Should macroprudential policy target corporate lending? Evidence from credit standards and defaults[*]

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March 2024

Abstract

We provide compelling evidence of the association between credit standards at loan origination in the corporate sector and default risk, a topic that has received little attention in the literature in comparison to the study of this relationship in the mortgage market. Using data from the Spanish credit register merged with corporate balance sheet information spanning the last financial cycle, we demonstrate that leverage and debt burden ratios at loan origination are key predictors of future corporate loan defaults. We also show that the deterioration of lending standards is strongly correlated to the accumulation of cyclical systemic risk during periods of financial expansions. Specifically, limits on the debt-to-assets ratio and the interest coverage ratio could serve as effective tools to mitigate credit risk during economic expansions. We identify that the strength of these associations varies significantly across different sectors and is dependent on firms' size, age and the existence of prior relationships with the bank. Real estate firms and small and medium-sized enterprises exhibit the strongest relationship between credit standards and future default. Overall, our findings provide strong support for the effectiveness of macroprudential measures targeting the corporate sector and contribute to providing guidance for the implementation of BBM in key segments of corporate credit.

Keywords: Bank credit, Defaults, Lending standards, Macroprudential policy, Non-financial corporations.

JEL classification: C32, E32, E58, G01, G28.

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[*]This paper is the sole responsibility of its authors. The views represented here do not necessarily reflect those of the Bank of Spain or the Eurosystem.

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Acknowledgments: We thank Ángel Estrada, David Martinez-Miera, Gabriel Jiménez, Javier Mencía, and Carlos Pérez, for their useful comments and suggestions. We are also grateful to the participants of the internal research seminar at Banco de España, the 16th International Risk Management Conference, the 2023 International Conference in Finance, Banking and Accounting, for the comments received. We are especially grateful to Marco Lo Duca for the discussion of the paper at the Fifth ECB/IMF macroprudential policy and research conference and to the participants to this conference, as well as to an anonymous referee.

1. Introduction

Recent empirical studies identify a strong association between the deterioration in mortgage lending standards and default risk (Haughwout et al., 2008; Galán and Lamas, 2023), an association further amplified by its correlation to future financial crises (Claessens et al., 2013; Cerutti et al., 2017). In contrast, the relationship between lending standards in credit to non-financial corporations (NFC) and default risk has received very little attention in the literature. This is particularly remarkable given the substantial imbalances observed in corporate credit prior to the global financial crisis (GFC), and the elevated non-performing loan ratios (NPL) of credit to this sector during the crisis. We fill this gap by examining the association between lending standards at the origination of NFC credit and future default risk. Our findings provide useful insights for the design of macroprudential policies aimed at mitigating systemic risk derived from corporate credit, akin to those widely used in the mortgage market.

The prominent role of non-financial private sector debt in previous financial crises (Schularik and Taylor, 2012; Claessens et al., 2012) prompted the introduction of broad macroprudential policy measures, such as the countercyclical capital buffer. However, the existence of pockets of heightened systemic risks in specific segments raises the question of whether targeted macroprudential measures are necessary. In this regard, the connection between house prices and credit before the GFC) has focused the attention on mortgage debt as a determinant of systemic vulnerabilities (Jordà et al., 2016; Galati et al., 2016; Rünstler and Vlekke, 2017). In particular, previous literature has found that the softening of lending standards was a primary driver of the large volumes of mortgages granted during the run-up to the GFC, and that this relaxation was strongly correlated with the severity of the crisis (Duca et al., 2010; Kelly et al., 2018; Schelkle, 2018).

Nonetheless, NFC credit played a relevant role in the build-up of systemic vulnerabilities associated to excessive credit growth ahead of the GFC. In the Euro Area, corporate debt increased by 96% between 1999 and 2008, surpassing the growth rate of credit to households (HH) by about 10 pp. This lending growth was particularly pronounced in sectors related to construction and real estate development, a trend that can be attributed to the documented relationship between house prices and credit. Moreover, after the crisis, the relative importance of corporate credit has steadily increased. Between 2008 and 2019, credit to NFC in the 43 countries reporting data to the Bank for International Settlements (BIS) grew by 63%, reaching about 100% of GDP. This represents more than double the growth rate observed for credit to HH.[1] These developments in terms of credit volume are highly concerning not only due to the potential imbalances with respect to fundamentals, but also because of the link between the deterioration of lending standards in periods of high credit growth and the build-up

[1] The growth rate of credit to HH in the 43 countries reporting data to the BIS was 27% between 2008 and 2019, which represents 60% of GDP. Using data from the Statistical Data Warehouse (SDW) of the European Central Bank (ECB), it is also observed that in the European Union (EU), corporate debt has increased by 50% between 2013 and 2021, which also doubles the growth rate observed in the HH sector.

of systemic risk, an association that has been demonstrated for mortgages and can also be present in NFC credit.

From a policy standpoint, recent regulatory developments have introduced macroprudential measures targeting NFC credit, primarily in the form of lender-based tools such as sectoral capital buffers (e.g. the Systemic Risk Buffer in Europe), or risk-weight add-ons to exposures in specific sectors.[2] While these measures may have a secondary objective of smoothing the supply of credit during financial expansions, their primary objective is to enhance bank resilience. indeed, empirical literature has found little and inconclusive evidence of reductions in cyclical systemic vulnerabilities through the use of lender-based measures (see Araujo et al., 2020, for a meta-analysis of studies on the impact of macroprudential measures on credit growth).[3]

In this regard, borrower-based measures (BBM), a widely employed macroprudential tool to mitigate systemic risk stemming from mortgage credit, have been shown to complement capital measures, operating through different mechanisms (see O'Brien and Ryan, 2017; Apergis et al., 2022; Valderrama, 2023 for a discussion). Capital measures enhance banks' solvency, increasing their resilience to losses arising from the materialization of financial risk following broad macrofinancial shocks. Conversely, BBM aim to enhance borrowers' resilience by reducing the probability of borrower defaults when risks materialize, thereby mitigating systemic vulnerabilities and safeguarding the financial system from specific shocks, such as income shocks (e.g. the COVID-19 pandemic) or interest rate shocks (e.g. sudden tightening of monetary policy). BBM also act by moderating credit demand during financial expansions, having more direct effects on mitigating the accumulation of cyclical vulnerabilities (Valderrama, 2023). These measures have not only been shown to have significant effects on reducing the probability of mortgage defaults (Nier et al., 2019; Galán and Lamas, 2023), but also to have stronger and more significant effects on curbing credit and house price growth compared to capital measures (Cerutti et al., 2017, Araujo et al., 2020).

Against this background, we investigate the relationship between credit standards at origination and default risk in NFC lending, which could provide justification for complementing capital measures with BBM in the corporate sector. To achieve this, we employ bank-firm level data on corporate credit granted in Spain during the period 2000-2020, encompassing a full credit cycle. Specifically, we combine credit registry data with balance sheet information for over 10.9 million bank-firm transactions, representing more than 50% of all corporate loan recipients in Spain during that timeframe. Examining the association between credit standards and corporate-loan default in Spain is particularly relevant given the remarkable expansion of credit experienced prior to the GFC, when NFC credit surged by 357% between 1999 and

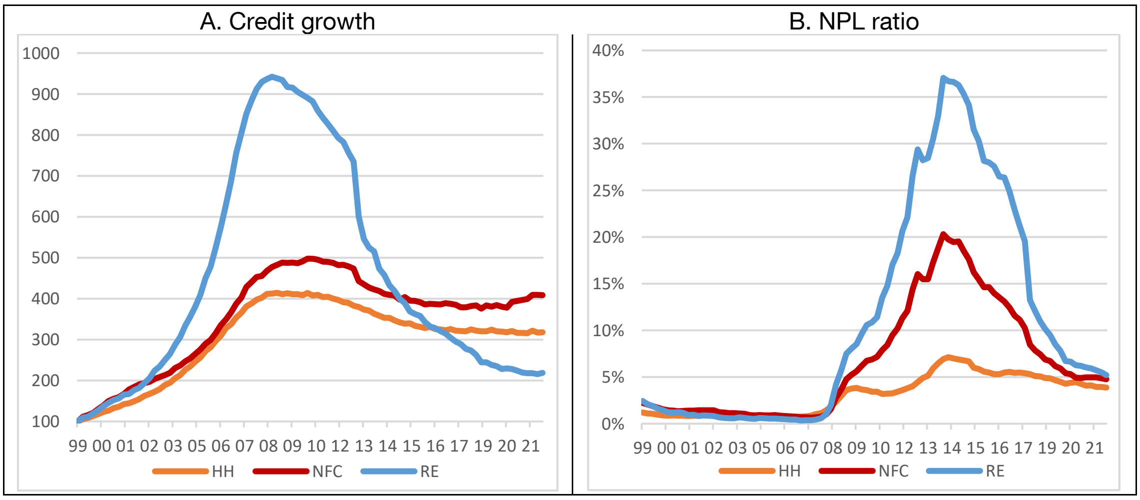
[2] European Union Capital Regulatory Directive (CRD) V (Directive (EU) 2019/878) and Capital Requirements Regulation (CRR) II (Regulation (EU) 2019/876).

[3] This is because, under favourable macro-financial conditions, banks are able to adapt to higher capital requirements by retaining earnings or raising new equity, rather than constraining credit supply (Behn et al., 2022). Additionally, Bedayo and Galán (2024) find that, in the medium term, banks tend to increase lending following an increase in buffer requirements, with only the most capital-constrained banks cutting lending in the very short-run.

2008, a growth rate 20% higher than that observed for HH credit (see Figure 1). Moreover, within NFC credit, certain sectors exhibited exceptionally high growth rates during that period. Notably, credit to construction companies and real estate developers grew by a staggering 812%. The elevated credit growth rates observed before the GFC were strongly correlated with the default rates observed following the onset of the crisis. While the NPL ratio for HH credit peaked at 7% during the crisis, the NPL ratio for NFC credit almost tripled that value (20%), reaching 37% in the RE sector. The relevance of specific sectors within corporate credit in the build-up of systemic vulnerabilities underscores the importance of conducting this analysis by subsectors.

In particular, we divide NFC credit into three subsectors of interest: construction and real estate companies (RE), small and medium-size enterprises in other sectors (SME), and large corporations in other sectors. This approach aligns with the findings of previous studies, which identify the benefits of a separate analysis by size and relevant subsectors. Müller and Verner (2021) show that credit developments in the non-tradable sector (predominantly RE) exhibit a particularly strong correlation with future economic contractions and their severity. SMEs have also been shown to present specific risk characteristics compared to large corporations (Altman and Sabato, 2007; Antunes et al., 2016). The identification of RE as a separate subsector is also in line with the targeted application of macroprudential tools within the Banco de España's macroprudential framework.[4]

Figure 1. Credit growth and NPL in Spain (1999-2021). HH, NFC and RE.



Note: In Panel A, three indexes of credit growth with base 1999Q1=100 are computed. RE includes credit to construction and real estate companies. In Panel B, the ratio of non-performing loans to total loans in each sector is represented.

Our results indicate that lending standards at origination of corporate loans serve as significant predictors of defaults in this credit segment. Specifically, the leverage ratio, represented by the proportion of total debt to total assets, the ratio of total debt to income, and other debt burden measures such as the interest coverage ratio, exhibit positive and significantly significant associations with future defaults. Moreover, we observe that the relationship between credit standards and default risk varies across

[4] See, Banco de España's Circular 5/2021.

the financial cycle and across sectors, being more pronounced for RE companies and SMEs. Additionally, we identify that firm age and the novelty of the bank-firm relationship are crucial characteristics that influence the association between credit standards and default risk.

These findings hold after the inclusion of bank, subsector, location, and year fixed effects, as well as controls for the existence of collateral and a comprehensive set of firm characteristics. The results are also robust across different measures of credit (bank lending or total debt), alternative definitions of defaults, and various model specifications, including those that account for potential selection biases. In terms of policy our findings suggest that the implementation of BBM targeting corporate lending may effectively mitigate the risk of defaults in this credit segment and strengthen financial stability during adverse economic shocks.

Our analysis reveals that limits based on indicators such as the loan-to-assets ratio and the interest coverage ratio can be effective tools to reduce risk across various segments of NFC credit, mirroring the effectiveness of similar limits implemented in the HH sector (Cerutti et al., 2017; Akinci and Olmsted-Rumsey, 2018; Morgan et al., 2019). Moreover, we identify relevant non-linearities and interactions between lending standards, suggesting that combining these measures could enhance their effectiveness. These findings provide strong justification for the use of targeted macroprudential measures in the NFC segment, specifically in the form of limits to lending standards at origination, and offer useful insights for their implementation.

Overall, our study bridges the gap between the corporate default literature and research on the implementation of macroprudential policy. Specifically, we build on the corporate default literature by examining bank loan defaults, rather than firm or corporate bond defaults, which have been the focus of previous studies that primarily rely on market-based information. Additionally, our study stands out from most previous research due to the availability of granular loan-level data and the extensive coverage of our sample, which expands beyond large or listed companies. Unlike previous studies incorporating firm balance sheet information into default estimations, which typically focus on short-term horizons and the current firms' position, we assess future defaults over the entire loan's lifespan based on variables at origination. This approach is crucial for macroprudential purposes, as measures restricting credit standards are implemented at loan origination. Notably, unlike the extensive literature on mortgage default, there is a dearth of studies on the association between credit standards and default in corporate credit.

The document comprises seven sections besides this introduction. Section 2 provides an overview of the existing literature. Section 3 describes the datasets employed and the evolution of lending standards and defaults in Spain during the period under study. Section 4 describes the empirical strategy. Section 5 presents the main results and provides some guidance for policy implementation. A set of robustness exercises and extensions is presented in Section 6. Finally, Section 7 concludes the paper and summarizes the policy implications.

2. Literature review

Jordà et al. (2016) and Rünstler and Vlekke (2017) identify that when credit boom periods are accompanied by house price bubbles the subsequent crises are longer and more severe. This finding, together with the fact that credit and house price growth were two characteristics observed in many countries ahead of the GFC, has motivated empirical research on the association between mortgage lending and financial risk. The availability of micro data on mortgage loans has also facilitated the study of the conditions of the granted mortgages at origination and their relationship with future default. Haughwout et al. (2008), Nier et al. (2019) and Galán and Lamas (2023) are examples of empirical studies identifying significant associations between default risk and lending standards, such as the loan-to-value (LTV) and the loan service-to-income (LSTI) ratios, using micro data at the loan- and borrower-level.

This branch of studies has also identified relevant thresholds for setting BBM in the mortgage market, through calibration exercises, where the relevance of placing simultaneously limits linked to leverage and borrowers' income is highlighted (Kelly and O'Toole, 2018; Gornicka and Valderrama, 2020). In this context, default risk is the main channel through which the deterioration of lending standards at origination leads to systemic vulnerabilities, as identified by Duca et al. (2010) and Schelkle (2018).

This empirical evidence has motivated the wide use of BBM targeting the mortgage sector after the GFC, and facilitated studies identifying the effectiveness of BBM. Claessens et al. (2013), Cerutti et al. (2017) and Akinci and Olmstead-Rumsey (2018) are some examples of studies performing cross-country analyses and identifying that BBM are effective on reducing credit to HH, which would suggest benefits on smoothing credit growth in this sector. In general, these effects have been found to be more relevant than those of capital based measures.

Araujo et al. (2020) conduct a meta-analysis including over 6000 estimates on the impact of macroprudential measures on macroeconomic outcomes, and find that BBM have larger and more significant effects on curbing credit growth. In this regard, Valderrama (2023) provides a comprehensive analysis of the use of macroprudential tool and their effects, showing that BBM have more direct effects on reducing the build-up of cyclical vulnerabilities than capital measures. Certainly, BBM have been shown to complement capital measures, by acting through different channels (see O'Brien and Ryan, 2017; Apergis et al., 2022). Galán (2020) also assesses the impact of BBM and capital measures on the GDP growth distribution, identifying differences in the term structure of their impact over time that justify using both types of measures in order to obtain larger and more persistent benefits on improving growth-at-risk.

The effects of lending standards on default risk of corporate loans have been less explored. In general, the more developed and related area is the one that studies corporate default and its link with debt, based on the Merton model (Merton, 1974). These studies focus on the implicit probability of default (PD) of firms, mainly based on market information on equity, credit default swaps (Chan-Lau, 2006), and bond spreads

(Elton et al., 2001), among others. Other studies have assessed explicit PD using accounting information of firms. That is, financial ratios related to profitability, solvency, liquidity, and other CAMEL variables (Beaver, 1966, Altman, 1968, Blanco et al., 2023). Another group of studies combine market and accounting data (Schumway, 2001; Campbell et al., 2011) to explain firm defaults or implied probabilities of credit default swaps. More recently, macro variables have also been found to be important factors explaining corporate loans default (Figlewski et al., 2012). However, these studies tend to focus on bond defaults, use limited samples of typically large or listed firms, and consider defaults in relatively short horizons.

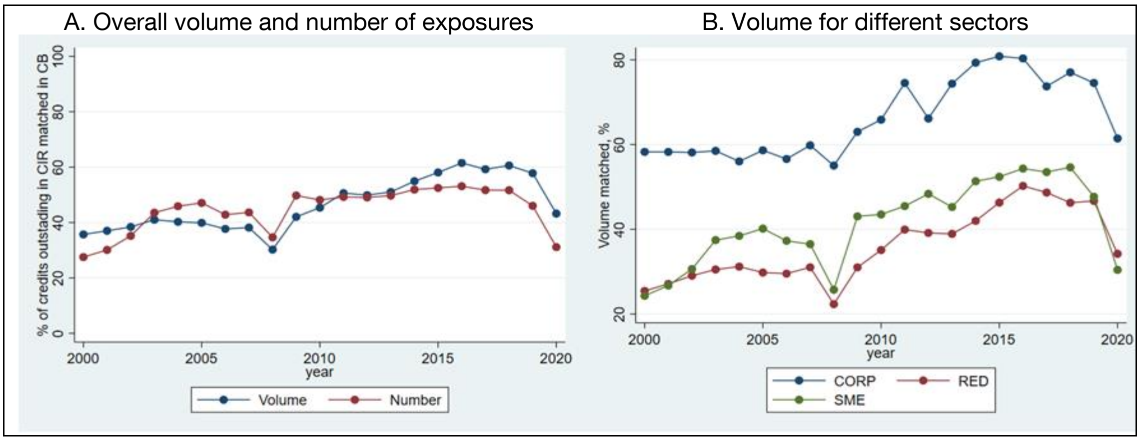
Very few studies have analysed explicitly the relationship between lending standards and credit default in NFC. Some of the closest studies find that indicators related to loan interests expense and cash flows are relevant determinants of NFC default (Goncalvez et al., 2014; Antunes et al., 2016, Blanco et al., 2023). In particular, current values of financial ratios involving relationships between equity, debt, assets and income have been identified to have significant associations with defaults. However, these studies focus on the current situation of firms as reflected by financial statements rather than on credit conditions at the origination of the loan. This is very relevant for macroprudential policy purposes, since limits to credit standards are imposed at the moment of granting a loan, and could have important effects on future defaults, as identified in mortgage credit. From a more general perspective, Brandao-Marques et al. (2022) conduct a cross-country study and find that indicators associated to corporate leverage, interest coverage, and debt-to-income ratios are highly associated with corporate financial vulnerabilities and the riskiness of credit, which motivates a more specific study of their impact on default risk and the appropriateness of measures linked to limits to these ratios.

As to NFC subsectors, Antunes et al. (2016) and Blanco et al. (2023) find that a granular analysis by corporate subsectors provides more accurate PD estimates. In this regard, Altman and Sabato (2007) and Goncalvez et al. (2014) identify that SMEs share special characteristics that make necessary a separate analysis of defaults in these type of firms. Certainly, the build-up of systemic vulnerabilities related to credit growth has been found to be heterogeneous across sectors. Recently, Müller and Verner (2021) show that credit developments in the non-tradable sector have different implications on the real economy than those derived from the tradable sector. In particular, the non-tradable sector, which would encompass not only HH credit but also credit to NFC operating in this sector (i.e. construction and real estate development). These findings as well as the relative high importance of SMEs and real estate activities in Spain motivates to distinguish these sectors in our analysis.

3. Data

Our analysis relies on two confidential databases managed by Banco de España: the Spanish Credit Register (CIR) and Central Balance Sheet Data Office (CB).[5] CIR contains information of all the exposures over €6,000 of credit institutions in Spain, at a monthly frequency.[6] Before 2016 information on individual exposures is not available, instead the total exposure of a lender with a borrower is disaggregated by exposure type, currency and past-due status, as well as in buckets of collateral and maturity.[7] We focus on direct exposures to Spanish non-financial corporations. CB contains annual balance sheet information of Spanish non-financial corporations. In principle, all non-financial corporations should appear in CB, but the actual coverage of the database is far from being complete, as shown in Figure 2 (see also Duro et al., 2022).[8]

Figure 2. Fraction of exposures in the CIR database for which firm balance sheet data is available in CB.



Note: CORP indicates large firms, RED indicates real estate and construction companies, and SME indicates small and middle size companies.

The fraction of CIR exposures covered is around 50%, with a mild upwards trend. There is a dip in 2008, which is likely related to the change in the Spanish General Accounting Plan that year. There is also a noticeable decrease in 2019 and 2020 which is likely due to the Covid-19 pandemic and lags in reporting. The coverage is also larger for large companies than for SMEs and RE firms. While the fraction of exposures matched is substantial, it might lead to the introduction of selection bias, an issue that will be

[5] While the data sets are confidential, access to anonymized samples can be obtained via BE lab (https://www.bde.es/bde/en/areas/analisis-economi/otros/que-es-belab/).
[6] From 2016 the €6,000 threshold has been reduced, but we keep it throughout in order to obtain a uniform sample.
[7] There are 8 collateral buckets: real guarantees covering 100% in the form of money deposits, real state or naval mortgages, rated financial instruments and merchandise; real guarantees covering 100% in other form; partial real guarantees covering more than 50%; public sector guarantees of at least 75%; guarantee form CESCE (Spanish company for exports credit insurance) of at least 75%; guarantee from a Spanish credit institution of at least 75%; guarantee from a foreign credit entity of at least 75%; other guarantees. There are 6 maturity buckets: average maturity lower than 3 months; more than 3 moths less than a year; more than a year less than 3 years; more than 3 years, less than 5 years; more than 5 years; indeterminate maturity. Further details about the CIR database can be found in https://www.boe.es/buscar/act.php?id=BOE-A-1995-22113.
[8] We only consider data that fulfil the quality controls of CB.

considered in Section 6. CB includes information on assets, income and financial expenses which allows us to construct credit standard ratios. The coverage of CB is very limited before 2000, and there is a lag of up to 3 years before the data for a given year can be considered complete, which lead us to focus our analysis in the period 2000-2020. Importantly, our sample includes the GFC and the Spanish real estate crisis, when a period of high credit growth was followed by a large increase in default rates (see Figure 1).

To construct our dataset, we fist aggregate the exposures at the firm-bank group level.[9] Aggregating different exposures of a firm with a given bank is necessary to avoid the appearance of new exposures when the conditions of a contract change. Similarly, aggregating at the bank-group level, as of the final sample date, avoids the appearance of new exposures after bank mergers.[10] When aggregating, the exposure is considered collateralized if any of the aggregated exposures have any form of collateral; similarly, the past due status is defined as the worse of that of the aggregated exposures.

Next, we need to identify new exposures, since our main goal is to assess the relation between credit standards at origination and future default. A new exposure is identified when the firm-bank group relation was not present the previous month, or when the monthly increase in the exposure is larger than 10%.[11] The forwards-in-time past-due status is computed following each firm-bank relation for months after origination, until the month when the relation ceases to appear in the CIR database (when we assume the exposure is extinguished due to repayment or write-off). In this way, we end up with a cross-section of new exposures at the bank-firm-month level, which includes information on future past-due status.

Our main dependent variable of interest is ev*erDefault*, which is a binary variable taking the value one when the exposure is ever past due for more than three months, affecting at least 5% of the exposure. Note that this definition computed as indicated above can lead to the following problem. Suppose that firm *F* takes a loan with Bank *B* in year 1, and a new loan in year 2; suppose further that both loans are not fully paid by year 3, when the second loan is first past due for more than three months. Then our definition would lead to both loans having *everDefault*=1. Since this can lead to an overestimation of defaults, we define an alternative default status variable which assigns default status equal to 1 only to the new exposure closest to the default event; this second variable

[9] While credit institutions in the CIR database are not only banks, but also credit cooperatives, specialised credit institutions, mutual guarantee companies, counter-guarantee companies, the Spanish State Limited Company for Agricultural Guarantees (SAECA), as well as Banco de España and the Deposit guarantee funds, we focus only on banks and credit cooperatives, and through the paper we use "bank" to refer to these institutions for ease of notation and because banks hold the large majority of the exposures.

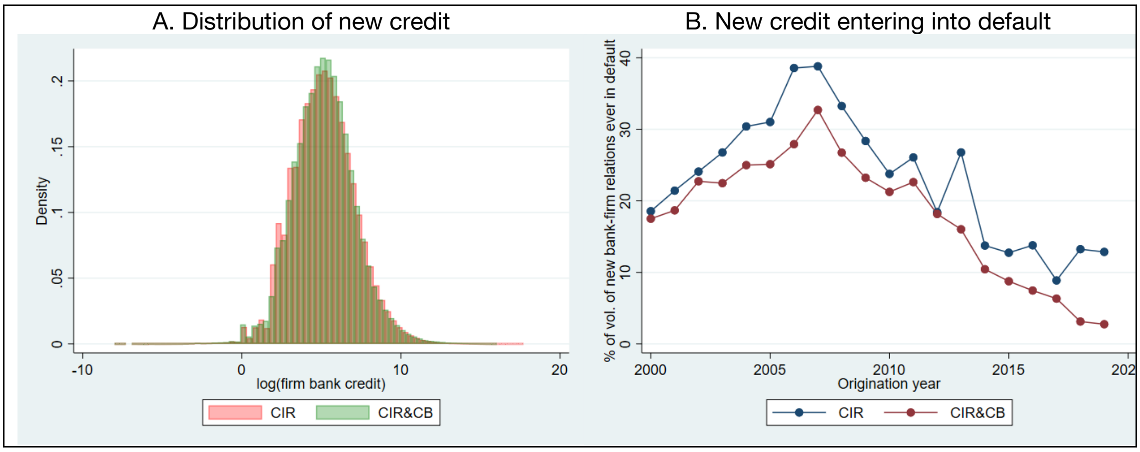
[10] Bank groups are defined based on December 2020 data; in this way, if Bank A and Bank B merged in, say, 2015, they are considered as part of the same group during the complete sample.

[11] The 10% monthly increase threshold to identify new exposures allows us to avoid including increases due to penalties like unpaid interests or measurement error; it also allows us to focus on relatively material increases when the bank needs to assess the creditworthiness of the firm. The 10% increase applies to the used plus available funds, to avoid identifying new exposures when credit lines are drawn (since that would be the result of a firm using the available funds, rather than a new granting of credit by the bank).

can lead to an underestimation of defaults, and considering it in addition to our main variable allows us to check the robustness of our findings, see section 6.

The representativeness of the subsample of new bank exposures for which we have firm balance sheet information is explored in Figure 3. We can see that the distribution of log new exposure sizes is very similar in the two subsamples. The fraction of new exposures that ever enter in default by origination year for the two subsamples is similar, although the subsample with balance sheet information has somewhat lower rates. This difference again raises the spectre of a possible selection bias, and will be explored in Section 6.

Figure 3. Representativeness of the subsample of CIR exposures with firm balance sheet information.



Note: In Panel A, the distribution of log new credit size is compared for the whole sample and the matched subsample. In Panel B, the percentage of new credit volume that enters into default in the two subsets by year of origination is displayed.

3.1. Credit standards and defaults

Once we have a dataset with new bank exposures and firm balance sheet data, we can compute credit standards at origination. Here we focus primarily on two main categories of indicators, one regarding leverage, and another one accounting for income. These categories are standard in the literature of mortgage lending because of its relation to the triggers of defaults (Foote et al., 2008). In particular, in the housing market, the LTV ratio, which is a measure of the loan amount with respect to the value of the collateral acting as a guarantee, is associated to strategic default decisions related to negative equity as well as to refinancing capacity when the borrower faces a liquidity shortfall (Burrows, 1998). Also, indicators of the loan amount and the loan service with respect to the borrowers' income are associated to cash flow issues leading to default (Böheim and Taylor 2000). Both types of indicators at the origination of the loan have been found to be significantly associated to future mortgage defaults (Kelly and O'Toole, 2018; Galán and Lamas, 2023). The wide implementation of BBM in the mortgage market relies on limits to credit standards based on these indicators[12].

[12] See, for example, https://www.esrb.europa.eu/national_policy/other/html/index.en.html

In the case of corporate lending, the most standard measure of leverage would be represented by the debt-to-assets ratio (DTA). In general, the assets of a company are the main loan guarantee in operations with no specific collateral. This measure is also related to the technical definition of corporate default departing from the Merton model (Merton, 1974). As to income-based measures, similar measures to those in the mortgage market can be computed, such as the debt-to-income ratio (DTI), the debt service-to-income ratio (DSTI), and the interest coverage ratio (ICR). These ratios would capture the payment capacity of the firm related to cash flow shocks. The definitions used are the following:

$$DTA = \frac{Outstanding\ bank\ debt + nonbank\ debt}{Total\ assets}$$

$$DTI = \frac{Outstanding\ bank\ debt + nonbank\ debt}{EBITDA}$$

$$DSTI = \frac{Financial\ expenses}{EBITDA}$$

$$ICR = \frac{EBITDA}{Interest\ expenses}$$

The two first ratios (DTA and DTI) use debt as numerator. As debt we will use all the outstanding bank exposures of the firm in the CIR database, plus the non-bank debt reported in CB.[13] Asset data are taken directly from CB. As income measure in DTI and DSTI, we use EBITDA from CB.[14] The numerator in DSTI is financial expenses (available in CB). The interest coverage ratio is computed EBITDA over interest expenses (available in CB). We exclude from the analysis observations with negative assets (this affects less than 0.003% of the observations). Income, however, can meaningfully be negative for some firms and periods, which leads to discontinuities in the ratios.[15] To avoid this problem, we assign to DTI, DSTI and ICR the value 0 when EBITDA becomes negative, and will include a dummy variable for negative income in all the regressions.[16] Since the purpose of our exercise is to identify the effects of credit standards at the origination credit, all balance sheet data is evaluated at the end of the previous year, in order to avoid using information not available when the credit was granted.

[13] An alternative would be to use directly total debt from CB. We prefer to use bank debt from CIR because it is considered to have higher quality (see Duro et al., 2022). We exclude from non-bank debt short-term liabilities without cost, which include suppliers and other commercial creditors.

[14] During the considered period, EBITDA did not have a harmonized accounting definition in Spain. The variable we use as EBITDA proxy is gross economic profit (*resultado económico bruto de la explotación*), see https://www.bde.es/f/webbde/SES/Secciones/Publicaciones/PublicacionesAnuales/CentralBalances/16/Fich/cb16nm.pdf for details (in Spanish).

[15] Note that, for a given level of debt, DTI becomes larger -signalling more indebtedness- as the income becomes smaller; however, if the income becomes negative, DTI becomes smaller (negative).

[16] Inputting the value 0 and adding a dummy variable to observations with negative EBITDA does not affect the estimation of the coefficients of DTI, DSTI and ICR, as can be shown using the Frisch–Waugh–Lovell Theorem. Moreover, in order to avoid outliers having an outsize effect in the regressions, the credit standard indicators are winsorized at the sector-specific 99th percentile, except for the ICR, for which winsorization is performed at the 90th percentile (as for ICR larger values correspond to lower indebtedness, values in the right tail are less relevant for default prediction).

In Table 1 we show descriptive statistics of our default variable and credit standards over the cycle. In general, we observe that corporate loans originated before the GFC and during crisis years present a higher default rate than those originated after the crisis. This is true for the three sectors, but particularly important for companies in the real estate and construction sector, where one-quarter of loans granted before the crisis defaulted. In contrast, loans originated after the crisis present default rates between 3 and 4 times lower than those granted before the crisis. We also observe that this is correlated to credit standards at the origination of loans, which describe a cyclical pattern. During the pre-crisis and crisis years, there was an important deterioration of these standards, while they improved during the recovery years. In particular, the DTA and DTI of firms receiving loans in the years before the crisis were especially high, and again RE firms presented the highest values. Notice that for RE companies and SMEs, the DTA is even larger than 1 for a fraction of firms before the crisis. This is related to two issues.

On the one hand, given that the frequency of the balance sheet data available (yearly) is lower than that of the debt (monthly), in the DTA computation, assets correspond to the value at the end of the previous year, while debt includes bank debt obtained in the current year; therefore, debt is not necessarily smaller or equal to assets, as would be implied by the standard balance sheet identity. On the other hand, these high values indicate very large leverage of these firms during that period, mainly fuelled by the boom of the construction and real estate sector. This could be related to the role of expectations on prices, mainly of real estate assets. Banks might have granted loans to very highly leveraged firms, expecting that the value of their assets would continue to grow at high rates, which would lower the DTA in the mid-term. This is something that has also been documented in the case of house prices and mortgages during the boom period (Galán and Lamas, 2023).[17] During the crisis, these two indicators moderated, indicating a lower leverage of firms. However, the lower earnings faced by firms during the crisis and the increase in the interest rates observed during the first years of the crisis, led to a deterioration of debt burden indicators, such as the DSTI and the ICR. These two indicators improve importantly during the recovery phase. Overall, the cyclical pattern of credit standards suggests that its deterioration at loan origination over the financial cycle could be associated with credit default risk.

[17] Galán and Lamas (2023) identify that Spanish banks granted a high share of mortgages with a loan-to-price ratio greater than 1, in the expectation of house prices to grow in the upcoming years and the collateral value to cover the higher loan amount granted at the origination.

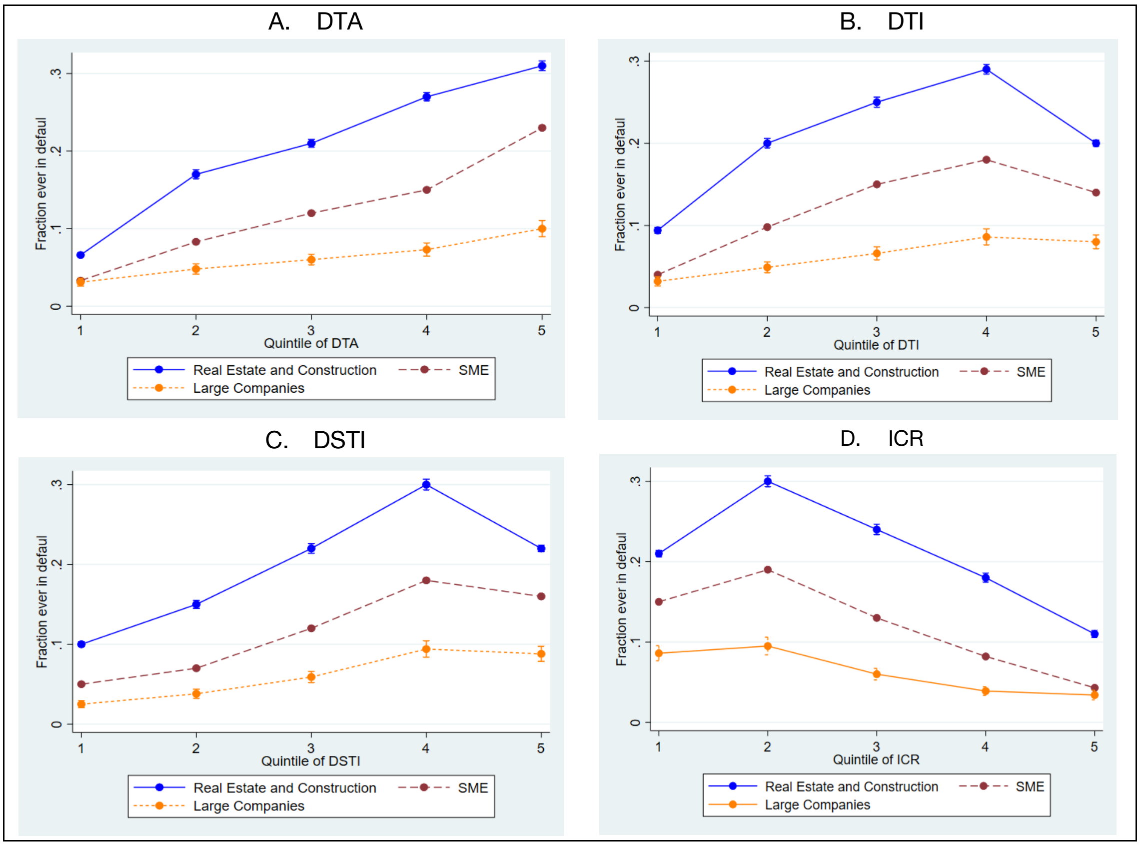
Table 1. Summary statistics. Default frequency and credit standards over the cycle by sector.

	Real estate and construction					**SME**					**Large companies**				
Stats	Mean	p50	p25	p75	N (million)	Mean	p50	p25	p75	N (million)	Mean	p50	p25	p75	N (million)
Pre-crisis: year<2009															
everDef	0.25	0.00	0.00	1.00	0.65	0.16	0.00	0.00	0.00	5.04	0.11	0.00	0.00	0.00	0.14
DTA	1.20	1.06	0.70	1.42	0.53	1.04	0.99	0.68	1.28	4.44	0.52	0.45	0.22	0.75	0.13
DTI	18.33	8.41	2.72	17.97	0.53	13.15	7.79	3.38	14.97	4.43	9.49	3.67	1.10	8.71	0.13
DSTI	0.28	0.15	0.01	0.37	0.59	0.29	0.18	0.05	0.39	4.86	0.25	0.10	0.02	0.24	0.14
ICR	8.15	3.54	1.55	9.22	0.53	7.53	3.74	1.82	8.71	4.58	26.99	7.66	2.93	23.85	0.13
Crisis: 2008<year<2014															
everDef	0.22	0.00	0.00	0.00	0.15	0.14	0.00	0.00	0.00	2.23	0.08	0.00	0.00	0.00	0.12
DTA	0.53	0.41	0.19	0.67	0.12	0.46	0.38	0.19	0.60	1.63	0.39	0.34	0.15	0.53	0.11
DTI	12.62	3.79	0.00	11.07	0.12	7.59	3.61	0.51	8.08	1.63	8.80	2.83	0.50	7.17	0.11
DSTI	0.33	0.12	0.00	0.43	0.15	0.30	0.16	0.00	0.42	2.17	0.28	0.08	0.01	0.27	0.12
ICR	6.70	2.18	0.17	6.45	0.13	6.89	2.81	1.18	7.36	2.01	26.06	5.36	1.58	21.25	0.11
Post-crisis: year>2013															
everDef	0.06	0.00	0.00	0.00	0.25	0.05	0.00	0.00	0.00	4.00	0.03	0.00	0.00	0.00	0.26
DTA	0.48	0.33	0.13	0.59	0.19	0.46	0.38	0.18	0.60	3.01	0.37	0.32	0.14	0.52	0.23
DTI	12.41	3.32	0.10	10.44	0.19	8.10	3.94	0.91	9.00	3.00	8.81	2.67	0.53	7.34	0.23
DSTI	0.21	0.05	0.00	0.23	0.23	0.22	0.10	0.01	0.30	3.91	0.21	0.04	0.00	0.18	0.25
ICR	11.07	4.58	1.16	17.24	0.20	10.27	4.90	1.94	15.04	3.55	38.12	9.62	2.55	46.87	0.23

Note: Values for DTA, DTI and DSTI are windsorized at the percentile 99, while ICR is at percentile 90. When the income is negative, DTI, DSTI and ICR are assigned the value zero. Higher values of DTA, DTI and DSTI indicate more deteriorated standards, while the opposite occurs for ICR, for which higher values correspond to lower debt burden.

As a first preliminary analysis of the relation between credit standards and defaults, we portray in Figure 4 the unconditional default frequency for the quintiles of the credit standards in the three corporate sectors considered. Figure 4 shows that there is a high correlation between the standards at origination and default frequency. The fraction of exposures entering into default increases between 2 and 4 times when moving from the lowest to the highest quantile of indebtedness. The association is larger for SMEs and RE firms, and is monotonic for DTA. This indicates that the higher the value of DTA at the origination of bank loans the higher the default frequency observed. The relationship between income-based credit standards and defaults exhibits some non-linearity. In particular, a higher proportion of debt, interests or debt service with respect to income is positively correlated to defaults until the fourth quintile, but it tends to stabilize or even decrease for the highest quintile. In all cases, SMEs and RE companies show the highest default frequency across quintiles, while large firms present the lowest default rates. This suggests that small companies and those operating in the real estate sector, which traditionally have accumulated important systemic vulnerabilities in Spain, are the most affected by negative shocks. This would support performing a separate analysis of the relationship between lending standards and defaults for this type of firms.

Figure 4. Average default rate at different quantiles of credit standards at origination.



Note: Higher values of DTA, DTI and DSTI indicate more deteriorated standards, while the opposite occurs for ICR, for which higher values correspond to lower debt burden. Error bars correspond to two standard deviations.

4. Empirical strategy

Although we can observe a relevant correlation between more relaxed credit standards at origination and future defaults unconditionally, the association a priori is not completely clear. On the one hand, more leveraged firms and those with a larger financial burden with respect to their income would be in a more fragile position to face negative shocks, and therefore would present higher default risk. On the other hand, banks could grant credit to more indebted firms only when they are financially strong based on some other firm characteristics, which would weaken the association between credit standards and default risk. Thus, in order to assess the relation between credit standards at origination and defaults while controlling by firm and loan characteristics, the bank granting the loan, and other macrofinancial conditions at the time of origination of the loan, we estimate the following linear probability model:

$$everDefault_{ibt} = \alpha + \beta L.S._{it} + \sum_{j=1}^{J} \delta_j X_{j,i,b,t} + B_b + Sec_i + Loc_i + T_t + \varepsilon_{ibt}, \qquad (1)$$

where *everDefault*$_{ibt}$ indicates whether a credit granted to firm *i* by bank *b* at time *t* ever entered in default as defined above (i.e. being in arrears for more than 3 months). This is regressed on our credit standards of interest ($L.S._{it}$), firm and loan controls (X_{ibt}), as well as bank (B_b), sector (Sec_i), location (Loc_i) and time (T_t) fixed effects. Firm and loan controls include age (years since founding), size (log total assets), liquidity (current assets/current liabilities), profitability (ROE) and a dummy for whether or not the loan is collateralized. Industry fixed effects are at the 2 digit NACE code, location fixed effects are at the postal code level, and time fixed effects are at year level. An important variable missing in the CIR database (before 2016) is loan interest rate; thus, as a proxy for loan interest rate we use a firm-level variable, constructed as the ratio of interest payments to total debt (available in CB). All time-varying controls are evaluated at the end of the year prior to loan origination. We cluster standard errors at the firm level.

Following the discussion above, all the regressions are estimated by splitting the sample into the three sectors of main interest. That is, RE companies, SMEs from other sectors, and the rest of corporate firms, which would include basically large companies of sectors other than construction and real estate.[18]

5. Results

We present the estimation results based on Equation (1) by the corporate subsectors described above. We initially include only one lending standards indicator at a time and start by adding different controls until we saturate the specification as much as possible. In tables 1 to 3, we present the results for models including our leverage indicator in the three subsectors.

In general, we find that the DTA ratio at the origination of a corporate loan is highly significant in explaining default risk. It is positively associated to default, indicating that the higher the leverage of a firm at the moment of being granted with a new loan the higher the probability of incurring in the default of the loan. This result is robust across all the specifications and sectors. That is, after controlling by relevant observed characteristics of the firm as well as by unobserved characteristics related to the subsector where the firm operates, the location of the firm, the bank granting the loan, and macro conditions at the time of origination. Although the significance of the DTA is robust across the three sectors analysed, we identify that there are some differences between them. In particular, the estimated coefficients in the more saturated specifications (model 9) become statistically different between SMEs and the rest of firms. That is, SMEs present larger elasticities to equivalent changes in the DTA ratio. While for large firms an increase of 1pp in the DTA would increase the probability of default in about 0.05 pp, this increase almost doubles for SMEs. This would suggest that SMEs present higher risk in credit operations derived from its leverage, thereby, implying that the DTA ratio would be a more relevant indicator of default risk for this type of firms.

[18] In Section 6 we present several robustness exercises including the estimation of logit and probit models.

Table 2. Estimation results for Debt-to-Assets ratio. RE firms.

Constr. & Real state	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DTA	0.063***	0.090***	0.093***	0.10***	0.079***	0.079***	0.076***	0.074***
	(0.0012)	(0.0015)	(0.0015)	(0.0017)	(0.0016)	(0.0016)	(0.0016)	(0.0015)
Log(Assets)		0.047***	0.053***	0.055***	0.047***	0.048***	0.047***	0.048***
		(0.0013)	(0.0012)	(0.0013)	(0.0012)	(0.0012)	(0.0012)	(0.0011)
Liquidity		-0.0011***	-0.0011***	-0.0011***	-0.00080***	-0.00077***	-0.00055***	-0.00048***
		(0.000041)	(0.000041)	(0.000047)	(0.000044)	(0.000043)	(0.000043)	(0.000043)
ROE		0.0044***	0.0044***	0.0036***	0.0019*	0.0018*	0.00084	0.0011
		(0.0010)	(0.0010)	(0.0011)	(0.0010)	(0.0010)	(0.0010)	(0.00099)
Guarantee		0.090***	0.085***	0.090***	0.092***	0.092***	0.11***	0.10***
		(0.0025)	(0.0024)	(0.0025)	(0.0024)	(0.0024)	(0.0024)	(0.0023)
Firm Age		-0.0047***	-0.0044***	-0.0046***	-0.0029***	-0.0029***	-0.0028***	-0.0027***
		(0.00022)	(0.00021)	(0.00023)	(0.00022)	(0.00022)	(0.00021)	(0.00019)
Group			-0.17***	-0.18***	-0.12***	-0.11***	-0.11***	-0.096***
			(0.011)	(0.012)	(0.011)	(0.011)	(0.011)	(0.0091)
Int. rate				0.0022***	0.0023***	0.0022***	0.0017***	0.0014***
(firm level)				(0.00015)	(0.00015)	(0.00015)	(0.00015)	(0.00013)
Observations	837,390	809,859	809,859	749,620	749,620	749,620	749,620	748,991
R^2_A	0.021	0.074	0.079	0.078	0.11	0.11	0.12	0.17
Year FE	NO	NO	NO	NO	YES	YES	YES	YES
Bank FE	NO	NO	NO	NO	NO	YES	YES	YES
Sector FE	NO	NO	NO	NO	NO	NO	YES	YES
ZIP FE	NO	NO	NO	NO	NO	NO	NO	YES

Note: Liquidity is defined as current assets/current liabilities, Guarantee is a dummy taking the value 1 if the bank-firm relation has some form of collateral, Firm Age is in years, Group is a dummy taking the value 1 if the firm is part of a group, Int. rate (firm level) is defined as firm interest expenses over total debt, sector fixed effects are at the 2-digit NACE code. Robust standard errors, clustered by firm, in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Regarding other characteristics of firms, our results are, in general, in line with previous studies on corporate default drivers. In particular, larger firms in terms of assets, with lower liquidity, and younger at the moment of the loan origination present higher default risk. Although, at a first glance the results on size and profitability seem counterintuitive, previous studies have found similar associations (Altman and Sabato, 2007). The reasons behind these findings are usually attributed to poorer screening that banks perform to larger and more profitable firms within a common sector. Nonetheless, within large NFC, results regarding profitability are the opposite, suggesting that within this type of firms, the more profitable companies are less risky (see Table 3). Something similar occurs with loans with guarantees, which are found to be riskier than other similar loans. Jimenez and Saurina (2004) attribute this also to softer loan approval conditions that banks tend to follow in credit operations with collateral. Finally, we find that our firm-level proxy for the interest rate of the loan operations is positively associated to defaults, signalling the higher risk of these loans at the origination. This indicates that banks partially anticipate the higher risk of some firms and demand higher interest rate to grant them credit.

Table 3. Estimation results for Debt-to-Assets ratio. SMEs.

SME	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DTA	0.097***	0.11***	0.11***	0.12***	0.11***	0.11***	0.11***	0.11***
	(0.00067)	(0.00082)	(0.00081)	(0.00096)	(0.0010)	(0.0010)	(0.0010)	(0.00098)
Log(Assets)		0.027***	0.030***	0.033***	0.031***	0.031***	0.033***	0.034***
		(0.00041)	(0.00042)	(0.00047)	(0.00046)	(0.00046)	(0.00047)	(0.00046)
Liquidity		-0.0033***	-0.0033***	-0.0030***	-0.0027***	-0.0026***	-0.0023***	-0.0025***
		(0.00012)	(0.00012)	(0.00016)	(0.00015)	(0.00015)	(0.00015)	(0.00015)
ROE		-0.0046***	-0.0044***	-0.0051***	-0.0038***	-0.0038***	-0.0037***	-0.0037***
		(0.00037)	(0.00037)	(0.00040)	(0.00040)	(0.00040)	(0.00039)	(0.00039)
Guarantee		0.068***	0.067***	0.071***	0.069***	0.068***	0.068***	0.066***
		(0.0010)	(0.0010)	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0010)
Firm Age		-0.0021***	-0.0020***	-0.0021***	-0.0016***	-0.0016***	-0.0016***	-0.0015***
		(0.000058)	(0.000057)	(0.000062)	(0.000062)	(0.000062)	(0.000063)	(0.000062)
Group			-0.091***	-0.092***	-0.068***	-0.067***	-0.066***	-0.064***
			(0.0023)	(0.0025)	(0.0024)	(0.0024)	(0.0024)	(0.0023)
Int. rate				0.0020***	0.0017***	0.0016***	0.0016***	0.0015***
(firm level)				(0.000042)	(0.000042)	(0.000042)	(0.000042)	(0.000041)
Observations	9,044,191	8,728,487	8,728,487	7,972,687	7,972,687	7,972,687	7,972,687	7,972,152
R^2_A	0.032	0.052	0.054	0.054	0.067	0.071	0.074	0.093
Year FE	NO	NO	NO	NO	YES	YES	YES	YES
Bank FE	NO	NO	NO	NO	NO	YES	YES	YES
Sector FE	NO	NO	NO	NO	NO	NO	YES	YES
ZIP FE	NO	NO	NO	NO	NO	NO	NO	YES

Note: Liquidity is defined as current assets/current liabilities, Guarantee is a dummy taking the value 1 if the bank-firm relation has some form of collateral, Firm Age is in years, Group is a dummy taking the value 1 if the firm is part of a group, Int. rate (firm level) is defined as firm interest expenses over total debt, sector fixed effects are at the 2-digit NACE code. Robust standard errors, clustered by firm, under variable coefficients. *** p<0.01, ** p<0.05, * p<0.1.

Table 4. Estimation results for Debt-to-Assets ratio. Large companies.

Large	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DTA	0.067***	0.073***	0.063***	0.067***	0.060***	0.063***	0.061***	0.045***
	(0.0061)	(0.0067)	(0.0066)	(0.0073)	(0.0070)	(0.0070)	(0.0070)	(0.0053)
Log(Assets)		0.0078***	0.0088***	0.0090***	0.0072***	0.0079***	0.0091***	0.0081***
		(0.0011)	(0.0011)	(0.0012)	(0.0011)	(0.0012)	(0.0012)	(0.0012)
Liquidity		-0.0043***	-0.0045***	-0.0052***	-0.0041***	-0.0041***	-0.0046***	-0.0038***
		(0.00083)	(0.00085)	(0.00095)	(0.00091)	(0.00092)	(0.00093)	(0.00079)
ROE		-0.0069***	-0.0065***	-0.0072***	-0.0070***	-0.0072***	-0.0072***	-0.0051***
		(0.0021)	(0.0021)	(0.0022)	(0.0022)	(0.0022)	(0.0020)	(0.0017)
Guarantee		0.081***	0.078***	0.079***	0.079***	0.077***	0.075***	0.062***
		(0.0070)	(0.0069)	(0.0070)	(0.0069)	(0.0069)	(0.0069)	(0.0055)
Firm Age		0.000041	-1.0e-05	0.000012	0.00013	0.00017	0.000080	0.00022
		(0.00015)	(0.00015)	(0.00015)	(0.00015)	(0.00015)	(0.00015)	(0.00015)
Group			-0.040***	-0.041***	-0.0045	-0.0048	-0.0037	-0.0024
			(0.0042)	(0.0044)	(0.0058)	(0.0058)	(0.0058)	(0.0047)
Int. rate				0.0011***	0.00081***	0.00082***	0.00068***	0.00027**
(firm level)				(0.00018)	(0.00018)	(0.00018)	(0.00018)	(0.00013)
Observations	473,158	456,268	456,268	430,754	430,754	430,754	430,754	430,567
R^2_A	0.0092	0.023	0.029	0.029	0.042	0.045	0.060	0.19
Year FE	NO	NO	NO	NO	YES	YES	YES	YES
Bank FE	NO	NO	NO	NO	NO	YES	YES	YES
Sector FE	NO	NO	NO	NO	NO	NO	YES	YES
ZIP FE	NO	NO	NO	NO	NO	NO	NO	YES

Note: Liquidity is defined as current assets/current liabilities, Guarantee is a dummy taking the value 1 if the bank-firm relation has some form of collateral, Firm Age is in years, Group is a dummy taking the value 1 if the firm is part of a group, Int. rate (firm level) is defined as firm interest expenses over total debt, sector fixed effects are at the 2-digit NACE code. Robust standard errors, clustered by firm, under variable coefficients. *** p<0.01, ** p<0.05, * p<0.1.

Regarding our income-based lending standard measures, we also find strong positive associations to default risk. In Table 5, we show for the three NFC sectors, the estimation results using our most saturated specifications. Although, not presented here, we also perform the same control variables increasing estimations showed in the case of DTA, and find similar robustness in terms of significance of our variables of interest when adding more controls. In general, a higher debt burden in terms of firm profits is significantly and positively associated to a higher default probability across sectors.[19] Nonetheless, the association between these credit standards and default risk is significantly lower for large companies compared to RE firms and SMEs. Even, in the case of our indicator of total debt to income, the positive estimated relation is not statistically significant for these companies. This may suggest that although credit standards in relation to profits provide useful information of risk in all type of firms, large companies are less sensitive to changes in debt burden and to the size of debt with respect to profits. This implies that for these firms, higher values of credit standards are needed to reach an equivalent risk propensity.

Table 5. Estimation results for income-based lending standards.

Sector:	Construction and Real State			SME			Large Companies		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
DTI	0.00037***			0.0011***			0.000063		
	(0.000024)			(0.000019)			(0.000047)		
Ind(DTI<0)	0.011***			0.028***			0.0053		
	(0.0023)			(0.00090)			(0.0039)		
DSTI		0.049***			0.084***			0.0070***	
		(0.0019)			(0.00095)			(0.0021)	
Ind(DSTI<0)		0.023***			0.041***			0.0066*	
		(0.0023)			(0.00085)			(0.0039)	
ICR			-0.0038***			-0.0040***			-0.00012***
			(0.000092)			(0.000034)			(0.000026)
Ind(ICR<0)			-0.034***			-0.023***			0.000094
			(0.0025)			(0.00092)			(0.0039)
Log(Assets)	0.034***	0.032***	0.033***	0.022***	0.021***	0.022***	0.0065***	0.0060***	0.0061***
	(0.0010)	(0.00094)	(0.0010)	(0.00044)	(0.00040)	(0.00043)	(0.0012)	(0.0011)	(0.0012)
Liquidity	-0.00071***	-0.00070***	-0.00065***	-0.0072***	-0.0061***	-0.0044***	-0.0058***	-0.0055***	-0.0053***
	(0.000044)	(0.000041)	(0.000050)	(0.00016)	(0.00015)	(0.00016)	(0.00079)	(0.00077)	(0.00090)
ROE	0.0046***	0.0057***	0.0072***	0.0025***	0.0044***	0.0056***	-0.0048***	-0.0041**	-0.0028*
	(0.0010)	(0.00094)	(0.0010)	(0.00040)	(0.00036)	(0.00038)	(0.0017)	(0.0016)	(0.0017)
Guarantee	0.11***	0.11***	0.11***	0.075***	0.073***	0.071***	0.065***	0.065***	0.064***
	(0.0022)	(0.0021)	(0.0023)	(0.0011)	(0.00100)	(0.0010)	(0.0055)	(0.0054)	(0.0055)
Firm Age	-0.0028***	-0.0028***	-0.0028***	-0.0020***	-0.0020***	-0.0020***	0.00018	0.00018	0.00021
	(0.00019)	(0.00018)	(0.00019)	(0.000063)	(0.000059)	(0.000060)	(0.00015)	(0.00015)	(0.00015)
Group	-0.057***	-0.053***	-0.053***	-0.043***	-0.038***	-0.033***	-0.0038	-0.00068	0.00080
	(0.0091)	(0.0089)	(0.0090)	(0.0023)	(0.0022)	(0.0023)	(0.0047)	(0.0034)	(0.0035)
Int. rate	0.0014***	0.00076***	0.00037***	0.0016***	0.00063***	0.00055***	0.000048	1.3e-06	-0.000073
(firm level)	(0.00013)	(0.00012)	(0.00012)	(0.000042)	(0.000035)	(0.000035)	(0.00013)	(0.00012)	(0.00012)
Observations	748,165	855,303	783,602	7,970,317	9,590,334	9,130,902	430,459	465,572	441,359
R^2_A	0.16	0.16	0.17	0.075	0.079	0.084	0.19	0.19	0.19
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Sector FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
ZIP FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: Ind(DTI<0), Ind(DSTI<0) and Ind(ICR<0) are dummy variables taking the value 1 when income (EBITDA) is negative. Robust standard errors, clustered by firm, under variable coefficients. *** p<0.01, ** p<0.05, * p<0.1.

Similarly, to our findings with the DTA ratio, SMEs also present the largest elasticities of these indicators to default probability. As discussed in Section 3, we include in the estimation of models with credit standards based on profits, an indicator variable that identifies firms exhibiting negative income (EBITDA), which, if not differentiated, may alter the identification of the effects. For DTI and DSTI the indicator variable for negative income has positive sign (and is statistically significant, except for DTI in large companies), indicating a higher association with default for these firms. In the case of the ICR, the coefficients for negative income are negative for SMEs and RE firms,

[19] Note that, while lager values of DTA, DTI and DSTI indicate more deteriorated credit standards, the opposite is true for ICR, which explains the negative signs for ICR in Table 5.

indicating that defaults for these firms are lower than what the model would predict with ICR=0. This might be due to the fact that firms with negative income at origination only obtain new credit from stablished bank relations, for which unobserved factors are more important.

5.1. Effects over the cycle

Our sample covers a whole financial cycle in Spain, from which the first years (2000-2008) represented an expansionary period characterized by strong credit growth and relaxation of credit standards. This was followed by a very deep crisis (2009-2013), marked by a sharp increase in the bank NPL ratio as a consequence of a large number of defaults, and tighter credit conditions (see Figure 1). The subsequent period (2014-2020) were recovery years, when NPL ratios quickly decreased and corporate credit started to grow moderately again. Thus, it is important to analyse whether the link between credit standards and future defaults is dependent on the phase of the cycle when credit was originated. Table 6 analyses this question for the different sectors, using our preferred specification (the one with full fixed effects and controls), by interacting the credit standard measures at origination with period dummy variables, as indicated by the following equation:

$$everDefault_{ibt} = \beta_{pre} L.S._{it}\,\text{Ind}(\text{t} < 2009) + \beta_{crisis} L.S._{it}\,\text{Ind}(2009 \leq \text{t} < 2014) + \beta_{post} L.S._{it}\,\text{Ind}(\text{t} > 2013) + \sum_{j=1}^{J} \delta_j X_{j,i,b,t} + B_b + Sec_i + Loc_i + T_t + \sum_{\tau=2000}^{2020} E_{i,b,t,\tau} + \varepsilon_{ibt}, \quad (2)$$

where $E_{i,b,t,\tau}$ are dummy variables taking the value 1 if the credit from bank *b* to firm *i* originated at time *t* is still active at year τ and have not defaulted. This aims to capture macroeconomic factors taking place after the origination year.

Table 6. Effect of lending standards over the cycle.

	Construction and Real State			SME			Large Companies		
L. S.:	DTA	DTI	ICR	DTA	DTI	ICR	DTA	DTI	ICR
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
pre-crisis * L. S.	0.065***	0.00034***	-0.0041***	0.11***	0.00096***	-0.0050***	0.052***	0.000059	-0.00026***
	(0.0014)	(0.000028)	(0.0001)	(0.0010)	(0.000024)	(0.00005)	(0.0090)	(0.000088)	(0.00006)
crisis * L. S.	0.12***	0.00056***	-0.0044***	0.16***	0.0013***	-0.0051***	0.053***	0.00014	-0.00028***
	(0.0066)	(0.000059)	(0.0002)	(0.0021)	(0.000042)	(0.00006)	(0.0076)	(0.000093)	(0.00005)
post-crisis * L. S.	0.058***	0.000021	-0.00053***	0.097***	0.00074***	-0.0018***	0.031***	0.000014	-0.000045*
	(0.0029)	(0.000031)	(0.0001)	(0.0014)	(0.000026)	(0.00004)	(0.0055)	(0.000053)	(0.00003)
Observations	748,991	748,165	783,602	7,972,152	7,970,317	9,130,902	430,567	430,459	441,359
R^2_A	0.27	0.26	0.27	0.17	0.15	0.16	0.23	0.23	0.23
Firm, collateral controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Orig. year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Bank, sector, Zip FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
cycle * Ind(L. S. <0)		YES	YES		YES	YES		YES	YES
Exist. year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: *pre-crisis*, *crisis* and *post-crisis* are dummy variables taking the value 1 for origination years from 2000 to 2008, from 2009 to 2013 and from 2014 to 2020, respectively. Exist. year FE are a set of dummy variables, one for each year from 2000 to 2020, which take the value 1 if the credit is active in the corresponding year, and has not defaulted earlier. For DTI and ICR (columns 2, 3, 5, 6, 8 and 9) a dummy of negative standard is interacted with pre-crisis, crisis and post-crisis dummies (cycle). Robust standard errors, clustered by firm, under variable coefficients. *** p<0.01, ** p<0.05, * p<0.1.

In Table 6 we show the results from this model. We observe that the effect of the lending standards is stronger for credit originated during crisis years. This is especially evident for DTA in SMEs and RE companies. This result is interesting since the pre-crisis period was characterized by a credit boom and relaxed credit standards, so one could expect that the standards would be more informative for credit originated before the crisis. However, the fact that pre-crisis DTA is less associated with default risk, might be related to the asset overvaluation presented in the boom period. As argued for the case of household credit (see Galán and Lamas. 2023), overvaluation had affected more the assets of companies in the real estate and construction sector, which had a starring role during the boom in Spain. In contrast, lending standards of loans granted during the post-crisis period show weaker effects on default risk, although still highly statistically significant (except DTI for RE and large companies). This is reasonable since during this period credit conditions have not been relaxed while the financial situation of firms has improved.[20] The relation between ICR and default is similar for credit originated before the crisis and during the crisis, but is markedly lower for credit originated after the crisis. This fact might result from the direct effect that policy interest rate has in the ICR. Form a policy perspective, combining limits on DTA and ICR might lead to policies that are more robust across the financial cycle. Results are robust to regressions run independently after splitting the sample by origination year in the pre-crisis, crisis and post-crisis periods.

5.2. Nonlinearities and interactions

Finally, we explore potential non-linearities regarding the effects of corporate lending standards on default risk as it is suggested by the unconditional relation showed in Figure 4. We perform this exercise by adding quadratic terms of the ratios analysed above to Equation (1). In Table 7, we report the results for the three sectors. In all the cases, except in DTA for large companies, we find a statistically significant coefficient of the quadratic terms of our credit standard measures, indicating that a deterioration of these values implies decreasing marginal effects on the probability of default.

In order to examine the economic significance of the identified effects and to get insights for the practical implementation of macroprudential tools based on these indicators, we compute the predictive margins at relevant values of these ratios in the three sectors.[21] In Figure 5, we plot the result for DTA, DTI and ICR evaluated at relevant values of these standards . In general, we observe that default probabilities are strongly associated to the value of the different credit standards. For instance, in RE companies, the probability of default is over 2.6 higher for firms with DTA of 0.95 than for firms with DTA=0.1. In fact, real estate companies with a DTA of 0.95 have default probabilities above 20%. The association is also strong, although of smaller magnitude for DTI and ICR.

[20] It is also possible that these coefficients are affected by the shorter time that has passed for these loans since their origination, as these loans were originated between 0 and 6 years before the sample limit, which is comparable to the average maturity of corporate loans (6 years).

[21] The predictive margin is computed by setting the value of the variables of interest in the estimated model and jointly averaging over the values of all the other variables.

Table 7. Non-linear effects of lending standards.

Sector:	Construction and Real State			SME			Large		
L.S.:	DTA	DTI	ICR	DTA	DTI	ICR	DTA	DTI	ICR
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
L. S.	0.19***	0.0020***	-0.012***	0.23***	0.0048***	-0.016***	0.053***	0.00091***	-0.00071***
	(0.0033)	(0.000079)	(0.0004)	(0.0022)	(0.000059)	(0.0002)	(0.012)	(0.00018)	(0.0001)
L. S .^2	-0.022***	-7.0e-06***	0.00022***	-0.039***	-0.000036***	0.00034***	-0.0061	-5.4e-06***	0.0000037***
	(0.00052)	(3.1e-07)	(0.00001)	(0.00061)	(5.0e-07)	(0.000004)	(0.0080)	(1.0e-06)	(7e-07)
Ind(L. S. < 0)		0.031***	-0.063***		0.058***	-0.063***		0.011***	-0.0056
		(0.0024)	(0.0030)		(0.00098)	(0.0011)		(0.0042)	(0.0041)
Log(Assets)	0.048***	0.033***	0.033***	0.033***	0.022***	0.023***	0.0080***	0.0065***	0.0060***
	(0.0011)	(0.0010)	(0.0010)	(0.00046)	(0.00044)	(0.00043)	(0.0012)	(0.0012)	(0.0012)
Liquidity	-0.00021***	-0.00069***	-0.00069***	-0.00050***	-0.0059***	-0.0046***	-0.0037***	-0.0054***	-0.0050***
	(0.000044)	(0.000044)	(0.000050)	(0.00015)	(0.00016)	(0.00016)	(0.00079)	(0.00079)	(0.00090)
ROE	0.00011	0.0061***	0.0084***	-0.0032***	0.0051***	0.0076***	-0.0051***	-0.0037**	-0.0021
	(0.00098)	(0.0010)	(0.0010)	(0.00039)	(0.00040)	(0.00038)	(0.0017)	(0.0017)	(0.0017)
Guarantee	0.099***	0.11***	0.11***	0.063***	0.073***	0.070***	0.062***	0.064***	0.063***
	(0.0022)	(0.0023)	(0.0023)	(0.0010)	(0.0011)	(0.0010)	(0.0055)	(0.0055)	(0.0054)
Firm Age	-0.0021***	-0.0027***	-0.0027***	-0.0012***	-0.0019***	-0.0020***	0.00022	0.00019	0.00023
	(0.00019)	(0.00019)	(0.00019)	(0.000062)	(0.000063)	(0.000060)	(0.00015)	(0.00015)	(0.00015)
Group	-0.099***	-0.057***	-0.052***	-0.059***	-0.041***	-0.034***	-0.0023	-0.0034	0.0011
	(0.0091)	(0.0091)	(0.0090)	(0.0023)	(0.0023)	(0.0022)	(0.0047)	(0.0047)	(0.0035)
Int. rate	0.0016***	0.0016***	0.00027**	0.0017***	0.0019***	0.00036***	0.00028**	0.00011	-0.000081
(firm level)	(0.00013)	(0.00013)	(0.00012)	(0.000041)	(0.000042)	(0.000035)	(0.00013)	(0.00013)	(0.00012)
Observations	748,991	748,165	783,602	7,972,152	7,970,317	9,130,902	430,567	430,459	441,359
R^2_A	0.18	0.16	0.17	0.098	0.080	0.090	0.19	0.19	0.19
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Sector FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
ZIP FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: Ind(L.S<0) is a dummy variable taking the value 1 when income (EBITDA) is negative in the case of DTI and ICR. Robust standard errors, clustered by firm, under variable coefficients. *** p<0.01, ** p<0.05, * p<0.1.

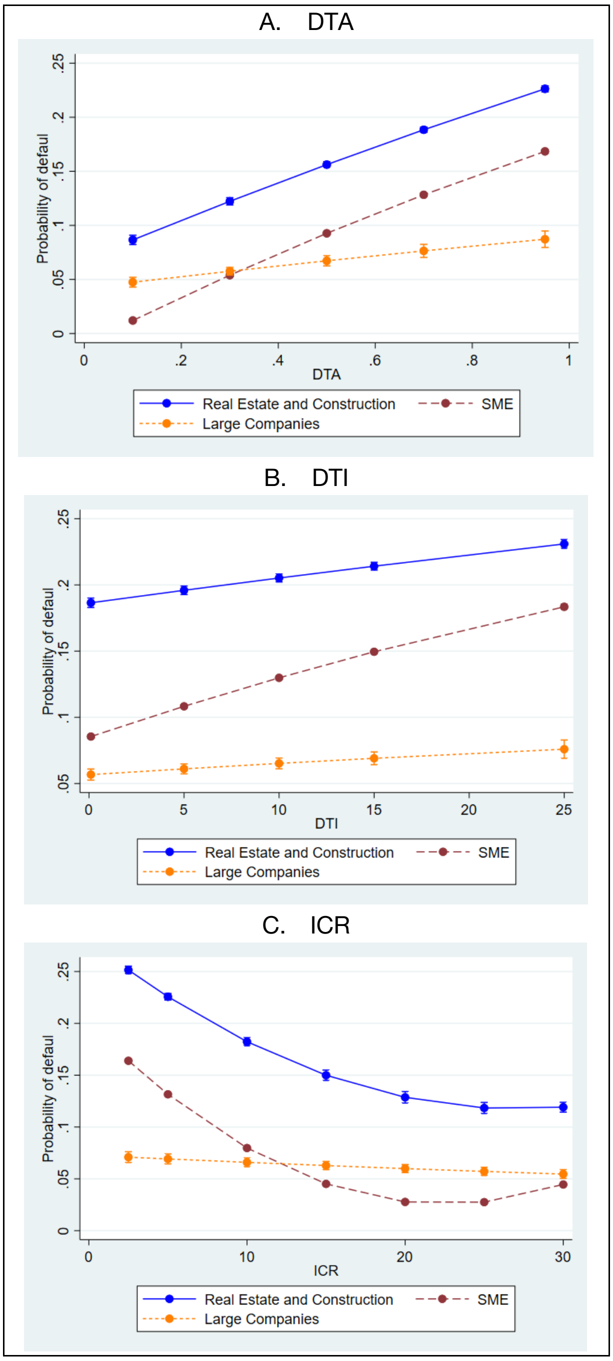
Predictive probabilities for SMEs are, in general, lower than those observed for RE companies, though marginal effects are larger. The predicted default probability of SMEs is almost 14 times higher for firms with DTA=0.95 than for those with DTA=0.1. Changing the ICR from 30 to 2.5, increases the predicted probability of default by more than 3.5 times. For large companies, default probability is significantly lower than for the other types of firms at almost all relevant values of the three credit standard measures. The marginal effects in this sector are also smaller, but still quite sizable. The default rate goes from 4.7% when the DTA=0.1to 8.7% when DTA=0.95, which represents over a 83% increase.[22] The figure indicates that DTA has the stronger association with defaults, followed by ICR. Another interesting characteristic is that the identified non-linear effects are not very important when assessed at relevant values of the ratios, except for the ICR. In the case of this ratio, a saturation of the decrease in default with higher ICR is observed around ICR=20.

We also account for potential non-linearities derived from interactions between lending standards. In particular, between our leverage measure (DTA) and those based on income (DTI and ICR). The relevance of this type of interactions has been previously identified in the case of lending standards in the mortgage market (see Haughwout et al., 2008; Galán and Lamas, 2023, Lo Duca et al. 2023). Thus, we estimate two models including DTA and an income-base indicator, as well as quadratic terms and their interaction. The specification is the following, where ICR is replaced by DTI as an alternative:

[22] For DTI the increase is from 5.7% at DTI=0.1 to 7.6% at DTI=25 (34% increase) while for ICR it is from 5.5% at ICR=30 to 7.1% at ICR=2.5 (30% increase).

$$everDefault_{ibt} = \beta_1 DTA_{i,b,t} + \beta_2 DTA^2_{i,b,t} + \beta_3 ICR_{i,b,t} + \beta_4 ICR^2_{i,b,t} + \beta_5 DTA_{i,b,t} ICR_{i,b,t} + \sum_{j=1}^{J} \delta_j X_{j,i,b,t} + B_b + Sec_i + Loc_i + T_t + \varepsilon_{ibt} \quad (3)$$

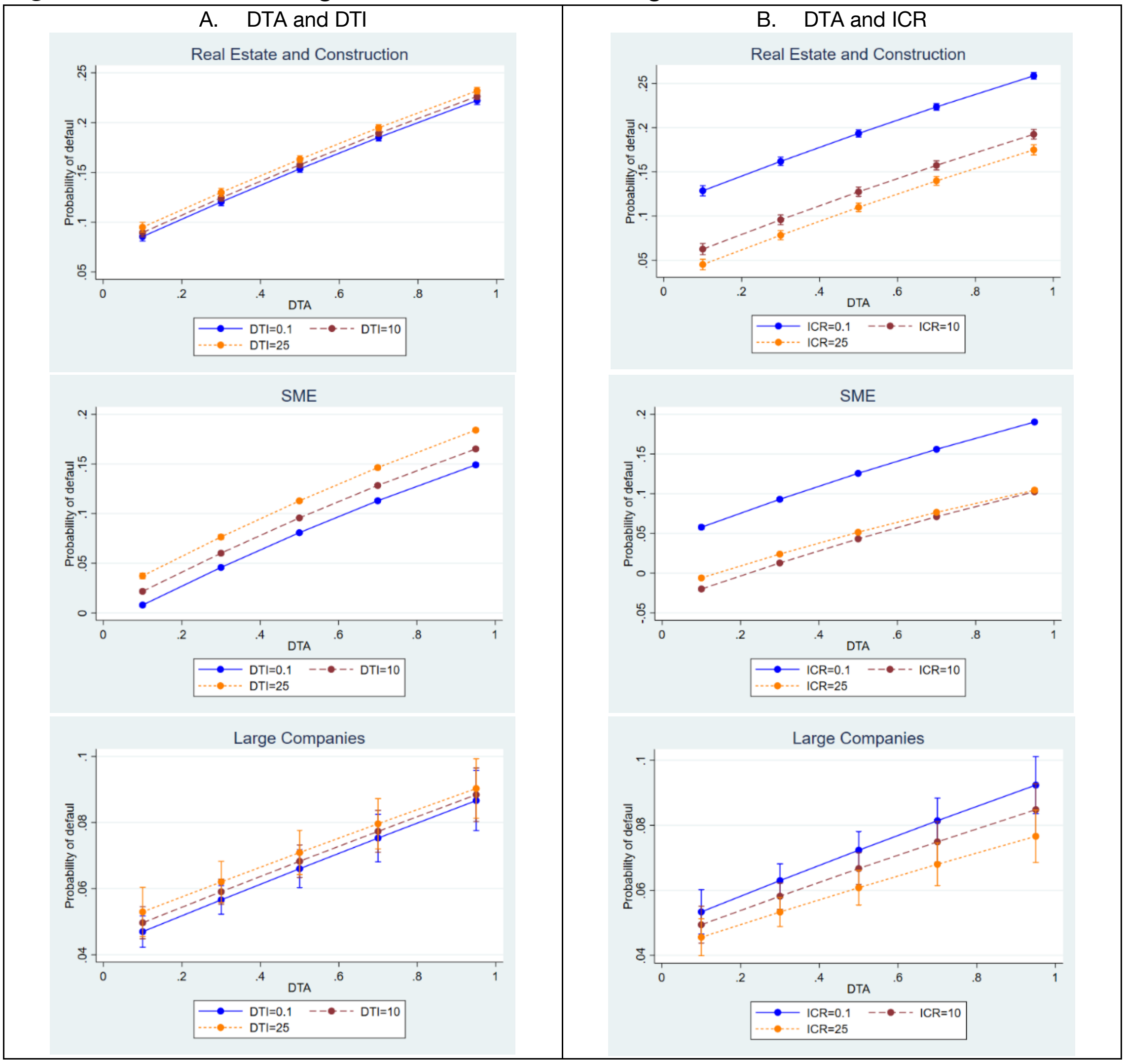
Figure 5. Predictive margins by values of the credit standards at origination by sector.



Note: The models include a linear and a quadratic term in the corresponding credit standard (DTA, DTI or ICR), and a dummy for negative income (EBITDA) in the models including DTI and ICR. Higher ICR values correspond to lower debt burden.

In Figure 6 we show the predictive margins. Various values of DTA are shown in the x-axis, while different curves correspond to the percentiles different values of DTI (top panels) or ICR (bottom panels). Here the margins are shown at fixed values of the standards included. We observe that once DTA is included, varying DTI has limited impact in the model (left panels of Figure 6). However, ICR affects the default probability substantially at different values of DTA. The fact that the lines are mostly parallel indicates that the interaction terms between DTA and ICR or DTI are of limited importance.

Figure 6. Predictive margins when DTA is used together with DTI or ICR.



Note: The models include a linear and a quadratic term for DTA and for DTI (Panel A) or ICR (Panel B), as well as interaction terms between DTA and DTI (Panel A) or ICR (Panel B), and a dummy for negative values of DTI or ICR. Error bars indicate 95% confidence intervals.

5.3. Young firms and new bank-firm relations

Beyond the position on the cycle, we find that other variables may moderate significantly the effect of the credit standards on default probabilities. Those are the age of the firm, whether the bank-firm relation is new, and, to some extent, the liquidity of the firm. Table 8 shows how these variables affect the association of the standards with defaults, in the model including DTA, ICR, quadratic terms and interaction (results in the model with DTA and DTI are shown in table A1.1 of the appendix). Columns (1), (5) and (9) show the results in the whole samples, without interactions for young firm or new bank-firm relation, for reference. In columns (2), (6) and (10) the sample is restricted to only firms younger than 5 years, while in columns (3), (7) and (11) the sample is restricted to include only new bank-firm relations. In the sample including only new bank-firm relations, the coefficient of DTA decreases by more than 40% compared with the corresponding baseline using the complete sample. In the sample including only young firms, the coefficient decreases between 15% (for SMEs) and 134% (for large companies). Columns (4), (8) and (12) include the whole sample, but interacting DTA and ICR with dummy variables for young firm and new bank-firm relation. The coefficient for the interactions are always statistically significant and range between 18% and 60% in the case of new bank-firm relations, and between 6% and 40% in the case of young firms. The effect over ICR is similar to that over DTA. Results are similar in the model with DTA and DTI, as shown in table A1.1 in the Annex. We also explore the interaction of our credit standard measures with the liquidity of the firm at credit origination. In addition, we find that the association between the standards and defaults is somewhat lower for firms with lower liquidity, see table A1.2 in the Annex.

Table 8. Firm age and new bank-firm relation significantly modulate the association of DTA and ICR with defaults.

	Construction and Real Estate				SME				Large Companies			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	All	age<5	New rel.	All	All	age<5	New rel.	All	All	age<5	New rel.	All
DTA	0.17***	0.13***	0.094***	0.17***	0.19***	0.16***	0.094***	0.19***	0.050***	-0.017	0.023***	0.050***
	(0.0039)	(0.0055)	(0.0029)	(0.0042)	(0.0025)	(0.0039)	(0.0014)	(0.0025)	(0.013)	(0.026)	(0.0074)	(0.014)
young * DTA				-0.012***				-0.011***				-0.020*
				(0.0029)				(0.0016)				(0.012)
NewRel. * DTA				-0.030***				-0.057***				-0.030***
				(0.0019)				(0.00087)				(0.0067)
ICR	-0.0079***	-0.0045***	-0.0036***	-0.0088***	-0.011***	-0.0089***	-0.0045***	-0.011***	-0.00032***	-0.00070**	-0.00023***	-0.00031**
	(0.00043)	(0.00080)	(0.00032)	(0.00044)	(0.00016)	(0.00035)	(0.000100)	(0.00016)	(0.00012)	(0.00033)	(0.000071)	(0.00012)
young * ICR				0.0012***				0.00073***				-0.000067
				(0.00019)				(0.000075)				(0.000067)
NewRel. * ICR				0.0024***				0.0016***				0.000054*
				(0.00011)				(0.000034)				(0.000029)
DTA^2	-0.020***	-0.015***	-0.011***	-0.018***	-0.031***	-0.024***	-0.015***	-0.028***	-0.0034	0.014	-0.0037	0.00078
	(0.00063)	(0.00084)	(0.00052)	(0.00063)	(0.00071)	(0.0010)	(0.00046)	(0.00072)	(0.0088)	(0.015)	(0.0052)	(0.0088)
ICR^2	0.00015***	0.000063***	0.000070***	0.00015***	0.00026***	0.00020***	0.00011***	0.00025***	2.2e-06***	3.2e-06*	1.3e-06***	2.1e-06***
	(0.000011)	(0.000020)	(7.7e-06)	(0.000010)	(4.1e-06)	(9.2e-06)	(2.5e-06)	(4.1e-06)	(6.7e-07)	(1.8e-06)	(3.9e-07)	(6.6e-07)
DTA * ICR	-0.000014	0.00037**	-0.000094	0.000020	-0.00094***	-0.00024**	-0.00041***	-0.00078***	-0.00034***	0.00015	-0.000062	-0.00032***
	(0.00011)	(0.00015)	(0.000091)	(0.00011)	(0.000060)	(0.000093)	(0.000039)	(0.000061)	(0.000076)	(0.00015)	(0.000050)	(0.000077)
Observations	689,211	172,078	180,045	689,694	7,604,958	1,105,184	1,452,101	7,610,420	408,680	26,286	71,974	408,702
Adjusted R^2	0.19	0.17	0.086	0.20	0.11	0.096	0.048	0.11	0.20	0.30	0.066	0.20
Year, bank, sector, ZIP FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm, loan controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Youg, NewRel dummies	NO	NO	NO	YES	NO	NO	NO	YES	NO	NO	NO	YES
Negative income dummy	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
age<5years	NO	YES	NO	NO	NO	YES	NO	NO	NO	YES	NO	NO
Only new firm-bank	NO	NO	YES	NO	NO	NO	YES	NO	NO	NO	YES	NO

Note: *young* is a dummy variable that takes the value 1 for firm younger than 5 years. *NewRel.* takes the value 1 if the bank-firm relation was not present the previous month. Columns (1), (5) and (9) correspond to column (8) of tables 1, 2 and 3, and are included here for reference. Robust standard errors, clustered by firm, under variable coefficients. *** p<0.01, ** p<0.05, * p<0.1.

Although these results might be counterintuitive, in the case of new bank-firm relations, banks might be more careful in evaluating the creditworthiness of the firm. Thus, despite having an adverse debt ratio, these firms might be subject to a stricter screening process by banks, which implies that these firms are safer than others granted with loans of similar credit standards due to characteristics that we do not observe. This might induce a downward bias in the estimate of the credit standard coefficient. In the case of young firms, having a solid business plan with good prospects might be more relevant than the current level of indebtedness, decreasing the informative power of the credit standard. Form a policy perspective, this last finding is particularly relevant, as it indicates that setting limits in credit standards might need to be different for young firms. Moreover, since these firms might be particularly dependent on bank credit for growing, more relaxed limits for young firms could help to ameliorate the negative economic consequences of the policy.

6. Complimentary and robustness exercises

In this section, we assess the robustness of our results to some econometric issues derived from the characteristics of our sample, to alternative estimation methods, and to different definitions of debt and defaults, which are two of our key variables in the analysis.

6.1. Selection bias

As indicated in Section 3, our merged sample between CIR and CB covers around half of all bank exposures to firms in the credit register. Although this a high coverage rate, the reason behind not having more matches between CIR and CB, is the lack of balance sheet information for more companies. This merged sample exhibits somewhat lower default frequencies than those reflected in the full CIR database. Thus, a concern might be that there is a bias in our merged sample towards "better" companies, that would be those reporting balance sheet data in the CB. This would lead these firms to default less than other companies being granted with credit of similar standards and could introduce a downward bias in the estimates of the effects of credit standards on default risk. We use a Heckman selection model to address this concern. The model estimates the probability of having balance sheet information via a probit model, and allows the residual of that model to be correlated with the residual of the linear probability model estimating defaults.

Non-parametric identification of this model requires some variable affecting the probability of having balance sheet data, but not affecting the default probability (i.e. an exclusion restriction). Thus, in order to achieve this, we include several variables (available for the full sample), which can plausibly affect the probability that the firm reports balance sheet data to the mercantile register. We include: i) the log of total bank borrowing, which has been previously found to be related to the probability of reporting to the mercantile register (Duro et al., 2022); ii) the year of origination, since we saw a small upwards trend in the coverage of the sample with balance sheet data (see Figure 2); iii) a dummy variable indicating whether the firm has loans registered as doubtful by any bank in the sample, since troubled firms might be less likely to report balance sheet data; and, iv) a dummy variable indicating whether the firm had no credit with any bank in the previous month, since new relations might correspond to new firms that are less likely to report balance sheet data to the mercantile register. Tables A2.1-3, show that our findings are robust to selection bias. That is, the coefficients of the credit standards are almost identical between the linear probability (columns 1, 3 and 5) and the Heckman models (columns 2, 4 and 6).

6.2. Default definitions

In our exercises, we define defaults as those loans being in arrears for more than 90 days. Although this is a quite standard definition, it is possible to consider either weaker or stronger default notions. Thus, we conduct robustness exercises to different definitions of defaults. On the one hand, we account for a definition that includes those loans that are declared as doubtful because even if these loans are not yet in arrears for 90 days, banks consider that there are reasons to think that they could become problematic. On the other hand, we use a stricter definition that only considers a defaulted loan when the firm is declared as insolvent. This is closer to the underlying definition in most of previous studies on corporate default.

In addition, as noted in Section 3, our main default variable, *everDefault*, can lead to an overestimation of defaults. This is so because, as we do not have individual loan information within a given bank-firm relation, a default in a bank-firm relation is assigned to all those bank-firm relations originated before the default, as long as the bank-firm relation does not end before the default event. Thus, as an alternative variable, we also consider one that assigns the default only to the loan that is originated the closest to (and earlier than) the default even. This alternative variable might be underestimating the defaults, but complements our main variable.

Results presented in tables A3.1-3 of the Annex show robustness of our credit standard indicators to these alternative default definitions. The coefficients of the credit standards are large and significant no matter the default definition used, corroborating their good properties signaling credit risk.

6.3. Non-bank debt

Another concern of our estimations regards the composition of debt between bank credit and non-bank debt. This may be mainly important for large companies that are more active in the use of non-bank debt given their easier access to other funding alternatives. Results shown in tables A4.1-3 of the Annex, show that the significance of DTA and DTI indicators hold whether bank, non-bank or total debt is considered, although the association is stronger with bank credit.

6.4 Alternative specifications

So far we have been using a linear probability model, due to its simplicity and flexibility. But since our main dependent variable is binary, it might be thought that a probit or logit model might be more appropriate. In Figure A.5 we compare the predictive margins for the linear probability model with those of the probit and logit models. The figure shows that the three models yield results that are barely distinguishable. Only when using the ICR for large companies, when non-linear effects are larger, the differences are more noticeable, but still within the confidence intervals. We conclude that our results are robust to the use of different model specifications and that our baseline linear probability model is appropriate.

7. Conclusions and policy implications

The connection between house prices and credit growth as a key characteristic of systemic risk accumulation prior to the GFC (Jordà et al., 2016; Rünstler and Vlekke, 2017), and the studies identifying significant associations between mortgage lending standards and default risk (Duca et al. 2010; Schelkle 2018), have spurred the widespread implementation of BBM targeted at the mortgage market in the aftermath of the crisis. In contrast, targeted macroprudential measures in the corporate sector have been less prevalent, despite the elevated credit growth to this sector prior to the GFC and its growing significance in recent years. Additionally, most of these measures have focused on the lender side. However, recent findings highlighting the benefits of complementarity between BBM and lender-based measures, and the superior efficacy of the former in mitigating cyclical vulnerabilities (Araujo et al., 2020; Apergis et al., 2022; Valderrama, 2023), suggest the need to examine the role of corporate credit standards in influencing default risk, a topic that has received little attention in the literature. Against this backdrop, we investigate the association between lending standards at the origination of NFC credit and default risk, using a comprehensive loan-level dataset of corporate lending in Spain covering approximately half of the bank borrowing firms in Spain over the past financial cycle.

Our findings demonstrate a significant association between lending standards at the origination of corporate loans and loan defaults, echoing the established relationship observed in the mortgage market. Specifically, the leverage ratio, represented by the DTA ratio, and debt burden ratios in relation to profits, such as the ICR, emerge as crucial predictors of future default risk. Notably, these credit standards hold particular relevance for SMEs and RE companies. Indeed, these sectors have been recognized as being particularly susceptible to systemic vulnerabilities (Altman and Sabato, 2007; Müller and Verner 2021).

Our analysis further reveals that credit standards have differential effects across the financial cycle, exhibiting a stronger influence during periods of excessive credit growth, particularly for leverage ratios. Additionally, we identify relevant non-linear effects that suggest thresholds at which limits to lending standards would be more effective in mitigating default risk. Moreover, we uncover significant interactions between credit standards, suggesting that a combination of tools targeting both leverage and debt burden would enhance the effectiveness of potential measures in reducing corporate default risk. This aligns with the findings that simultaneous implementation of LTV and LTI limits for mortgages amplify their effectiveness (Kelly and O'Toole, 2018; Galán and Lamas, 2023).

Furthermore, our results uncover heterogeneous effects of credit standards, particularly in relation to the age of firms and the existence of a previous bank-firm relationship. In particular, we demonstrate that the association between credit standards and default risk is weaker for younger firms and new bank-firm relationships, suggesting that unobserved factors may play a more prominent role in these instances. Our results exhibit strong robustness to various considerations, such as the use of bank lending or total debt, alternative (stricter and softer) definitions of defaults, and different model specifications, including those that account for potential selection biases.

Our findings support the effectiveness of macroprudential tools targeting corporate lending in the form of BBM. These measures could effectively reduce corporate credit default risk, thereby enhancing financial stability during adverse shocks, mirroring the success of similar measures implemented in the HH sector (Cerutti et al., 2017; Akinci and Olmsted-Rumsey, 2018; Morgan et al., 2019). BBM in the corporate sector would complement other lender-based measures aimed at strengthening bank resilience to corporate exposures by enhancing firms' resilience to both systemic and specific shocks (i.e. income or interest rate shocks) and mitigating the accumulation of systemic vulnerabilities associated with this sector (Apergis et al., 2022; Brandao-Marques et al., 2022). However, it is important to raise some cautions on the potential implementation of these measures. Given the significant role of firms in economic activity, it is essential to consider the potential costs of restricting credit in terms of productivity and growth. Additionally, the differentiation by sectors is crucial. In this regard, our findings suggest that, in addition to systemically important sectors like real estate and construction, distinctions based on firm size, age, and new relationships with banks should be considered when designing these policies. The position in the financial cycle and health of firms are also essential for calibrating these policies to prevent credit restrictions from impacting illiquid but solvent firms during financial stress events. Similar to BBM in the mortgage sector, implementing speed limits (allowed fraction of loans above limits) linked to firm characteristics and the economic cycle could provide a useful mechanism to address these concerns. Overall, our results contribute to providing guidance for the implementation of BBM in key segments of corporate credit.

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Annex.

A1. Additional tables

Table A1.1. Firm age and new bank-firm status significantly modulate the association of DTA and DTI with defaults.

	Construction and Real Estate				SME				Large Companies			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	All	age<5	New rel.	All	All	age<5	New rel.	All	All	age<5	New rel.	All
DTA	0.18***	0.13***	0.090***	0.18***	0.20***	0.16***	0.093***	0.21***	0.049***	-0.0023	0.022***	0.049***
	(0.0034)	(0.0045)	(0.0024)	(0.0037)	(0.0023)	(0.0033)	(0.0012)	(0.0023)	(0.012)	(0.021)	(0.0062)	(0.012)
NewRel. * DTA				-0.027***				-0.060***				-0.032***
				(0.0016)				(0.00082)				(0.0062)
young * DTA				-0.014***				-0.013***				-0.016
				(0.0024)				(0.0014)				(0.010)
DTI	0.00042***	0.00024*	0.00038***	0.00060***	0.0015***	0.0011***	0.00061***	0.0016***	0.00030*	0.00012	0.00040***	0.00030*
	(0.000081)	(0.00013)	(0.000067)	(0.000085)	(0.000061)	(0.00012)	(0.000041)	(0.000062)	(0.00017)	(0.00034)	(0.00013)	(0.00017)
NewRel * DTI				-0.00023***				-0.00039***				1.5e-06
				(0.000033)				(0.000021)				(0.000061)
young * DTI				-0.000049				-0.000027				0.000056
				(0.000047)				(0.000039)				(0.00012)
DTA^2	-0.021***	-0.014***	-0.0099***	-0.018***	-0.036***	-0.025***	-0.016***	-0.032***	-0.0021	0.010	-0.0013	0.0022
	(0.00053)	(0.00065)	(0.00040)	(0.00053)	(0.00063)	(0.00088)	(0.00038)	(0.00064)	(0.0084)	(0.013)	(0.0053)	(0.0085)
DTI^2	-1.9e-06***	-1.3e-06***	-1.4e-06***	-1.9e-06***	-0.000014***	-0.000012***	-5.9e-06***	-0.000013***	-2.1e-06**	-7.7e-07	-1.9e-06**	-2.0e-06**
	(3.1e-07)	(4.8e-07)	(2.6e-07)	(3.1e-07)	(4.9e-07)	(9.1e-07)	(3.4e-07)	(4.8e-07)	(1.0e-06)	(1.9e-06)	(7.7e-07)	(1.0e-06)
DTA * DTI	0.000017	0.000024	0.000044**	8.0e-06	0.00027***	0.00027***	0.00015***	0.00022***	-0.00011	0.000051	-0.00015**	-0.00013
	(0.000020)	(0.000025)	(0.000018)	(0.000021)	(0.000024)	(0.000037)	(0.000020)	(0.000025)	(0.000100)	(0.00025)	(0.000068)	(0.000100)
Observations	748,165	199,742	211,029	748,697	7,970,317	1,233,030	1,604,342	7,975,981	430,459	29,387	77,571	430,488
Adjusted R^2	0.18	0.16	0.083	0.19	0.099	0.090	0.043	0.10	0.19	0.29	0.066	0.20
Year bank sector ZIP FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm, loan controsl	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Youg, NewRel dummies	NO	NO	NO	YES	NO	NO	NO	YES	NO	NO	NO	YES
Negative income dummy	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
age<5years	NO	YES	NO	NO	NO	YES	NO	NO	NO	YES	NO	NO
Only new firm-bank	NO	NO	YES	NO	NO	NO	YES	NO	NO	NO	YES	NO

Note: young is a dummy variable that takes the value 1 for firm younger than 5 years. NewRel. takes the value 1 if the bank-firm relation was not present the previous month. Robust standard errors, clustered by firm, under variable coefficients. *** p<0.01, ** p<0.05, * p<0.1.

Table A1.2. Firm liquidity modulates the association of the standards with defaults.

	Construction and Real Estate				SME				Large Companies			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	All	Liq>p75	Liq<p25	All	All	Liq>p75	Liq<p25	All	All	Liq>p75	Liq<p25	All
DTA	0.17***	0.22***	0.14***	0.17***	0.19***	0.19***	0.17***	0.19***	0.050***	0.062***	0.048**	0.053***
	(0.0039)	(0.0058)	(0.0056)	(0.0044)	(0.0025)	(0.0040)	(0.0037)	(0.0027)	(0.013)	(0.017)	(0.019)	(0.014)
liquid * DTA				0.027***				-0.0026				0.0055
				(0.0039)				(0.0021)				(0.011)
Illiquid * DTA				0.0024				-0.022***				-0.030***
				(0.0032)				(0.0017)				(0.0100)
ICR	-0.0079***	-0.0065***	-0.0071***	-0.0086***	-0.011***	-0.0076***	-0.0098***	-0.011***	-0.00032***	-0.00021	0.00041	-0.00030**
	(0.00043)	(0.00060)	(0.00071)	(0.00045)	(0.00016)	(0.00022)	(0.00030)	(0.00016)	(0.00012)	(0.00014)	(0.00025)	(0.00012)
liquid * ICR				0.0013***				0.00036***				0.000025
				(0.00017)				(0.000060)				(0.000047)
Illiquid * ICR				0.0018***				0.00076***				0.000079
				(0.00020)				(0.000078)				(0.000056)
DTA * DTA	-0.020***	-0.026***	-0.016***	-0.020***	-0.031***	-0.031***	-0.025***	-0.027***	-0.0034	-0.010	-0.016	0.0011
	(0.00063)	(0.0012)	(0.00084)	(0.00064)	(0.00071)	(0.0014)	(0.00096)	(0.00074)	(0.0088)	(0.012)	(0.011)	(0.0089)
ICR * ICR	0.00015***	0.00014***	0.00015***	0.00015***	0.00026***	0.00018***	0.00025***	0.00026***	2.2e-06***	1.5e-06*	-1.3e-06	2.0e-06***
	(0.000011)	(0.000014)	(0.000018)	(0.000011)	(4.1e-06)	(5.5e-06)	(8.3e-06)	(4.1e-06)	(6.7e-07)	(7.5e-07)	(1.4e-06)	(6.7e-07)
DTA * ICR	-0.000014	-0.00086***	0.000098	-0.000093	-0.00094***	-0.0016***	-0.00036***	-0.0011***	-0.00034***	-0.00047***	-0.00037***	-0.00038***
	(0.00011)	(0.00019)	(0.00016)	(0.00011)	(0.000060)	(0.00012)	(0.000085)	(0.000063)	(0.000076)	(0.00012)	(0.00014)	(0.000079)
Observations	689,211	157,652	169,466	691,371	7,604,958	1,691,045	1,936,712	7,613,025	408,680	92,859	104,589	408,713
Adjusted R^2	0.19	0.26	0.20	0.19	0.11	0.11	0.11	0.11	0.20	0.23	0.23	0.20
Year, bank, sector, ZIP FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm, loan controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Liquidity dummies	NO	NO	NO	YES	NO	NO	NO	YES	NO	NO	NO	YES
Negative income dummy	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Liquidity>p75	NO	YES	YES	NO	NO	YES	NO	NO	NO	YES	NO	NO
Liquidity<p25	NO	NO	YES	NO	NO	NO	YES	NO	NO	NO	YES	NO

Note: liquid is a dummy variable that takes the value 1 if the liquidity ratio (liquid assets over liquid liabilities) of the firm is in the sector-specific top quartile. Illiquid is a dummy variable that takes the value 1 if the liquidity of the firm is in the sector-specific bottom quartile. Robust standard errors, clustered by firm, under variable coefficients. *** p<0.01, ** p<0.05, * p<0.1.

A2. Addressing selection bias

As indicated in the main text, our sample including balance sheet information (necessary to construct the credit standards) covers around half of all bank exposures to firms in the credit register. The sample including balance sheet information exhibits somewhat lower default frequencies than those reflected in the full sample, raising the concern that there might be a selection bias that may affect our results. Here we use a Heckman selection model to address this concern. The model estimates the probability of having balance sheet information via a probit model, and allows the residual of that model to be correlated with the residual of the linear probability model estimating defaults:

$$D_{i,b,t} = Ind\left(\sum_{l=1}^{L} \gamma_l Z_{l,i,t} + \eta_{i,b,t} > 0\right),$$

$$[everDefault_{ibt} | D_{i,b,t} = 1] = \beta L.S._{it} + \sum_{j=1}^{J} \delta_j X_{j,i,b,t} + B_b + Sec_i + Loc_i + T_t + [\varepsilon_{ibt} | \eta_{i,b,t} = 1],$$

where $D_{i,b,t}=1$ if the observation appears in the sample with balance sheet information and zero otherwise, Z are firm variables relevant for selection, and the residual in the default equation, $\varepsilon_{i,b,t}$, can be correlated with $\eta_{i,b,t}$ in the selection equation. If $E[\varepsilon_{i,b,t} | \eta_{i,b,t} = 1] \neq 0$ there is a selection bias, and if $E[C_{i,b,t}\, \varepsilon_{i,b,t} | \eta_{i,b,t} = 1] \neq 0$ the bias can affect the coefficient β. Non-parametric identification of this model requires that some component of Z does not appear in the default equation (i.e. an exclusion restriction). Thus, in order to achieve this, we include several variables (available for the full sample) which can plausibly affect the probability that the firm reports balance sheet data to the mercantile register. We include: i) the log of total bank borrowing, which has been previously found to be related to the probability of reporting to the mercantile register (Duro et al., 2022), ii) the year of origination, since we saw a small upwards trend in the coverage of the sample with balance sheet data (see Figure 2), iii) a dummy variable indicating whether the firm has any loan registered as doubtful by any bank in the sample, since troubled firms might be less likely to report balance sheet data), and iv) a dummy variable indicating whether the firm had no credit with any bank in the previous month, since new relations might correspond to new firms that are less likely to report balance sheet data to the mercantile register.

We estimate the model via joint maximum likelihood. Tables A2.1-3, show that our findings are robust to selection bias. That is, the coefficients of the credit standards are almost identical between the linear probability (columns 1, 3 and 5) and the Heckman models (columns 2, 4 and 6). The signs of the coefficients in the selection equation are mostly in line with expectations. The sign of the log of total bank borrowing is positive, except for real estate and construction firms; that of year of origination is always positive; that of any doubtful credit is negative, except for large corporations in some cases (with low statistical significance); that of new firm is always negative.

Table A2.1. Estimation results of Heckman models. Real estate and construction companies.

L. S.:	DTA	DTA	DTA	DTI	DTI	DTI	ICR	ICR	ICR
Model:	OLS	Heckman	Selection	OLS	Heckman	Selection	OLS	Heckman	Selection
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
L. S.	0.195***	0.20***		0.00208***	0.0021***		-0.013***	-0.013***	
	(0.00372)	(0.0038)		(8.59e-05)	(0.000087)		(0.0005)	(0.00046)	
L. S. ^2	-0.0226***	-0.022***		-7.47e-06***	-7.4e-06***		0.00024***	0.00024***	
	(0.000576)	(0.00059)		(3.38e-07)	(3.4e-07)		-0.00001	(0.000011)	
Ind(L. S. <0)				0.0311***	0.033***		-0.0682***	-0.066***	
				(0.00259)	(0.0026)		(0.00325)	(0.0033)	
Log(Assets)	0.0494***	0.050***		0.0340***	0.034***		0.0339***	0.034***	
	(0.00119)	(0.0012)		(0.00112)	(0.0011)		(0.00115)	(0.0012)	
Liquidity	-0.000220***	-0.00020***		-0.000738***	-0.00070***		-0.000715***	-0.00067***	
	(4.30e-05)	(0.000044)		(4.30e-05)	(0.000044)		(4.94e-05)	(0.000050)	
ROE	-0.000174	-0.00016		0.00631***	0.0063***		0.00896***	0.0089***	
	(0.00103)	(0.0010)		(0.00106)	(0.0011)		(0.00107)	(0.0011)	
Guarantee	0.1000***	0.099***		0.110***	0.11***		0.108***	0.11***	
	(0.00242)	(0.0024)		(0.00242)	(0.0024)		(0.00244)	(0.0025)	
Age	-0.00214***	-0.0022***		-0.00285***	-0.0029***		-0.00287***	-0.0029***	
	(0.000212)	(0.00021)		(0.000210)	(0.00021)		(0.000207)	(0.00021)	
Group	-0.113***	-0.11***		-0.0681***	-0.068***		-0.0613***	-0.062***	
	(0.0110)	(0.011)		(0.0109)	(0.011)		(0.0109)	(0.011)	
Int. rate (firm level)	0.00184***	0.0018***		0.00190***	0.0019***		0.000381***	0.00034***	
	(0.000146)	(0.00015)		(0.000151)	(0.00015)		(0.000130)	(0.00013)	
Log(Total bank debt)			-0.0087***			-0.0064***			-0.0024
			(0.0018)			(0.0019)			(0.0019)
Year			0.028***			0.028***			0.034***
			(0.00048)			(0.00048)			(0.00049)
Doubful Firm			-0.100***			-0.096***			-0.092***
			(0.0060)			(0.0061)			(0.0061)
New Firm			-0.25***			-0.25***			-0.29***
			(0.0033)			(0.0033)			(0.0033)
Observations	749,620	2,545,733	2,545,733	748,788	2,544,934	2,544,934	784,184	2,581,514	2,581,514
Year, bank, sector FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Zip code FE	2dig	2dig	2dig	2dig	2dig	2dig	2dig	2dig	2dig

Liquidity is defined as current assets/current liabilities, Guarantee is a dummy taking the value 1 if the bank-firm relation has some form of collateral, Firm Age is in years, Group is a dummy taking the value 1 if the firm is part of a group, Int. rate (firm level) is defined as firm interest expenses over total debt, Year is year of origination, Doubtful Firm is a dummy taking the value 1 if the firm has credit registered as doubtful by any bank in the sample in the corresponding month, New firm is a dummy taking the value 1 if the frim did not have a credit with any bank in the previous month. Sector fixed effects are at the 2-digit NACE code. Robust standard errors, clustered by firm, in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A2.2. Estimation results of Heckman models. SMEs.

L. S.:	DTA	DTA	DTA	DTI	DTI	DTI	ICR	ICR	ICR
Model:	OLS	Heckman	Selection	OLS	Heckman	Selection	OLS	Heckman	Selection
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
L. S.	0.227***	0.23***		0.00495***	0.0049***		-0.016***	-0.016***	
	(0.00221)	(0.0022)		(6.09e-05)	(0.000061)		-0.0002	(0.00016)	
L. S.^2	-0.0398***	-0.039***		-3.71e-05***	-0.000037***		0.00035***	0.00035***	
	(0.000628)	(0.00063)		(5.11e-07)	(5.1e-07)		(4e-06)	(4.1e-06)	
Ind(L. S.<0)				0.0589***	0.059***		-0.0633***	-0.061***	
				(0.000998)	(0.0010)		(0.00115)	(0.0012)	
Log(Assets)	0.0317***	0.031***		0.0218***	0.020***		0.0220***	0.021***	
	(0.000469)	(0.00047)		(0.000445)	(0.00045)		(0.000437)	(0.00044)	
Liquidity	-0.000457***	-0.00043***		-0.00596***	-0.0057***		-0.00454***	-0.0043***	
	(0.000155)	(0.00016)		(0.000159)	(0.00016)		(0.000163)	(0.00017)	
ROE	-0.00339***	-0.0033***		0.00518***	0.0051***		0.00771***	0.0076***	
	(0.000394)	(0.00040)		(0.000405)	(0.00041)		(0.000390)	(0.00039)	
Guarantee	0.0641***	0.063***		0.0735***	0.071***		0.0709***	0.069***	
	(0.00107)	(0.0011)		(0.00107)	(0.0011)		(0.00104)	(0.0010)	
Age	-0.00122***	-0.0012***		-0.00193***	-0.0019***		-0.00204***	-0.0020***	
	(6.30e-05)	(0.000063)		(6.39e-05)	(0.000064)		(6.06e-05)	(0.000061)	
Group	-0.0605***	-0.060***		-0.0425***	-0.042***		-0.0349***	-0.034***	
	(0.00239)	(0.0024)		(0.00235)	(0.0024)		(0.00231)	(0.0023)	
Int. rate (firm level)	0.00174***	0.0017***		0.00189***	0.0019***		0.000356***	0.00035***	
	(4.20e-05)	(0.000042)		(4.33e-05)	(0.000044)		(3.56e-05)	(0.000036)	
Log(Total bank debt)			0.036***			0.039***			0.041***
			(0.00079)			(0.00081)			(0.00082)
Year			0.012***			0.012***			0.021***
			(0.00019)			(0.00019)			(0.00019)
Doubful Firm			-0.17***			-0.16***			-0.16***
			(0.0025)			(0.0025)			(0.0025)
New Firm			-0.31***			-0.31***			-0.32***
			(0.0014)			(0.0014)			(0.0014)
Observations	7,972,687	16,632,495	16,632,495	7,970,851	16,630,742	16,630,742	9,131,376	17,792,359	17,792,359
Year, bank, sector FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Zip code FE	2dig	2dig	2dig	2dig	2dig	2dig	2dig	2dig	2dig

Liquidity is defined as current assets/current liabilities, Guarantee is a dummy taking the value 1 if the bank-firm relation has some form of collateral, Firm Age is in years, Group is a dummy taking the value 1 if the firm is part of a group, Int. rate (firm level) is defined as firm interest expenses over total debt, Year is year of origination, Doubtful Firm is a dummy taking the value 1 if the firm has credit registered as doubtful by any bank in the sample in the corresponding month, New firm is a dummy taking the value 1 if the frim did not have a credit with any bank in the previous month. Sector fixed effects are at the 2-digit NACE code. Robust standard errors, clustered by firm, in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A2.3. Estimation results of Heckman models. Large companies.

L. S.:	DTA	DTA	DTA	DTI	DTI	DTI	ICR	ICR	ICR
Model:	OLS	Heckman	Selection	OLS	Heckman	Selection	OLS	Heckman	Selection
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
L. S.	0.0721***	0.060***		0.00139***	0.0013***		-0.0012***	-0.0011***	
	(0.0131)	(0.013)		(0.000242)	(0.00024)		(0.0001)	(0.00014)	
L. S.^2	-0.0101	-0.0051		-7.79e-06***	-7.3e-06***		6e-06***	6.0e-06***	
	(0.00920)	(0.0092)		(1.36e-06)	(1.3e-06)		(8e-07)	(7.8e-07)	
Ind(L. S.<0)				0.0216***	0.022***		-0.00441	-0.0020	
				(0.00468)	(0.0047)		(0.00458)	(0.0046)	
Log(Assets)	0.00897***	0.0062***		0.00732***	0.0044***		0.00724***	0.0042***	
	(0.00129)	(0.0012)		(0.00124)	(0.0012)		(0.00124)	(0.0012)	
Liquidity	-0.00424***	-0.0040***		-0.00653***	-0.0058***		-0.00615***	-0.0056***	
	(0.000898)	(0.00091)		(0.000897)	(0.00090)		(0.000964)	(0.00097)	
ROE	-0.00730***	-0.0072***		-0.00449**	-0.0044**		-0.00271	-0.0027	
	(0.00202)	(0.0020)		(0.00204)	(0.0020)		(0.00210)	(0.0021)	
Guarantee	0.0730***	0.071***		0.0754***	0.073***		0.0736***	0.071***	
	(0.00673)	(0.0067)		(0.00681)	(0.0068)		(0.00673)	(0.0067)	
Age	9.60e-05	0.000061		5.32e-05	0.000020		7.51e-05	0.000045	
	(0.000153)	(0.00015)		(0.000153)	(0.00015)		(0.000151)	(0.00015)	
Group	-0.00217	-0.0020		-0.00398	-0.0035		0.000724	0.00034	
	(0.00557)	(0.0056)		(0.00558)	(0.0056)		(0.00429)	(0.0043)	
Int. rate (firm level)	0.000643***	0.00060***		0.000438***	0.00042***		0.000182	0.00020	
	(0.000170)	(0.00017)		(0.000164)	(0.00016)		(0.000148)	(0.00015)	
Log(Total bank debt)			0.15***			0.15***			0.15***
			(0.0033)			(0.0032)			(0.0033)
Year			0.047***			0.047***			0.048***
			(0.0011)			(0.0011)			(0.0011)
Doubful Firm			0.024*			0.026*			0.011
			(0.014)			(0.014)			(0.014)
New Firm			-0.26***			-0.26***			-0.25***
			(0.0091)			(0.0091)			(0.0093)
Observations	430,754	828,816	828,816	430,642	828,707	828,707	441,532	839,757	839,757
Year, bank, sector FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Zip code FE	2dig	2dig	2dig	2dig	2dig	2dig	2dig	2dig	2dig

Liquidity is defined as current assets/current liabilities, Guarantee is a dummy taking the value 1 if the bank-firm relation has some form of collateral, Firm Age is in years, Group is a dummy taking the value 1 if the firm is part of a group, Int. rate (firm level) is defined as firm interest expenses over total debt, Year is year of origination, Doubtful Firm is a dummy taking the value 1 if the firm has credit registered as doubtful by any bank in the sample in the corresponding month, New firm is a dummy taking the value 1 if the frim did not have a credit with any bank in the previous month. Sector fixed effects are at the 2-digit NACE code. Robust standard errors, clustered by firm, in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

A3. Alternative default definitions

Table A.3.1. Estimation results with alternative default definitions. Real estate and construction companies.

Dependent variable	everDefault	everDoubful	written off	firstDefault	everDefault	everDoubful	written off	firstDefault	everDefault	everDoubful	written off	firstDefault
L. S.:	DTA	DTA	DTA	DTA	DTI	DTI	DTI	DTI	ICR	ICR	ICR	ICR
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
L.S.	0.187***	0.200***	0.123***	0.0693***	0.00196***	0.00212***	0.00120***	0.00117***	-0.012***	-0.012***	-0.0075***	-0.0054***
	(0.00331)	(0.00335)	(0.00288)	(0.00121)	(7.94e-05)	(8.14e-05)	(6.64e-05)	(3.35e-05)	(0.0004)	(0.0004)	(0.0003)	(0.0001)
L.S.^2	-0.0215***	-0.0228***	-0.0138***	-0.00740***	-6.99e-06***	-7.51e-06***	-4.58e-06***	-3.60e-06***	0.00022***	0.00023***	0.00014***	0.00011***
	(0.000519)	(0.000532)	(0.000438)	(0.000211)	(3.14e-07)	(3.22e-07)	(2.62e-07)	(1.41e-07)	(0.00001)	(0.00001)	(8e-06)	(3e-06)
Ind(L.S.<0)					0.0312***	0.0368***	0.00909***	0.0438***	-0.0628***	-0.0624***	-0.0494***	-0.00147
					(0.00243)	(0.00254)	(0.00190)	(0.00106)	(0.00299)	(0.00309)	(0.00240)	(0.00123)
Log(Assets)	0.0484***	0.0506***	0.0366***	0.0142***	0.0332***	0.0344***	0.0258***	0.00907***	0.0330***	0.0344***	0.0262***	0.00926***
	(0.00106)	(0.00105)	(0.000953)	(0.000345)	(0.00100)	(0.000999)	(0.000879)	(0.000307)	(0.00104)	(0.00105)	(0.000905)	(0.000315)
Liquidity	-0.000210***	-0.000230***	-0.000169***	0.000246***	-0.000694***	-0.000758***	-0.000459***	-1.26e-05	-0.000692***	-0.000759***	-0.000481***	5.04e-05
	(4.40e-05)	(4.68e-05)	(3.11e-05)	(2.73e-05)	(4.38e-05)	(4.67e-05)	(3.09e-05)	(2.70e-05)	(5.03e-05)	(5.37e-05)	(3.63e-05)	(3.14e-05)
ROE	0.000111	6.73e-05	0.000169	-0.000421	0.00614***	0.00663***	0.00387***	0.00296***	0.00844***	0.00889***	0.00574***	0.00269***
	(0.000985)	(0.00102)	(0.000803)	(0.000442)	(0.00101)	(0.00105)	(0.000821)	(0.000445)	(0.00102)	(0.00106)	(0.000826)	(0.000440)
Guarantee	0.0993***	0.114***	0.0278***	0.0829***	0.109***	0.124***	0.0357***	0.0839***	0.108***	0.123***	0.0337***	0.0847***
	(0.00225)	(0.00232)	(0.00188)	(0.000901)	(0.00225)	(0.00232)	(0.00188)	(0.000900)	(0.00227)	(0.00235)	(0.00188)	(0.000899)
Firm age	-0.00206***	-0.00178***	-0.00129***	-0.00116***	-0.00269***	-0.00246***	-0.00174***	-0.00129***	-0.00273***	-0.00249***	-0.00175***	-0.00141***
	(0.000190)	(0.000182)	(0.000142)	(5.51e-05)	(0.000188)	(0.000191)	(0.000139)	(5.49e-05)	(0.000187)	(0.000192)	(0.000139)	(5.62e-05)
Group	-0.0986***	-0.0694***	-0.0830***	-0.0296***	-0.0570***	-0.0252***	-0.0529***	-0.0165***	-0.0523***	-0.0215**	-0.0501***	-0.0143***
	(0.00910)	(0.00893)	(0.00732)	(0.00277)	(0.00912)	(0.00902)	(0.00726)	(0.00274)	(0.00902)	(0.00896)	(0.00714)	(0.00273)
Int. rate	0.00163***	0.00184***	0.00111***	-9.95e-05***	0.00163***	0.00186***	0.00105***	9.02e-05**	0.000266**	0.000426***	0.000233**	-0.000406***
(firm level)	(0.000131)	(0.000131)	(0.000107)	(3.81e-05)	(0.000135)	(0.000136)	(0.000111)	(3.93e-05)	(0.000117)	(0.000119)	(9.49e-05)	(3.40e-05)
Observations	748,991	748,991	748,991	748,991	748,165	748,165	748,165	748,165	783,602	783,602	783,602	783,602
R^2_A	0.18	0.19	0.15	0.08	0.16	0.17	0.13	0.08	0.17	0.18	0.14	0.08
Year, bank, sector, ZIP FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: everDefault, for each new loan, takes the value 1 if before the bank-firm relation disappears at some point there is an overdue for more than 90 days. EverDoubful is as everDefault, but the triggering event is being classified as doubtful by the bank. Written off is as everDefault, but the triggering event is being written-off by the bank. 1stDefault is like everDefault, but when a default event takes place, it is only associated to the new loan originated closest to (and earlier than) the default event. Liquidity is defined as current assets/current liabilities, Guarantee is a dummy taking the value 1 if the bank-firm relation has some form of collateral, Firm Age is in years, Group is a dummy taking the value 1 if the firm is part of a group, Int. rate (firm level) is defined as firm interest expenses over total debt, sector fixed effects are at the 2-digit NACE code. Robust standard errors, clustered by firm, under variable coefficients. *** p<0.01, ** p<0.05, * p<0.1.

Table A3.2. Estimation results with alternative default definitions. SMEs.

Dependent variable	everDefault	everDoubful	written off	firstDefault	everDefault	everDoubful	written off	firstDefault	everDefault	everDoubful	written off	firstDefault
L. S.:	DTA	DTA	DTA	DTA	DTI	DTI	DTI	DTI	ICR	ICR	ICR	ICR
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
L.S.	0.225***	0.250***	0.127***	0.0460***	0.00485***	0.00532***	0.00280***	0.00118***	-0.016***	-0.017***	-0.0087***	-0.0034***
	(0.00215)	(0.00223)	(0.00164)	(0.000458)	(5.91e-05)	(6.14e-05)	(4.62e-05)	(1.33e-05)	(0.0002)	(0.000161)	(0.0001)	(0.00003)
L.S.^2	-0.0392***	-0.0440***	-0.0202***	-0.00642***	-3.64e-05***	-3.97e-05***	-2.13e-05***	-7.94e-06***	0.00034***	0.00038***	0.00019***	0.00008***
	(0.000615)	(0.000639)	(0.000473)	(0.000155)	(4.96e-07)	(5.14e-07)	(3.92e-07)	(1.21e-07)	(4e-06)	(4e-06)	(3e-06)	(8e-07)
Ind(L.S.<0)					0.0576***	0.0669***	0.0292***	0.0268***	-0.0626***	-0.0663***	-0.0390***	-0.000760***
					(0.000985)	(0.00106)	(0.000713)	(0.000284)	(0.00113)	(0.00119)	(0.000810)	(0.000294)
Log(Assets)	0.00799***	0.0197***	0.00158**	0.000780***	0.0224***	0.0242***	0.0196***	0.00305***	0.0227***	0.0245***	0.0197***	0.00313***
	(0.00119)	(0.00139)	(0.000713)	(0.000213)	(0.000437)	(0.000453)	(0.000343)	(7.70e-05)	(0.000431)	(0.000447)	(0.000334)	(7.54e-05)
Liquidity	-0.00369***	-0.00715***	-0.00174***	-0.000617***	-0.00593***	-0.00690***	-0.00362***	-0.000348***	-0.00457***	-0.00536***	-0.00291***	-0.000161***
	(0.000794)	(0.00103)	(0.000488)	(0.000234)	(0.000157)	(0.000171)	(0.000106)	(4.51e-05)	(0.000162)	(0.000177)	(0.000107)	(4.60e-05)
ROE	-0.00507***	-0.00628***	-0.00256***	-0.00260***	0.00514***	0.00549***	0.00340***	0.000990***	0.00762***	0.00822***	0.00469***	0.00113***
	(0.00171)	(0.00221)	(0.000970)	(0.000557)	(0.000398)	(0.000423)	(0.000298)	(0.000133)	(0.000383)	(0.000409)	(0.000282)	(0.000129)
Guarantee	0.0622***	0.0847***	0.0340***	0.0214***	0.0726***	0.0920***	0.0242***	0.0359***	0.0700***	0.0897***	0.0226***	0.0359***
	(0.00547)	(0.00645)	(0.00425)	(0.00141)	(0.00105)	(0.00113)	(0.000780)	(0.000284)	(0.00102)	(0.00110)	(0.000742)	(0.000271)
Firm age	0.000223	0.000342*	0.000236**	4.71e-05*	-0.00189***	-0.00192***	-0.00107***	-0.000504***	-0.00200***	-0.00205***	-0.00109***	-0.000541***
	(0.000154)	(0.000178)	(0.000113)	(2.56e-05)	(6.30e-05)	(6.64e-05)	(4.68e-05)	(1.04e-05)	(6.00e-05)	(6.33e-05)	(4.36e-05)	(1.00e-05)
Group	-0.00235	0.0114**	-0.00786***	-0.000971	-0.0410***	-0.0317***	-0.0279***	-0.00663***	-0.0343***	-0.0241***	-0.0241***	-0.00542***
	(0.00473)	(0.00575)	(0.00288)	(0.001000)	(0.00228)	(0.00256)	(0.00138)	(0.000509)	(0.00224)	(0.00252)	(0.00135)	(0.000501)
Int. rate	0.000281**	0.000194	1.79e-05	3.54e-05	0.00186***	0.00199***	0.00109***	0.000211***	0.000363***	0.000332***	0.000247***	-0.000113***
(firm level)	(0.000131)	(0.000171)	(7.04e-05)	(2.84e-05)	(4.23e-05)	(4.47e-05)	(2.94e-05)	(8.34e-06)	(3.49e-05)	(3.70e-05)	(2.35e-05)	(6.96e-06)
Observations	430,567	430,567	430,567	430,567	7,970,317	7,970,317	7,970,317	7,970,317	9,130,902	9,130,902	9,130,902	9,130,902
R^2_A	0.192	0.191	0.220	0.0373	0.0804	0.0825	0.0683	0.0260	0.0897	0.0927	0.0740	0.0265
Year, bank, sector, ZIP FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: everDefault, for each new loan, takes the value 1 if before the bank-firm relation disappears at some point there is an overdue for more than 90 days. EverDoubful is as everDefault, but the triggering event is being classified as doubtful by the bank. Written off is as everDefault, but the triggering event is being written-off by the bank. 1stDefault is like everDefault, but when a default event takes place, it is only associated to the new loan originated closest to (and earlier than) the default event. Liquidity is defined as current assets/current liabilities, Guarantee is a dummy taking the value 1 if the bank-firm relation has some form of collateral, Firm Age is in years, Group is a dummy taking the value 1 if the firm is part of a group, Int. rate (firm level) is defined as firm interest expenses over total debt, sector fixed effects are at the 2-digit NACE code. Robust standard errors, clustered by firm, under variable coefficients. *** p<0.01, ** p<0.05, * p<0.1.

Table A3.3. Estimation results with alternative default definitions. Large companies.

Dependent variable	everDefault	everDoubful	written off	firstDefault	everDefault	everDoubful	written off	firstDefault	everDefault	everDoubful	written off	firstDefault
L. S.:	DTA	DTA	DTA	DTA	DTI	DTI	DTI	DTI	ICR	ICR	ICR	ICR
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
L.S.	0.0532***	0.0861***	0.0242***	0.0172***	0.000907***	0.00145***	0.000571***	0.000327***	-0.00071***	-0.00090***	-0.00045***	-0.00016***
	(0.0117)	(0.0147)	(0.00771)	(0.00243)	(0.000179)	(0.000204)	(0.000119)	(4.40e-05)	(0.0001)	(0.0002)	(0.00006)	(0.00002)
L.S.^2	-0.00605	-0.0181*	0.00323	-0.00285	-5.45e-06***	-8.35e-06***	-3.45e-06***	-1.60e-06***	4e-06***	5e-06***	2e-06***	9e-07***
	(0.00805)	(0.00962)	(0.00597)	(0.00192)	(1.01e-06)	(1.18e-06)	(6.67e-07)	(2.89e-07)	(7e-07)	(8e-07)	(4e-07)	(1e-07)
Ind(L.S.<0)					0.0111***	0.0239***	0.00681**	0.0121***	-0.00561	0.000533	-0.00335	0.00705***
					(0.00417)	(0.00531)	(0.00267)	(0.00127)	(0.00405)	(0.00532)	(0.00268)	(0.00130)
Log(Assets)	0.00799***	0.0197***	0.00158**	0.000780***	0.00653***	0.0180***	0.000555	0.000534**	0.00603***	0.0179***	0.000387	0.000529**
	(0.00119)	(0.00139)	(0.000713)	(0.000213)	(0.00116)	(0.00137)	(0.000709)	(0.000209)	(0.00117)	(0.00141)	(0.000713)	(0.000214)
Liquidity	-0.00369***	-0.00715***	-0.00174***	-0.000617***	-0.00540***	-0.00965***	-0.00265***	-0.00112***	-0.00504***	-0.00952***	-0.00237***	-0.00121***
	(0.000794)	(0.00103)	(0.000488)	(0.000234)	(0.000791)	(0.00102)	(0.000504)	(0.000231)	(0.000896)	(0.00114)	(0.000558)	(0.000231)
ROE	-0.00507***	-0.00628***	-0.00256***	-0.00260***	-0.00370**	-0.00361	-0.00163	-0.00142**	-0.00210	-0.00243	-0.00114	-0.00151***
	(0.00171)	(0.00221)	(0.000970)	(0.000557)	(0.00173)	(0.00223)	(0.000994)	(0.000558)	(0.00172)	(0.00227)	(0.000948)	(0.000580)
Guarantee	0.0622***	0.0847***	0.0340***	0.0214***	0.0639***	0.0868***	0.0350***	0.0217***	0.0630***	0.0860***	0.0343***	0.0220***
	(0.00547)	(0.00645)	(0.00425)	(0.00141)	(0.00551)	(0.00648)	(0.00428)	(0.00142)	(0.00545)	(0.00644)	(0.00422)	(0.00141)
Firm age	0.000223	0.000342*	0.000236**	4.71e-05*	0.000190	0.000306*	0.000216*	4.55e-05*	0.000227	0.000336*	0.000224**	3.96e-05
	(0.000154)	(0.000178)	(0.000113)	(2.56e-05)	(0.000154)	(0.000179)	(0.000113)	(2.55e-05)	(0.000153)	(0.000179)	(0.000112)	(2.55e-05)
Group	-0.00235	0.0114**	-0.00786***	-0.000971	-0.00339	0.00976*	-0.00842***	-0.00151	0.00108	0.0108**	-0.00417**	-0.000338
	(0.00473)	(0.00575)	(0.00288)	(0.001000)	(0.00474)	(0.00576)	(0.00288)	(0.000995)	(0.00351)	(0.00433)	(0.00210)	(0.000804)
Int. rate	0.000281**	0.000194	1.79e-05	3.54e-05	0.000108	-4.53e-05	-7.65e-05	-6.57e-06	-8.08e-05	-0.000251	-0.000172***	-5.86e-05**
(firm level)	(0.000131)	(0.000171)	(7.04e-05)	(2.84e-05)	(0.000127)	(0.000169)	(6.62e-05)	(2.77e-05)	(0.000120)	(0.000162)	(6.26e-05)	(2.56e-05)
Observations	430,567	430,567	430,567	430,567	430,459	430,459	430,459	430,459	441,359	441,359	441,359	441,359
R^2_A	0.197	0.196	0.224	0.043	0.191	0.189	0.218	0.0373	0.192	0.189	0.217	0.0379
Year, bank, sector, ZIP FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: everDefault, for each new loan, takes the value 1 if before the bank-firm relation disappears at some point there is an overdue for more than 90 days. EverDoubful is as everDefault, but the triggering event is being classified as doubtful by the bank. Written off is as everDefault, but the triggering event is being written-off by the bank. 1stDefault is like everDefault, but when a default event takes place, it is only associated to the new loan originated closest to (and earlier than) the default event. Liquidity is defined as current assets/current liabilities, Guarantee is a dummy taking the value 1 if the bank-firm relation has some form of collateral, Firm Age is in years, Group is a dummy taking the value 1 if the firm is part of a group, Int. rate (firm level) is defined as firm interest expenses over total debt, sector fixed effects are at the 2-digit NACE code. Robust standard errors, clustered by firm, under variable coefficients. *** p<0.01, ** p<0.05, * p<0.1.

A4. Bank and Non-bank debt

Table A4.1. Estimation results separating bank and non-bank debt with DTA.

	Construction and Real State				SME				Large Companies			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
DTA	0.19***				0.23***				0.053***			
	(0.0033)				(0.0022)				(0.012)			
DTA^ 2	-0.022***				-0.039***				-0.0061			
	(0.00052)				(0.00061)				(0.0080)			
DTAbank		0.23***		0.24***		0.30***		0.30***		0.19***		0.18***
		(0.0034)		(0.0036)		(0.0023)		(0.0025)		(0.020)		(0.021)
DTAbank^2		-0.033***		-0.033***		-0.080***		-0.082***		-0.081***		-0.081***
		(0.00065)		(0.00069)		(0.00094)		(0.00100)		(0.020)		(0.021)
DTAnonbank			0.047***	0.093***			0.049***	0.091***			-0.049***	-0.024
			(0.010)	(0.0100)			(0.0051)	(0.0050)			(0.018)	(0.018)
DTAnonbank^2			-0.0035	-0.029***			-0.0085**	-0.042***			0.041*	0.014
			(0.0074)	(0.0076)			(0.0041)	(0.0040)			(0.022)	(0.021)
Ind(DTAnonbank<0)			0.027***	0.029***			0.0071***	0.0092***			-0.0032	-0.0026
			(0.0035)	(0.0034)			(0.00086)	(0.00084)			(0.0058)	(0.0058)
DTAbank*DTAnonbank				-0.018***				0.0091***				0.056**
				(0.0025)				(0.0021)				(0.024)
Log(Assets)	0.048***	0.045***	0.035***	0.047***	0.033***	0.029***	0.021***	0.030***	0.0080***	0.0088***	0.0063***	0.0091***
	(0.0011)	(0.00099)	(0.00099)	(0.0010)	(0.00046)	(0.00042)	(0.00042)	(0.00044)	(0.0012)	(0.0011)	(0.0011)	(0.0012)
Liquidity	-0.00021***	-0.00056***	-0.00057***	-0.00040***	-0.00050***	-0.0031***	-0.0067***	-0.0017***	-0.0037***	-0.0030***	-0.0065***	-0.0033***
	(0.000044)	(0.000041)	(0.000045)	(0.000044)	(0.00015)	(0.00014)	(0.00016)	(0.00015)	(0.00079)	(0.00075)	(0.00080)	(0.00078)
ROE	0.00011	0.0014	0.0027***	0.00052	-0.0032***	-0.0023***	-0.00088**	-0.0027***	-0.0051***	-0.0041**	-0.0055***	-0.0045***
	(0.00098)	(0.00090)	(0.00097)	(0.00094)	(0.00039)	(0.00035)	(0.00037)	(0.00036)	(0.0017)	(0.0016)	(0.0017)	(0.0017)
Guarantee	0.099***	0.080***	0.12***	0.083***	0.063***	0.052***	0.077***	0.052***	0.062***	0.054***	0.065***	0.054***
	(0.0022)	(0.0022)	(0.0022)	(0.0022)	(0.0010)	(0.00099)	(0.0010)	(0.0010)	(0.0055)	(0.0053)	(0.0055)	(0.0053)
Age	-0.0021***	-0.0023***	-0.0028***	-0.0021***	-0.0012***	-0.0014***	-0.0019***	-0.0012***	0.00022	0.000089	0.00015	0.000096
	(0.00019)	(0.00018)	(0.00018)	(0.00018)	(0.000062)	(0.000057)	(0.000061)	(0.000059)	(0.00015)	(0.00015)	(0.00015)	(0.00016)
Group	-0.099***	-0.089***	-0.059***	-0.096***	-0.059***	-0.044***	-0.045***	-0.049***	-0.0023	0.000012	-0.0041	-0.00053
	(0.0091)	(0.0088)	(0.0091)	(0.0089)	(0.0023)	(0.0022)	(0.0022)	(0.0022)	(0.0047)	(0.0033)	(0.0047)	(0.0047)
Int. rate (firm level)	0.0016***	0.00045***	0.0013***	0.00075***	0.0017***	0.00070***	0.0013***	0.00093***	0.00028**	0.000057	-0.000089	0.000033
	(0.00013)	(0.00011)	(0.00012)	(0.00012)	(0.000041)	(0.000033)	(0.000038)	(0.000036)	(0.00013)	(0.00012)	(0.00013)	(0.00012)
Observations	748,991	856,339	796,890	796,890	7,972,152	9,592,711	8,949,156	8,949,156	430,567	465,692	437,245	437,245
R^2_A	0.18	0.18	0.16	0.19	0.098	0.10	0.073	0.11	0.19	0.20	0.19	0.20
Year, bank, sector, Zip code FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: DTA includes bank and non-bank debt in the numerator. DTAbank includes only bank debt. DTAnonbank includes only non-bank debt. Liquidity is defined as current assets/current liabilities, Guarantee is a dummy taking the value 1 if the bank-firm relation has some form of collateral, Firm Age is in years, Group is a dummy taking the value 1 if the firm is part of a group, Int. rate (firm level) is defined as firm interest expenses over total debt, sector fixed effects are at the 2-digit NACE code. Robust standard errors, clustered by firm, under variable coefficients. *** p<0.01, ** p<0.05, * p<0.1.

Table A4.2. Estimation results separating bank and non-bank debt with DTI.

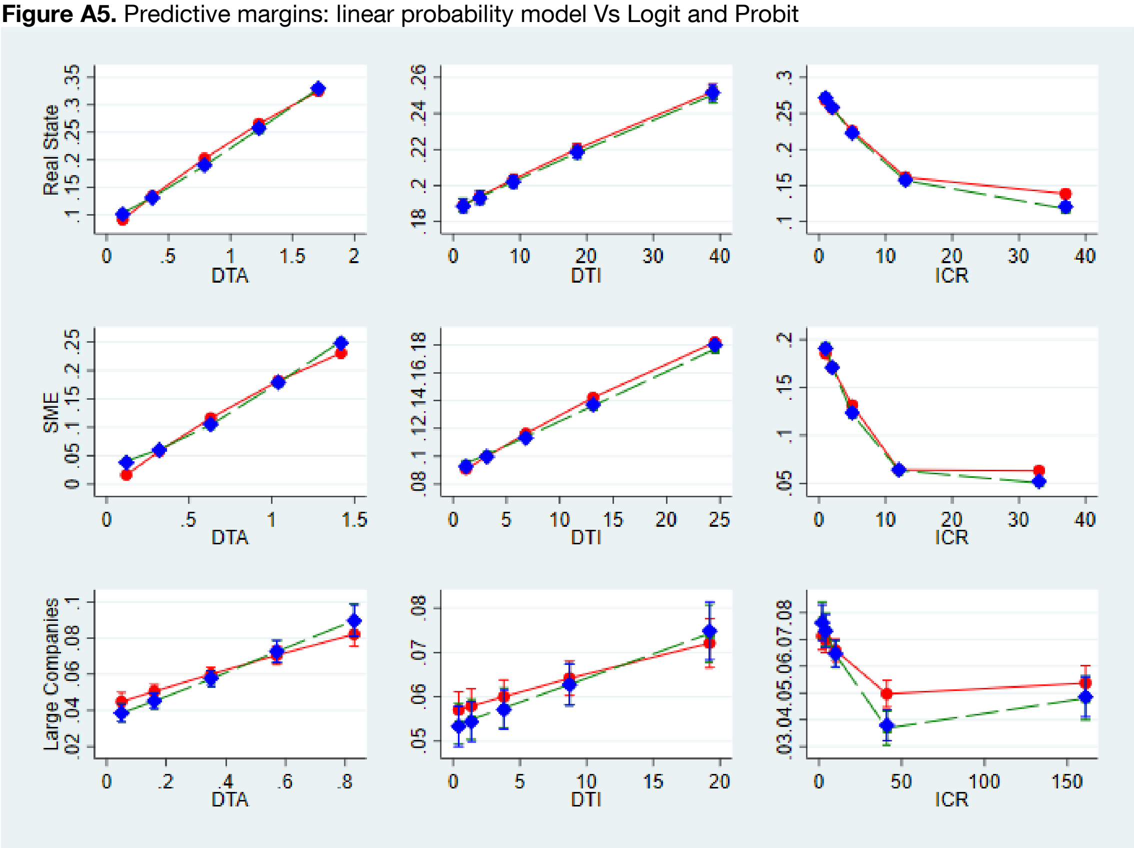
	Construction and Real State				SME				Large Companies			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
DTI	0.0020***				0.0048***				0.00091***			
	(0.000079)				(0.000059)				(0.00018)			
DTI^2	-7.0e-06***				-0.000036***				-5.4e-06***			
	(3.1e-07)				(5.0e-07)				(1.0e-06)			
Ind(DTI<0)	0.031***				0.058***				0.011***			
	(0.0024)				(0.00098)				(0.0042)			
DTIbank		0.0048***		0.0052***		0.011***		0.011***		0.0044***		0.0048***
		(0.00012)		(0.00013)		(0.000099)		(0.00010)		(0.00047)		(0.00049)
DTIbank^2		-0.000029***		-0.000032***		-0.00014***		-0.00015***		-0.000059***		-0.000061***
		(8.4e-07)		(9.2e-07)		(1.5e-06)		(1.6e-06)		(6.9e-06)		(7.3e-06)
Ind(DTIbank<0)		0.043***		0.047***		0.071***		0.076***		0.021***		0.021***
		(0.0022)		(0.0030)		(0.00088)		(0.0010)		(0.0039)		(0.0059)
DTInonBank			0.0016***	-0.00032			0.0034***	0.00072***			-0.00016	-0.00090***
			(0.00021)	(0.00022)			(0.00013)	(0.00013)			(0.00031)	(0.00032)
DTInonBank^2			-0.000017***	-0.000015***			-0.000063***	-0.000069***			-1.4e-06	7.0e-08
			(2.2e-06)	(2.4e-06)			(2.5e-06)	(2.6e-06)			(3.4e-06)	(3.7e-06)
Ind(DTInonBank<0)			0.0083***	-0.0048*			0.012***	-0.0045***			0.0021	-0.0039
			(0.0022)	(0.0028)			(0.00071)	(0.00074)			(0.0037)	(0.0051)
DTIbank * DTInonBank				0.000012***				0.000046***				7.2e-06**
				(1.2e-06)				(1.6e-06)				(3.3e-06)
Observations	748,165	855,303	796,024	796,024	7,970,317	9,590,334	8,947,182	8,947,182	430,459	465,572	437,135	437,135
R^2_A	0.16	0.16	0.16	0.17	0.080	0.087	0.073	0.090	0.19	0.19	0.19	0.19
Year, bank, sector, Zip code FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm, loan FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: DTI includes bank and non-bank debt in the numerator. DTIbank includes only bank debt. DTInonbank includes only non-bank debt. Liquidity is defined as current assets/current liabilities, Guarantee is a dummy taking the value 1 if the bank-firm relation has some form of collateral, Firm Age is in years, Group is a dummy taking the value 1 if the firm is part of a group, Int. rate (firm level) is defined as firm interest expenses over total debt, sector fixed effects are at the 2-digit NACE code. Robust standard errors, clustered by firm, under variable coefficients. *** p<0.01, ** p<0.05, * p<0.1.

A5. Logit and probit models

Graph A5 displays the predictive margins of our preferred model (full controls and quadratic terms) for the different sectors and standards, using a linear probability model (used in the main text), a logit and a probit. In general, the results of the three models are extremely close, indicating robustness to model specification. The differences are somewhat larger when using the ICR and for large corporations, when non-linear effects are more important. Even in this case, the differences are mostly not statistically significant, with point estimates of the other models generally falling within the 95% confidence interval of the linear probability model. We conclude that the linear probability model used throughout the text is adequate for the analysis performed.

Figure A5. Predictive margins: linear probability model Vs Logit and Probit



Note: The model includes a linear and a quadratic term in the corresponding credit standard (DTA in the left panels, DTI in the central ones and ICR in the right ones), a dummy for negative income (EBITDA) in the central and right panels, controls for log of total assets, liquidity (defined as current assets/current liabilities), ROE, firm age (in years), firm-level interest rate (defined as firm interest expenses over total debt), a dummy taking the value 1 if the firm is part of a group, a dummy taking the value 1 if the bank-firm relation has some form of collateral, origination year, bank, ZIP code and sector (at the 2-digit NACE code) fixed effects. For real estate companies and SMEs, DTA is larger than 1 for the highest percentiles. This is because assets correspond to the value at the end of the previous year, while debt includes bank debt obtained in the current year. This approach is followed because the frequency of the balance sheet data available (yearly) is lower than that of the debt (monthly), and should be kept in mind when interpreting the values of the standards. In the case of the ICR both numerator and denominator correspond to end of previous year, since both come from balance sheet data. The red dots connected by a solid line correspond to the linear probability model, the green squares connected by a dashed line correspond to the logit model, while the unconnected blue diamonds correspond to the logit model. Error bars correspond to 95% confidence intervals (smaller than the symbol for Real estate and SMEs – first two rows–).