	-0.366***	-0.0674***	-0.400***	1		
(8) Short-term funding ratio	0.0532***	0.0823***	0.532***	-0.222***	-0.339***	-0.0403***	0.502***	1	
(9) Long-term funding ratio	0.0420***	-0.200***	0.249***	-0.315***	0.0841***	-0.441***	0.911***	0.102***	1

Matching Appendix

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.

Sample Selection Analysis

Although our matched database increases the level of granularity at which we can observe potential transmission of banking funding to the real economy, we are constrained by missing firm-bank relations in Orbis and imperfect coverage on variables in both Orbis and Bankfocus. The incompleteness of both datasets may result in sample selection bias, since firms that possess sufficient coverage may have different characteristics than firms that do not. To assess potential sample selection bias, we explore the determinants (and ultimately, representativeness) of firms in our sample. We assess firms reporting a bank relation as well as firms that are included in the baseline sample by employing several sample selection models (Probit models) in a similar fashion as Giannetti and Ongena (2012). While firm characteristics are time-variant, we focus on the year 2018 since this is the year in which we observe the bank relation. Table 15 reports the results of the sample selection models.

Table 15: Probit: Sample Selection

Variable	Reported bank	Reported bank	Base sample	Base sample
Firm total assets	0.109***	0.220***	0.203***	0.231***
	(0.001)	(0.001)	(0.001)	(0.001)
Firm age	0.427***	0.595***	0.405***	0.411***
	(0.002)	(0.002)	(0.002)	(0.002)
Firm ROA	0.672***	0.102***	-0.086***	0.026**
	(0.008)	(0.008)	(0.011)	(0.013)
Firm leverage	0.174***	0.338***	0.419***	0.450***
	(0.004)	(0.005)	(0.006)	(0.006)
Constant	-3.267***	-4.004***	-5.565***	-6.691***
	(0.009)	(0.017)	(0.013)	(0.022)
Country FE	No	Yes	No	Yes
Observations	1,672,342	1,672,342	1,672,342	1,672,342
Pseudo R-squared	0.131	0.371	0.183	0.203

Notes. This table reports regression coefficients of four Probit models. The dependent variable in the first two columns equals 1 if a firm in our initial dataset has reported a bank relation and 0 otherwise. The dependent variable in last two columns equals 1 if a firm is included in the sample of the baseline model and 0 otherwise.

The presence or absence of a firm's bank relation in Orbis is independent of the methodology of this study. However, including a firm in the baseline model depends on judgements made involving spelling or inconsistency errors of bank relations as provided in Orbis and the selection of variables used in this study. Column (1) and column (2) evaluate the determinants of a firm reporting a bank relation in Orbis. Both columns demonstrate that larger firms are more likely to report a bank relation. This result is intuitive, since larger firms are more likely to report extensively, for instance in annual reports, and Orbis obtains the bank relation mostly through such annual reports. Both columns also display that firms reporting a bank relation in Orbis tend be more profitable and older. At last, we note column (1) and column (2) evaluate leverage as a positive determinant of a firm reporting a bank relation. This is reassuring, as it supports the assumption that firm-bank relations in Orbis primarily concern lending relations. Subsequently, column (3) and column (4) consider if firm characteristics can explain whether a firm can be matched to a bank entity in BankFocus. The results of both models are generally similar to the results of column (1) and column (2). An exemption to this is that column (3), which lacks country fixed effects, displays firm profitability having a statistically significant negative relation with the likelihood of being included in the baseline sample. As the baseline model as well as the robustness models consistently include country fixed effects, we conclude that sample selection bias is unlikely.