

# Credit Without Collateral: Firm Size and Debt Structure\*

Beatriz González<sup>†</sup>

Andrea Sy<sup>‡</sup>

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## Abstract

Using data on the quasi-universe of Spanish firms, we find that the use of unsecured debt follows a U-shaped pattern across the firm size distribution, indicating heavy reliance on unsecured debt by both the smallest and largest firms. Among smaller firms, unsecured debt is associated with higher interest rates and greater utilization, consistent with tighter financing constraints. Among larger firms, it is used on more favorable terms, consistent with firms deliberately avoiding collateral costs. Despite its widespread use, unsecured borrowing is positively correlated with unpledged collateral, consistent with collateral continuing to shape firms' debt capacity even when not explicitly pledged.

*Keywords:* debt structure; secured debt; unsecured debt; financing constraints; credit registry data

*JEL Classifications:* G32; G21; D22

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<sup>†</sup>González: Banco de España & CEMFI. Email: beatrizgonzalez@bde.es

<sup>‡</sup>Sy: CEMFI & Banco de España. Email: andrea.sy@cemfi.es

# 1 Introduction

A large body of literature has emphasized the role of collateral in bank lending. A well-established view is that collateral mitigates informational asymmetries between borrowers and lenders, such that small and opaque firms must pledge collateral to obtain credit (secured credit), while larger, more established firms with verifiable cash flows can borrow with no collateral (unsecured credit). This implies that reliance on collateral for borrowing should decline as firm quality or size increases.

However, empirical evidence on collateral use across the full size distribution of firms remains limited. Existing studies typically rely on data from publicly-listed firms or larger private firms with loan exposures above \$1 million in the US.<sup>1</sup> This leaves out a substantial fraction of firms in the economy, giving us an incomplete picture of how collateral is actually used across firms of different sizes.

In this paper, we exploit the quasi-universe of matched firm-bank data from Spain spanning from 2000 to 2019 to provide a comprehensive view of debt structure across the entire firm size distribution. We merge administrative firm-level balance sheet information on Spanish firms with supervisory data on all loans extended by banks to firms. This allows us to cover even the small *private* firms that are often underrepresented in empirical studies of capital structure. Given the heavy reliance of startups and small and medium enterprises (SMEs) on bank loans as their main external funding source (Robb and Robinson, 2014; OECD, 2015), the Spanish credit register data provides a rich setting to study firms' collateral and borrowing choices.

Our novel finding is that the use of unsecured debt follows a U-shaped pattern across the firm size distribution, implying that it is widely used not only by the largest firms, but also by the smallest *private* firms. We establish this pattern using a binscatter plot of the share of unsecured debt in total firm debt against total assets, our measure of firm size, controlling for sector and year fixed effects. This pattern is robust across time periods and sectors and among firms with different loan portfolio compositions. It also holds when focusing only on drawn credit, ruling out the possibility that a high unsecured borrowing reflects undrawn credit lines.

While prior evidence suggests that smaller firms rely more heavily on secured debt, this conclusion is drawn from datasets that exclude small loan exposures. The Spanish credit register includes all loans above €6,000, allowing us to observe very small firms and credit relationships absent from U.S. data. When we restrict the sample to loans above €100,000, a threshold comparable to those in prior datasets, the U-shaped pattern disappears and the unsecured share increases monotonically with firm size, consistent with earlier findings. This exercise shows that the widely documented monotonic pattern is partly an artifact of reporting thresholds that truncate the lower tail of the firm size distribution. Once the full distribution is observed, unsecured borrowing is prevalent not only among large firms but also among the smallest firms, revealing a fundamentally non-monotonic relationship between firm size and collateral use.

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<sup>1</sup>See, for example, Lian and Ma (2021), Caglio et al. (2024), Rampini and Viswanathan (2025)

We further address potential data concerns behind the prevalence of unsecured debt among very small firms. In particular, we show that the pattern is not driven by the presence of self-employed firms, by firms that lease rather than own assets, or by the use of personal guarantees in place of physical collateral. These checks support the conclusion that unsecured borrowing is common among the smallest firms.

To better understand the forces underlying this U-shaped relationship, we document a set of empirical patterns regarding the terms and use of secured and unsecured credit. First, unsecured loans tend to carry higher interest rate spreads and smaller volumes than secured loans, particularly for smaller firms, though these differences become less pronounced as firm size increases. Second, smaller firms draw a larger share of their available unsecured credit, consistent with tighter financing conditions. Third, the use of unsecured debt follows a U-shaped pattern across firm age, a standard proxy of financial constraints. Fourth, firms are more likely to begin borrowing with unsecured debt. Fifth, the U-shaped pattern in unsecured debt use appears in both high and low tangibility firms, but is more pronounced in the high tangibility group, driven by a large decline in unsecured share among mid-sized firms.

Taken together, these patterns highlight systematic differences in how unsecured credit is used across the firm size distribution. Among smaller firms, the combination of higher spreads and greater utilization may reflect tighter financing conditions. Among mid-sized firms, the lower share of unsecured debt, particularly among those with high asset tangibility, suggests greater reliance on secured credit as collateral becomes more available and valuable. Among larger firms, the more favorable terms and lower utilization of unsecured debt suggest that they may be less constrained and may choose to avoid the costs associated with pledging collateral.

We provide additional evidence on risk and lender behavior that helps rationalize the observed debt structure patterns. Loan delinquencies follow a U-shaped pattern across firm size, but expected default probabilities (PDs) decline with size. Among small firms, higher delinquencies and higher expected PDs are consistent with tighter financial constraints. Among large firms, high delinquencies despite low PDs may not fully reflect underlying risk and could relate to institutional or behavioral factors, with large firms using unsecured loans to preserve borrowing flexibility rather than out of necessity. To assess the role of lender characteristics, we examine bank specialization and portfolio diversification. Firms borrowing from sector-specialized banks are slightly more likely to use unsecured credit, but the U-shaped pattern remains, indicating that lender specialization plays a limited role in shaping firms' debt structure. We also show that banks issue smaller unsecured loans to smaller firms and maintain very low exposure to each, a pattern consistent with banks limiting risk on unsecured loans.

Finally, we examine whether collateral (asset-based borrowing) constraints remain relevant amid the widespread use of unsecured (or cash flow-based) debt. Using an empirical framework that relates unsecured leverage to unpledged collateral following [Benmelech et al. \(2025\)](#), we find that across the entire firm size distribution, firms with more unpledged assets borrow more on an unsecured basis. This evidence suggests that even when debt is unsecured, firms'

borrowing capacity remains tied to underlying asset values, indicating that collateral constraints continue to shape debt structure choices.

Overall, our findings challenge the view that unsecured borrowing is used primarily by large firms. Rather, unsecured debt is widely used not only by large firms, but also by small firms, while mid-sized firms rely most heavily on secured borrowing. By documenting how firms sort into secured and unsecured debt contracts and how contractual characteristics and the utilization of unsecured credit vary with firm size, this paper provides new evidence on debt structure and underscores the continued relevance of asset-based borrowing constraints in shaping firms' financing choices.

**Related Literature.** This paper contributes to the extensive literature that examines the role of collateral in capital structure, focusing specifically on the choice between secured and unsecured debt. Earlier work links collateral use to firm risk, with mixed evidence, with [Berger and Udell \(1990\)](#) associating it with riskier firms, whereas [Jimenez et al. \(2006\)](#) finding the opposite. More recent studies document that smaller firms are more likely to pledge collateral ([Lian and Ma, 2021](#); [Chodorow-Reich et al., 2022](#); [Luck and Santos, 2024](#); [Caglio et al., 2024](#); [Rampini and Viswanathan, 2025](#)), alongside a broader decline in secured debt usage over time ([Benmelech et al., 2024](#)). In parallel, some papers highlight the importance of cash flow-based debt, defined to include unsecured debt and blanket liens, among non-financial listed firms ([Lian and Ma, 2021](#)) and firms with loan exposures above \$1 million ([Caglio et al., 2024](#)) in the US. Building on this, we leverage a quasi-universal panel of firm-bank-loan linkages in Spain to study secured versus unsecured debt choices, with particular emphasis on smaller private firms, which are underrepresented in prior work. A key novel finding is the non-monotonic relationship between collateral use and firm size – the smallest firms rely heavily on unsecured debt, mid-sized firms more on secured debt, while the largest firms again tend to rely more on unsecured borrowing.

Our approach aligns with studies that use extensive credit registry data to study corporate borrowing. [Jimenez et al. \(2006\)](#) highlight the role of firm risk in collateral use using Spanish data while [Ivashina et al. \(2022\)](#) document the use of secured (or "asset-based") and unsecured (or "cash flow-based") debt in Spain and Peru and examine the implications of debt heterogeneity for the bank lending channel. More recently, [Degryse et al. \(2025\)](#) use AnaCredit, the euro area credit registry, to detail the composition and value of collateral across countries and estimate the elasticity of loan amounts to collateral values at origination. While these papers focus on loan-level collateralization and aggregate credit supply effects, we shift the lens to firm-level heterogeneity, documenting a robust U-shaped pattern in unsecured debt use across the size distribution. We further complement this literature by leveraging contractual terms, loan utilization, and loan performance data to better understand the mechanisms underlying firms' sorting into secured versus unsecured debt.

Moreover, we relate our work to papers that document differences in the contractual terms

on secured and unsecured debt (Berger and Udell, 1990; Benmelech et al., 2022, 2024),<sup>2</sup> as well as differences by collateral pledged (Benmelech and Bergman, 2009; Caglio et al., 2024; Luck and Santos, 2024). These papers have shown that for US firms, pledging collateral is associated with lower spreads, especially if collateral is more redeployable, and higher borrowing capacity. Our findings in the Spanish context broadly mirror these results, providing external validity through broader coverage of private firms and a different institutional setting.

Relatedly, this literature raises an empirical puzzle of why firms do not always borrow on a secured basis, despite its lower interest rate (Rampini and Viswanathan, 2025). Pan et al. (2025) attribute this to collateral costs that offset the lower interest rates associated with secured debt. According to Rampini and Viswanathan (2025), the benefit of secured debt is not in its price, but rather in its greater borrowing capacity. Our finding that both the interest rate wedge and the loan volume gap between secured and unsecured loans shrink with firm size, alongside large firms' greater reliance on unsecured debt, is consistent with collateral costs that make secured debt less attractive, especially as the loan volume gap diminishes with firm size.

We also add to the literature on debt structure. A substantial body of theoretical and empirical work has studied studying heterogeneity in debt characteristics such as instrument type (e.g. bank loans, credit lines, leases, etc.), maturity and priority (e.g., Rauh and Sufi (2010), Colla et al. (2013), Colla et al. (2020), Donaldson et al. (2020), Benmelech et al. (2022), Donaldson et al. (2025), Donaldson and Piacentino (2025)). Yet most empirical works focus on US listed firms, leaving ample scope to study non-US and private firms (Colla et al., 2020). Aghaee et al. (2025) conduct a cross-country study linking various dimensions of debt structure to legal origin. We contribute by examining debt priority (i.e., use of collateral), focusing on cross-sectional variation in debt structure using data on the near-universe of firms in Spain.

The remainder of this paper is organized as follows. Section 2 briefly describes the datasets we use and presents descriptive statistics. Section 3 outlines the main empirical findings. Section 4 discusses the implications of these results. Finally, Section 5 concludes. We provide further details and robustness checks in the Appendix.

## 2 Data

In this section, we introduce the data sources used in this paper (Section 2.1) and briefly discuss the different types of commercial credit used in Spain and show the wide usage of secured loans and unsecured loans, which will be our focus for the remainder of the paper (Section 2.2). We then present descriptive statistics for the main variables of interest (Section 2.3).

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<sup>2</sup>Kosekova et al. (2025) take a different perspective on the classification of debt instruments and compare interest rates on loans, credit lines, revolving credit, trade financing and financial leases in their study that use the Eurosystem credit registry, AnaCredit, to examine the structure of firm-bank relationships across major euro area economies.

## 2.1 Overview of Data Sources

We provide a brief description of the datasets that we use for our empirical analysis and leave the discussion of other details in Appendix A.1.

**Central de Balances Integrada (CBI).** This dataset contains firm-level balance sheet information on the quasi-universe of firms in Spain from 2000 to 2019. In Appendix A.1, we detail the steps taken to clean the balance sheet data. In Appendix A.2, we discuss the coverage of this dataset and show in Figure A.1 that the firm size distribution in this data matches closely the one reported in the official statistics. Appendix A.3 lists the variable definitions of the balance sheet items.

**Central de Información de Riesgos (CIR).** The CIR, maintained by Banco de España, contains detailed information on all outstanding loans extended to non-financial firms by all banks operating in Spain. This database has a reporting threshold of €6,000, and thus covers nearly all firms that have outstanding bank debt. In CIR, we observe drawn and undrawn credit, which we sum to obtain the total amount of outstanding credit that a bank extends to a firm.<sup>3</sup> Unless otherwise specified, we use the total amount of outstanding credit in our analysis. Importantly, the dataset has information on whether hard collateral (“*Garantía real*”) has been pledged by a firm or not, allowing us to distinguish between the use of secured loans and unsecured loans among firms, following Ivashina et al. (2022), as detailed in Appendix A.4.1. All information reported is in accordance with the Banco de España Circular 3/1995 on the Central Credit Register. We use data from 2000 to 2019. Although the data are available on a monthly frequency, we use year-end stocks to merge with the CBI data. Variables constructed for subsequent analysis are winsorized at 1% on both tails.

*Data used for analysis:* Since the CIR dataset is at the *loan level*, meaning that a firm can have multiple outstanding loans with one or more banks, we first aggregate the *loan-level* data to the *firm level* by summing up all outstanding loans of firms (irrespective of the bank) and use this aggregated *firm-level* data to merge with CBI using the tax identifier (*NIF*) information.

**New CIR.** This new version of the credit register (henceforth “*new CIR*”) contains an expanded set of information on loan terms, such as the loan interest rate (starting 2018), maturity, specific types of collateral pledged in secured loans, types of guarantee, types of credit products, etc. previously not available in the earlier vintage of the CIR database. We use data from 2018 and 2019. Just like the earlier vintage of CIR, the data are available on a monthly frequency but we use year-end stocks to merge with CBI. The classification of loan types based

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<sup>3</sup>Despite this, credit lines and term loans cannot be uniquely told apart because this dataset does not have information on product types. For example, a fully drawn position can be either a term loan or a fully drawn credit line. Hence, we complement our analysis with the new vintage of the credit register (“*new CIR*”), which contains product type information, despite its shorter time dimension.

on the variables in this dataset is discussed in Appendix A.4.1. Other variable definitions and data details are discussed in Appendix A.1.

*Data used for analysis:* As with the CIR data, to conduct *firm-level* analysis with this dataset, we aggregate the granular contract-level information to the firm level by summing up the loan volume to the firm level. To construct measures of the *firm-level* interest rate spread, the contract-level information are weighted by the size of each contract relative to the aggregated loan volume. The aggregated *firm-level* data is merged with CBI using the tax identifier.

**Final datasets for analysis.** The empirical analysis mainly uses two different merged datasets: (1) merged CBI and CIR data from 2000 to 2019; and (2) merged CBI and *new* CIR data from 2018 to 2019, which we use only when exploring more granular information that the longer panel of CIR data does not have.

## 2.2 Types of Commercial Credit in Spain

There are four main types of loans utilized by firms in Spain, as first documented and discussed in Ivashina et al. (2022), namely: secured loans, unsecured loans, trade finance and leasing.<sup>4</sup> Secured loans are backed by specific physical assets, which under Spanish law can be real estate mortgages, movable assets or pledged financial instruments (see Appendix A.4.2 for more details). Often, the use of this type of loan entails transaction costs in perfecting the security interest (i.e., registering the asset in a collateral registry). Consequently, this gives creditors priority claims over the pledged assets in insolvency proceedings. Unsecured loans are not backed by hard collateral. In the event of a liquidation, creditors are ranked junior relative to secured creditors and general preference claimants (e.g., workers, social security, tax claims) in the priority ordering of claims. Trade finance involves a bilateral transaction between a buyer and a seller, usually intermediated by a letter of credit from a bank and backed by the goods being transacted.<sup>5</sup> In leasing, a lender finances the purchase of an asset that a firm uses in exchange for rental payments, thereby separating ownership and use of the asset in question.<sup>6</sup>

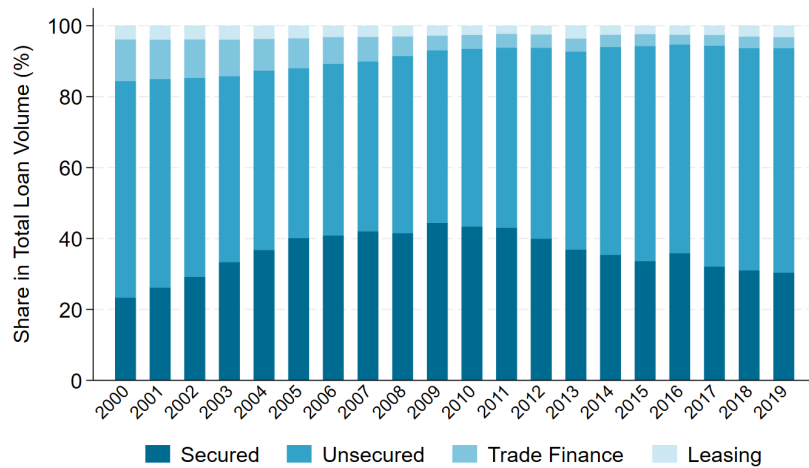
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<sup>4</sup>Note that the terminology we use here differs from Ivashina et al. (2022). In their paper, they use the classification "asset-based loans" and "cash flow loans", in line with Lian and Ma (2021). According to Lian and Ma (2021), cash flow loans encompass both unsecured loans and blanket liens. However, since blanket liens are not recognized by Spanish law, cash flow loans are synonymous with unsecured loans in the Spanish credit register data. Hence, it is more accurate to label these loan types as secured and unsecured loans.

<sup>5</sup>This type of loan is widely used in international trade. This is distinct from *trade credit*, which is credit directly extended by a firm to other firms, and is reflected in the balance sheet of firms as accounts payables for buyers and as accounts receivables for suppliers.

<sup>6</sup>Following Ivashina et al. (2022), we treat leasing as a distinct category, since the separation of ownership and control of the asset implies that the said asset can be repossessed with ease by the lender in the event of a default. In practice, there are two main types of lease instruments – capital leases and operating leases. In Lian and Ma (2021), capital leases are classified under asset-based borrowing of firms, since these are leases that are eventually booked into a firm's balance sheet (i.e. lease to own). In the CIR data, leasing comprises both capital and operating leases.

**Figure 1:** Aggregate Shares of the Different Loan Types in Spain (% in Total Loan Volume)



*Note:* This figure shows the share of each type of commercial credit in total loan volume across the years, using the merged CBI and CIR data from 2000 to 2019.

In [Figure 1](#), we show that secured loans and unsecured loans make up the majority of commercial and industrial loans in Spain, consistent with what has been documented in [Ivashina et al. \(2022\)](#) using data from 2002 to 2010. This is also true within the cross-section of firms of different ages, sizes and sectors (see [Figure B.1](#) of [Appendix B.1](#)). Thus, as in their paper, we exclude trade finance and leasing from all subsequent analysis and focus only on secured loans and unsecured loans. This is consistent with the rest of the literature (e.g., [Lian and Ma \(2021\)](#), [Benmelech et al. \(2022\)](#), [Benmelech et al. \(2024\)](#), [Rampini and Viswanathan \(2025\)](#)) that has focused on the distinction between these two categories of credit.<sup>7,8</sup>

## 2.3 Summary Statistics

[Table 1](#) provides descriptive statistics on the main variables used from the CIR–CBI (2000–2019) and *new* CIR–CBI (2018–2019) datasets. Panel A shows firm-level characteristics, while Panels B and C condition on specific loan and product types.

Panel B shows that, on average, unsecured loans carry interest rate spreads about 1.6 percentage points higher than secured loans (4.58% vs. 2.96%), and their loan volumes are roughly 60% smaller (€389,090 vs. €239,290). This pattern persists when focusing on term loans specifically. Among unsecured products, credit cards have notably higher spreads, averaging 12.35%, compared to 3.86% for credit lines and 3.71% for term loans.

Panel C reports the prevalence of personal guarantees across firms. At least half of the firms in our sample have loans backed by personal guarantees. Interestingly, we find that a

<sup>7</sup>A separate strand of literature looks at the difference between secured borrowing and leasing (e.g., [Eisfeldt and Rampini \(2009\)](#); [Rampini and Viswanathan \(2013\)](#)).

<sup>8</sup>In [Appendix B.3](#), we show that the role of the corporate bond market as a source of debt financing for firms remains very minimal. As such, focusing solely on bank debt while abstracting from market debt does not materially affect our analysis. In [Appendix B.4](#), we examine the role of equity as an alternative source of external financing, and show that it plays a secondary role to debt.

larger fraction of firms with secured loans also provide personal guarantees (60%) compared to those with unsecured loans (49%).

**Table 1: Summary Statistics**

	Mean	p25	p50	p75	sd	N Obs.
<b>Panel A: Firm Characteristics (CIR–CBI 2000–2019)</b>						
Secured debt share	0.25	0.00	0.00	0.58	0.39	5513306
Unsecured debt share	0.75	0.42	1.00	1.00	0.39	5513306
Assets (log '000)	6.09	5.02	6.00	7.06	1.59	5513306
Firm Age	12.04	5.00	10.00	17.00	9.58	5511120
Tangibility	0.32	0.07	0.24	0.53	0.29	5513306
Profitability	0.07	0.01	0.06	0.14	0.30	4911682
<b>Panel B: Loan Terms and Utilization</b>						
<i>Loan Spreads and Volumes (new CIR–CBI 2018–2019)</i>						
Spread (%): Secured	2.96	1.04	2.21	4.07	2.77	170439
Spread (%): Unsecured	4.58	2.15	3.59	5.44	4.09	449515
Volume ('000€): Secured loans	389.09	25.70	84.44	234.12	1226.49	202730
Volume ('000€): Unsecured loans	239.29	9.98	32.37	115.92	774.38	606482
<i>By Product Type</i>						
Spread (%): Term Loans (Secured)	2.99	1.03	2.19	4.11	2.79	153793
Spread (%): Term Loans (Unsecured)	3.71	2.05	3.31	4.82	2.45	303261
Spread (%): Credit Lines (Unsecured)	3.86	2.38	3.60	4.94	2.29	234990
Spread (%): Credit Cards (Unsecured)	12.35	6.95	11.00	18.05	7.35	162523
Volume ('000€): Term Loans (Secured)	396.87	23.16	75.00	201.12	3258.74	183397
Volume ('000€): Term Loans (Unsecured)	214.99	10.02	30.75	104.64	701.49	372544
Volume ('000€): Credit Lines (Unsecured)	230.54	20.00	50.00	145.00	651.94	282211
Volume ('000€): Credit Cards (Unsecured)	9.92	3.00	6.00	11.41	13.52	424168
<i>Utilization Rates</i>						
Utilization Rate: All Unsecured <sup>a</sup>	0.68	0.37	0.88	1.00	0.38	4839868
Utilization Rate: Credit Lines (Unsecured) <sup>b</sup>	0.53	0.04	0.62	0.92	0.39	282211
Utilization Rate: Credit Cards (Unsecured) <sup>b</sup>	0.21	0.01	0.11	0.31	0.26	424168
<b>Panel C: Personal Guarantees (new CIR–CBI 2018–2019)</b>						
Share firms w/ HH guarantees	0.55	0.00	1.00	1.00	0.50	655740
Share firms w/ HH guarantees   Secured	0.60	0.00	1.00	1.00	0.49	202730
Share firms w/ HH guarantees   Unsecured	0.49	0.00	0.00	1.00	0.50	606482

*Note:* Descriptive statistics in Panels B and C are conditional on firms with positive balances in the corresponding loan or product type.

<sup>a</sup> Based on CIR–CBI 2000–2019 data, used to capture longer history of utilization behavior.

<sup>b</sup> Based on *new* CIR–CBI 2018–2019 data

### 3 Empirical Analysis

This section presents our main empirical findings, which are based on the use of matched firm-bank data for Spain. In Section 3.1, we document patterns in the usage of secured and unsecured loans within the cross-section of firms. In Section 3.2, we conduct a series of empirical checks

that can help shed light on possible mechanisms driving the borrowing patterns we observe. In Section 3.3, we provide additional evidence on delinquencies, default risk, and supply-side factors to complement our analysis of unsecured borrowing.

### 3.1 Secured and Unsecured Debt Across the Firm Size Distribution

In this section, we explore cross-sectional heterogeneity in the use of secured and unsecured loans among firms in Spain. Conventional wisdom holds that small firms, being more opaque and having less verifiable cash flows, can only access credit by pledging collateral. We revisit this view by leveraging the extensive coverage of our dataset to provide a comprehensive picture of borrowing patterns across the firm size distribution.

To show how the average *within firm* composition of credit varies across the firm size distribution, we construct a binscatter plot of the share of unsecured debt in total debt (measured *within a firm*) against  $\log(\text{Assets})$  as a measure of size, controlling for age, sector and year variation.<sup>9</sup> Since smaller firms tend to be younger, controlling for age ensures our findings are not confounded by life cycle effects. Including sector fixed effects (FE) allows us to control for systematic differences in borrowing patterns across sectors.<sup>10</sup> Year fixed effects account for changes in borrowing patterns over time, including those caused by aggregate shocks. For example, Benmelech et al. (2024) show that the secured debt issuance is countercyclical and has experienced a secular decline over time. Total assets proxy not only for firm size but also, but to a certain extent, the availability of collateral, as many components of firm assets can be used as collateral. Using the share of unsecured debt in total debt within a firm provides a summary statistic of both the extensive and intensive margin of the use of the two types of credit. Firms that only use secured loans have 0% share and those that only use unsecured loans have 100% share, whereas firms that use both types simultaneously have a share greater than 0% but less than 100%. As shown in Table B1, in the cross-section of non-housing firms, 12.6% have secured loans, 64.5% use unsecured loans, and 22.9% use both types of loans simultaneously.<sup>11</sup>

#### 3.1.1 Main Result: The use of unsecured debt exhibits a U-shaped pattern across the firm size distribution.

In Figure 2, we present a binscatter plot showing the share of unsecured debt across the firm size distribution. Firms are grouped into bins based on  $\log(\text{Assets})$ , and the average unsecured debt share is plotted for each bin. This non-parametric approach allows us to uncover nonlinear relationships without imposing a specific functional form.<sup>12</sup>

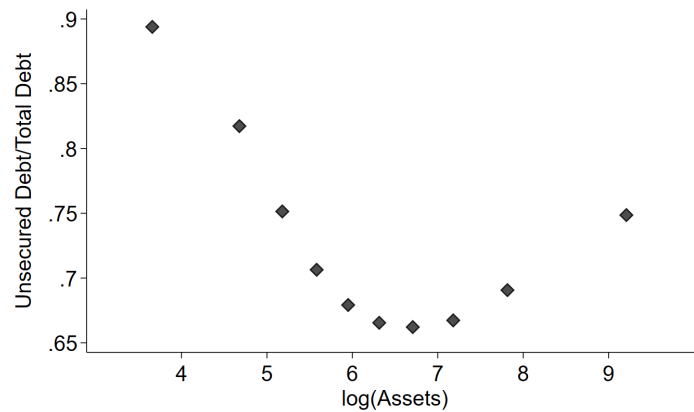
<sup>9</sup>See Cattaneo et al. (2024) for more details on the use of binscatter plots.

<sup>10</sup>In Figure B.6, we show that unsecured loans are used broadly across most sectors.

<sup>11</sup>The fact that many firms use just one type of loan at any given point in time is consistent with debt specialization documented in Colla et al. (2013). That the use of secured (asset-based) loans and unsecured (cash flow) loans are not mutually exclusive was also documented in Drechsel (2023) and Ivashina et al. (2022).

<sup>12</sup>Appendix B.2.1 presents regression evidence on the relationship between firm size and unsecured debt use.

**Figure 2: Share of Unsecured Debt in Total Debt Across Size**



*Notes:* This figure shows a binscatter plot of the share of unsecured debt in total debt within equal-sized bins of  $\log(\text{Assets})$ , a measure of firm size. The analysis controls for age, sector FE and year FE, and uses the merged CBI and CIR data from 2000 to 2019. The nonparametric curve estimates are obtained using the `binsreg` package (see Cattaneo et al. (2025)).

The plot reveals a non-monotonic U-shaped pattern in the use of unsecured debt across the firm size distribution. Firms in the bottom decile borrow predominantly without collateral, with an average unsecured debt share of 0.89. This share declines steadily among small to mid-sized firms, reaching a minimum of 0.66 around the 6<sup>th</sup> to 7<sup>th</sup> decile, indicating that mid-sized firms rely more heavily on secured debt. At the right tail, the share of unsecured debt rises again among the largest firms, averaging 0.75 in the top decile, reflecting widespread reliance on unsecured credit among large firms and consistent with existing literature (e.g., Lian and Ma (2021), Caglio et al. (2024), Rampini and Viswanathan (2025)). Overall, this pattern highlights that unsecured borrowing is particularly common at both ends of the firm size distribution, while mid-sized firms rely more on secured debt.

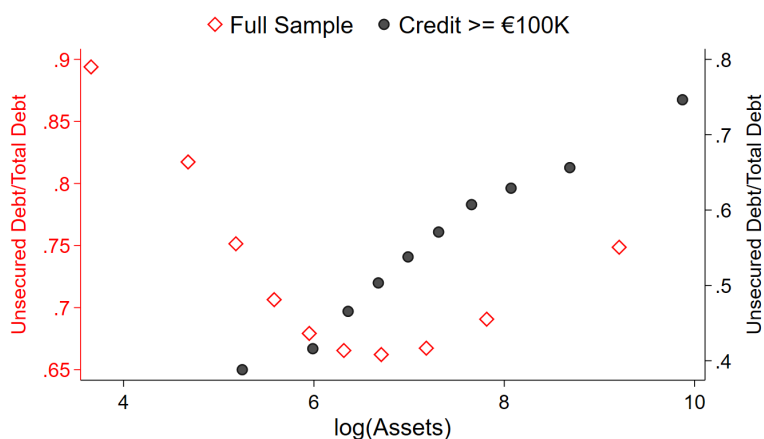
### 3.1.2 Reporting Thresholds and the Coverage of Small Firms

While the borrowing patterns we document among smaller firms may appear to contrast with existing literature that finds a greater reliance on secured borrowing among small firms (e.g., Lian and Ma (2021), Caglio et al. (2024), Rampini and Viswanathan (2025)), an important distinction lies in sample coverage. The Spanish credit register (CIR) include all loans above a reporting threshold of €6,000, capturing a broad spectrum of small-firm lending. In contrast, the U.S. datasets used in these studies typically focus on larger borrowers, which are either publicly-traded firms or privately-held firms that borrow at least \$1 million.

To illustrate the effect of reporting thresholds, we reestimate the binscatter after restricting the sample to loans greater than €100,000, a cutoff that excludes many small loan exposures. As shown in Figure 3, the U-shaped pattern observed in the full sample disappears: the unsecured debt share increases monotonically with firm size, in line with prior findings.

These results indicate that higher reporting thresholds disproportionately exclude small firms borrowing limited amounts without pledging collateral. The right tail, where larger firms

**Figure 3:** Share of Unsecured Debt in Total Debt Across the Size Distribution: Full Sample vs. Credit  $\geq$  €100,000



*Notes:* This figure shows binscatter plots of the share of unsecured debt in total debt within equal-sized bins of  $\log(\text{Assets})$ , controlling for age, sector FE and year FE, using the merged CBI and CIR data from 2000 to 2019, for the full sample, and for the subsample of observations with at least €100,000 in outstanding loans.

rely on unsecured borrowing, remains intact, so our findings do not contradict prior evidence for larger firms.

Overall, our exercise suggests that a higher reporting threshold misses out downward sloping part of the U-shaped pattern that we document in Section 3.1, potentially overstates the prevalence of secured loans in the cross-section and cuts out many small firms that borrow in small quantities (see Table B13 and Table B21).<sup>13</sup> By including these smaller borrowers, we provide a more comprehensive picture of how firms of different sizes borrow and bring new insights on the borrowing behavior of small private firms.

### 3.1.3 Robustness Checks

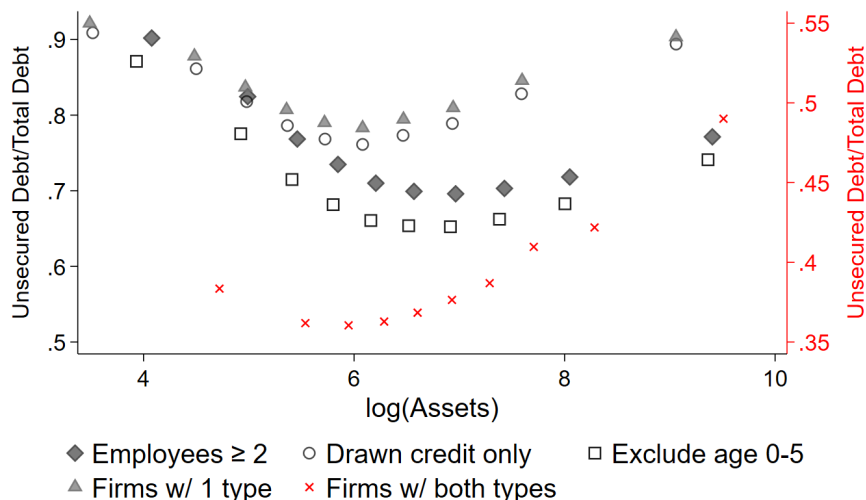
We conduct a comprehensive set of robustness checks to confirm that the U-shaped relationship between firm size and the use of unsecured credit is robust and not driven by compositional or measurement issues.

First, while we control for sector and year variation in establishing our main result, we show that this U-shaped pattern holds across time periods (see Figure B.5) and broadly holds across sectors when analyzed separately (see Figure B.9). Second, we demonstrate that the pattern persists when firms are grouped by loan portfolio composition, i.e., those using only one loan type versus those using both secured and unsecured loans, suggesting that the result is not driven solely by firms using only one loan type (see Figure 4). Third, the pattern holds even when focusing exclusively on drawn credit, indicating that the high unsecured share among small firms is not due to unused credit lines (see Figure 4). This ensures that the pattern we document reflects actual credit use by firms. Fourth, to rule out age-driven effects on the left

<sup>13</sup>In Figure B.19, we show that the cross-sectional distribution of firms changes across different reporting thresholds.

tail, we exclude firms younger than five years and still observe the same pattern (see [Figure 4](#)).

**Figure 4:** Share of Unsecured Debt in Total Debt By Size – Robustness Checks



*Notes:* This figure shows binscatter plots of the share of unsecured debt in total debt within equal-sized bins of  $\log(\text{Assets})$ , a measure of firm size. Each plot in the figure corresponds to a distinct sample restriction: (i) firms with two or more employees; (ii) drawn credit only; (iii) firms with only one loan type (secured or unsecured); (iv) firms with both loan types; and (v) firms older than five years (excluding those aged 0–5). All specifications control for age, sector FE and year FE, and uses the merged CBI and CIR data from 2000 to 2019.

Beyond these basic checks, we address several potential data-related concerns about the widespread use of unsecured credit among very small firms. These include: (1) the presence of self-employed or owner-operated firms; (2) the tendency of small firms to rent or lease equipment instead of purchasing it; (3) the possibility that the high usage of unsecured loans merely reflects heavy reliance on credit lines; and (4) the use of personal guarantees as substitutes for physical collateral. We leverage the granularity of the *new* CIR data to directly address the latter two issues.

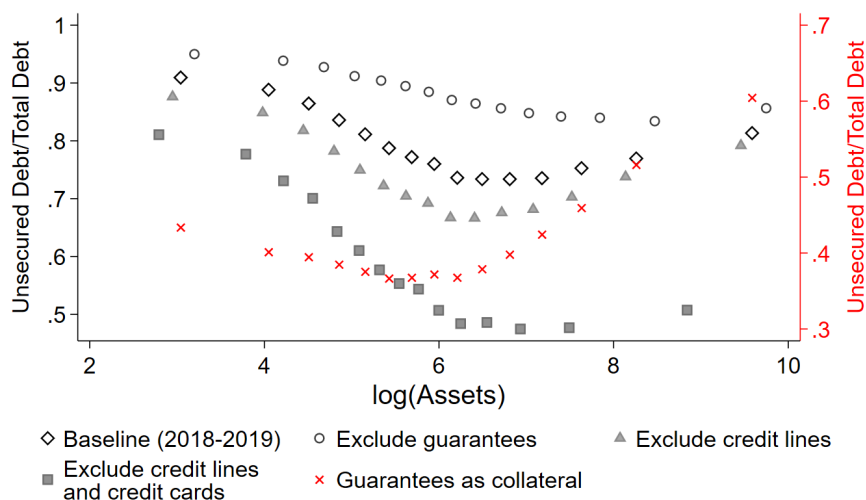
**Self-employed firms.** Some of the smallest firms in our sample may be self-employed individuals that seem to lack capital that can serve as collateral and hence cannot borrow using secured loans. However, these firms may simply be operating from their home office, e.g. as consultants, and have established a legal entity for tax or regulatory reasons. As such, excluding such firms from the analysis may imply that we will observe more usage of secured loans among small firms that employ workers. To alleviate this concern, we show that the U-shaped pattern remains robust when we restrict our sample to firms with at least two employees (see [Figure 4](#)).<sup>14</sup>

**Leasing as collateralized finance.** Small firms may opt to lease equipment rather than use secured loans, especially when financially constrained. As [Rampini and Viswanathan \(2025\)](#) argue, leasing can be considered as another type of collateralized finance that allows constrained firms to borrow more. If so, this can explain why we observe very little usage of hard collateral among such firms. However, in [Figure B.10](#), we show that even if we capitalize

<sup>14</sup>In unreported results, we find that this holds when we restrict the sample to firms with at least five employees.

all leases as secured loans, our result still holds.<sup>15</sup> We provide further discussion on the role of leases in Appendix B.2.5.

**Figure 5: Share of Unsecured Debt in Total Debt By Size (2018–2019) – Robustness Checks**



*Notes:* This figure shows a binscatter plot of the share of unsecured debt in total debt within equal-sized bins of  $\log(\text{Assets})$ , a measure of firm size. Each plot in the figure corresponds to a distinct sample restriction: (i) the baseline sample (all loans for 2018–2019); (ii) excluding credit lines and credit card debt; (iii) excluding all guaranteed loans; (iv) classifying guarantees as collateral; and (v) excluding credit lines only. All specifications control for age, sector FE and year FE, and uses the merged CBI and *new* CIR data from 2018 to 2019.

**Credit lines and credit cards.** Some might argue that unsecured debt among small firms is driven by the use of credit lines, which often do not require collateral.<sup>16</sup> In Figure 5, we show that even if we exclude all credit lines, the U-shaped pattern on the use of unsecured loans along the size distribution holds. As an extra check, we also exclude credit card debt, which is typically unsecured, and find the pattern persists (see Figure 5). This suggests that even standard products such as term loans are frequently unsecured for small firms.

**Personal guarantees.** Finally, one can argue that banks may require firm owners to pledge a personal guarantee in lieu of hard collateral. In Figure 5, we show that if we exclude all guaranteed loans, the U-shaped pattern is preserved. More importantly, even if we classify all personal guarantees as collateral, the documented U-shaped pattern is preserved (see Figure 5). However, the overall unsecured share declines, especially among the smallest firms — falling from about 90% to 45% in the lowest size bin — reflecting the widespread use of guarantees among micro firms.<sup>17</sup> It is crucial to highlight that personal guarantees are also common in secured loans among small and young firms (see Figure B.23).<sup>18</sup> This suggests that personal

<sup>15</sup>Leases in the data include both capital leases and operating leases.

<sup>16</sup>While this is generally true, there are papers, e.g., Lian and Ma (2021) and Chodorow-Reich et al. (2022), showing that some credit lines are secured.

<sup>17</sup>See the ‘Guarantees as collateral’ binscatter estimate in Figure 5, which uses a secondary y-axis with a different scale and color.

<sup>18</sup>To align with our empirical framework, we construct a binscatter plot of the share of firms using personal guarantees against firm size, estimating the relationship separately by loan type, that is, whether firms use secured debt or unsecured debt. Figure B.24 shows that across asset size bins, the share of firms using unsecured debt with personal guarantees is not higher than the share of firms using secured debt with personal guarantees.

guarantees may reflect broader lender concerns beyond firms' lack of physical assets to pledge. Consistent with this interpretation, unsecured loans backed by personal guarantees do not carry lower spreads or larger volumes relative to unsecured loans without guarantees. If anything, they are priced slightly worse, suggesting that guarantees are required for riskier borrowers rather than acting as a substitute for hard collateral (see [Table B18](#) and [Table B19](#)). In [Appendix B.6](#), we elaborate on the distinct role of personal guarantees and explain why they should not be treated as equivalent to hard collateral.

### 3.1.4 Decomposition by Product Type

Why is the use of unsecured loans so prevalent among firms, especially small private firms? As shown in [Figure 5](#), this pattern is not solely driven by credit lines. Even when the analysis is restricted to term loans, unsecured borrowing remains prevalent among small firms. To further investigate, we leverage the detailed product-type breakdown in the *new* CIR data to decompose unsecured debt into term loans, credit lines, credit cards, and other loans. [Figure B.12](#) shows that unsecured borrowing among firms is not limited to credit lines. Unsecured term loans and credit cards are widely used as well. In particular, the extensive use of credit cards by small firms helps explain the persistence of unsecured borrowing in this segment, even when all personal guarantees are classified as collateral, given that this type of credit instrument is mostly neither secured (see [Figure B.12](#) and [Figure B.14](#)) nor guaranteed (see [Table B17](#)).<sup>19</sup>

Consistent with the diverse composition of unsecured debt, we find that a majority of firms use more than one type of unsecured credit product (see [Table B3](#)). Specifically, around 44% of firms with unsecured debt rely on a single product type, while the rest use two or more. Among firms that use only one unsecured product, credit cards are the most common, accounting for nearly 20% of cases, followed by term loans (14%) and credit lines (6%) (see [Table B4](#)). This suggests that even among single-product users, unsecured borrowing is not limited to revolving credit and that term loans and credit cards play a significant role.

### 3.1.5 Leverage Patterns

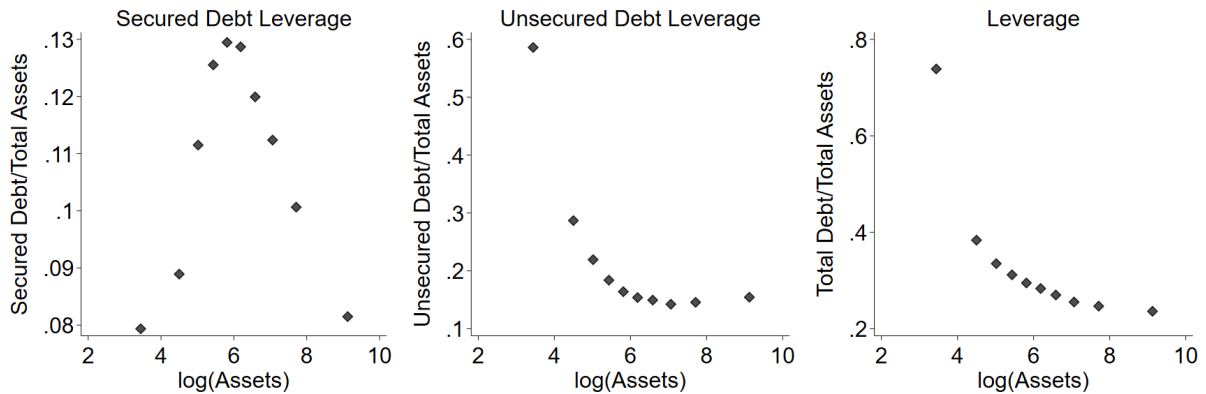
Finally, we examine leverage patterns across the firm size distribution to understand the mechanics behind the U-shaped pattern in unsecured debt use. To do this, we construct binscatter plots similar to our headline result in [Section 3.1.1](#). [Figure 6](#) plots the secured debt leverage, unsecured debt leverage and overall leverage against  $\log(\text{Assets})$ .

We find that overall leverage declines monotonically with firm size, which means that smaller firms borrow heavily relative to their asset base compared to larger firms. Unsecured

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<sup>19</sup>The use of business credit cards as a financing source for SMEs has been documented in [Robb and Robinson \(2014\)](#), [Benetton and Buchak \(2025\)](#) and [Akcigit et al. \(2025\)](#). In [Figure B.12](#), we show that at least 50% of small firms with unsecured loans use credit cards. However, its share in aggregate loan volume is much lower compared to the fraction of firms that use this product (see [Figure B.13](#)) because the committed amount (credit limit) on a credit card is generally far lower than that of a term loan or a credit line. See [Appendix B.2.6](#) for details.

**Figure 6: Secured, Unsecured and Total Leverage Across Firm Size**



*Notes:* This figure shows a binscatter plot of the share of secured debt leverage, unsecured debt leverage and total leverage within equal-sized bins of  $\log(\text{Assets})$ , a measure of firm size. The analysis controls for age, sector FE and year FE, and uses the merged CBI and CIR data from 2000 to 2019.

leverage falls steadily as firm size increases, with the bottom decile at nearly 60%, the 6th decile around 15%, the 8th decile at 14%, and the top decile back up to 15%, reflecting the slight uptick in the largest firms. In contrast, secured debt leverage follows an inverted U-shape with respect to size. It starts at roughly 8% for the smallest decile of firms, peaks at around 13% for mid-sized firms, and subsequently declines for the largest firms.

Taken together, these patterns clarify the U-shaped pattern in the share of unsecured debt relative to total debt. Small firms appear almost entirely unsecured because secured leverage is negligible, mid-sized firms rely most on secured borrowing, and large firms borrow little overall relative to their scale but disproportionately unsecured as secured leverage falls even faster.

### 3.2 Exploring the U-Shaped Pattern in Unsecured Debt

To better understand the U-shaped relationship between firm size and unsecured debt use, this section examines a series of empirical patterns that can help shed light on the underlying mechanisms. Section 3.2.1 compares loan contract terms between secured and unsecured debt. Section 3.2.2 analyzes how utilization rates vary with firm size. Section 3.2.3 examines how unsecured debt varies along firm age, another standard proxy of financial constraints. Section 3.2.4 explores the extensive margin of credit, specifically whether initial loans that firms use are secured or unsecured, as an indicator of how firms enter the credit market. Section 3.2.5 examines how asset tangibility affects unsecured debt use across the size distribution. Finally, Section 3.2.6 synthesizes these patterns to assess whether unsecured borrowing among small firms reflects constrained access to credit, while among larger firms it may instead represent a deliberate financing choice.

### 3.2.1 Loan Contract Features: Secured vs. Unsecured Debt

We explore the differences in loan terms between secured loans and unsecured loans. The widespread use of unsecured debt by large firms is not surprising, as these firms typically have more verifiable cash flows and a stronger reputation, reducing the need for collateral. However, the prevalence of unsecured debt among small firms raises the question of whether these loans offer contractual advantages for smaller borrowers. We investigate this question using merged CBI and *new* CIR data from 2018 to 2019, which has information on loan interest rates.

To examine how loan terms on secured and unsecured debt vary with firm size, we construct binscatter plots of the interest rate spread and the logarithm of total outstanding loan volume,  $\log(\text{Credit})$ , by loan type, across bins of firm size. We define the interest rate spread on a loan as the difference between the loan interest rate and the T-bill rate matched to the corresponding maturity. In constructing these binscatter estimates, we control for firm age, asset tangibility, profitability, sector fixed effects, and year fixed effects. Controlling for age helps net out life cycle effects, while the fixed effects account for systematic differences in borrowing patterns across sectors and over time. We control for asset tangibility and profitability because both influence loan pricing and availability. Tangible assets can be pledged as collateral, which is especially relevant for secured debt, while higher profitability signals stronger repayment capacity.<sup>20</sup> Both reduce lenders' perceived credit risk and may lead to more favorable loan terms.

**Figure 7** shows two key patterns. First, for both secured and unsecured debt, the interest rate spread declines with firm size, while loan volume increases. These results suggest that although both very small and large firms rely heavily on unsecured borrowing, the conditions they face differ markedly. Smaller firms face higher financing costs and smaller loan amounts, whereas large firms have lower spreads and larger loan volumes.

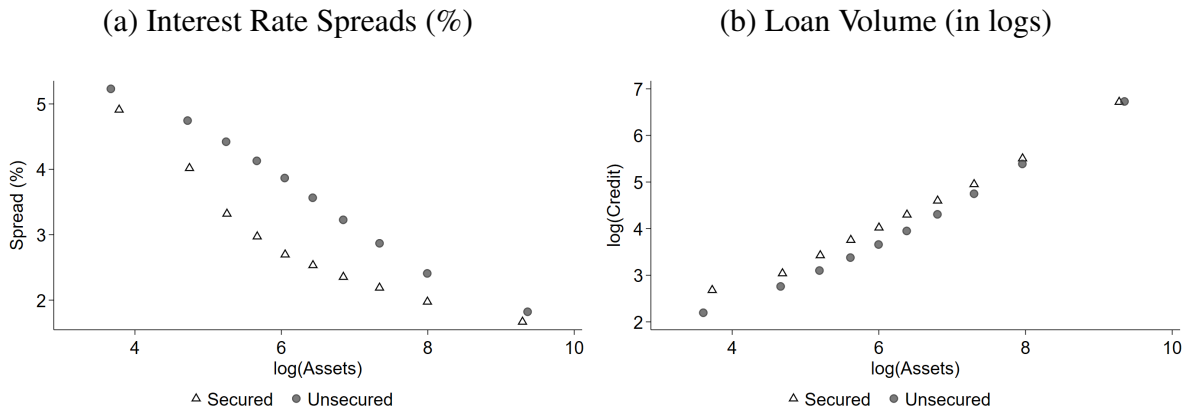
Second, unsecured debt is associated with higher spreads and smaller loan volumes compared to secured debt across the firm size distribution, except among the largest firms where this difference is small.<sup>21</sup> To ensure that the observed difference in loan terms between secured and unsecured debt are not driven solely by idiosyncratic differences across firms, but also reflect differences inherent to the loan contracts themselves, we replicate the analysis using *loan-level* regressions with firm  $\times$  year fixed effects following [Khwaja and Mian \(2008\)](#) in [Appendix B.7.1](#). This approach allows us to compare secured and unsecured loans within the same firm and year, holding borrower characteristics constant, and thus isolate differences that are specific to loan type. As shown in [Figure B.26](#) and [Figure B.27](#), the qualitative conclusions remain unchanged.

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<sup>20</sup>Note that [Rampini and Viswanathan \(2025\)](#) and [Benmelech et al. \(2025\)](#) emphasize that tangible assets matter for unsecured debt too, because unsecured debt is implicitly collateralized.

<sup>21</sup>Note that credit card debt is excluded from the baseline analysis due to its characteristically high interest rates, which can skew the results. In [Figure B.25](#), we replicate the analysis including all credit card debt. The qualitative patterns remain similar, though average interest rate spreads on unsecured debt are higher, and average loan volumes are lower.

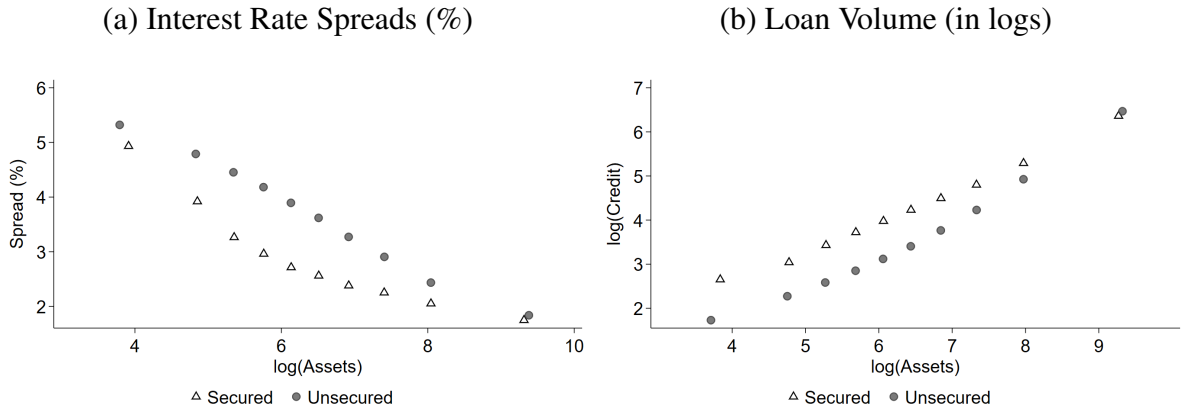
**Figure 7: Loan Contract Terms on Secured and Unsecured Debt**



*Notes:* This figure shows a binscatter plot of (a) the interest rate spread; and (b) loan volume (measured as  $\log(\text{Credit})$ ) within equal-sized bins of  $\log(\text{Assets})$ , a measure of firm size. The analysis controls for age, tangibility, profitability, sector FE and year FE, and uses the merged CBI and *new* CIR data from 2018 to 2019. Credit card debt is excluded.

**Product-level analysis.** We now turn to a more granular analysis of unsecured debt by product type. While secured debt is largely composed of term loans (see [Figure B.14](#)), unsecured debt spans a wider range of products, including credit lines and credit cards, resulting in greater heterogeneity in its composition (see [Figure B.12](#)).

**Figure 8: Loan Contract Terms on Secured and Unsecured Term Loans Across Firm Size**



*Notes:* This figure shows a binscatter plot of (a) the interest rate spread; and (b) loan volume (measured as  $\log(\text{Credit})$ ) on term loans, within equal-sized bins of  $\log(\text{Assets})$ , a measure of firm size. The analysis controls for age, tangibility, profitability, sector FE and year FE, and uses the merged CBI and *new* CIR data from 2018 to 2019.

To assess whether the unsecured–secured gap in spreads is simply due to product composition, particularly the presence of high-cost products like credit cards, we compare secured and unsecured term loans in [Figure 8](#). We find that unsecured term loans still carry higher spreads and smaller volumes, especially for smaller firms, consistent with our baseline results. Among the largest firms, this gap largely disappears. These patterns suggest that unsecured debt has higher spreads not merely because of its product mix, but due to more fundamental differences

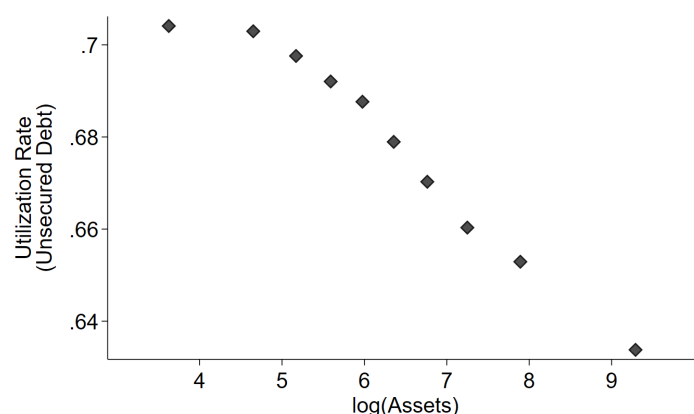
in credit terms.<sup>22</sup>

### 3.2.2 Utilization Rates in Unsecured Debt

Next, we examine utilization rates on unsecured debt. Since secured debt is mostly term loans (see [Figure B.14](#)), which are typically fully utilized, we focus only on unsecured debt. We define the utilization rate as the ratio of the drawn amount to the total outstanding (or committed) amount. The goal of this exercise is to link utilization rates to financing constraints, the idea being that firms facing tighter constraints are more likely to draw down a larger share of their available credit, resulting in higher utilization rates.<sup>23</sup>

In [Figure 9](#), we find that the utilization rate on unsecured debt declines with firm size, indicating that smaller firms tend to draw down a larger share of their available credit. This pattern is consistent with the idea that smaller firms face tighter financing constraints. To address the concern that this decline in utilization merely reflects a disproportionate increase in committed credit relative to drawn amounts as firm size increases, we show that unsecured debt leverage, defined as drawn unsecured credit relative to assets, also declines with firm size (see [Figure B.29](#)), which suggests less reliance on debt relative to their scale.

**Figure 9:** Utilization Rate of Unsecured Debt Across Firm Size



*Notes:* This figure shows a binscatter plot of the utilization rate on unsecured debt within equal-sized bins of  $\log(\text{Assets})$ , a measure of firm size. The analysis controls for age, sector FE and year FE, and uses the merged CBI and CIR data from 2000 to 2019.

However, treating unsecured debt as a single category masks important differences in utilization behavior across various product types. We turn our attention to credit lines and credit cards, since term loans are fully utilized by definition and the residual category is of negligible importance.

<sup>22</sup>In [Appendix B.7.1](#), we show that credit lines and credit cards, which are predominantly unsecured, also exhibit a declining spread with firm size, though at different levels.

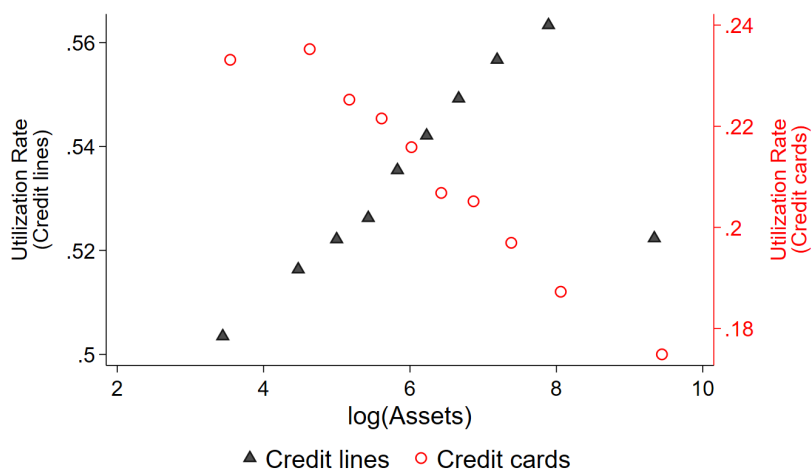
<sup>23</sup>While high utilization rates can be interpreted as a symptom of financing constraints, i.e. firms drawing down due to liquidity needs (e.g., [Chodorow-Reich et al. \(2022\)](#)), this is not the only possible interpretation. Low utilization can also reflect limited need for external funding, particularly among firms with strong internal cash flows or lower investment demand. As such, utilization should be viewed as a suggestive indicator of constraints.

In [Figure 10](#), we find contrasting utilization patterns across credit lines and credit cards. Credit card utilization declines steadily with firm size, falling from around 24% among the smallest firms to roughly 16% for the largest.<sup>24</sup> This pattern is consistent with what [Benetton and Buchak \(2025\)](#) find for SMEs in the US. In contrast, the level of credit line utilization is higher, and increases from about 50% to 56% across most of the distribution before dipping slightly to 52% at the top. The utilization behavior across firm size is consistent with [Amberg et al. \(2025\)](#) for Swedish firms.

These patterns suggest a shift in how firms use unsecured debt as they grow. Smaller firms appear to rely more on credit cards, typically associated with short-term or emergency financing, while larger firms shift toward credit lines, which are more suited for managing liquidity and working capital needs. The slight decrease in credit line utilization at the very top of the size distribution may indicate that larger firms are less reliant on external credit to manage liquidity needs.<sup>25</sup>

Overall, unsecured utilization declines with firm size despite rising credit line utilization. This reflects differences across unsecured products, namely that credit card utilization falls steadily, credit line utilization rises then dips at the top, and term loans remain nearly fully utilized. The combination of these trends and the distribution of firms using each product drives the decline, highlighting the roles of both product mix and the extensive margin of product use.<sup>26</sup>

**Figure 10:** Utilization of Unsecured Debt Across Firm Size: Credit Lines and Credit Cards



*Notes:* This figure shows a binscatter plot of the utilization rate on unsecured credit lines and credit cards within equal-sized bins of  $\log(\text{Assets})$ , a measure of firm size. The analysis controls for age, sector FE and year FE, and uses the merged CBI and *new* CIR data from 2018 to 2019.

<sup>24</sup>One potential concern with the decline in credit card utilization as firm size increases is that it may be mechanically driven by rising credit limits, while drawn amounts remain flat. However, as shown in [Figure B.30](#), both the drawn and committed amounts on credit cards increase with firm size, suggesting that the decline in utilization is not a mechanical effect.

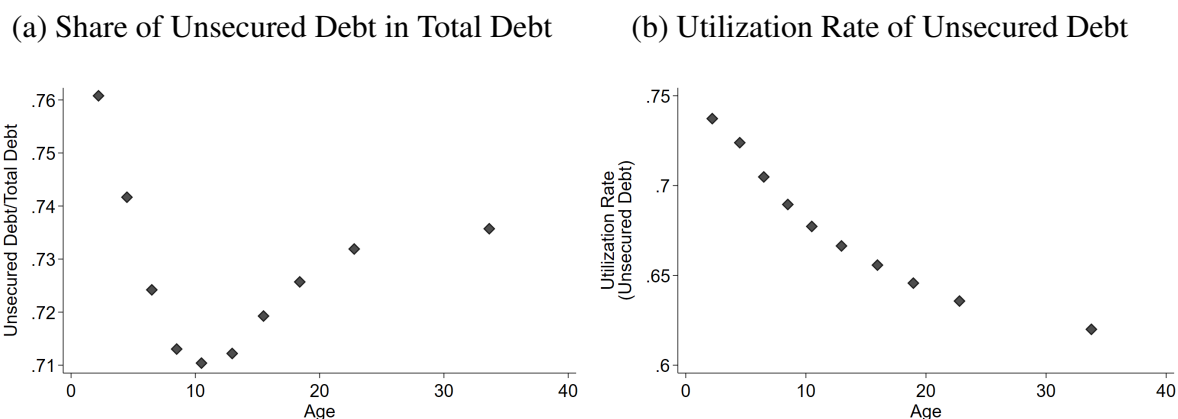
<sup>25</sup>In [Figure B.31](#), we show that the unsecured debt leverage in credit lines and credit cards declines with firm size.

<sup>26</sup>[Figure B.12](#) illustrates that, using *year-end* stock data from the *new* CIR, credit card usage among firms exceeds that of credit lines, subject to the caveats we discuss in [Appendix B.2.6](#).

### 3.2.3 Unsecured Debt Across Firm Age

To provide additional suggestive evidence linking financing constraints to unsecured borrowing, we examine how the unsecured debt share and unsecured debt utilization rate vary with firm age. Firm age, like size, is a well-established proxy for financing constraints (e.g., [Hadlock and Pierce \(2010\)](#); [Cloyne et al. \(2023\)](#)).

**Figure 11:** Unsecured Debt Share and Unsecured Debt Utilization Across Age



*Notes:* This figure shows a binscatter plot of (a) the share of unsecured debt in total debt; and (b) utilization rate of unsecured debt within equal-sized bins of age. The analysis controls for size (measured using  $\log(\text{Assets})$ ), sector FE and year FE, and uses the merged CBI and CIR data from 2000 to 2019.

As [Figure 11](#) shows, the unsecured debt share follows a U-shaped pattern over the firm age distribution. Both younger and older firms rely disproportionately on unsecured debt while middle-aged firms use more secured borrowing. Utilization rates of unsecured debt monotonically decline with firm age. These documented patterns by firm age closely mirror those observed across the firm size distribution.

### 3.2.4 The Extensive Margin of Firm Borrowing

A natural explanation for the prevalence of unsecured borrowing among small firms is relationship lending. We test this by looking at the extensive margin of borrowing of firms. To identify this margin, we take the first year in which a firm appears in both the CIR and CBI data sets. In the CBI data, we restrict the sample to firms incorporated from 2000 onward to ensure that what we capture is not left-censored data. A firm is classified as borrowing for the first time if it satisfies the condition  $\min(\text{year}_{CIR}) \geq \min(\text{year}_{CBI})$ , which means that its first observed credit event does not precede its first observed appearance in the CBI dataset.<sup>27</sup>

<sup>27</sup>It is important to note that our measure of the extensive margin borrowing relies on year-end stocks of CIR. This approach may understate the true incidence of borrowing *within* a given year. For example, if a firm obtains a credit line early in the year, e.g. in March, and fully repays it before the year-end reporting date, and this is the only borrowing the firm undertakes that year, then this borrowing event would not be captured in our dataset. For such instances, our measure will incorrectly classify the firm as not having accessed credit. Thus, the extensive margin measure we use provides a lower bound.

In [Table 2](#), we show that over 80% of firms that borrow for the first time use unsecured debt, highlighting its central role at the extensive margin. Only around 16% of firms use secured debt ('Secured' + 'Both' in [Table 2](#)). As shown in [Figure B.32](#) and [Figure B.33](#), these patterns are broadly consistent across sectors, with the exception of the housing sector. Because these firms are observed at the moment they first appear in the credit registry, they have not yet established a borrowing history. The widespread use of unsecured credit when firms borrow for the first time therefore indicates that relationship lending is unlikely to be the primary driver of unsecured borrowing among small firms.

**Table 2: Extensive Margin of Borrowing**

	Share of Firms (%)
Secured	10.69
Unsecured	83.69
Both secured and unsecured	5.62

*Notes:* This table reports the share of firms whose first observed loan is either secured, unsecured, or a combination of both. The extensive margin of borrowing is defined based on the earliest year in which a firm appears with loan information in both datasets. This part uses the merged CBI and CIR data from 2000–2019.

Next, we look at firm characteristics when firms borrow for the first time. Although a small share of firms simultaneously take on secured and unsecured debt, we focus on a cleaner comparison between firms that rely exclusively on unsecured or secured credit at entry into credit markets.<sup>28</sup> In [Table 3](#), we find that there are no economically significant differences in firm age, whether the debt they take out for the first time is unsecured or secured. However, we observe distinct patterns in loan terms. At the extensive margin, secured debt is associated with a lower interest rate spread and larger loan volume, consistent with our baseline result in [Section 3.2.1](#). Furthermore, we find that a substantial share of first-time loans are backed by personal guarantees, with a slightly higher share for firms using secured loans, consistent with our result for the entire sample (see Panel C of [Table 1](#) and [Figure B.23](#)). This supports the idea discussed in [Section 3.1.3](#) and [Appendix B.6](#) that lenders may not necessarily view collateral and personal guarantees as substitutes, but may instead require the latter as a commitment device. While unsecured credit is inherently riskier, this risk is typically priced in through higher spreads relative to secured credit.

### 3.2.5 Tangibility and Unsecured Debt Use: Patterns Across Firm Sizes

Finally, we explore how the relationship between unsecured debt use and firm size varies with the asset tangibility of firms. Since tangible assets can serve as collateral, they can facilitate secured borrowing. For instance, [Lian and Ma \(2021\)](#) find that the amount of secured debt a firm holds correlates positively with the value of its physical assets. To understand whether collateral capacity influences the use of unsecured debt, we split the sample by median tangible

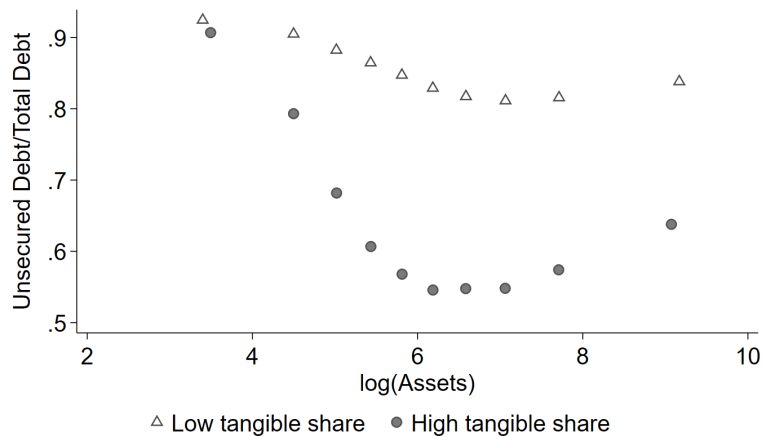
<sup>28</sup>A more comprehensive set of descriptive statistics is provided in [Table B24](#).

**Table 3: Extensive Margin of Borrowing Summary Statistics**

	Unsecured		Secured		T-stat
	Mean	Std Dev	Mean	Std Dev	(3)–(1)
	(1)	(2)	(3)	(4)	(5)
Firm Age	1.81	2.30	1.92	2.41	9.64
Loan volume ('000)	130.83	790.87	342.73	1032.72	43.64
Interest Rate Spread (%)	4.65	3.16	3.20	3.07	-11.22
Share of firms with HH guarantee (%)	63.05	48.27	70.97	45.42	4.96

*Notes:* This table compares firm and loan characteristics at the time of their first borrowing, depending on whether they use unsecured debt or secured debt. Firm age and loan volume are from the merged CBI and CIR data from 2000–2019 and are restricted to firms incorporated from 2000 onward. The interest rate spread and share of firms with personal (HH) guarantees use the merged CBI and *new* CIR data from 2018–2019 and are restricted to firms incorporated from 2018–2019.

asset share and examine how unsecured debt use varies across the firm size distribution for each subsample.

**Figure 12: Share of Unsecured Debt in Total Debt Across Firm Size – Low vs. High Tangibility**

*Notes:* This figure shows binscatter plots of the share of unsecured debt in total within equal-sized bins of  $\log(\text{Assets})$ , a measure of firm size, separately for firms with below- and above-median asset tangibility. Tangibility (tangible share) is measured as tangible assets over total assets. The analysis controls for age, sector FE and year FE, and uses the merged CBI and CIR data from 2000 to 2019.

In [Figure 12](#), we find that the U-shaped pattern in unsecured debt use is present in both subsamples, but more pronounced in the high tangibility group. In addition, the difference in unsecured debt use between high- and low-tangibility firms varies meaningfully across the size distribution. In the bottom decile, the gap is close to zero, suggesting that very small firms rely heavily on unsecured credit regardless of their asset composition, likely due to limited absolute collateral value. As firm size increases, the gap widens steadily up until the 6<sup>th</sup> decile, then narrows somewhat in the top two deciles. This pattern implies that tangible assets play a larger role in enabling secured borrowing among mid-sized firms. Among large firms, however, higher tangibility does not reduce unsecured debt use. Instead, the U-shape steepens, consistent with the view that large firms avoid the costs of pledging collateral ([Rampini and Viswanathan](#),

2025), even when they have tangible assets to pledge.

### 3.2.6 Linking the Empirical Patterns

The empirical patterns that we document in Section 3.2.1–3.2.5 can be summarized as follows:

1. **Loan terms:** Unsecured debt is associated with higher spreads and smaller loan volumes than secured debt, especially for smaller firms. However, these differences shrink as firm size increases.
2. **Utilization rates:** Smaller firms draw a larger share of their available unsecured credit.
3. **Firm age:** Younger firms use unsecured debt more heavily; the unsecured debt share follows a U-shaped pattern in firm age.
4. **Extensive margin:** Firms are more likely to begin borrowing with unsecured debt.
5. **Tangibility:** The U-shaped pattern in unsecured debt use is more pronounced among high-tangibility firms, with the gap relative to low-tangibility firms peaking at mid-size and narrowing only slightly at the top of the size distribution.

Overall, the patterns documented in this section suggest that unsecured debt may play distinct roles across the firm size distribution. Its prevalence among both the smallest and largest firms, albeit under very different terms, points to differing underlying motivations for its use.

Small firms appear to rely heavily on unsecured debt because they are constrained. Their substantially higher leverage relative to assets (see [Figure 6](#)) is consistent with this interpretation. In addition, unsecured loans to small firms carry higher spreads and smaller loan volumes, and higher utilization rates, implying reliance on more expensive credit out of necessity. This interpretation is supported by the fact that younger firms, which are typically more financially constrained, rely more heavily on unsecured debt. Furthermore, most first-time borrowers begin with unsecured credit. Moreover, among small and mid-sized firms, those with higher tangible asset shares tend to use less unsecured debt, although this gap is negligible for the smallest firms, likely because the absolute value of their tangible assets is too limited to significantly ease collateral constraints. This suggests that asset tangibility may help ease such constraints primarily for mid-sized firms.

At the other end of the size spectrum, large firms also make substantial use of unsecured credit, but under more favorable terms, i.e. lower spreads and larger volumes, and lower overall utilization rates. Consistent with being less financially constrained, these firms are also far less levered relative to assets, as shown in [Figure 6](#). These firms may opt for unsecured borrowing to avoid the costs associated with pledging collateral. When these costs, such as legal fees, the loss of operational and financial flexibility ([Benmelech et al., 2024](#); [Pan et al., 2025](#); [Rampini and Viswanathan, 2025](#)), outweigh the marginal benefits, unsecured debt becomes the preferred

choice despite access to secured debt. As emphasized by [Rampini and Viswanathan \(2025\)](#) and [Pan et al. \(2025\)](#), the cost of secured debt is not fully reflected in the interest rate alone, since the use of collateral imposes implicit or outright costs for firms.<sup>29</sup> Instead, the primary benefit of secured debt lies in enabling firms to access larger loan amounts ([Rampini and Viswanathan, 2025](#)). Our finding, that the pricing and volume wedge between secured and unsecured loans narrows significantly for large firms, supports this view. Additionally, for large firms, higher asset tangibility does not reduce unsecured debt use, consistent with the notion that these firms avoid collateral costs even when they have assets to pledge.

### 3.3 Additional Evidence

In this section, we present supplementary evidence that complements the core findings on unsecured debt use. In Section [3.3.1](#), we examine patterns in firms' loan delinquency rates, providing insight into the risk profiles associated with different types of borrowing. In Section [3.3.2](#), we analyze the expected probability of default (PD) of firms to assess how credit risk varies across the firm size distribution. In Section [3.3.3](#), we explore the role of lender specialization and its potential impact on borrowing patterns. Finally, in Section [3.3.4](#), we provide a brief discussion of other supply-side factors that might be at work. Taken together, these help provide useful context on the financing choices that firms make.

#### 3.3.1 Loan Delinquencies Across Firm Size

In this section, we examine how firm-level loan delinquencies vary by firm size. Since unsecured debt shows a U-shaped pattern, examining loan delinquencies helps us better understand the credit risk profiles across firms of different sizes. To this end, we compute the non-performing loan (NPL) ratio, defined as the ratio between the total amount of non-performing loans and the total loan volume, where a loan is considered non-performing if it is 90 days or more past due.

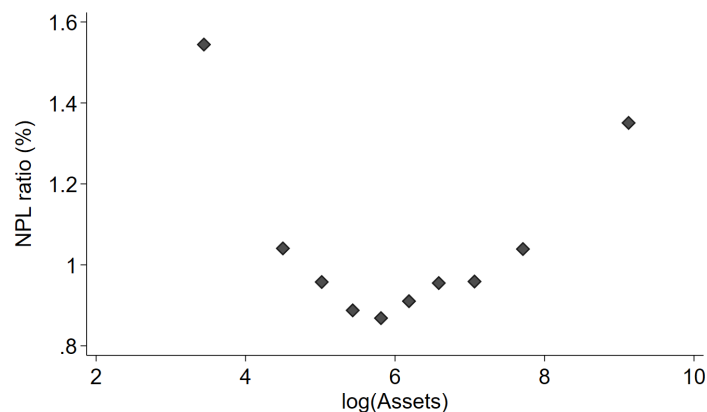
In [Figure 13](#), we show that the NPL ratio exhibits a U-shaped pattern across firm size. This result persists when considering the share of firms with overdue unsecured loans (see [Figure B.34](#)) and when focusing only on first-time delinquencies (see [Figure B.35](#)). The relatively higher share of delinquencies among small firms is unsurprising. Smaller firms typically operate with weaker cash flows and limited financial buffers, making them more vulnerable to liquidity shocks. This is consistent with the view that unsecured borrowing at the lower end of

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<sup>29</sup>[Pan et al. \(2025\)](#) quantify this *shadow cost* of pledging collateral to be of the same order of magnitude as the gap between the secured and unsecured credit spreads of small firms. The authors exploit a regulatory quirk in the US Small Business Administration (SBA) disaster loan programs that exempts firms from pledging collateral for loan volumes below a certain threshold. They observe bunching below the threshold and use a bunching estimation procedure to back out the implied cost of posting collateral, primarily capturing the margin of asset encumbrance. Note that their setting is highly specific and neatly excludes other margins such as direct transaction costs due to the nature of the loan programs.

the firm size distribution may reflect financing constraints. Among large firms, however, the observed higher delinquency rate could stem from a combination of factors. These firms are less financially constrained, but their extensive use of unsecured debt exposes them to repayment risk when liquidity conditions tighten. In addition, the complexity of managing large and diversified debt portfolios may increase the probability that some loans become non-performing, even if overall credit risk remains contained. Overall, the higher delinquency rates at both ends of the size distribution potentially reflect different underlying dynamics.

**Figure 13:** NPL ratio (%) across firm size



*Notes:* This figure shows a binscatter plot of the NPL ratio (%) within equal-sized bins of  $\log(\text{Assets})$ , a measure of firm size. The analysis controls for age, sector FE and year FE, and uses the merged CBI and CIR data from 2000 to 2019.

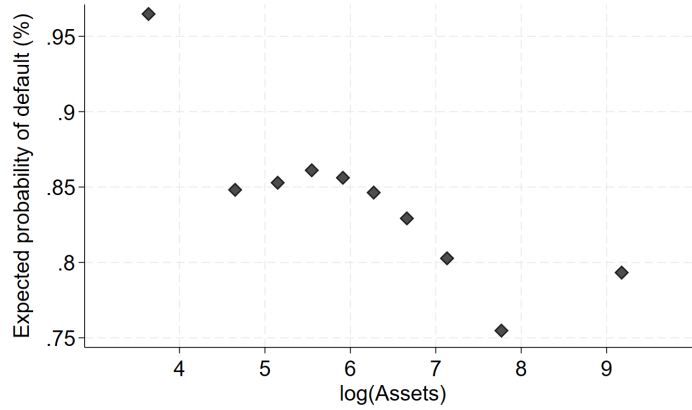
### 3.3.2 Expected Probability of Default by Firm Size

Since delinquencies may not fully capture the underlying credit risk, particularly for large firms with refinancing capacity, we construct expected default probabilities (PDs) as a forward-looking proxy using observed firm characteristics, following the approach of [Blanco et al. \(2023\)](#) for Banco de España’s internal credit assessment.<sup>30</sup> According to [Blanco et al. \(2023\)](#), their methodology captures not only the ex-ante risk of formal default (e.g., bankruptcy filings), but also the likelihood of repayment problems such as delinquency. See Appendix [B.10.2](#) for details on the estimation procedure.

In [Figure 14](#), we find that the expected PDs decline along the firm size distribution, in contrast to the U-shaped pattern in observed delinquencies. The elevated PDs for small firms are consistent with higher structural risk, such as weaker financials or limited buffers, supporting the view that their unsecured borrowing reflects tighter financing constraints. However, for large firms, the combination of low estimated PDs and relatively higher NPL ratio suggests that missed payments do not necessarily reflect higher fundamental risk. Because the data do not allow us to observe repayment motives or lender actions directly, it is difficult to pin down the underlying mechanisms. One interpretation consistent with the evidence is that delinquencies

<sup>30</sup>Note that the expected PDs are model-based estimates and do not represent lenders’ internal assessments.

**Figure 14:** Expected Probability of Default of Firms Across the Size Distribution (%)



*Notes:* This figure shows a binscatter plot of the expected probability of default of firms within equal-sized bins of  $\log(\text{Assets})$ , a measure of firm size. The analysis controls for age, sector FE and year FE, and uses the merged CBI and CIR data from 2000 to 2019.

among large firms may reflect institutional or behavioral factors rather than financial distress. Large borrowers may face different repayment incentives or monitoring practices, for example due to their size or established credit relationships. Under this view, large firms might use unsecured loans to maintain borrowing flexibility rather than out of necessity.

### 3.3.3 The Role of Lending Specialization

Finally, we consider the role of lender specialization to bring the supply side more explicitly into focus. After all, the type of credit a firm uses is an equilibrium outcome shaped by both credit demand of firms and credit supply of lenders. Lender specialization is particularly relevant in this context, as specialized lenders may possess superior screening capabilities, better access to soft information, or business models tailored to specific market segments (Paravisini et al., 2023). These advantages can affect the terms of credit offered and increase lenders' willingness to work with more opaque borrowers in their area of expertise (Blickle et al., 2023).

In particular, we focus on banks' sector specialization, a widely documented feature of lending markets (e.g., Blickle et al. (2023); Di and Pattison (2023); Giometti et al. (2025)). We construct our measure of bank sector specialization in two steps, following Paravisini et al. (2023). First, we create a concentration measure defined as the ratio of total loan volume  $i$  granted by bank  $b$  to all firms in sector  $s$  at time  $t$  relative to the total credit supplied by bank  $b$  to firms in all sectors at time  $t$ :

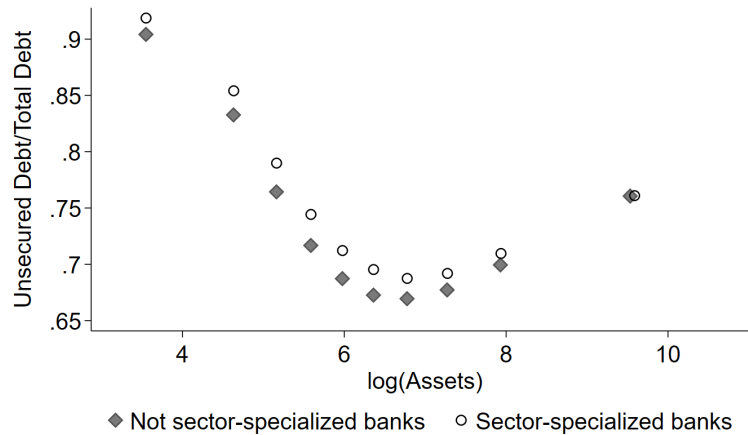
$$\text{Concentration}_{b,s,t} = \frac{\sum_{i \in b,s,t} \text{Loan}_i}{\sum_{s'} \sum_{i \in b,s',t} \text{Loan}_i}$$

where  $\text{Loan}_i$  denotes the outstanding amount of credit extended by bank  $b$  to firm  $i$  at time  $t$ . This measure is defined at the 2-digit sector level. Second, we define a binary indicator for relative specialization  $S_{b,s,t}$ , which is equal to one if a bank's sectoral concentration exceeds

the 75<sup>th</sup> percentile of the distribution for that sector-year. In other words, a bank is classified as relatively specialized in sector  $s$  at time  $t$  if its share of lending to that sector is above the 75<sup>th</sup> percentile across all banks in that same sector-year. That is,

$$S_{b,s,t} = \mathbb{I}(\text{Concentration}_{b,s,t} \geq p75_{s,t})$$

**Figure 15:** Unsecured Debt Across Firm Size: Sector-Specialized vs. Non-Specialized Banks



*Notes:* This figure shows a binscatter plot of the share of unsecured debt in total debt within equal-sized bins of  $\log(\text{Assets})$ , a measure of firm size. The plot compares unsecured debt of firms borrowing from sector-specialized banks versus those borrowing from non-sector-specialized banks. The analysis controls for age, sector FE and year FE, and uses the merged CBI and CIR data from 2000 to 2019.

In [Figure 15](#), we show that the U-shaped pattern on the use of unsecured debt across the firm size distribution shifts slightly upward for firms borrowing from sector-specialized banks. We find a similar pattern when considering instead the local-sector specialization of banks (see [Figure B.38](#)), another form of lending focus that has been documented in the literature (e.g., [Duquerroy et al. \(2022\)](#); [Casado and Martinez-Miera \(2025\)](#)).<sup>31</sup> This suggests that specialized lenders may be somewhat more willing to extend unsecured credit, possibly due to better screening or deeper sector knowledge. Nonetheless, the overall pattern remains the same, which implies that the demand side likely plays a more important role than this specific aspect of the supply side.

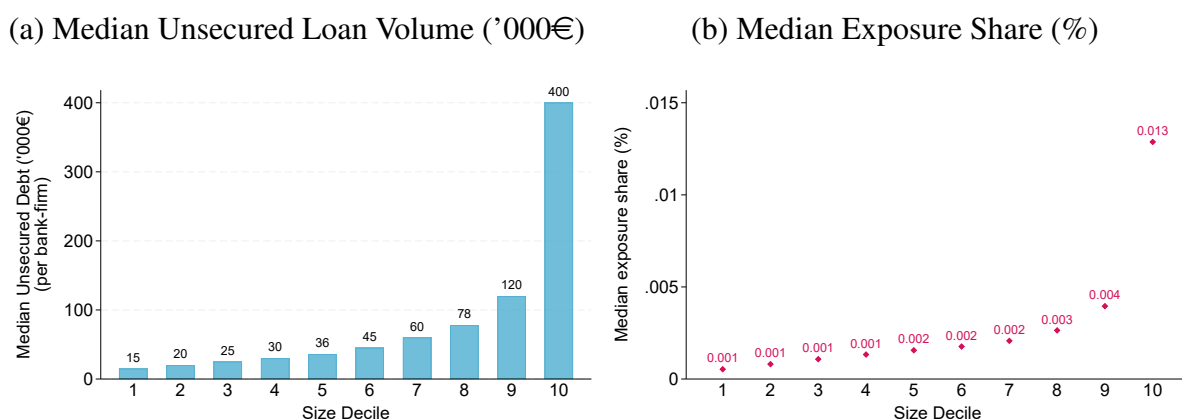
### 3.3.4 Discussion of Other Potential Channels

While lending specialization represents one potential channel through which lender characteristics may shape credit outcomes, other supply-side factors could also play a role. One possibility is portfolio diversification, whereby banks may be more willing to extend unsecured credit to small firms by spreading risk across a large number of borrowers. The risk is potentially priced in via higher interest rates (see [Section 3.2.1](#)), which allows lenders to absorb higher individual

<sup>31</sup>This specialization measure is constructed in the same way as before, but based on the 1-digit sector–province level, to ensure a sufficient number of observations within each bucket.

default risk while maintaining a reasonable overall portfolio performance. Additionally, unsecured loans to small firms tend to be modest in size (see Panel A of Figure 16). Moreover, the median unsecured exposure, measured as a firm’s outstanding unsecured loan volume with a bank relative to that bank’s total corporate loan portfolio, is very low for small firms (see Panel B of Figure 16), which further limits potential losses on any single exposure. This could help explain the persistence of unsecured borrowing among small firms, despite their higher observed delinquency rates and expected PDs, which remain low in absolute terms. While we do not directly test this mechanism, it offers a complementary perspective in explaining the U-shaped pattern on unsecured borrowing across the firm size distribution.

**Figure 16:** Median Unsecured Loan Volume and Exposure Share, by Size Decile



Notes: This figure shows (a) the median amount of unsecured debt outstanding that a firm has with a bank, by size decile; and (b) the median share a firm’s outstanding unsecured debt in a bank’s total corporate loan portfolio, by size decile. The analysis uses the merged CBI and CIR data from 2000 to 2019.

## 4 Implications of Unsecured Debt for Collateral Constraints

What does the widespread use of unsecured debt imply about the role of assets in supporting the debt capacity of firms, and ultimately on how borrowing constraints should be modeled? While most macroeconomic models with borrowing constraints emphasize the need to pledge hard collateral to borrow (i.e., "asset-based borrowing"), recent papers show that a sizable fraction of total borrowing is not explicitly backed by hard collateral (Lian and Ma, 2021; Ivashina et al., 2022; Caglio et al., 2024). Instead, many firms appear to borrow on the basis of expected cash flows (i.e., "cash flow-based borrowing"), weakening the traditional financial accelerator channel, which operates through the procyclicality of collateral values (Lian and Ma, 2021).<sup>32</sup>

However, Rampini and Viswanathan (2025) emphasize that unsecured debt may be *implicitly* backed by assets. That is, creditors may take into account the presence of *unencumbered* assets when deciding whether to lend, even if no specific collateral is pledged (Benmelech

<sup>32</sup>However, Pan et al. (2025) show that the presence of collateral cost may prevent firms from borrowing up to their limit. As a result, firms face a trade-off between this cost and investment return, making the financial amplification mechanism state-dependent, particularly on productivity.

et al., 2025).<sup>33</sup> Benmelech et al. (2025) formalize this by introducing a notion of *unpledged collateral*, the portion of tangible assets not already committed to secured creditors, and show that unsecured leverage correlates positively with this measure.

We follow their approach and construct a measure of unpledged tangibility as the difference between tangible fixed assets and secured debt, scaled by total assets. We then estimate the following regression specification:

$$\text{unsecured leverage}_{i,t} = \beta_0 + \beta_1 \cdot \text{unpledged tangibility}_{i,t-1} + \Gamma' \mathbf{X}_{i,t-1} + \delta_i + \lambda_t + \varepsilon_{i,t} \quad (1)$$

where  $\mathbf{X}_{i,t-1}$  are control variables including  $\log(\text{Assets})$ ,  $\log(\text{age})$  and profitability,  $\delta_i$  are the firm fixed effects and  $\lambda_t$  are the year fixed effects.<sup>34</sup>

As shown in Table 4, we find a statistically significant positive correlation between unpledged tangible assets and unsecured leverage. The relationship holds across firm size deciles (see columns (2) to (4)),<sup>35</sup> indicating that whether a firm is small or large, asset availability plays an important role in supporting unsecured borrowing, consistent with the view of Rampini and Viswanathan (2025) and Benmelech et al. (2025). This correlation is visually confirmed by the binscatter plot in Figure B.43 in Appendix B.11.

**Table 4:** Unpledged Tangibility and Unsecured Leverage

	(1) All	(2) Deciles 1–4	(3) Deciles 5–8	(4) Deciles 9–10
L.Unpledged Tangibility	0.068*** (0.001)	0.042*** (0.003)	0.081*** (0.002)	0.073*** (0.002)
Firm Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	3,442,394	1,147,636	1,444,398	773,149
R-squared	0.703	0.716	0.753	0.740

Notes: Standard errors clustered at the firm level in parentheses. \*\*\*p<0.01, \*\*p<0.05, \*p<0.1. Firm controls include  $\log(\text{Assets})$ ,  $\log(\text{age})$ , and profitability. This part uses the merged CBI and CIR data from 2000–2019.

These findings underscore that asset-based borrowing constraints remain relevant even when collateral is not explicitly pledged, as emphasized by Rampini and Viswanathan (2025), Benmelech et al. (2025) and Donaldson and Piacentino (2025).<sup>36</sup>

<sup>33</sup>In Appendix B.11, we revisit existing evidence linking debt composition to firm characteristics.

<sup>34</sup>Unlike Benmelech et al. (2025), we do not include Tobin’s Q as a control variable since most of the firms in our sample are privately-held and therefore do not have any readily available market price.

<sup>35</sup>Recall that size deciles are constructed using  $\log(\text{Assets})$ , as explained in Section 3.1.

<sup>36</sup>According to Donaldson and Piacentino (2025), the correct form of the borrowing constraint is  $b \leq X + Y$ , where  $X$  is the pledgeable part of output (i.e., collateral) and  $Y$  is the non-pledgeable part of output (i.e., cash flows). This formulation implies that the prevalence of cash flow-based lending does not invalidate models that feature collateral constraints. Examples of recent work modeling borrowing constraints in this way are di Giovanni et al. (2025) and Guntin and Kochen (2025).

## 5 Conclusion

This paper revisits the role of collateral in corporate capital structure by examining how its use varies across the firm size distribution. Using matched firm–bank data from Spain covering virtually all loan exposures, we document a robust U-shaped pattern on the use of unsecured debt. Both the smallest and largest firms rely heavily on unsecured borrowing, while mid-sized firms borrow more frequently with collateral. This pattern is observable because our dataset includes very small firms that have small loan exposures, which are typically absent from prior studies, highlighting the importance of comprehensive coverage for understanding debt structure across the firm size distribution.

These results show that firms of different sizes face systematically different borrowing conditions, relying on unsecured and secured debt for distinct reasons. Unsecured debt is widespread, but its terms and utilization vary across firms. These findings provide a factual basis for understanding credit provision and financing constraints, offering insights into how firms access debt and how collateral continues to influence borrowing behavior.

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# Appendix

## A Data Appendix

### A.1 Data Sources

**Central de Balances Integrada (CBI).** The CBI is an administrative database of detailed financial statements of the quasi-universe of non-financial firms in Spain. The database is maintained by the Central Balance Sheet Data Office of Banco de España and all information is obtained from mandatory filings of annual accounts in the Mercantile Registries.

We clean the data as follows:

1. There are cases for which financial statements are missing for some firm-year observations. Following [Albrizio et al. \(2023\)](#), we maximize coverage by utilizing the fact that firms can have multiple records for a given year, based on the current and next year's filings. When the current year financial statement is not available, we use the following year's values to fill this gap. When both current and next year's filings are available, we prioritize the current year's values except for when the current filings are flagged as low quality records in the database. In such cases, we use the following year's values instead.
2. We keep firms that have a legal status of corporation or limited liability company. This is inferred from the Spanish tax identification number of firms (*CIF* in Spanish or *NIF* in English), which consists of a letter, representing the legal status, followed by eight digits unique to a firm.<sup>1</sup> We treat observations that switch legal status as observations of the same firm.
3. When a firm has multiple records of its industry classification, we use the most frequent one.
4. When a firm reports different dates of incorporation across the years in which it appears in the database, we take the earliest year as the actual year when a firm starts its business.
5. We implement standard cleaning procedures on firm balance sheet information, following [Kalemli-Ozcan et al. \(2024\)](#). In particular, we drop observations with missing or negative values of assets and revenues. We also drop observations with negative values of tangible fixed assets, inputs, employees, and wage bill.
6. We follow [Almunia et al. \(2018\)](#) in excluding the following sectors: financial services, public administration and defense, education, health and social work, and membership activities (NACE codes K, O, P, Q, and S). We also drop observations without sector classification.
7. We also exclude firms in the housing sector, namely construction and real estate, for most of the empirical analysis, unless otherwise specified (e.g., when presenting descriptive statistics

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<sup>1</sup>See <https://www.strongabogados.com/tax-id-spain.php#types> for the full list of legal forms of firms in Spain.

across sectors), given their extremely high share of secured borrowing relative to the rest of the sectors (see [Figure B.6](#)) which may affect the results.<sup>2</sup>

8. Variables constructed for subsequent analysis are winsorized at 1% on both tails.

Note that financial statement items in CBI are measured in thousands of euros.

**New CIR.** In this new version of the credit register that started in 2016, all information is reported in accordance with the Banco de España Circular 1/2013 on the Central Credit Register. This database, at the loan contract level, contains an expanded set of information on loan terms. Each loan contract (observation) has information on interest rate (starting 2018), maturity, types of collateral pledged, types of guarantee, types of credit products, loan-to-value ratios, etc. previously not available in the CIR database. We use data from 2018 to 2019 to ensure that we have information on the loan interest rate. As with the CIR database, these data are available at a monthly frequency, but we use year-end stocks to merge with CBI data.

We calculate the residual maturity as the difference between the maturity year and the current year provided in the data. We compute the interest rate spread as the difference between loan-level interest rates and the T-bill rates at different maturities. For example, if a given loan operation has a residual maturity of one year, we calculate the spread as the difference between the loan interest rate and the one year T-bill rate. For this calculation, we use the categorical variable *codigo plazo residual* to indicate whether the loan is maturing in 1–3 months, 3–6 months, 6–12 months, 1 year, 3 years, etc.). The residual maturity, loan interest rate, and spread are winsorized at 0.5% on the upper tail.

The classification of loan types is discussed in [Appendix A.4.1](#).

*Data used for loan-level analysis:* Relative to the *CIR* data, the *new CIR* data are at a more *disaggregated* level. This dataset is at the loan contract level, and in practice, a firm can have multiple loan contracts for the same collateral type and same guarantee type from the same bank, e.g., two different loans issued at two differing dates.<sup>3</sup> One issue with the use of such highly disaggregated data for analysis is that results can be affected by the presence of firms with disproportionately many outstanding loan contracts with banks, and such instances are more likely among large firms. To circumvent this issue when we conduct loan-level analysis using this dataset, we proceed by aggregating the granular contract-level information to slightly more aggregated measures of loan volume, interest rate, interest rate spreads and residual maturity.<sup>4</sup> We sum the loan volume to the

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<sup>2</sup>For example, [Martín et al. \(2021\)](#) show that a housing firm obtained a larger volume of credit relative to a non-housing firm from the same bank. Since a significant share of secured borrowing in Spain occurs within the housing sector, differences in loan and firm characteristics across loan types may partly reflect sector-specific dynamics rather than general patterns. While exploiting within-sector variation can partially address this, we focus our main analysis on non-housing sector firms to avoid conflating firm-level borrowing behavior with housing-sector credit distortions.

<sup>3</sup>A key distinction on the level of disaggregation between the earlier vintage of the *CIR* data and the *new CIR* data is that, in *CIR*, loan contracts that share the same loan term characteristics (e.g., loan risk class, collateral, maturity) are bundled together as one observation, whereas in the *new CIR*, these are separate observations.

<sup>4</sup>[Kosekova et al. \(2025\)](#) also do some level of aggregation of Anacredit, which is also at the loan contract level.

bank–collateral type–guarantee type–product type–residual maturity category (*codigo plazo residual*) level. The interest rate and the interest rate spread are weighted by the size of each contract relative to the aggregated loan volume. The aggregated measure of residual maturity is taken as the maximum over the residual maturity of individual contracts at the level of aggregation, and therefore should be taken as the upper bound of the results we document regarding this variable.

**BEV.** The *Base de datos de Emisiones de Valores (BEV)* is a value-by-value database of fixed income issues made by Spanish issuers domestically and abroad, available at monthly frequency starting 2010. This dataset contains information such as the sector of the issuing entity (e.g., non-financial corporations, public sector, financial intermediaries), the type of fixed income instrument (e.g., straight bonds, perpetual bonds, convertible bonds, commercial paper), outstanding balance of the debt securities, interest rate, type of collateral, securitization, and date of issuance. As with the credit register, we merge it with CBI data using the tax identifier.

**Other Data.** We use industry-specific capital deflators and value-added deflators taken from EU-KLEMS to deflate capital and other variables, respectively. We use the Treasury bill rates across different maturities (e.g., 1-3 months, 1 year) obtained from the Statistical Bulletin of Banco de España as the risk-free rate needed to compute the spreads.

## A.2 Coverage and Representativeness of CBI

**Coverage** The cleaned CBI dataset covers a total of 1,923,594 firms, with an average of 802,191 firms per year. In [Table A1](#), we tabulate the cross-sectional distribution of firms in the dataset.<sup>5</sup>

**Table A1:** Size and Age Distribution of Firms

	Size Group				Age Group			
	Micro	Small	Medium	Large	0–5	6–10	11–15	16+
<b>% of Total</b>	84.63%	13.04%	0.90%	0.43%	36.08%	22.75%	17.07%	24.1%

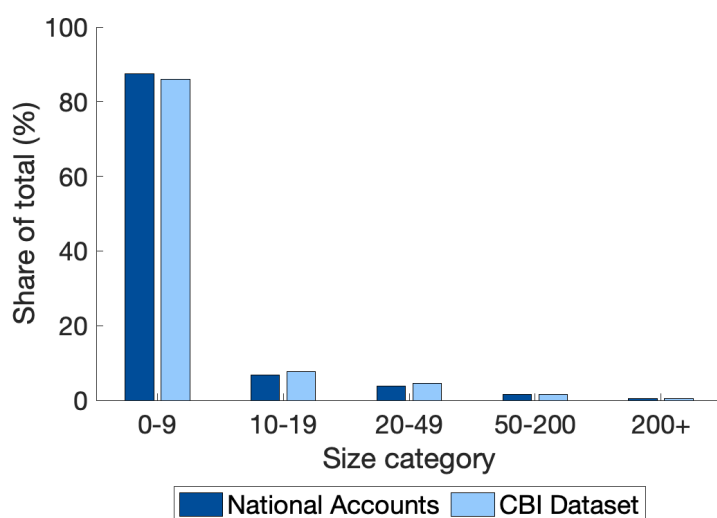
*Note:* This part uses the CBI data from 2000–2019.

**Representativeness** To evaluate representativeness of the cleaned CBI dataset used for the analysis in this paper, we compare the firm size distribution of the dataset relative to what can be computed using official statistics from the Spanish National Institute of Statistics (INE). As shown in [Figure A.1](#), the firm size distribution in CBI matches closely that of the one in the official statistics. Furthermore, as documented in [Almunia et al. \(2018\)](#), the CBI covers over 80% of non-financial

<sup>5</sup>The size categories follow the European Commission’s definition of SMEs. Micro firms are those with less than 10 employees and <€2 million assets or <€2 million revenues. Small firms are firms with less than 50 employees and <€10 million assets or <€10 million revenues. Medium-sized firms are those with less than 250 employees and <€43 million assets or <€50 million revenues. To remain in the same size class, a firm needs to be within a given threshold for two consecutive accounting periods. This prevents sudden reclassification due to exceptional temporary shocks. See <https://ec.europa.eu/docsroom/documents/42921/attachments/1/translations/en/renditions/native>.

firms in Spain, over 75% of total employment and replicates well the aggregate dynamics of output, employment and wage bill.

**Figure A.1:** Size Distribution of Firms By Employment Bins



*Notes:* This figure plots the average share of the number of firms in each employment size category relative the total number of firms, both in CBI and the official census reported by the Spanish National Institute of Statistics (INE) from 2000–2019.

### A.3 Variable Definitions

**Aggregated sectors.** For purposes of constructing summary plots and tables, we aggregate the categories of the NACE 1-letter codes as follows:

**Table A2:** Aggregated Industry Classification

NACE 1-letter	Description	Aggregated Classification
A	Agriculture, Forestry And Fishing	Primary sector
B	Mining And Quarrying	Primary sector
C	Manufacturing	Manufacturing
D	Electricity, Gas, Steam And Air Conditioning Supply	Utilities
E	Water Supply; Sewerage, Waste Management And Remediation Activities	Utilities
F	Construction	Construction
G	Wholesale And Retail Trade	Wholesale And Retail Trade
H	Transportation And Storage	Transportation And Storage
I	Accommodation And Food Service Activities	Hospitality & Entertainment
J	Information And Communication	Information And Communication
L	Real Estate Activities	Real Estate Activities
M	Professional, Scientific And Technical Activities	Professional & Admin. Services
N	Administrative And Support Service Activities	Professional & Admin. Services
R	Arts, Entertainment And Recreation	Hospitality & Entertainment

**Table A3** summarizes the definitions of the variables used in the empirical analysis. For variables sourced from the CBI, the corresponding item codes are provided in parentheses.<sup>6</sup>

**Table A3:** Definition of Variables

Variable	Description	Source
Age	The number of years since firm incorporation (any – anyconst)	CBI
log(Assets)	Defined as log(Assets); (Assets = c200135)	CBI
Tangibility	The ratio of tangible fixed assets (c200093) to total assets	CBI
Leverage	The ratio of total interest-bearing debt (c200151 + c209166) to total assets	CBI
Profitability	The ratio of EBITDA (c200030) to lagged total assets	CBI
Liquidity	The ratio of cash and short-term financial investments (c200129 + c200128) to total assets	CBI
Employees	Average number of employees of a firm in a year (c200084)	CBI
Sales (or revenue)	The value of output (c200075)	CBI
log(age)	Defined as log(age+1)	CBI
Loan Volume	Drawn credit + undrawn credit; (or ‘Total debt’ in binscatter plots)	CIR; new CIR
Unsecured debt leverage	The ratio of unsecured loan volume to total assets	CIR + CBI; new CIR + CBI
Unpledged capital	The difference between tangible fixed assets and secured debt <sup>a</sup>	CIR + CBI
Unpledged tangibility	The ratio of unpledged capital to total assets	CIR + CBI
Secured debt share	The ratio of secured loan volume to total loan volume (i.e. secured debt/total debt)	CIR; new CIR
Unsecured debt share	The ratio of unsecured loan volume to total loan volume (i.e. unsecured debt/total debt)	CIR; new CIR
Utilization rate	The ratio of drawn credit to total credit	CIR; new CIR
log(Credit)	Defined as log(Loan Volume)	new CIR
Interest rate spread	The difference between the interest rate of an outstanding loan operation and T-bill rate (of corresponding maturity)	new CIR
Residual maturity	The number of years until maturity of a loan	new CIR
Overdue loan	Loan that has been delinquent for at least 3 months	CIR
NPL ratio	The ratio of the total amount of non-performing loans (NPL) to total loan volume	CIR

<sup>a</sup> Negative values are treated as missing observations and excluded from the analysis in order to avoid taking a stand on the interpretation of negative unpledged capital.

<sup>6</sup>A user guide can be downloaded from <https://www.bde.es/wbe/en/para-ciudadano/servicios/belab/contenido/microdatos-disponibles/microdatos-empresas-individuales-cbi.html>.

## A.4 Classification of Variables in CIR

### A.4.1 Classification of Loan Types

**CIR.** We follow [Ivashina et al. \(2022\)](#) to classify the different loan types in the data. As discussed in their paper, two variables from CIR are needed for this purpose: *Clase* (loan risk class) and *Garantia* (collateral). The classification is as follows:

1. *Credito comercial (clase A)*: Trade finance
2. *Credito financiero (clase B)*
  - (a) With hard collateral (categories of *Garantia* that specify *garantia real*): Secured loans<sup>7</sup>
  - (b) No hard collateral (other remaining categories of *Garantia*): Unsecured loans ("cash flow" loans in [Ivashina et al. \(2022\)](#))
3. *Operaciones de arrendamiento financiero (clase K)*: Leasing

We follow [Ivashina et al. \(2022\)](#) in excluding factoring in the data and all other contingent claims (i.e. all other categories of *Clase*).<sup>8</sup>

**New CIR.** In this new version of the database, the variables *Clase* and *Garantia* are replaced by more comprehensive variables, *Tipo de producto* (type of product) and *Tipo garantia real principal* (type of real guarantee) respectively. We create a mapping between the old and new versions of the variables as follows:

1. All categories of *Credito comercial* (V25–V29) in *Tipo de producto* are coded as *clase A*, corresponding to *Trade finance*. The categories of *credito comercial* corresponding to factoring (V30–V31) are dropped.
2. All categories of *Credito financiero* (V32–V49) in *Tipo de producto* are coded as *clase B*, except for *descubiertos* or bank overdrafts (V44) that are characterized by very high interest rates, which we drop.
  - (a) Secured loans correspond to all categories of *Tipo garantia real principal*, except for “*Sin garantia real*” (no real guarantee), i.e. G11–G16 under *Credito financiero*. Appendix [A.4.2](#) provides further discussion on this variable.

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<sup>7</sup>This is slightly different from the definition of "asset-based" loans used in [Ivashina et al. \(2022\)](#), which take all categories of *Garantia*, except for *Resto de situaciones*, as secured loans. Their definition does not make a distinction between hard collateral and guarantees. To have a consistent mapping with this vintage and the new vintage of CIR, the distinction is important, as the new vintage has separate variable entries for collateral (*Tipo garantia real principal*) and guarantees (*Tipo garantia personal principal*). For example, there may be loans with a public sector guarantee but no collateral pledged. The definition we use allows us to have consistency in definitions across vintages of the credit register. Note that this slight departure from the definition used in [Ivashina et al. \(2022\)](#) affects only < 1% of observations.

<sup>8</sup>As explained in [Ivashina et al. \(2022\)](#), factoring involves the sale of accounts receivables, which is different from using them as collateral to take out a loan.

(b) Unsecured loans are classified as the subcategory of *Credito financiero* with *Tipo garantia real principal* of “*Sin garantia real*” (G19).

3. The categories of *Arrendamiento* (V51–V52) are coded as *clase K*, corresponding to *Leasing*. The subcategories are financial leases (V51) and operating leases (V52).

#### A.4.2 Classification of Other Variables in the New CIR

**Collateral Types.** The specific types of collateral that a firm pledges is given by the variable *Tipo garantia real principal* in the new CIR, following the Banco de España Circular 1/2013 on the Central Credit Register. There are three main types of hard collateral pledged by firms: real estate mortgages, pledged financial instruments, and movable assets, which we discuss in more detail below.<sup>9</sup>

1. Real estate mortgages – *Tipo garantia real principal* codes G11 and G12, which are the primary mortgage and the rest of mortgages pledged by a firm respectively. These must be registered at the Land Registry.
2. Pledged financial instruments (G13) – e.g., securities, deposits.
3. Movable assets – e.g., vehicles, machines, equipment, vessels, receivables, inventory
  - Naval mortgages (G14)
  - Movable assets registered in the Movable Assets Registry (G15) – with non-possessory pledge, and thus requires registration. This involves administrative costs associated with the registration process that are typically passed on to borrowers, thereby making the loan more expensive.
  - Movable assets with possessory pledge (G16) – which means that the asset being pledged as collateral is held by the lender until the debt is paid off and thus does not require to be recorded in the Movable Assets Registry.

**Credit product types.** The specific types of credit instruments in secured loans and unsecured loans are given by the variable *Tipo de producto* in the new CIR, covering the categories V32 to V49, as discussed in Appendix A.4.1. There are four main types of credit instrument used by firms: term loans (V40), credit lines (V34), credit cards (V41), and other loans. Other loans include all other remaining categories (12% of total) of *Tipo de producto*, such as loans with staged provisions (V36) or demand loans (V49).

**Guarantee Types.** The specific types of guarantees in loans are given by the variable *Tipo garantia personal principal* in the new CIR, covering the categories G00 to G09. There are

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<sup>9</sup>For a more detailed discussion on the legal aspects of secured lending in Spain, see <https://www.araozyrueda.com/wp-content/uploads/2021/06/Legal-500-Country-Comparative-Guides-RBL-2021.pdf>.

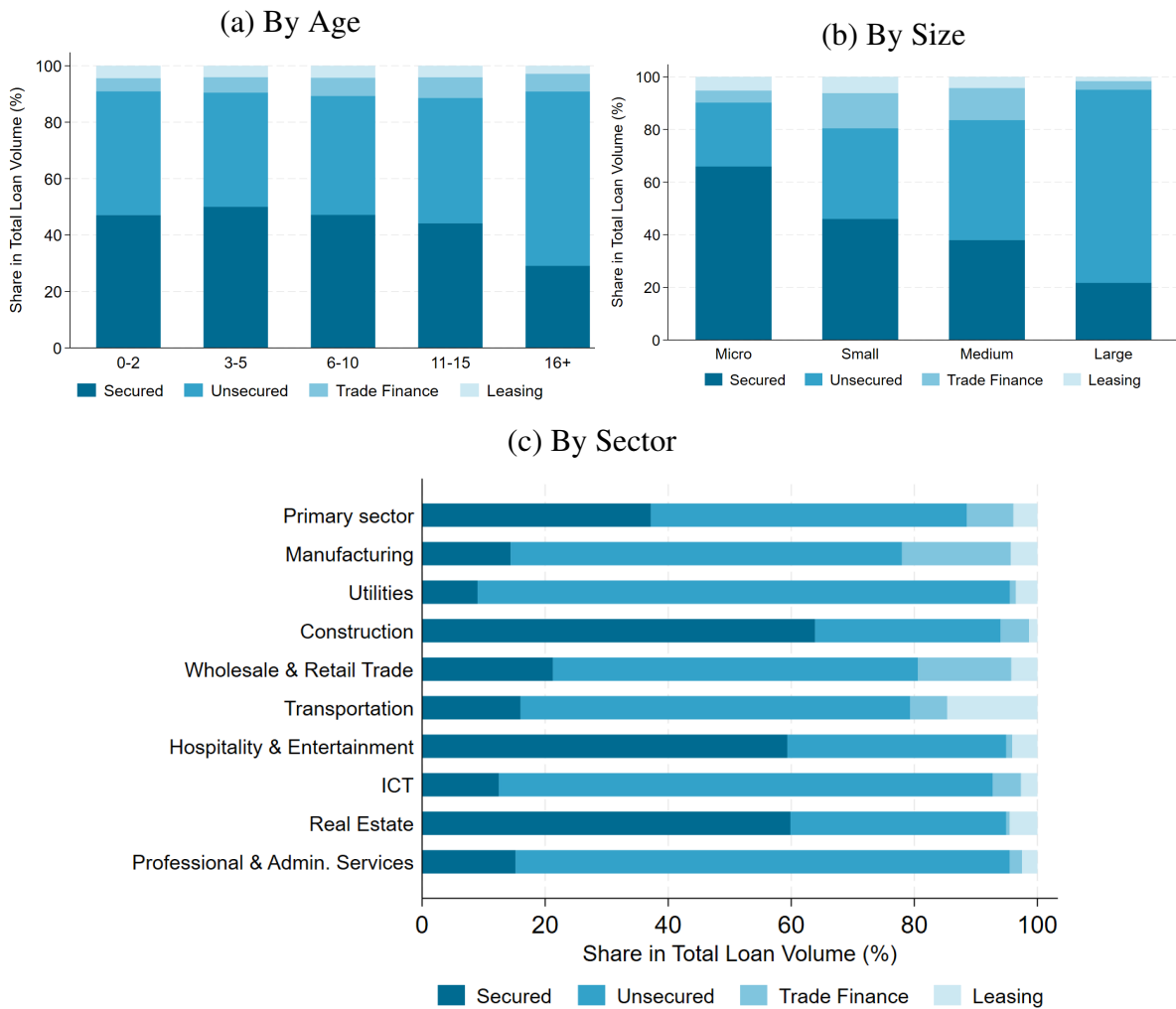
three main types of guarantees observed in loan contracts: no guarantee (G00), personal guarantee (G09), and other guarantees. Other guarantees pertain to all other remaining categories (8% of total) of *Tipo garantia personal principal*, such as those guaranteed by the public sector, credit institutions, and other entities.

## B Additional Empirical Analysis

### B.1 Composition of Commercial Credit in the Cross-section

In Figure 1 of Section 2.2, we note that across the years, secured loans and unsecured loans constitute the majority share of total lending volume in Spain. Here, we show in Figure B.1 that this observation generally holds true across firms of different age groups, size groups and sectors of activity. While the patterns are almost homogeneous across the age distribution, there is some variation across firm sizes and sectors.

Figure B.1: Aggregate Shares of the Different Loan Types in Spain (% in Total Loan Volume)



*Note:* This figure shows the share of each type of commercial credit in total loan volume within each category of age, size and sector, using the merged CBI and CIR data from 2000 to 2019.

To reiterate, for all subsequent analyses, we abstract from trade finance and leasing given their smaller (and declining in the case of trade financing) share in total commercial lending in Spain. *Loan types* or *credit types* will therefore refer only to secured loans and unsecured loans.

**Table B1: Loan Types (% in Total Number of Firms)**

	Baseline	Including Housing
Secured	12.6	20.4
Unsecured	64.5	56.3
Both	22.9	23.3

*Note:* This part uses the merged CBI and CIR data from 2000–2019.

## B.2 Secured and Unsecured Debt Across Firms

### B.2.1 Regression Analysis on the U-Shape of Unsecured Debt Use

To formally test the non-linear relationship between firm size and unsecured debt share suggested by the binscatter plot in [Figure 2](#), we estimate the following quadratic regression:

$$\text{unsecured debt share}_{it} = \beta_0 + \beta_1 \log(\text{Assets}_{it}) + \beta_2 [\log(\text{Assets}_{it})]^2 + \mathbf{X}'_{it} \boldsymbol{\gamma} + \zeta_{s(i)} + \eta_t + \varepsilon_{it} \quad (2)$$

where  $\mathbf{X}$  are firm-level control variables such as  $\log(\text{age})$  and the lags of tangibility, profitability, leverage and liquidity ratio, and  $\zeta_{s(i)}$  and  $\eta_t$  are the sector and year fixed effects respectively.

**Table B2: Nonlinear Relationship Between Firm Size and Unsecured Debt Share**

	(1)	(2)	(3)	(4)
L.log(Assets)	-0.214*** (0.001)	-0.227*** (0.001)	-0.224*** (0.002)	-0.233*** (0.001)
L.[log(Assets)] <sup>2</sup>	0.015*** (0.000)	0.015*** (0.000)	0.015*** (0.000)	0.016*** (0.000)
log(age)			-0.031*** (0.001)	-0.032*** (0.001)
L.Tangibility			-0.388*** (0.002)	-0.403*** (0.002)
L.Profitability			0.030*** (0.001)	0.025*** (0.001)
L.Leverage			-0.285*** (0.002)	-0.303*** (0.002)
L.Liquidity Ratio			-0.041*** (0.002)	-0.033*** (0.002)
Sector FE	–	Yes	–	Yes
Year FE	–	Yes	–	Yes
Firm Controls	–	–	Yes	Yes
Observations	4,421,290	4,421,290	3,930,795	3,930,795
R-squared	0.027	0.064	0.189	0.214

*Notes:* Standard errors clustered at the firm level in parentheses. \*\*\*p<0.01, \*\*p<0.05, \*p<0.1. This part uses the merged CBI and CIR data from 2000–2019.

In [Table B2](#), we document a statistically significant non-linear relationship between firm size and unsecured debt share. Specifically, the estimated coefficients on  $\log(\text{Assets})$  and its square

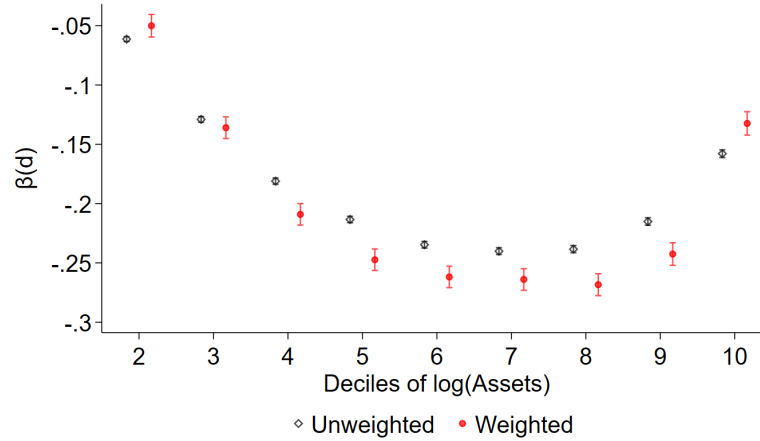
imply a U-shaped pattern, with a turning point at around 7.1–7.6 (in log points) across model specifications,<sup>10</sup> consistent with the visual evidence from the binscatter plot in [Figure 2](#).

To validate the visual pattern observed in [Figure 2](#), we assign firms to size deciles based on their  $\log(\text{Assets})$  in a given year, and estimate the following regression to test the relationship between firm size and unsecured debt share:

$$\text{unsecured debt share}_{it} = \alpha + \sum_{d=2}^{10} \beta_d \cdot \text{Decile}_{d(i),t} + \gamma \log(\text{age}) + \zeta_{s(i)} + \eta_t + \varepsilon_{it} \quad (3)$$

where  $\text{Decile}_{d(i),t}$  is a dummy variable indicating whether firm  $i$  belongs to asset decile  $d(i)$  in year  $t$ , for  $d = \{2, \dots, 10\}$ ,  $\zeta_{s(i)}$  and  $\eta_t$  are the sector and year fixed effects respectively. The lowest decile (decile 1) is the omitted baseline category. This means that the estimated coefficients  $\beta_d$  in [Equation 3](#) represent the average difference in unsecured debt share for firms in decile  $d$  relative to firms in the bottom asset decile.

**Figure B.2:** Estimated  $\beta_d$  from [Equation 3](#) – Unsecured Debt Share (Relative to Bottom Decile)



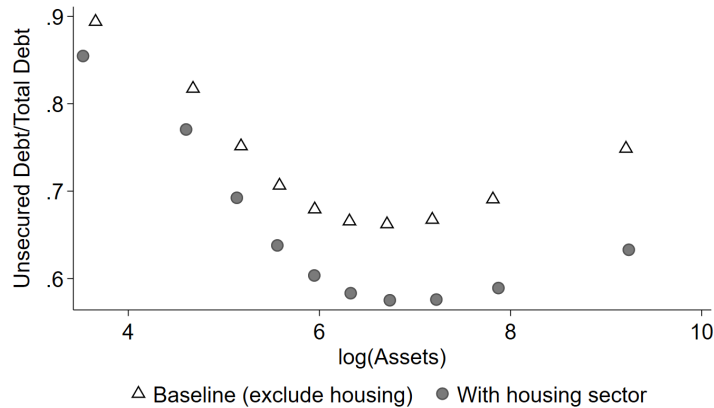
*Notes:* This figure plots coefficient estimates on  $\beta_d$  and 95% confidence intervals from [Equation 3](#). The base group is the bottom decile of firms. The  $\beta$ 's are the average difference in unsecured debt share relative to this base group. The regression controls for age, sector FE and year FE, and uses the merged CBI and CIR data from 2000 to 2019. The figure includes results from both an unweighted specification and one weighted by loan volume, allowing comparison of average effects and those scaled by loan volume.

In [Figure B.2](#), we find that all the estimated coefficients are negative, which means that on average, firms across deciles have lower unsecured debt shares relative to the smallest firms. For example, firms in the 7<sup>th</sup> decile have almost 25% lower unsecured debt share relative to the bottom decile of firms. Nonetheless, the estimates trace out a U-shaped pattern, which reinforces the result in [Figure 2](#). The main difference between this analysis and that in [Section 3.1](#) is that the binscatter regression is based on bin-by-bin local averages of unsecured debt share across the firm size distribution, effectively allowing for bin-specific intercepts. In contrast, the decile-based regression here imposes a common intercept and estimates differences in unsecured debt share relative to the bottom decile. As a result, we do not observe the unsecured debt shares in absolute levels, but only how each decile compares to the omitted reference group.

<sup>10</sup>This is computed as  $-\beta_1/2\beta_2$ .

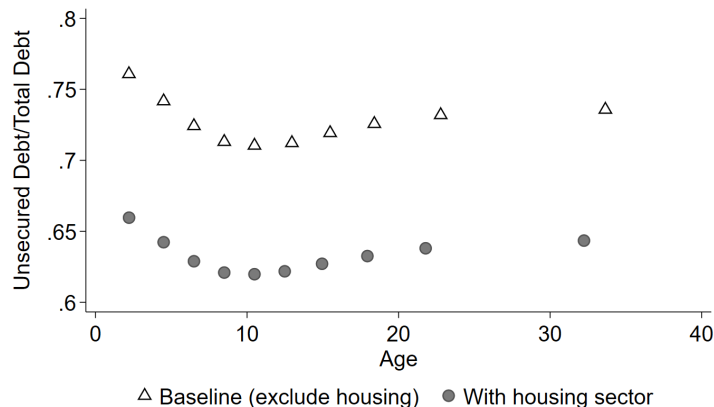
## B.2.2 Including the Housing Sector

**Figure B.3:** Share of Unsecured Debt in Total Debt Across Size – Baseline vs. With Housing



*Notes:* This figure shows binscatter plots of the share of unsecured debt in total debt within size (measured using  $\log(\text{Assets})$ ), controlling for age, sector FE and year FE, using the merged CBI and CIR data from 2000 to 2019.

**Figure B.4:** Share of Unsecured Debt in Total Debt Across Age – Baseline vs. With Housing



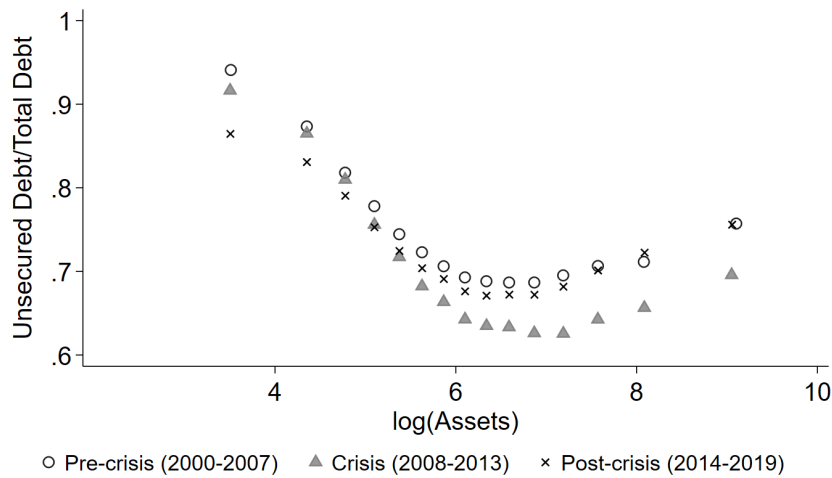
*Notes:* This figure shows binscatter plots of the share of unsecured debt in total debt within equal-sized bins of age, controlling for size (measured using  $\log(\text{Assets})$ ), sector FE and year FE, using the merged CBI and CIR data from 2000 to 2019.

## B.2.3 Across Time Periods

In [Figure B.5](#), we show that the U-shaped pattern that we document in the main text (see [Figure 2](#)) holds both in normal periods and in recessions. Consistent with [Benmelech et al. \(2024\)](#) that discusses the countercyclicality of secured debt in the US, we observe a lower share of unsecured loans in the crisis period. The drop is significant among medium to large firms, perhaps because these firms are better positioned to satisfy the tighter lending standards imposed by banks during periods of financial distress. Post-crisis, the share of unsecured debt among medium to large firms rebounded to pre-crisis levels, whereas it declined for the smallest firms. This divergence may reflect structural changes in Spain's banking landscape following the collapse of the *cajas*, which triggered a wave of bank mergers and widespread bank branch closures. These closures likely eroded the availability of soft information, such as personal relationships and local knowl-

edge, that small firms disproportionately rely on to access credit. In contrast, medium and large firms, with more collateral, were better positioned to navigate the tightened lending environment.

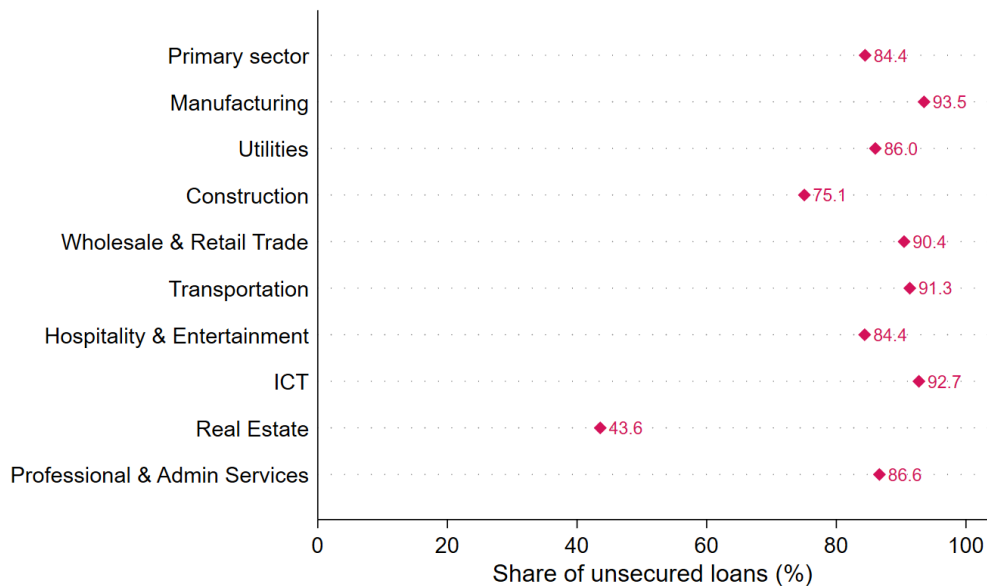
**Figure B.5: Share of Unsecured Debt in Total Debt Across Periods**



*Notes:* This figure shows binscatter plots of the share of unsecured debt in total debt within size (measured by assets) bins, controlling for age, sector FE and year FE, using the merged CBI and CIR data from 2000 to 2019.

### B.2.4 By Sector

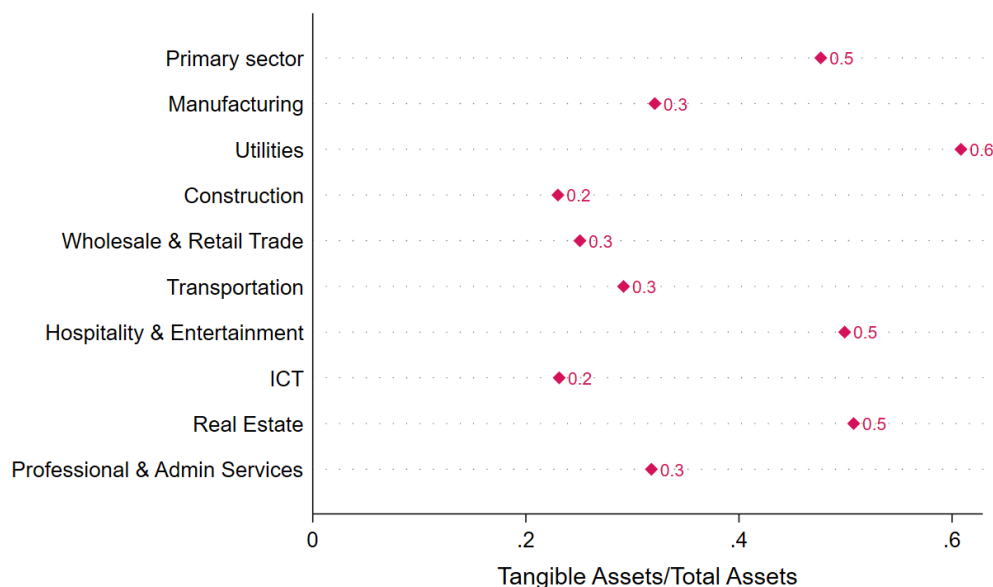
**Figure B.6: Share of Unsecured Loans (% in Total Number of Loans) – By Sector**



*Notes:* This figure is constructed using the merged CBI and *new* CIR loan-level data from 2018–2019. The sectors are aggregated categories from the NACE 1-letter codes, summarized in [Table A2](#).

In [Figure B.6](#), we show that unsecured loans constitute around at least 75% of the total number of outstanding loan operations in most sectors, apart from those in the housing sector (i.e. construction and real estate), where firms are likely to use the properties that they own as collateral to secure loans.

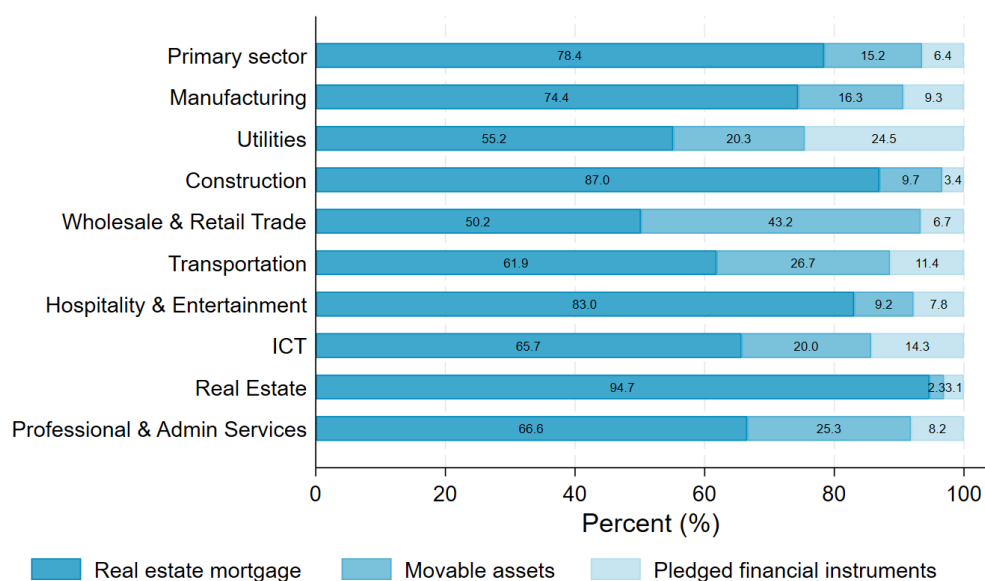
**Figure B.7: Average Share of Tangible Assets in Total Assets – By Sector**



*Notes:* This figure is constructed using the merged CBI and CIR loan-level data from 2000–2019. The sectors are aggregated categories from the NACE 1-letter codes, summarized in [Table A2](#).

In [Figure B.8](#), we also document that across the different types of collateral pledged to get secured loans, real estate mortgages are used most often (76.1% of total secured loans), followed by movable assets (18.4%) and pledged financial instruments (5.5%). However, the extent to which these types of assets are pledged as collateral varies across sectors. For example, in the wholesale and retail trade sectors, real estate mortgages and movable assets are used as collateral almost equally (50.2% and 43.2% respectively). In addition, in the utilities sector, 20.3% of total secured loans have movable assets as collateral, and 24.5% use pledged financial instruments.

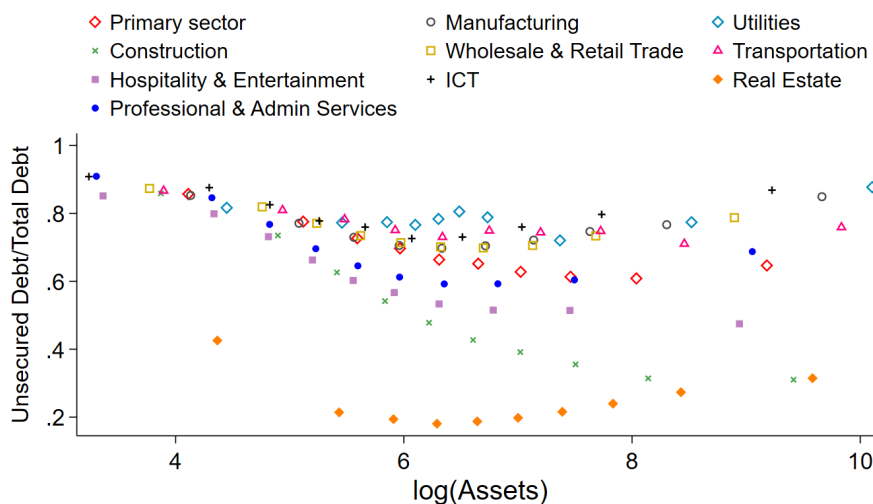
**Figure B.8: Collateral Types in Secured Loans (% in Total Number of Loans) – By Sector**



*Notes:* This figure is constructed using the merged CBI and *new* CIR loan-level data from 2018–2019. The sectors are aggregated categories from the NACE 1-letter codes, summarized in [Table A2](#).

In [Figure B.9](#), we show that the U-shaped pattern on the usage of unsecured loans along the firm size distribution holds broadly in most sectors of the economy, except the construction and hospitality sectors. The *level* of the unsecured debt share in the real estate sector is substantially lower, but nonetheless follows the same qualitative pattern documented in the main text.

**Figure B.9:** Share of Unsecured Debt in Total Debt Across Size – By Sector



*Notes:* This figure shows binscatter plots of the share of unsecured debt in total debt by sector, within deciles of size (measured by  $\log(\text{Assets})$ ), controlling for age and year FE, using the merged CBI and CIR data from 2000 to 2019.

### B.2.5 Role of Leases

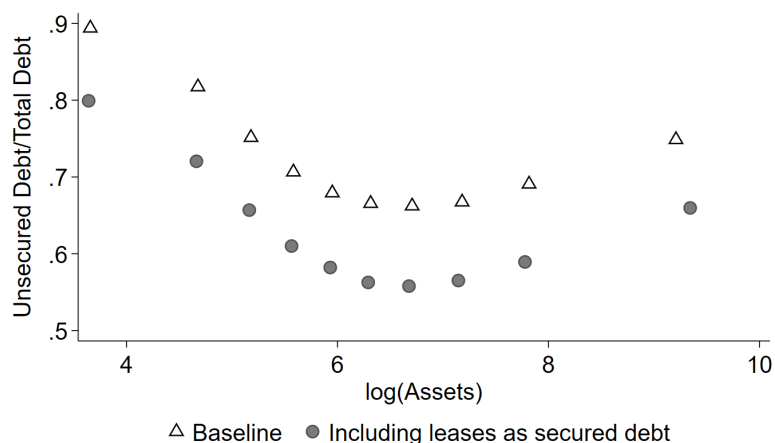
The observation that not many small firms use secured loans may mask the possibility that these firms are utilizing leases instead, as such firms tend to be more financially constrained ([Eisfeldt and Rampini, 2009](#)). As [Eisfeldt and Rampini \(2009\)](#) argue, leasing improves the debt capacity of firms. The most constrained firms tend to lease assets, less constrained firms borrow secured and the least constrained firms issue unsecured debt ([Rampini and Viswanathan, 2025](#)). In [Lian and Ma \(2021\)](#), financial leases are classified as secured loans, since they are eventually booked on the balance sheet of firms. Instead, in our baseline definition, we exclude leases because our data do not allow for the distinction between financial leases and operating leases, the latter of which is not booked on the balance sheet of firms for most of our sample period.<sup>11</sup>

However, as we show in [Figure B.10](#), even if we capitalize leases as part of secured loans, we retain the same U-shaped pattern that we document in the main text (in [Figure 2](#)), except that it slightly shifts down due to compositional effects. This can be explained by the fact that the share of leasing debt in the total debt of firms follows a somewhat inverted U-shaped pattern along the size distribution, ranging from a share of 9% to 14% of total debt, as we show in [Figure B.11](#). Although this may seem contrary to existing work (e.g., [Rampini and Viswanathan \(2025\)](#)) that suggests more usage of leases among the smallest (most constrained) firms, we note that this is driven by differences in sample coverage: our data include the near-universe of firms (including

<sup>11</sup>Operating leases are required to be booked into firms' balance sheets starting 2019, after the imposition of new lease accounting standards that mandated this.

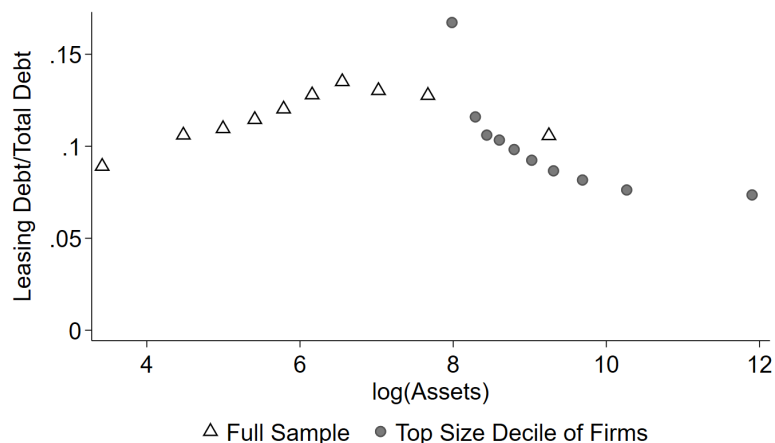
privately held firms) while Rampini and Viswanathan (2025) use Compustat data, which cover only publicly traded firms.<sup>12</sup> To illustrate this point, we also show in Figure B.11 that when we construct a binscatter plot only of the largest firms in our sample, the average share of leasing debt in the loan portfolio of firms monotonically declines along the size distribution.

**Figure B.10:** Share of Unsecured Debt in Total Debt By Size – (Role of Leases)



*Notes:* This figure shows a binscatter plot of the share of unsecured debt in total debt within equal-sized bins of  $\log(\text{Assets})$ , a measure of firm size. We report results under the baseline definition as well as an alternative that treats leases as secured debt. The analysis controls for age, sector FE and year FE, and uses the merged CBI and CIR data from 2000 to 2019.

**Figure B.11:** Share of Leases in Total Loan Volume Across the Firm Size Distribution



*Notes:* This figure shows a binscatter plot of the share of leasing debt in total debt within equal-sized bins of  $\log(\text{Assets})$ , a measure of firm size, for the full sample and top size decile of firms. The analysis controls for age, sector FE and year FE, and uses the merged CBI and CIR data from 2000 to 2019.

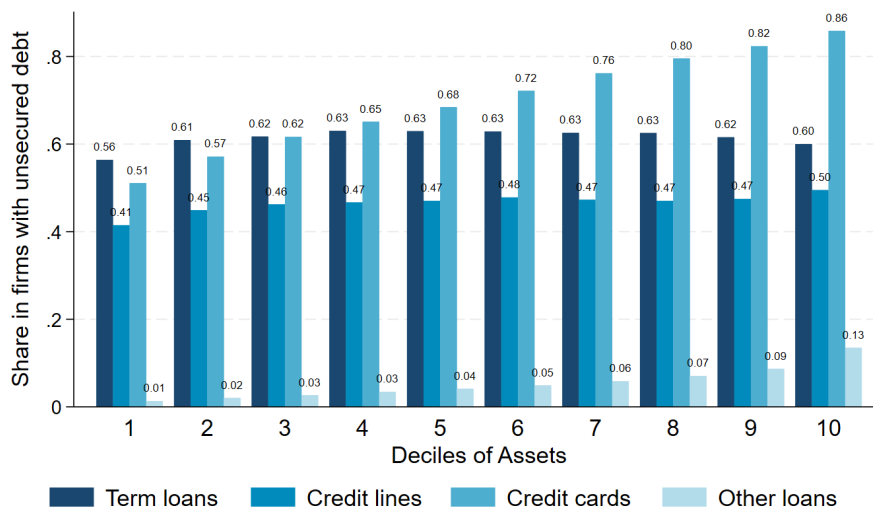
## B.2.6 Types of Credit Instruments in Secured and Unsecured Debt

In Figure B.12, we show that in firms that use unsecured debt, three different types of credit instrument are widely used, namely term loans, credit lines and credit cards. There are two important things to note here. First, since these are total outstanding loan amounts, they do not

<sup>12</sup>Instead, if we proxy financial constraints using firm age, we find that the use of leases declines as firms grow older.

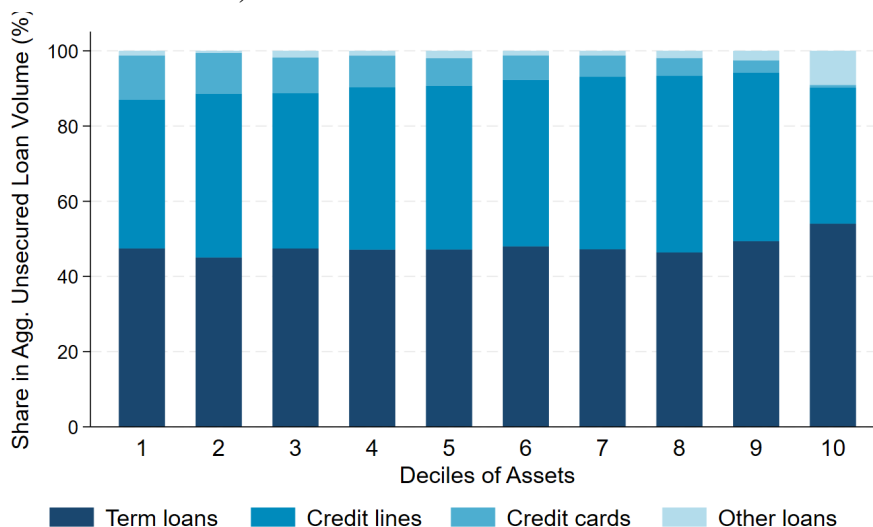
necessarily correspond to utilization. Credit lines and credit cards are typically not fully drawn down. Second, since these are measured using year-end stocks, the figure may overestimate or underestimate the dependence of firms on a particular credit product. Credit cards are a form of revolving credit without a fixed maturity date, and therefore tend to remain on the books of a bank for extended periods. In contrast, credit lines typically have short maturities and are often drawn and repaid within the same year, meaning they may not appear as prominently in year-end data. Hence, this figure should not be interpreted as indicating that firms rely more heavily on credit cards than on credit lines. The takeaway is that credit lines are not the only type of unsecured credit instrument that firms use.

**Figure B.12: Product Types in Unsecured Debt of Firms (2018–2019)**



*Notes:* This figure shows the share of firms with unsecured loans using each type of credit instrument: term loans, credit lines, credit cards and other loans, by size decile, using the merged CBI and *new* CIR data from 2018 to 2019.

**Figure B.13: Aggregate Shares of Different Product Types in Unsecured Debt of Firms (2018–2019) (% in Total Loan Volume)**



*Notes:* This figure shows the shares of different credit instruments: term loans, credit lines, credit cards and other loans in aggregate volume of unsecured debt, by size decile, using the merged CBI and *new* CIR data from 2018 to 2019.

**Table B3:** Distribution of Firms by Number of Unsecured Credit Product Types Used (%)

Number of Products	Share of Firms (%)
1	43.92
2	31.62
3	21.74
4	2.72

*Notes:* This table reports the distribution of firms by the number of unsecured credit product types they use. This part uses the merged CBI and *new* CIR data from 2018 to 2019.

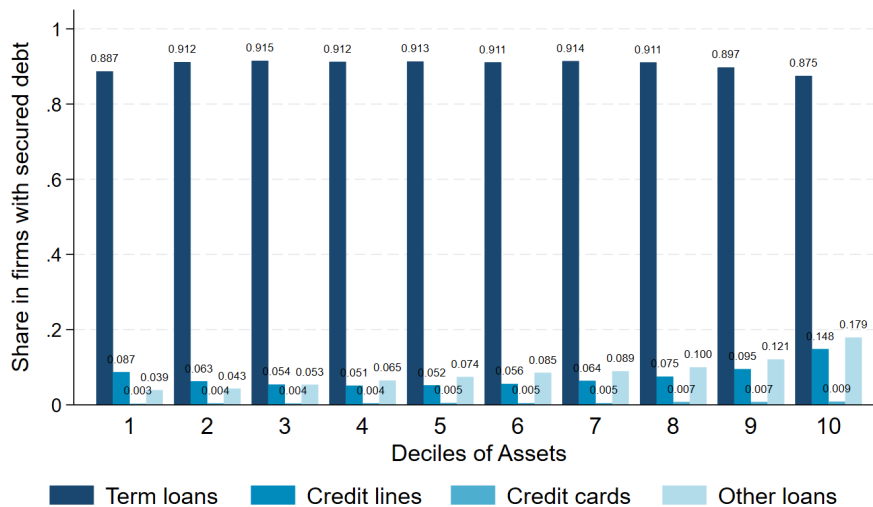
**Table B4:** Share of Firms with One Unsecured Credit Product

	Share of Firms
Unsecured: Term loans only	0.143
Unsecured: Credit lines only	0.062
Unsecured: Credit cards only	0.197

*Notes:* This table reports the share of firms using one unsecured credit product type only. This part uses the merged CBI and *new* CIR data from 2018 to 2019.

In [Figure B.14](#), we show that secured loans are mostly term loans. Other types of credit instruments such as credit lines are often not secured.

**Figure B.14:** Types of Credit Instruments in Secured Debt of Firms (2018–2019)



*Notes:* This figure shows the share of firms with secured loans using each type of credit instrument: term loans, credit lines, credit cards and other loans, by size decile, using the merged CBI and *new* CIR data from 2018 to 2019.

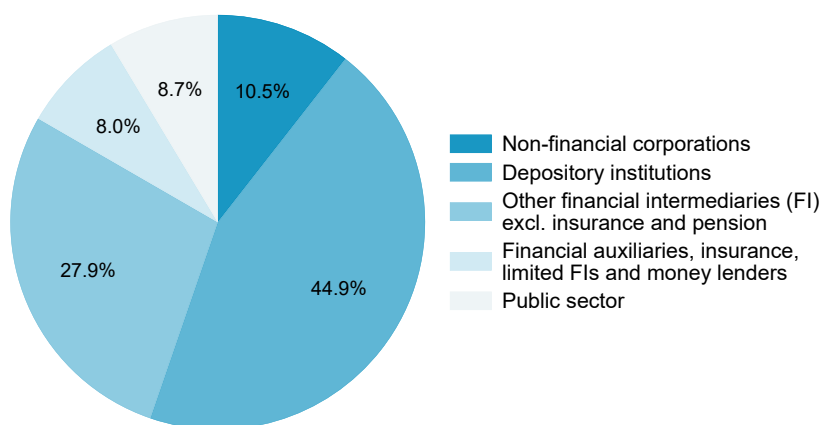
### B.3 The Role of Market Debt

One concern in focusing only on bank loans, by virtue of using credit register data, is that we abstract from the role of the corporate bond market as a source of credit for firms. While firm financing in Europe has been heavily bank-based, the landscape of corporate borrowing has been evolving in the past few decades ([Berg et al., 2021](#)), and in Europe in particular, the rise of market financing has been documented ([Darmouni and Papoutsis, 2025](#)).

In this section, we argue that the usage of market financing among non-financial firms in Spain is still at a very minute scale that the results we document in the main text on the use of secured debt and unsecured debt within the cross-section of firms will not suffer from large measurement errors, even at the right tail of the size distribution of firms where the use of market debt is more pervasive.

To this end, we use the *Base de datos de Emisiones de Valores (BEV)*, which contains information on debt securities issued by Spanish issuers, from 2010 to 2019, to examine the usage of debt securities by firms in Spain. First, we show in **Figure B.15** that financial intermediaries (i.e., categories excluding non-financial corporations and the public sector) are the primary issuers of market debt securities in Spain. Non-financial firms comprise less than a fifth of total issuers.

**Figure B.15:** Composition in Debt Securities Issuers in Spain



*Note:* This figure plots the share of different debt securities issuers in Spain, using BEV data from 2010–2019.

Second, in **Figure B.16**, we show that while there is an increasing trend in the usage of market debt, the number of non-financial firms issuing and holding them remains negligible in quantity, relative to the average number of firms per year that CBI covers. For example, in 2019, there are just around 120 firms with positive outstanding balance of debt securities.<sup>13</sup> Note that all of these debt securities issued by the non-financial corporate sector are without collateral, hence they count toward unsecured debt.<sup>14</sup>

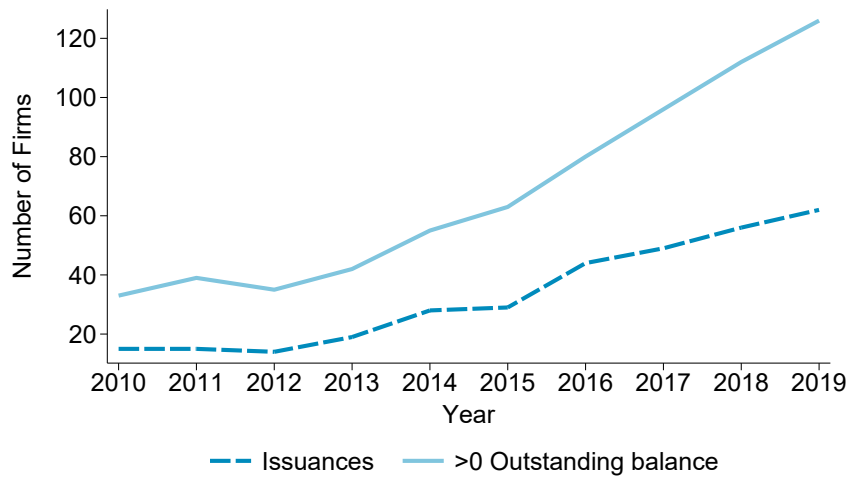
In **Figure B.17**, we present the different types of debt securities issued by non-financial firms. Over 60% of market debt issued are commercial paper, which are non-interest bearing and are sold at a discount. This is not directly comparable to unsecured loans that firms obtain from banks, unless we impute an implicit interest rate based on the discount relative to face value.

To conclude, since (1) debt securities are very seldom used by firms in Spain; and (2) the predominant type of market debt issued by firms is not comparable to a typical bank loan, we abstract from this margin for the rest of the paper.

<sup>13</sup>These firms are all in the top size decile by log(Assets).

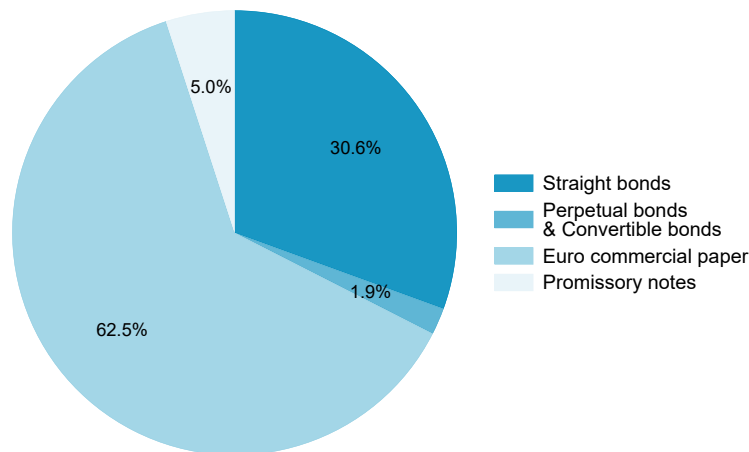
<sup>14</sup>Securitized (collateralized) debt instruments are mainly issued by investment funds of financial intermediaries (legal form V).

**Figure B.16:** Number of Non-Financial Firms Issuing and Holding Debt Securities



*Note:* This figure plots the number of non-financial firms in Spain issuing and holding debt securities, using merged BEV–CBI data from 2010–2019.

**Figure B.17:** Types of Debt Securities Issued by Non-Financial Firms



*Note:* This figure plots the types of debt securities issued by non-financial firms in Spain, using merged BEV–CBI data from 2010–2019.

## B.4 Debt vs. Equity as Financing Source

We provide a discussion on why we focus only on debt as a financing source and abstract from equity in our empirical analysis of Spanish firms. Recent papers such as [Kochen \(2023\)](#) and [Frank and Sanati \(2021\)](#) have emphasized the role of equity but we note that it plays a relatively minor role as funding source for firms in Spain, especially amongst the smaller and younger ones where financial constraints will matter more.

We proceed in two steps. First, we replicate the analysis in [Kochen \(2023\)](#) and show that equity injections matter only for the larger firms, and in particular, publicly-listed firms, which constitute less than 0.1% of total firms in Spain. [Kochen \(2023\)](#) defines equity injections as  $x_{it} = -\Delta\text{CAPI}_{it}$ , where CAPI is issued share capital in Amadeus, the database used in the paper. This corresponds to net paid-up capital in CBI. The frequency of equity injections is given by  $1_{x_i < 0}$ .

We tabulate the average frequency of equity injections in our sample by age, size and listing status below. We show that on average, less than 6% of firms receive equity injections at any given point in time ([Table B5](#)), but that publicly-listed firms use it a lot more often (38.5%) than the average private firm ([Table B6](#)).

**Table B5:** Frequency of Equity Injections By Age Group

Age Group	0–2	3–5	6–10	11–15	16+	All
% of Total	3.8%	6.1%	5.8%	6.4%	5.4%	5.5%

**Table B6:** Frequency of Equity Injections By Size and Listing Status

	Size Group				Listing Status	
	Micro	Small	Medium	Large	Public	Private
% of Total	4.8%	8.7%	9.9%	8.5%	38.5%	5.5%

Second, we use the Oaxaca-Blinder decomposition of [Frank and Sanati \(2021\)](#) to show that debt contributes more to firms' balance sheet growth relative to equity, especially among younger and smaller firms. In their paper, they formulate the decomposition of balance sheet growth by the following OLS regression

$$\Delta \log(A_t) = \beta_0 + \beta_1 \Delta \log(E_t) + \beta_2 \Delta \log(B_t) + \delta' \mathbf{X}_{it-1} + v_i + \xi_t + \varepsilon_{it}$$

where  $\Delta \log(A_t)$  is non-financial asset growth,  $\Delta \log(E_t)$  is equity growth,  $\Delta \log(B_t)$  is net debt growth,  $\mathbf{X}_{it-1}$  are firm-level controls, namely  $\log(\text{Assets})$ , tangibility and profitability,<sup>15</sup>  $v_i$  is the firm fixed effects;  $\xi_t$  is the year fixed effects. The results are shown in [Table B7](#) and [Table B8](#).<sup>16</sup>

As a final note, we also measure the average size of equity injections, defined in [Kochen \(2023\)](#) as follows:

$$dx_{it} = \frac{x_{it}}{k_{it+1}}, \quad \text{for } 1_{x_t < 0} = 1$$

where  $k_{it+1}$  = current equity – equity injection + net debt. Using this definition, we find that the average size of an equity injection to be 0.14, which is consistent with the estimated contribution of equity growth to the balance sheet growth of firms.

Given the low frequency of equity injections and lower relative contribution of equity growth to balance sheet growth of firms, we thus focus only on debt, and in particular bank debt as the main financing source of firms, consistent with existing literature that highlights the reliance of firms on bank financing (e.g. [Robb and Robinson \(2014\)](#)).

<sup>15</sup>They also include Tobin's Q as a control in their paper, but this measure is not available for private firms, which constitute the majority of our sample.

<sup>16</sup>We get the same qualitative results using total debt growth instead of net debt growth.

**Table B7:** Contribution of Different Financing Source to Asset Growth of Firms – By Age

	% Non-Financial Asset Growth				
	All Firms	Age=[0, 5]	Age=[6, 10]	Age=[11, 15]	Age=16+
% Equity Growth	0.166*** (0.001)	0.147*** (0.001)	0.146*** (0.001)	0.149*** (0.001)	0.179*** (0.001)
% Net Debt Growth	0.331*** (0.001)	0.414*** (0.001)	0.353*** (0.001)	0.296*** (0.001)	0.244*** (0.001)
Firm Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	4,609,944	793,967	1,118,786	968,673	1,468,208
R-squared	0.683	0.819	0.758	0.719	0.614

*Notes:* This table shows a modified Oaxaca-Blinder decomposition to examine the contribution of debt and equity to the asset growth of firms, following [Frank and Sanati \(2021\)](#). Standard errors clustered at the firm level in parentheses. \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ . Firm controls include  $\log(\text{Assets})$ , tangibility and profitability. For “All Firms”,  $\log(\text{age})$  is also included as control.

**Table B8:** Contribution of Different Financing Source to Asset Growth of Firms – By Size

	% Non-Financial Asset Growth				
	Listed Firms	Micro Firms	Small Firms	Medium Firms	Large Firms
% Equity Growth	0.359*** (0.036)	0.148*** (0.001)	0.164*** (0.001)	0.220*** (0.004)	0.282*** (0.004)
% Net Debt Growth	0.271*** (0.021)	0.329*** (0.001)	0.304*** (0.001)	0.282*** (0.003)	0.322*** (0.003)
Firm Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	1,685	3,555,362	774,837	106,801	118,735
R-squared	0.722	0.684	0.702	0.733	0.785

*Notes:* This table shows a modified Oaxaca-Blinder decomposition to examine the contribution of debt and equity to the asset growth of firms, following [Frank and Sanati \(2021\)](#). Standard errors clustered at the firm level in parentheses. \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ . Firm controls include  $\log(\text{age})$ , tangibility and profitability.

## B.5 Comparison with US Evidence

### B.5.1 Coverage and Firm Characteristics in the Cross-section

**Coverage.** To compare the borrowing behavior of Spanish firms relative to existing evidence on US firms, we take [Caglio et al. \(2024\)](#) as our benchmark. They use the new supervisory bank lending data for the US, covering both listed and private firms for loan commitments greater than \$1 million.<sup>17</sup> In contrast, our CIR dataset has a reporting threshold of €6,000.

In [Table B9](#), we compare the prevalence of cash flow loans in Spain and the US.<sup>18</sup> We ar-

<sup>17</sup>Note that the Fed Y-14 data has also been used by [Chodorow-Reich et al. \(2022\)](#) and [Luck and Santos \(2024\)](#) to document loan type use of US firms, but we use [Caglio et al. \(2024\)](#) as our benchmark given that just like in their paper we do not focus on the distinction between credit lines and term loans in examining loan types. [Lian and Ma \(2021\)](#) use Compustat data and thus cover only publicly-listed firms in the US in their analysis.

<sup>18</sup>Note that the comparability of the results depends on many factors, among which include differences in data

bitrarily impose reporting thresholds on loan-level commitments to see how the composition of credit changes as a consequence. We find that imposing higher reporting thresholds reduces the fraction of cash flow loans relative to the total number of loans. From 0.734 in the full sample, the fraction of unsecured loans drops to 0.456 when we restrict the volume of outstanding loans to at least €1 million, which is close to what has been reported in [Caglio et al. \(2024\)](#) for the US for a similar reporting threshold. In addition, when we restrict our data to credit larger than €100,000, we find a monotonically increasing share of cash flow loans along the size distribution (see [Figure 3](#)).

**Table B9:** Comparison with the US – Fraction of cash flow loans in Total Number of Loans

	Spain			US
	Full Sample	Credit $\geq$ €100K	Credit $\geq$ €1M	<a href="#">Caglio et al. (2024)</a>
Fraction cash flow loans	0.734	0.521	0.456	0.450

*Notes:* The fraction of cash flow loans is computed relative to the total number of loans. For the US, this is taken to be the sum of the mean shares of unsecured loans and blanket liens for “All Firms” from Table 5 of [Caglio et al. \(2024\)](#), for consistency with the definition of cash flow loans in [Lian and Ma \(2021\)](#). This part uses the merged CBI and CIR data from 2000–2019, and includes housing sector firms.

**Firm Characteristics** What does the average firm in Spain look like? In [Table B10](#), we present summary statistics on the outstanding loan volume, age, assets, employment and revenues of firms in the cross-section. For firms that borrow from banks, the median firm has a total outstanding loan commitment of €75,000, total assets and total revenues of over €400,000, all in real terms.

**Table B10:** Summary Statistics of Matched CBI–CIR Data

	Mean	Median
Loan volume (€'000)	408.81	74.63
Age	12.14	10.00
Assets (€'000)	1,816.30	423.05
Employees	18.21	5.00
Revenues (€'000)	1,652.91	414.93

*Notes:* This part uses the merged CBI and CIR data from 2000–2019. The loan volume, assets and revenues are deflated using the value-added deflator.

In [Table B11](#), we provide summary statistics by firm size and show that total outstanding loan commitments at the firm level are not huge in volume. At the loan level, given that firms can have multiple outstanding loan operations, these numbers will even be lower. For example, if we look at [Table B21](#) and [Table B22](#), the median loan volume of an unsecured loan is less than €50,000, and in fact of lower quantity for the young firms and micro-sized firms.

coverage, nature of firms and the institutional setting in each country. In [Table B10](#) and [Table B11](#), we show what an average firm in Spain looks like and compare it with the US, according to average asset holdings (see [Table B12](#)).

**Table B11: Summary Statistics of Matched CBI–CIR Data, By Size**

	Micro		Small		Medium		Large	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Loan volume (€'000)	160.83	53.44	551.89	208.52	2,356.32	943.00	3,268.84	709.81
Assets (€'000)	594.12	271.03	2,500.27	1,569.80	11,347.68	9,081.47	16,140.88	13,181.75
Employees	4.25	3.31	19.25	16.24	73.58	63.25	291.92	37.83
Revenues (€'000)	485.48	248.09	2,904.78	1,897.71	11,048.77	9,979.78	10,735.93	9,539.54

*Notes:* This part uses the merged CBI and CIR data from 2000–2019. The loan volume, assets and revenues are deflated using the value-added deflator.

The key takeaway here is given that micro and small firms on average borrow in lower quantities, having a high reporting threshold on outstanding loan commitments can potentially miss out a non-negligible fraction of firms in the economy. For example, if we look at the lending terms of SBA loans in the US, microloans for working capital purposes have a maximum amount of \$50,000, with average loan volume of \$13,000 granted to firms.<sup>19</sup> This suggests that there are SMEs in the US that also borrow in very small quantities.

**Table B12: Average Assets of Firms**

Restriction on Sample	SMEs	Large Firms
Full Sample	€1.3 M	€15 M
Credit $\geq$ €100,000	€2.7 M	€17.3 M
Credit $\geq$ €1 million	€10.5 M	€23.3 M
US firms (Credit $\geq$ \$1 million )	\$18.5 M	\$1.8 B

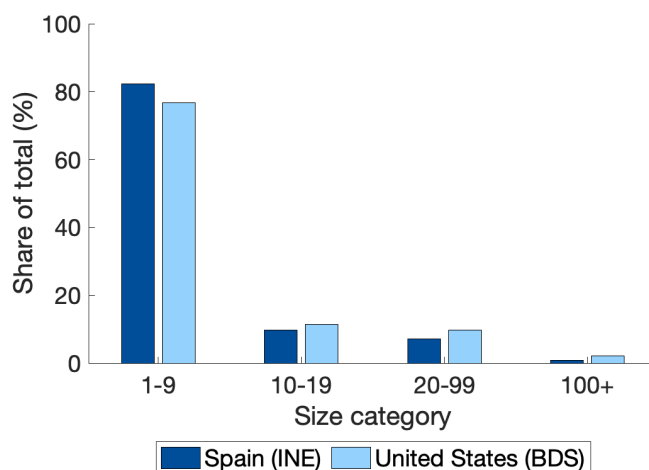
*Notes:* This part uses the merged CBI and CIR data from 2000–2019. For the US, the numbers are taken from Table 3 of [Caglio et al. \(2024\)](#) columns (1) and (2).

Looking at the total assets of firms, the average assets of a large firm in Spain is around €16 million, whereas for the US, according to [Caglio et al. \(2024\)](#), it is \$1.8 billion. For SMEs in Spain, the average assets of firms are €1.3 million, while for the US it is \$18.5 billion. There are two potential explanations, among many others, for the differences observed: first, by virtue of having a high reporting threshold for the Fed Y-14 data, this biases the sample towards larger firms overall (for SMEs and large firms). Second, it may also be that the average Spanish firm is just smaller than the average US firm (see [Table B12](#) and [Figure B.18](#)).

**Cross-sectional distribution of firms.** In [Table B13](#), we show the firm size distribution in the merged CBI–CIR data, for our baseline dataset and for when we impose different reporting thresholds on outstanding loan commitments at the loan level. Assuming that firms in Spain are just smaller and hence borrow in lower quantities relative to US firms, we can see for example what happens to the coverage and firm size distribution when we arbitrarily impose a reporting threshold of €100,000 (as opposed to the \$1 million reporting threshold of the US Fed Y-14

<sup>19</sup>See <https://www.sba.gov/funding-programs/loans/microloans>.

**Figure B.18:** Size Distribution of Firms (by Employment) – Spain vs. US



*Notes:* This figure plots the average share of the number of firms in each employment size category relative the total number of firms from 2000–2019 for the US, using data from the Business Dynamics Statistics (BDS) of the US Census Bureau, and for Spain, from the official census reported by the Spanish National Institute of Statistics (INE).

data). In this case, we lose around 75% of micro firms, 45% of small firms, and around 30% of medium and large firms, and the firm size distribution becomes biased towards larger firms.<sup>20</sup>

**Table B13:** Size Distribution of Firms in Matched CBI–CIR Data (% in Total Number of Firms)

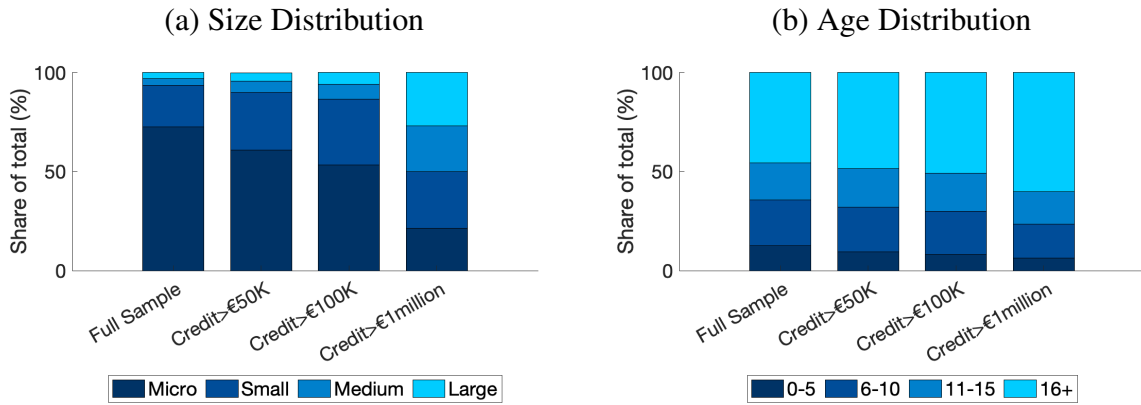
Restriction on Sample	Micro	Small	Medium	Large
No restriction	72.7%	21.0%	3.4%	2.9%
Credit $\geq$ €100,000	53.3% ( $\downarrow$ 74%)	33.2% ( $\downarrow$ 45%)	7.6% ( $\downarrow$ 30%)	5.9% ( $\downarrow$ 28%)
Credit $\geq$ €1 million	21.3% ( $\downarrow$ 99%)	28.5% ( $\downarrow$ 94%)	23.2% ( $\downarrow$ 72%)	27.0% ( $\downarrow$ 62%)

*Notes:* This part uses the merged CBI and CIR data from 2000–2019. The numbers in parentheses represent the decline in coverage relative to the no restriction benchmark.

In [Figure B.19](#), we show how imposing higher minimum reporting thresholds for loan volumes skews the observed firm distribution toward larger and older firms. As the cutoff increases, smaller and younger firms, which are most likely to face financial constraints, are increasingly excluded from the sample. This highlights the importance of using comprehensive data that captures even small loan exposures to avoid systematic bias in analyzing firm financing behavior.

<sup>20</sup>A similar point was made by [Amberg et al. \(2025\)](#) in their study of the utilization of credit lines in Sweden. They show that imposing a \$1 million reporting threshold reduces the number of firms in their sample by 93%.

**Figure B.19: Distribution of Firms Across Credit Thresholds**



*Notes:* This figure shows the size and age distribution of firms, when imposing different reporting thresholds on outstanding loan commitments at the loan level, using the merged CBI and CIR data from 2000–2019.

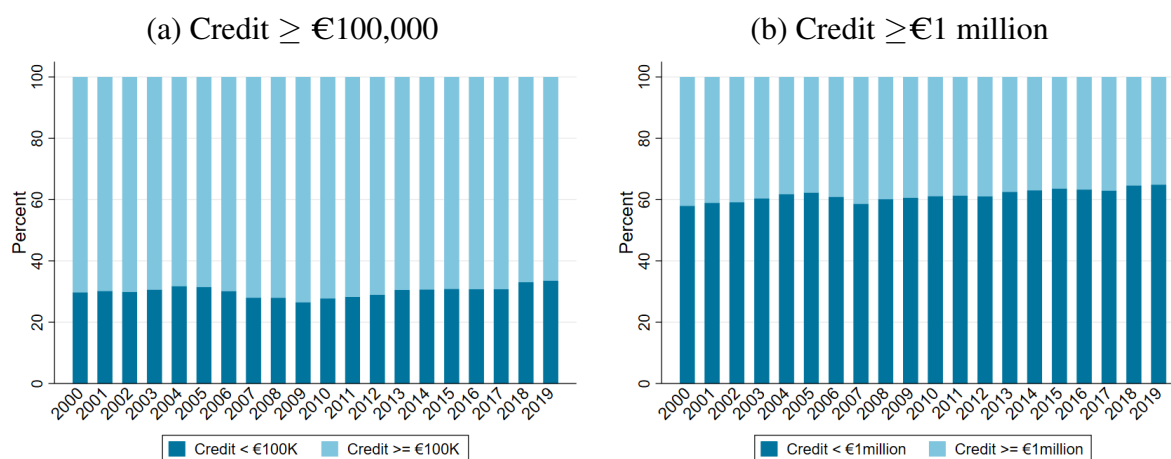
**Shares in the aggregate.** We show the shares in micro-aggregated employment and revenues across the firm size distribution in [Figure B.20](#) and the fraction of total employment and output that are dropped as a result of imposing credit reporting thresholds in [Figure B.21](#) and [Figure B.22](#) respectively. Micro and small firms comprise around 40% of micro-aggregated employment and 20% micro-aggregated output in CBI. For a loan reporting threshold of €100,000 (€1 million), we lose  $\approx 30\%$  ( $\approx 60\%$ ) of total employment and  $\approx 20\%$  ( $\approx 40\%$ ) of total output.

**Figure B.20: Shares in Micro-aggregated Employment and Output Across Size Groups**



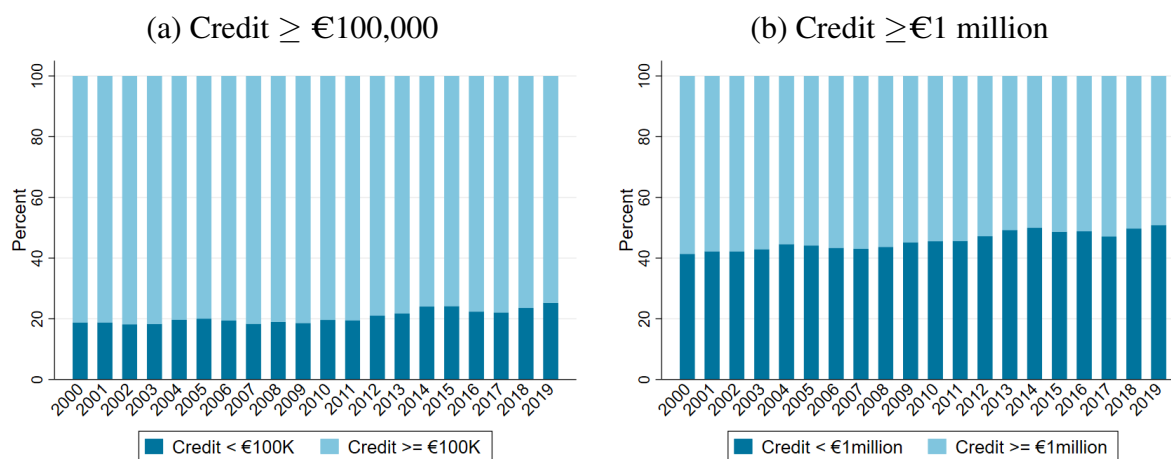
*Note:* This figure shows the micro-aggregated shares in total employment and revenues of firms of different size categories, using the merged CBI and CIR data from 2000 to 2019.

**Figure B.21: Shares in Micro-aggregated Employment – By Credit Thresholds**



*Note:* This figure shows the micro-aggregated shares in total employment of firms of different size categories after imposing different credit thresholds, using the merged CBI and CIR data from 2000 to 2019.

**Figure B.22: Shares in Micro-aggregated Output – By Credit Thresholds**



*Note:* This figure shows the micro-aggregated shares in total revenues of firms of different size categories after imposing different credit thresholds, using the merged CBI and CIR data from 2000 to 2019.

## B.5.2 Types of Collateral Used

In [Table B14](#), we show that real estate mortgages are the most common type of collateral used among the smaller firms, and as a share in total number of loans, it declines as the firm size increases. On the other hand, we find the opposite trend for movable assets in that it has the highest share in total number of loans among the largest firms.

**Table B14: Types of Collateral by Size Group (% in Total Number of Loans)**

Type of Collateral	Micro	Small	Medium	Large	MSMEs
Real estate mortgages	75.2	64.7	40.8	23.9	69.3
Movable assets	17.0	27.4	52.9	70.8	23.0
Pledged financial instruments	7.8	7.9	6.3	5.3	7.7

*Note:* This table is constructed using the merge CBI and *new* CIR loan-level data from 2018–2019.

The patterns that we observe on collateral usage across the firm size distribution are broadly consistent with the pattern in [Caglio et al. \(2024\)](#). Note though that this comes with the caveat on the comparability of the results given the difference in reporting thresholds. If we impose for example a reporting threshold of €100,000 on outstanding loan commitments, we still find the same patterns of declining share of real estate mortgages and increasing share of movable assets in the total number of loans as size increases. Yet, this is at the expense of having that across all size categories, the lion's share of the total number of loans will be taken up by real estate mortgages (70–90%), because loans backed by this type of collateral are typically much larger in volume relative to the rest (and thus survives the imposition of a high volume cutoff).

Nevertheless, while [Caglio et al. \(2024\)](#) emphasize the importance of accounts receivables and inventory (AR&I) as collateral among firms in the US,<sup>21</sup> in Spain, real estate mortgages remain to be the most important collateral for firms. Movable assets, which is a catchall collateral category that includes receivables, inventory and fixed assets, play a lesser role in Spanish firms.

A potential explanation for this is attributable to the institutional setting. According to an IMF Country Report ([IMF, 2017](#)), having to deal with the Movable Assets Registry is costly in terms of time and resources. In addition, regulations on the different types of security interests are not unified and there is legal uncertainty over some types of collateral like receivables. This then makes it more difficult to use receivables as collateral in Spain. In the framework of [Donaldson et al. \(2020\)](#), one can think of receivables (and movable assets in general) as imperfectly collateralizable assets that despite being productive, are costly to collateralize due to pecuniary (e.g. registration costs) and non-pecuniary reasons (e.g. uncertainties in the law).

### **B.5.3 Legal Infrastructure**

According to [Lian and Ma \(2021\)](#), default resolution in bankruptcy matters for the type of lending that a country predominantly has. They highlight the greater prevalence of cash flow lending in countries with reorganization-based bankruptcy systems (e.g. Chapter 11 in the US). They note that in the US, where cash flow lending is predominant, 90% of bankruptcy filings by value are Chapter 11.<sup>22,23</sup>

According to [Djankov et al. \(2008\)](#), both the US and Spain are classified as having a reorganization-based corporate bankruptcy regime. In the cross-country case study conducted by the authors to examine how debt enforcement will proceed for an insolvent but viable firm, the authors find that such a firm is likely to undergo reorganization in countries like the US and Spain. In both

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<sup>21</sup>[Chodorow-Reich et al. \(2022\)](#) highlight differences in collateral usage for credit lines and term loans among firms. They show that among small firms in the Fed Y-14 data, AR&I are the predominant type of collateral pledged in credit lines whereas real estate mortgages are the most important type of security interest pledged for term loans.

<sup>22</sup>However, according to [Corbae and D'Erasmus \(2021\)](#), most papers that study corporate bankruptcies in the US focus solely on Compustat firms. They also note that while for Compustat firms, 79% of the total number bankruptcy filings are Chapter 11, according to the bankruptcy statistics for all business filings from US courts (which includes small private firms), Chapter 11 bankruptcies account for just 25% of total filings by the end of December 2013.

<sup>23</sup>Occasionally, Chapter 11 bankruptcy filings get converted to Chapter 7 later on ([Corbae and D'Erasmus, 2021](#); [Kim, 2021](#)).

countries, upon insolvency filing, assets are automatically stayed. In Spain, the automatic stay was introduced as part of a wave of corporate bankruptcy reforms after the Great Recession (García-Posada and Vegas Sanchez, 2018).

In practice, there is an important difference between the insolvency proceedings in the US and Spain. In the US, firms can choose to file a petition under Chapter 7 (liquidation) or Chapter 11 (reorganization) bankruptcy proceedings. In Spain, there is only one in-court bankruptcy proceeding supervised by an insolvency administrator. A firm can be restructured if creditors and the insolvent firm can reach an agreement. Otherwise, if no agreement is reached or no restructuring plan was proposed to begin with, the insolvent firm gets liquidated. See García-Posada (2020) for a more detailed discussion.

Note that in Spain, despite the substantial amount of unsecured (cash flow-based) lending, most insolvency proceedings in practice, however, end up in liquidation. Excluding express bankruptcies, around 83% of the total number of bankruptcy filings end up in liquidation (corresponding to  $\approx 73\%$  of bankruptcy filings weighted by assets). According to García-Posada (2020), the fact that most court-based insolvencies in Spain end up in liquidation suggests that these proceedings are used only as a last resort, and are actually able to distinguish viable versus non-viable firms.

In Table B15, we provide descriptive statistics of firm characteristics, depending on the type of bankruptcy proceeding a firm underwent, whether it is liquidation or restructuring. Firms that are eventually liquidated are extremely unprofitable, while firms that are restructured are larger in terms of total assets or sales. The average share of unsecured debt in total debt is similar across groups.

**Table B15:** Firm Characteristics by Type of Bankruptcy

	Liquidation		Restructuring	
	Mean	Median	Mean	Median
Loan volume ('000)	1,417.60	457.25	2,479.48	874.59
Unsecured debt share	0.62	0.73	0.60	0.66
Age	17.12	15.00	20.23	18.00
Profitability	-0.25	-0.14	-0.08	-0.03
Assets ('000)	2,828.27	788.16	6,134.80	2,595.89
Sales ('000)	1,390.31	347.02	3,387.85	1,171.83
Employees	35.47	7.00	31.67	13.00
Leverage	0.78	0.63	0.65	0.57

*Notes:* This part uses the merged CBI and CIR data, merged with bankruptcy data for Spain from 2004–2019.

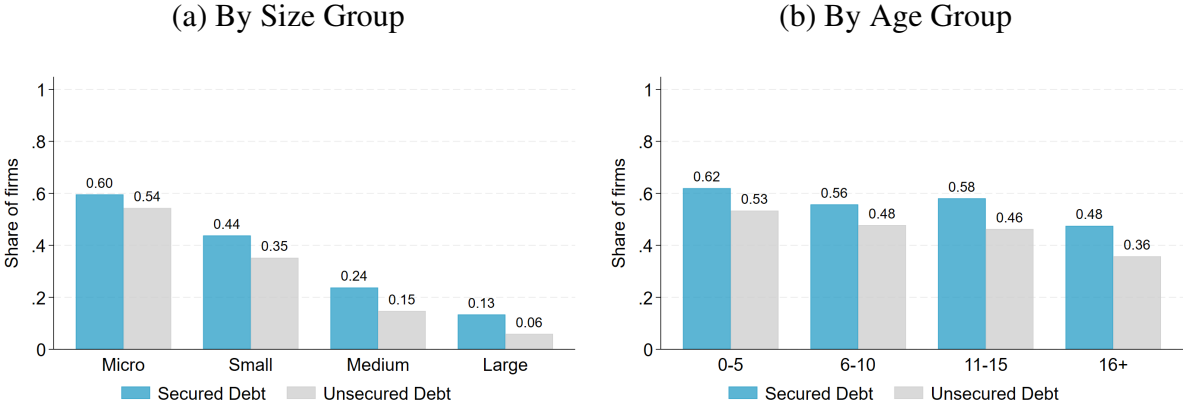
## B.6 The Role of Personal Guarantees

The fact that we observe a substantial usage of unsecured loans among very small and young firms is potentially capturing the role of *personal guarantees*. According to Avery et al. (1998) and Bahaj et al. (2020), there are two forms of personal commitment involved in small business financing: (1) personal collateral, which appears to be more common among sole proprietorships

and partnerships, and (2) personal guarantees, which are more likely among incorporated firms. Personal collateral shows up in a firm’s balance sheet in the form of equity injections because this would be a case where, for example, a firm owner uses his own property as collateral to take out a loan and pours in the acquired funds into the firm. Since this form of personal commitment does not show up as debt on the balance sheet, it is less of a concern for our setting. On the other hand, a personal guarantee is whereby the owner uses his or her own wealth as a guarantee to pay back loans. Essentially, it breaks the limited liability clause of incorporated firms, which is the main focus of this project, and raises the concern that it acts as *implicit collateral* of firms. But this matters more when we talk about what lenders can recover in the event of a default.

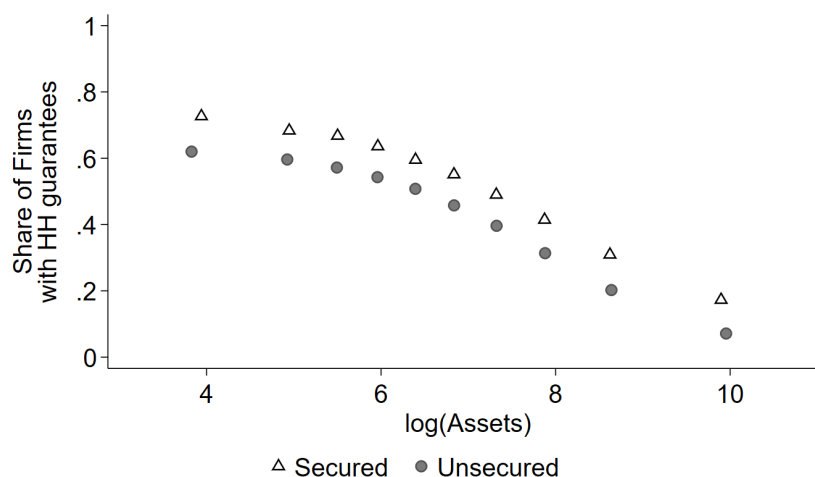
Which firms pledge personal guarantees? If personal guarantees were meant to substitute the lack of collateral of firms that do not use secured loans, then we should observe more personal guarantees tied to the use of unsecured loans. To shed light on this, we exploit the granular information in *new* CIR data, since we can disentangle these two margins as they are treated as separate entries in the data, within the same loan operation. We show in **Figure B.23** and **Figure B.24** that personal guarantees are more common among micro-sized and young firms, whether they use secured loans or unsecured loans. This seems to suggest that the fact that lenders require personal guarantees might reflect something about their assessment about the firm itself, beyond loan types.

**Figure B.23:** Loan Types – With and Without Personal Guarantees (Share in Total No. of Firms)



*Notes:* These figures show bar charts of the share of firms with personal (HH) guarantees by loan type – secured vs. unsecured, by (a) size group and (b) age group, using the merged CBI and *new* CIR data from 2018 to 2019.

**Figure B.24:** Share of Firms with Personal Guarantees Across Size – By Loan Type



*Notes:* This figure shows a binscatter plot of the share of firms with personal (HH) guarantees within equal-sized bins of  $\log(\text{Assets})$ , a measure of firm size, by loan type – secured vs. unsecured, controlling for age, sector FE and year FE, using the merged CBI and *new* CIR data from 2018 to 2019.

Furthermore, if a personal guarantee is supposed to compensate for the lack of hard collateral of a firm, then we would expect that unsecured loans with personal guarantees to have better loan conditions relative to unsecured loans without some type of personal guarantee. However, as we can see in [Table B16](#), this is clearly not the case.

**Table B16:** Spreads and Loan Volume – With and Without Personal Guarantees

	No Pers. Guar.		With Pers. Guar.	
	Mean	Median	Mean	Median
<b>Secured: Full Sample</b>				
Spread (%)	3.33	2.33	3.16	2.62
Loan volume (€'000)	267.96	62.54	151.47	66.56
<b>Unsecured: Full Sample</b>				
Spread (%)	3.42	2.79	4.42	4.14
Loan volume (€'000)	225.55	50.61	52.59	24.63
<b>Secured: Small Firms</b>				
Spread (%)	3.47	2.47	3.17	2.62
Loan volume (€'000)	170.65	51.81	139.09	65.01
<b>Unsecured: Small Firms</b>				
Spread (%)	3.88	3.26	4.47	4.20
Loan volume (€'000)	79.35	31.87	45.27	24.10
<b>Secured: Young Firms</b>				
Spread (%)	4.23	3.16	3.86	3.00
Loan volume (€'000)	252.16	45.05	144.20	60.97
<b>Unsecured: Young Firms</b>				
Spread (%)	4.32	3.67	4.70	4.43
Loan volume (€'000)	122.49	28.47	39.63	21.28

*Notes:* This part uses the merged CBI and *new* CIR data from 2018–2019 and excludes credit cards. Small firms refer to micro and small firms. Young firms are defined as firms with age  $\leq 10$  years.

In [Table B17](#), we report the share of loans backed by personal guarantees across different credit instruments. We find that credit cards are rarely backed by personal guarantees.

**Table B17: Personal Guarantees in Different Types of Credit Instruments (%)**

	Share of Loans (%)
Term loans	48.61
Credit lines	54.65
Credit cards	2.66
Other	49.64

*Notes:* This table reports the share of loans backed by personal guarantees across different credit instruments. This part uses the merged CBI and *new* CIR data from 2018 to 2019.

In [Table B18](#) and [Table B19](#), we show that even after controlling for relevant firm characteristics and sectoral variation, or exploiting within-firm variation, we nonetheless find that unsecured loans with personal guarantees do not have better loan terms. This is consistent with [Beyhaghi \(2022\)](#), who use the Fed Y-14 data (outstanding loans  $\geq$  \$1 million) to show that the loan rate for unsecured loans backed by personal guarantees is not lower relative to unsecured loans that are not guaranteed. In our case, leveraging the richer coverage of the Spanish data, we instead find that the interest rate spread is slightly higher and loan volume is a bit lower for unsecured loans backed by personal guarantees. If any, the fact that loan terms appear worse could reflect the underlying risk profile of the entrepreneur, and that including a personal guarantee just forces the entrepreneur to have more skin in the game.<sup>24</sup> That said, we acknowledge that personal guarantees can still play a critical role in facilitating credit access, particularly for borrowers who might otherwise be excluded. Even if they do not directly enhance loan conditions, their presence may be essential for lenders to extend credit in the first place.

<sup>24</sup>[Hoshi and Shibuya \(2024\)](#) show that firms with better credit ratings tend to go for loans without personal guarantees and are less likely to default ex-post. The setting that they examine allows them to focus on borrower-side selection, controlling for the lender-side channel.

**Table B18: Loan Volume and Spreads – With and Without Personal Guarantees**

	log(Credit)	Spread	log(Credit)	Spread	log(Credit)	Spread
$\mathbb{I}_{\text{Unsecured}}$	-0.560*** (0.007)	0.971*** (0.010)	-0.709*** (0.009)	0.985*** (0.013)	-0.843*** (0.014)	1.128*** (0.018)
$\mathbb{I}_{\text{Pers. guar.}}$	0.269*** (0.007)	0.066*** (0.011)	0.390*** (0.010)	-0.176*** (0.015)	0.386*** (0.015)	-0.059*** (0.021)
$\mathbb{I}_{\text{Unsecured}} \times \mathbb{I}_{\text{Pers. guar.}}$	-0.323*** (0.008)	0.486*** (0.012)	-0.273*** (0.011)	0.422*** (0.016)	-0.132*** (0.016)	0.269*** (0.022)
Firm Controls	Yes	Yes	–	–	–	–
Bank x Sector x Year FE	Yes	Yes	–	–	–	–
Bank x Year FE	–	–	Yes	Yes	–	–
Firm x Year FE	–	–	Yes	Yes	–	–
Bank x Firm x Year FE	–	–	–	–	Yes	Yes
Observations	1,057,367	1,078,343	866,009	887,247	493,955	508,309
R-squared	0.472	0.490	0.672	0.694	0.719	0.740

Notes: Standard errors clustered at the firm level in parentheses. \*\*\*p<0.01, \*\*p<0.05, \*p<0.1. The spread is expressed in percentage (%).  $\mathbb{I}_{\text{Unsecured}}$  is a dummy variable = 1 if the loan is an unsecured loan, and = 0 if secured loan.  $\mathbb{I}_{\text{Pers. guar.}}$  is a dummy variable = 1 if the loan has a personal guarantee, and = 0 otherwise. Firm controls include log(Assets), tangibility and profitability. This part uses the merged CBI and *new* CIR data from 2018–2019.

**Table B19: Loan Volume and Spreads in Small Firms – With and Without Personal Guarantees**

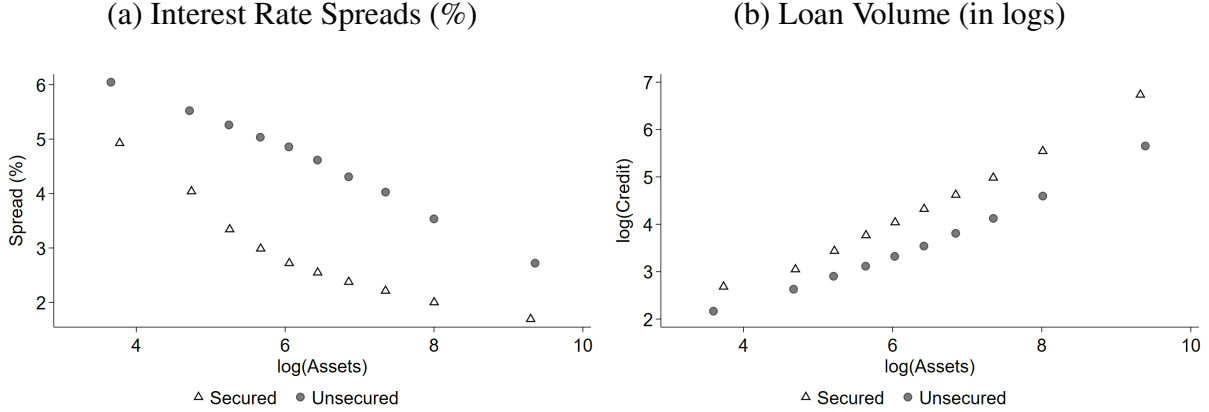
	log(Credit)	Spread	log(Credit)	Spread	log(Credit)	Spread
$\mathbb{I}_{\text{Unsecured}}$	-0.681*** (0.007)	1.123*** (0.010)	-0.801*** (0.010)	1.172*** (0.014)	-0.965*** (0.014)	1.332*** (0.020)
$\mathbb{I}_{\text{Pers. guar.}}$	0.242*** (0.007)	0.140*** (0.012)	0.345*** (0.011)	-0.080*** (0.016)	0.328*** (0.016)	0.037 (0.023)
$\mathbb{I}_{\text{Unsecured}} \times \mathbb{I}_{\text{Pers. guar.}}$	-0.230*** (0.008)	0.364*** (0.013)	-0.198*** (0.011)	0.285*** (0.017)	-0.034** (0.017)	0.121*** (0.023)
Firm Controls	Yes	Yes	–	–	–	–
Bank x Sector x Year FE	Yes	Yes	–	–	–	–
Bank x Year FE	–	–	Yes	Yes	–	–
Firm x Year FE	–	–	Yes	Yes	–	–
Bank x Firm x Year FE	–	–	–	–	Yes	Yes
Observations	927,507	945,078	719,943	736,948	420,209	431,821
R-squared	0.385	0.472	0.603	0.682	0.652	0.725

Notes: Standard errors clustered at the firm level in parentheses. \*\*\*p<0.01, \*\*p<0.05, \*p<0.1. “Small” firms refer to both micro and small firms. The spread is expressed in percentage (%).  $\mathbb{I}_{\text{Unsecured}}$  is a dummy variable = 1 if the loan is an unsecured loan, and = 0 if secured loan.  $\mathbb{I}_{\text{Pers. guar.}}$  is a dummy variable = 1 if the loan has a personal guarantee, and = 0 otherwise. Firm controls include log(Assets), tangibility and profitability. This part uses the merged CBI and *new* CIR data from 2018–2019.

## B.7 Loan Contract Features: Secured vs. Unsecured Debt

### B.7.1 Robustness Checks

**Figure B.25:** Loan Contract Terms on Secured and Unsecured Debt – Including Credit Cards



*Notes:* This figure shows a binscatter plot of (a) the interest rate spread; and (b) loan volume (measured as  $\log(\text{Credit})$ ) within equal-sized bins of  $\log(\text{Assets})$ , a measure of firm size. The analysis controls for age, tangibility, profitability, sector FE and year FE, and uses the merged CBI and *new* CIR data from 2018 to 2019.

**Loan-level regressions.** In Section 3.2.1, we presented binscatter estimates per size decile on the loan terms on secured and unsecured debt, using the merged CBI and *new* CIR data aggregated to the firm level. The baseline analysis cannot disentangle the supply and demand factors. As such, we follow the standard approach in the empirical banking literature and exploit *loan-level* data, which gives us multiple observations per firm and lender. This lets us better control for differences across borrowers and banks when comparing loan terms.<sup>25</sup> We assign firms to size deciles based on their  $\log(\text{Assets})$  in a given year, and estimate the following regression separately for each size bin:<sup>26</sup>

$$y_{lt} = \alpha + \beta \text{Unsecured}_{lt} + \Gamma' \mathbf{X}_{i(l)t} + \zeta_{p(l)} + \eta_{b(l)s(l)t} + \varepsilon_{lt} \quad \forall i \in \text{size bin} = \{1, 2, \dots, 10\} \quad (4)$$

where  $y_{lt} = \{\text{interest rate spread, } \log(\text{Credit})\}$  of a loan  $l$  of firm  $i$  at year  $t$  issued by bank  $b$ . The variable  $\text{Unsecured}_{lt}$  is an indicator equal to 1 if the loan is unsecured, and 0 if secured.  $\mathbf{X}_{i(l)t}$  are firm-level control variables including  $\log(\text{Assets})$ ,  $\log(\text{age})$ , tangibility and profitability, which can affect loan contract terms that banks offer to firms.  $\zeta_{p(l)}$  denotes product type fixed effects, to account for heterogeneity in the type of products underlying each loan type.  $\eta_{b(l)s(l)t}$  represents bank  $\times$  sector  $\times$  year fixed effects, which allows us to make a comparison across firms borrowing from banks within an industry within a year. We begin with this specification to include single-lender firms, for whom within-firm comparisons across loans are not feasible. By

<sup>25</sup>See Appendix A.1 for details on how the *loan-level* *new* CIR data was constructed using *contract-level* data.

<sup>26</sup>Since asset deciles are defined at the *firm level* and subsequently merged with *loan-level* data, firms with more loans, typically larger firms, contribute more observations to the loan-level dataset. As a result, higher asset deciles naturally contain a disproportionate number of loan-level observations compared to lower deciles. This uneven distribution arises mechanically from the fact that larger firms tend to borrow from multiple banks, thereby inflating their representation in the loan-level sample (see Table B20).

conditioning on firm characteristics and bank  $\times$  sector  $\times$  year fixed effects, we can still exploit meaningful cross-firm variation. This is important because approximately 50% of firms in Spain maintain only one lending relationship (Ivashina et al., 2022), and these are typically the smaller and younger ones.

To show that the contractual differences between secured and unsecured debt that we observe are not driven only by firm-specific heterogeneity, we follow the empirical strategy of Khwaja and Mian (2008) and include firm  $\times$  year FE in the regression. This allows us to exploit *within-firm* variation using *loan-level* data, effectively controlling for all time-varying firm-specific demand factors. In the standard Khwaja and Mian (2008) setting that does not make a distinction across loan types, firms need to have more than one banking relationship in a given year. In our setting, which compares loan types, the variation comes from firms that borrow both secured and unsecured loans in the same year, either from different banks or from the same bank.<sup>27</sup> We also include bank  $\times$  year FE to control for bank-specific supply variation, such as changes in banks' risk appetite, funding costs, or capital constraints. The regression equation is given by

$$y_{it} = \alpha + \beta \text{Unsecured}_{it} + \zeta_{p(i)} + \psi_{i(i)t} + \eta_{b(i)t} + \varepsilon_{it} \quad \forall i \in \text{size bin} = \{1, 2, \dots, 10\} \quad (5)$$

Finally, we estimate a more stringent specification that includes bank  $\times$  firm  $\times$  year fixed effects, allowing us to compare loan terms between secured and unsecured credit within the same bank-firm relationship in a given year. This approach effectively isolates variation in loan terms by zooming in on firms that simultaneously use both types of credit from the same lender, thereby holding constant all time-varying firm- and bank-specific factors.<sup>28</sup> An important caveat here is that the sample size drops substantially, particularly in the lower deciles (see Table B20). The regression equation is given by

$$y_{it} = \alpha + \beta \text{Unsecured}_{it} + \zeta_{p(i)} + \eta_{b(i)i(i)t} + \varepsilon_{it} \quad \forall i \in \text{size bin} = \{1, 2, \dots, 10\} \quad (6)$$

The results are presented in Figure B.26 and Figure B.27. The estimated coefficients ( $\beta$ 's) on the indicator variable  $\text{Unsecured}_{it}$  in Equation 4 to 6 capture the average difference in interest rate spreads and  $\log(\text{Credit})$  between unsecured and secured loans for each size decile. For instance, among firms in the bottom size decile, unsecured loans carry interest rate spreads that are approximately 150 basis points higher than secured loans (see Figure B.26), and average loan volumes that are about 55% smaller (see Figure B.27).<sup>29</sup> Among firms in the top size decile, the

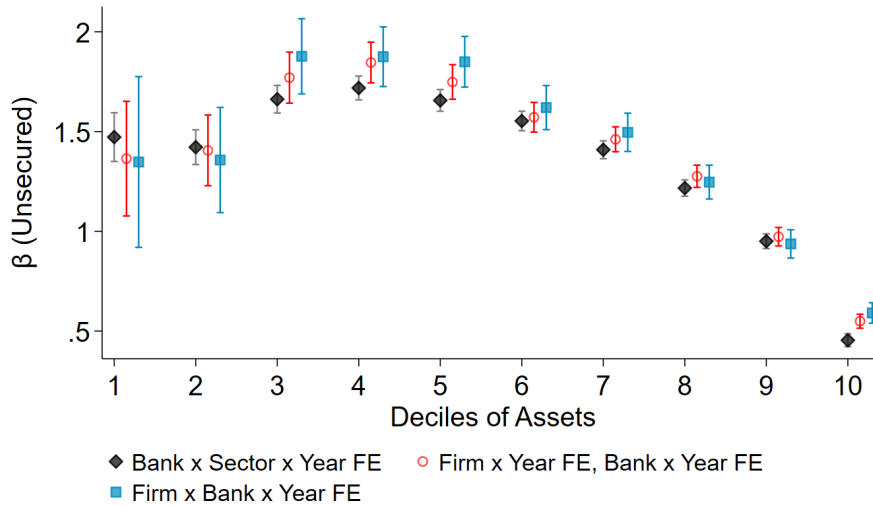
<sup>27</sup>There are two important points to be made here. First, a substantial fraction of firms rely on one loan type at any given point in time. According to Ivashina et al. (2022), this is true whether or not a firm has multiple lender relationships. Second, as Ivashina et al. (2022) point out, *bank-specific* loan demand due to the presence of loan types – for example, a firm borrowing secured (asset-based) from Bank A and concurrently borrowing unsecured (cash flow-based) from Bank B – is a pitfall of this identification strategy, since the identifying assumption of employing the firm  $\times$  year FE is that credit demand is *firm-specific* and independent of the supply side.

<sup>28</sup>Firms with multiple loans from the same bank tend to be larger than firms that have only one loan from a given bank (Luck and Santos, 2024), hence the results based on this specification may not be generalizable beyond the sample of firms included in those regressions.

<sup>29</sup>For the regression with  $\log(\text{Credit})$  as the dependent variable, percentage effects are given by  $\exp(\beta) - 1$ ; thus  $\beta = -0.8$  implies a reduction of about 55%.

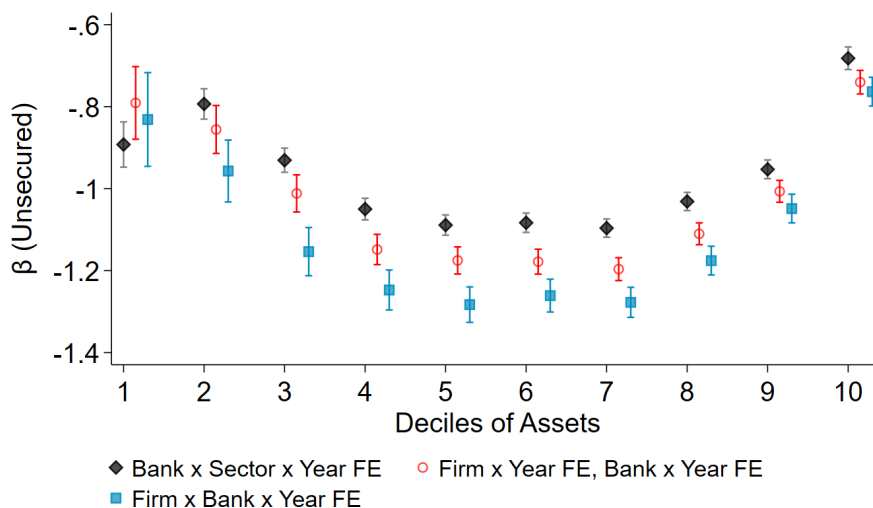
spread differential narrows to around 50 basis points. These patterns are broadly consistent with the results using binscatter plots (see [Figure 7](#) and [Figure B.25](#)), and with the findings of [Luck and Santos \(2024\)](#), who show that firms benefit from pledging collateral, but the price effect shrinks as firm size increases (i.e., firms becoming less risky).

**Figure B.26:** Regression Estimates for  $\beta$  from [Equation 4–6](#) – Interest Rate Spreads (%)



*Notes:* This figure plots coefficient estimates from [Equation 4–6](#) for each size bin (constructed using  $\log(\text{Assets})$ ). The  $\beta$ 's are the average difference in interest rate spreads between unsecured and secured loans. The analysis uses the merged CBI and *new* CIR *loan-level* data from 2018 to 2019.

**Figure B.27:** Regression Estimates for  $\beta$  from [Equation 4–6](#) –  $\log(\text{Credit})$



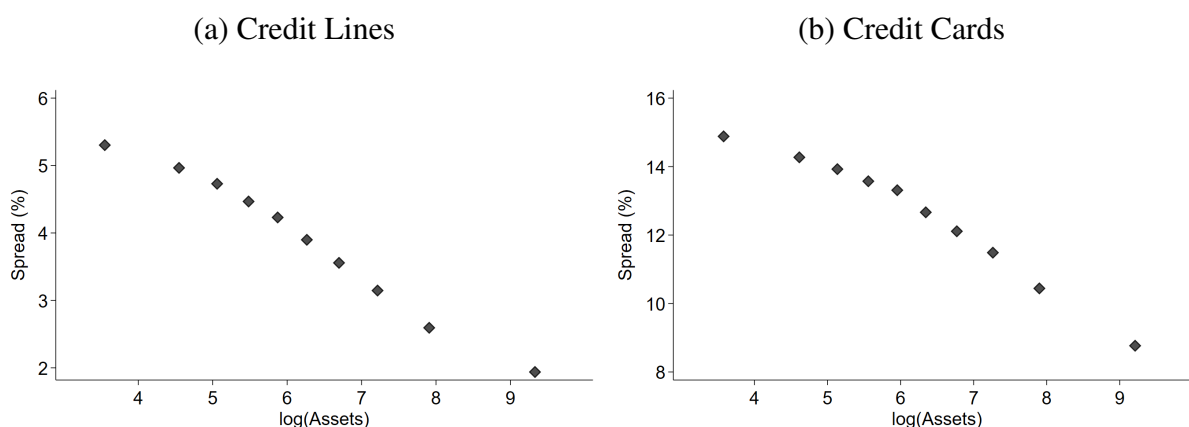
*Notes:* This figure plots coefficient estimates from [Equation 4–6](#) for each size bin (constructed using  $\log(\text{Assets})$ ). The  $\beta$ 's are the average difference in  $\log(\text{Credit})$  between unsecured and secured loans. The analysis uses the merged CBI and *new* CIR data from 2018 to 2019.

**Table B20:** Number of Observations for Regressions (Equation 4–6) By Size Decile

Size Decile	Equation 4	Equation 5	Equation 6
1	61697	41324	31886
2	78119	58588	42483
3	88770	70037	49940
4	98869	80903	56459
5	108937	91415	62919
6	121098	105182	71654
7	138125	124139	83746
8	157065	144323	95912
9	189002	178469	118483
10	258646	252575	172166
Fixed Effects	Bank $\times$ Sector $\times$ Year	Firm $\times$ Year, Bank $\times$ Year	Firm $\times$ Bank $\times$ Year

Notes: This table reports the number of observations used in the regressions Equation 4–6, whose point estimates for  $\beta$ 's are plotted in Figure B.26 and Figure B.27. This part uses the merged CBI and *new* CIR data from 2018 to 2019.

**Credit lines and credit cards.** In Figure B.28, we show that interest rate spreads on both credit lines and credit cards decline as firm size increases. However, credit cards consistently carry substantially higher spreads than credit lines across the entire firm size distribution, reflecting their typically higher cost of borrowing. This heterogeneity highlights the importance of decomposing unsecured debt by product type to have a comprehensive picture of the financing costs that firms face.

**Figure B.28:** Interest Rate Spreads (%) on Credit Lines and Credit Cards Across Firm Size

Notes: This figure shows a binscatter plot of the interest rate spread on (a) credit lines; and (b) credit cards, within equal-sized bins of  $\log(\text{Assets})$ , a measure of firm size. The analysis controls for age, tangibility, profitability, sector FE and year FE, and uses the merged CBI and *new* CIR data from 2018 to 2019.

### B.7.2 Additional Descriptive Statistics on Secured and Unsecured Debt

We provide some additional descriptive statistics on the lending volume of the two loan types, conditional on the use (i.e. positive outstanding balance), according to age and size. As we can see in Table B21, conditional on a firm using an secured loan, it will have a substantially larger

volume relative to an average unsecured loan (also conditional on using one), and this gap narrow down as firms get larger. A similar pattern emerges across age groups, as shown in [Table B22](#).

**Table B21:** Loan Volume ('000 Euro) Across Size Groups

Size Group	Secured		Unsecured	
	Mean	Median	Mean	Median
Micro	233.20	107.46	88.56	33.18
Small	527.55	227.01	346.73	130.79
Medium	1,489.47	627.40	1,487.34	650.51
Large	2,232.51	973.37	1,830.96	531.44

*Notes:* Values are deflated using the value-added deflator taken from EU-KLEMS. This part uses the merged CBI and CIR data from 2000–2019.

**Table B22:** Loan Volume ('000 Euro) Across Age Groups

Age Group	Secured		Unsecured	
	Mean	Median	Mean	Median
0-2	322.22	121.19	129.58	33.00
3-5	340.96	123.64	162.95	37.78
6-10	335.27	124.86	194.53	42.32
11-15	348.35	127.81	233.35	48.61
16+	498.18	156.43	414.54	68.49
Total	393.56	134.20	254.84	46.22

*Notes:* Values are deflated using the value-added deflator taken from EU-KLEMS. This part uses the merged CBI and CIR data from 2000–2019.

**Table B23:** Spreads and Residual Maturity on Loans

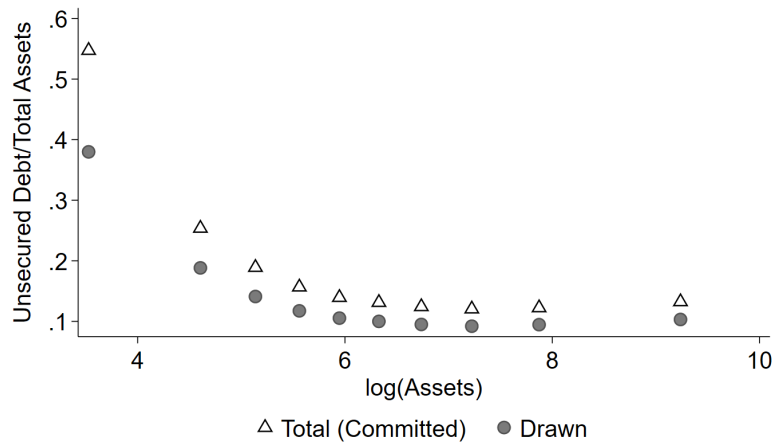
	Secured		Unsecured	
	Mean	Median	Mean	Median
<b>Micro &amp; Small</b>				
Spread (%)	3.18	2.48	4.05	3.68
Residual Maturity	7.02	6.00	2.25	1.00
<b>Medium &amp; Large</b>				
Spread (%)	2.45	1.92	2.23	1.96
Residual Maturity	6.13	5.00	2.33	1.00
<b>Young</b>				
Spread (%)	3.79	2.83	4.34	4.04
Residual Maturity (years)	7.34	6.00	2.42	1.00
<b>Old</b>				
Spread (%)	2.91	2.30	3.47	3.07
Residual Maturity (years)	6.82	5.00	2.18	1.00
<b>All Firms</b>				
Spread (%)	2.74	2.12	3.79	3.38
Residual Maturity (years)	7.06	6.00	2.25	1.00

*Notes:* Young firms are defined as firms with age  $\leq 10$  years, and old firms are those aged over 10 years. This part uses the merged CBI and *new* CIR *loan-level* data from 2018–2019 and excludes credit card debt, given their notoriously high interest rates.

Next, we provide summary statistics on the spreads and residual maturity of loans in [Table B23](#). Residual maturities differ sharply between secured and unsecured loans (e.g., medians of 6 vs. 1 year), reflecting the intrinsic nature of the contract. However, within each loan type, residual maturity varies little across firm size or age, suggesting that, conditional on being secured or unsecured, maturities are largely independent of firm characteristics.

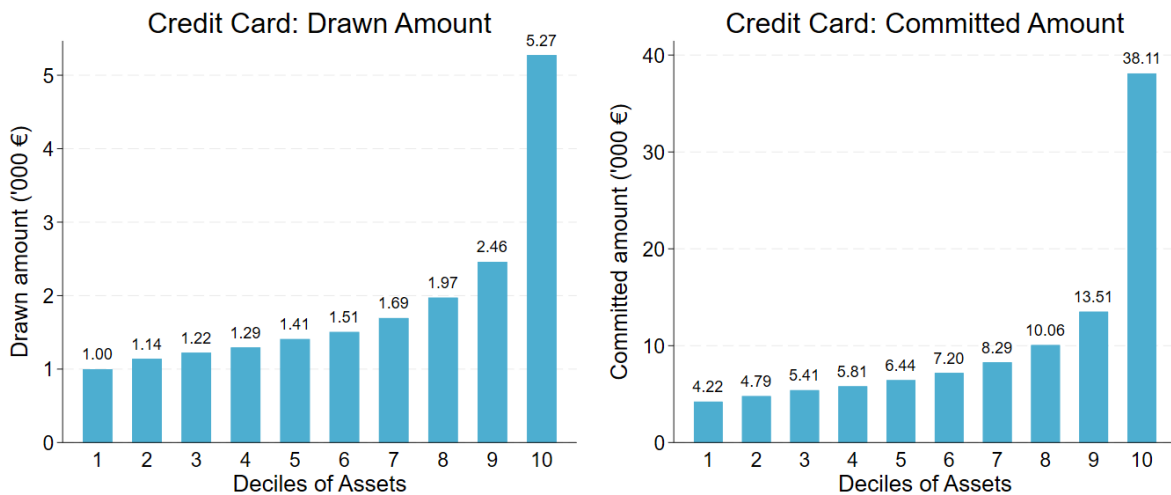
## B.8 Utilization of Unsecured Debt

**Figure B.29:** Unsecured Debt Leverage Across the Size Distribution



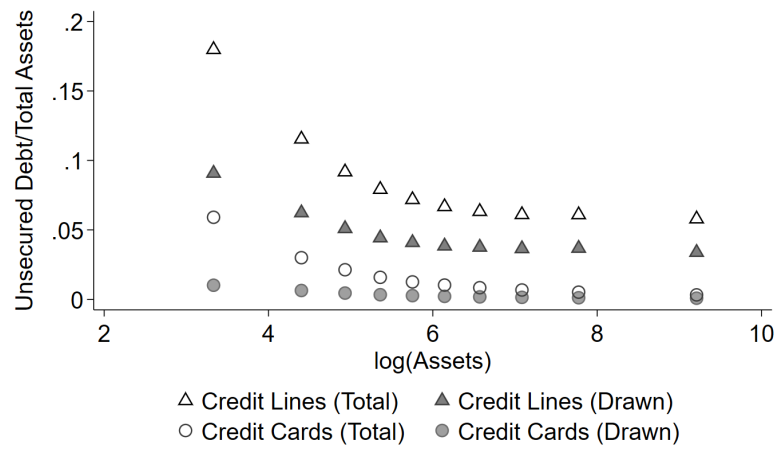
*Notes:* This figure shows binscatter plots of unsecured debt leverage for committed and drawn amounts, within equal-sized bins of  $\log(\text{Assets})$ , a measure of firm size. The analysis controls for age, sector FE and year FE, and uses the merged CBI and CIR data from 2000 to 2019.

**Figure B.30:** Average Drawn and Committed Amount on Credit Cards By Size



*Notes:* This figure shows a bar chart of the drawn and committed amount on credit card debt, by size decile (deciles of  $\log(\text{Assets})$ ). The analysis uses the merged CBI and *new* CIR data from 2018 to 2019.

**Figure B.31: Unsecured Debt Leverage Across the Size Distribution – By Product Type**



*Notes:* This figure shows binscatter plots of unsecured debt leverage by product type – credit lines and credit cards – for committed and drawn amounts, within equal-sized bins of  $\log(\text{Assets})$ , a measure of firm size. The analysis controls for age, sector FE and year FE, and uses the merged CBI and *new* CIR data from 2018 to 2019.

## B.9 Extensive Margin of Borrowing

### B.9.1 Summary Statistics

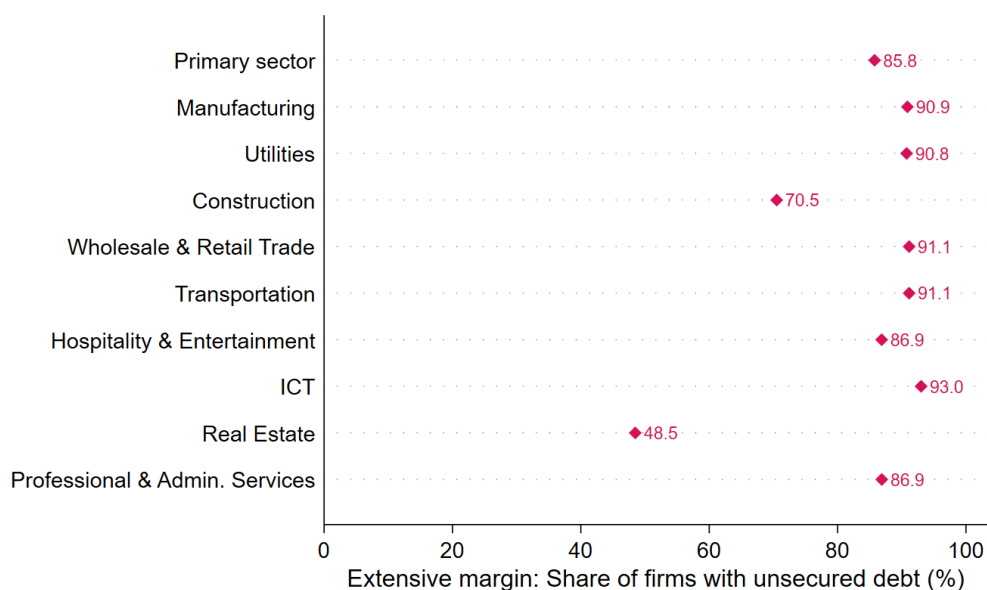
**Table B24:** Extensive Margin Summary Statistics

	Mean	p25	p50	p75	sd	N Obs.
<b>Panel A: Secured</b>						
Age	1.92	0.00	1.00	3.00	2.41	48622
Loan volume ('000)	342.73	53.50	123.57	263.40	1032.72	48622
Assets ('000)	833.26	120.21	258.19	566.29	2768.06	48622
Sales ('000)	307.71	16.21	84.00	247.66	1149.34	48622
Employees	2.29	0.00	1.00	2.47	5.41	48622
Tangibility	0.48	0.12	0.52	0.80	0.34	48622
Liquidity	0.17	0.02	0.08	0.23	0.22	48622
Interest Rate Spread (%)	3.26	1.06	2.10	5.08	3.19	700
Share of Firms with HH guarantee (%)	70.97	0.00	100.00	100.00	45.42	868
<b>Panel B: Unsecured</b>						
Age	1.81	0.00	1.00	2.00	2.30	380745
Loan volume ('000)	130.83	12.02	25.55	58.85	790.87	380745
Assets ('000)	626.90	50.07	115.57	296.42	2823.97	380745
Sales ('000)	560.96	52.70	151.20	394.73	1886.70	380745
Employees	3.78	0.33	1.62	4.00	8.34	380745
Tangibility	0.26	0.02	0.15	0.44	0.28	380745
Liquidity	0.22	0.03	0.12	0.34	0.26	380745
Interest Rate Spread (%)	4.65	2.73	4.13	5.73	3.16	10842
Share of Firms with HH guarantee (%)	63.05	0.00	100.00	100.00	48.27	13847
<b>Panel C: Both Secured and Unsecured</b>						
Age	1.64	0.00	1.00	2.00	1.95	25576
Loan volume ('000)	755.55	107.79	210.88	463.94	2049.77	25576
Assets ('000)	1677.55	183.68	389.50	921.14	4816.24	25576
Sales ('000)	826.17	58.10	193.50	552.82	2547.04	25576
Employees	4.92	0.25	2.00	4.94	10.73	25576
Tangibility	0.47	0.17	0.51	0.75	0.32	25576
Liquidity	0.12	0.01	0.05	0.16	0.19	25576
Interest Rate Spread (%)	2.88	1.24	2.31	4.05	2.32	903
Share of Firms with HH guarantee (%)	76.65	100.00	100.00	100.00	42.33	968

*Notes:* This table compares the firm and loan characteristics at the time of their first borrowing, depending on whether they use unsecured debt, secured debt or both. Firm characteristics are measured in the year identified as the extensive margin of borrowing. Except for the last two variables in each panel, the rest of the variables are from the merged CBI and CIR data from 2000–2019 and is restricted to firms incorporated from 2000 onward. The interest rate spread and share of firms with household (HH) guarantees use the merged CBI and *new* CIR data from 2018–2019 and is restricted to firms incorporated from 2018–2019.

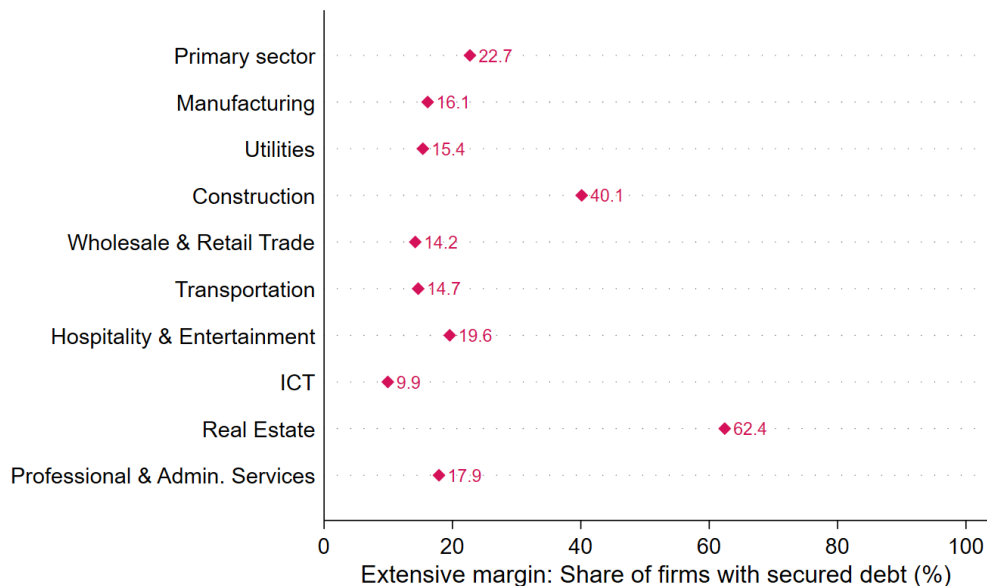
## B.9.2 By Sector

**Figure B.32:** Share of Firms with Unsecured Debt (Extensive Margin of Borrowing) – By Sector



*Notes:* This figure is constructed using the merged CBI and CIR data from 2000–2019. The sectors are aggregated categories from the NACE 1-letter codes, summarized in [Table A2](#).

**Figure B.33:** Share of Firms with Secured Debt (Extensive Margin of Borrowing) – By Sector

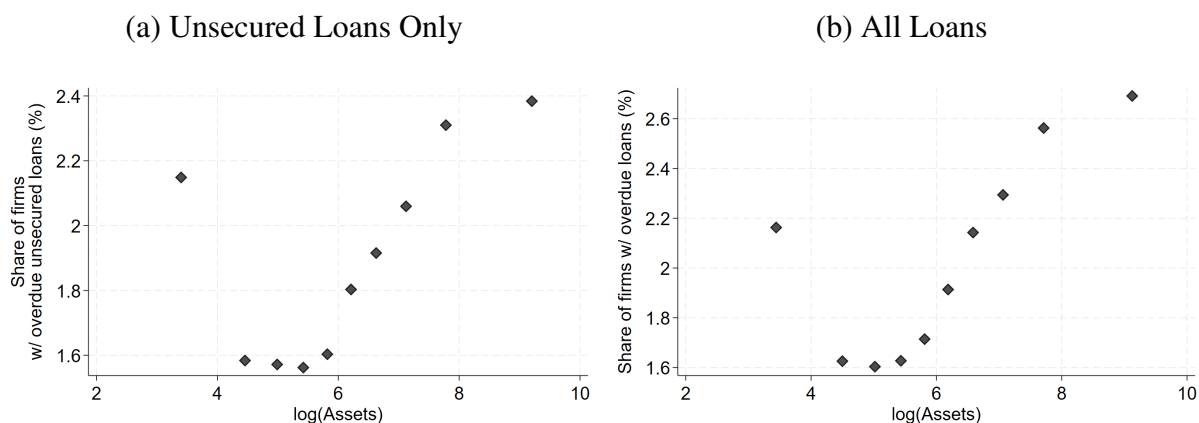


*Notes:* This figure is constructed using the merged CBI and CIR data from 2000–2019. The sectors are aggregated categories from the NACE 1-letter codes, summarized in [Table A2](#).

## B.10 Additional Descriptive Evidence

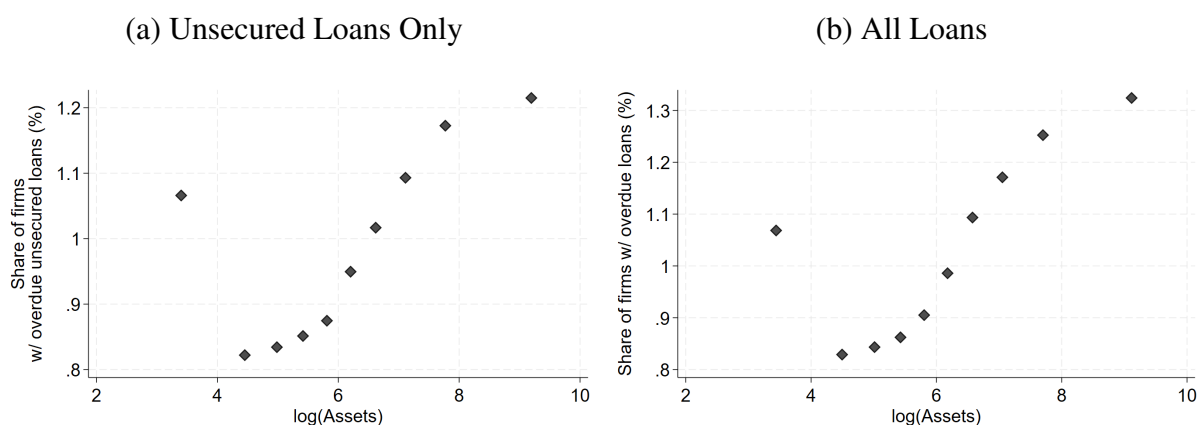
### B.10.1 Loan Delinquencies

**Figure B.34:** Share of Firms with Overdue Loans, All Cases (%)



*Notes:* This figure shows a binscatter plot of the share of firms with (a) overdue unsecured loans; and (b) overdue loans (secured or unsecured), within equal-sized bins of  $\log(\text{Assets})$ , a measure of firm size. The analysis controls for age, sector FE and year FE, and uses the merged CBI and CIR data from 2000 to 2019.

**Figure B.35:** Share of Firms with Overdue Loans, Excluding Recurrent Cases (%)



*Notes:* This figure shows a binscatter plot of the share of firms with (a) overdue unsecured loans; and (b) overdue loans (secured or unsecured); excluding recurrent cases, within equal-sized bins of  $\log(\text{Assets})$ , a measure of firm size. The analysis controls for age, sector FE and year FE, and uses the merged CBI and CIR data from 2000 to 2019.

### B.10.2 Expected Probability of Default

In this section, we elaborate on the methodology used to estimate the expected probability of default, following the approach of [Blanco et al. \(2023\)](#). Unlike their study, which uses monthly data, our dataset consists of year-end observations. Hence, we define a default event as any instance of a loan delinquency (i.e. overdue for at least three months). We follow [Blanco et al. \(2023\)](#) in excluding (1) firm-year observations from the time a firm has filed for bankruptcy; and (2) all observations after the first default event of a firm to avoid biasing our results towards firms with recurrent defaults. It is important to note that, due to differences in sample coverage and variable definitions (i.e. of what constitutes a default event), we estimate our own predictive

model rather than directly applying that of [Blanco et al. \(2023\)](#). [Table B25](#) shows the share of firms defined as having defaulted on their loans.

**Table B25:** Share of Firms with Overdue Loans (%)

	Excluding (1) (w/ recurrent delinquencies)	Excluding (1) & (2) (Default event definition)
0 (no NPLs)	97.73	98.87
1 (w/ NPLs)	2.27	1.13

*Notes:* This table reports the share of firms with loan delinquencies, after applying exclusion restrictions discussed in the text above. This part uses the merged CBI and CIR data from 2000 to 2019.

Prior to estimating the predictive model, we implement a variable selection procedure to identify the most relevant financial indicators. We include the firm-level predictors from [Blanco et al. \(2023\)](#), namely the own funds-to-assets ratio, liquidity ratio, financial expenses-to-sales ratio, net income-to-assets ratio, and sales-to-assets ratio. Additionally, we include leverage, tangibility,  $\log(\text{Assets})$ , EBITDA-to-assets ratio, receivables-to-sales ratio, inventory-to-sales ratio, and the current ratio (current assets-to-current liabilities). [Table B26](#) categorizes these variables to facilitate interpretation.

**Table B26:** Firm-Level Variables by Category for Variable Selection

Category	Variables
Capital Structure	Own funds-to-assets ratio, Leverage, Tangibility
Liquidity	Liquidity ratio, Current ratio, Receivables-to-sales ratio
Profitability	Net income-to-assets ratio, Financial expenses-to-sales ratio, EBITDA-to-assets ratio
Size	$\log(\text{Assets})$
Efficiency	Sales-to-assets ratio, Inventory-to-sales ratio

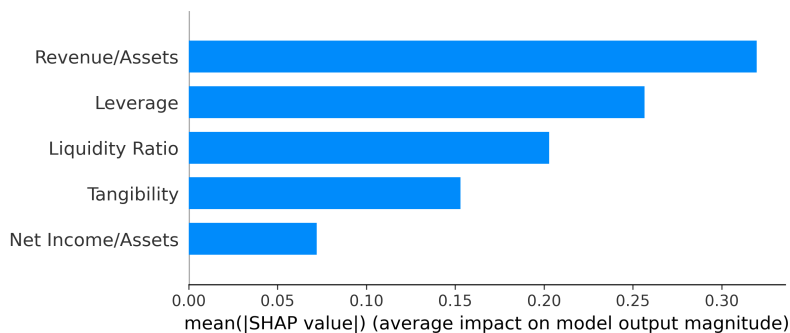
To predict the likelihood that firms have loans become delinquent (that is, to estimate the one-year-ahead probability of default), we adopt a two-step modeling approach. First, we apply a logistic regression model with L1 regularization (Lasso), using lagged predictors to ensure that only information available at the time of prediction is used. All predictor variables are standardized before model fitting to ensure comparability. We employ 5-fold cross-validation to select the optimal tuning parameter, using the area under the ROC curve (AUC) as the performance criterion. The Lasso penalty facilitates variable selection by shrinking the coefficients of less informative predictors to zero, thereby retaining only the most relevant variables.

Based on the Lasso results, we retain the five predictors with the largest absolute coefficients, namely leverage, sales (revenue)-to-assets ratio, liquidity ratio, tangibility and net income-to-assets ratio. To provide some intuition on why these predictors may matter, each reflects a key dimension of a firm's financial health that is relevant to its ability to service debt obligations. Leverage indicates how much of firm value is backed by debt, and a high level increases repayment risk. The revenue-to-assets ratio reflects efficiency and cash flow generation while the

liquidity ratio captures the ability to meet short-term obligations. Tangibility captures a firm’s collateral availability and, to some extent, its financial slack (Benmelech et al., 2024). Finally, net income-to-assets ratio is a measure of profitability.

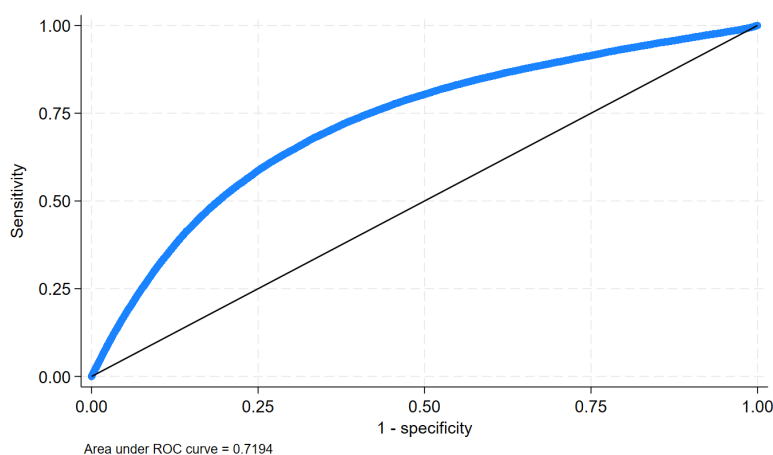
In the second step, we estimate a standard logistic regression model using only these selected variables. Figure B.36 shows the SHAP (SHapley Additive exPlanations) values, which quantify the contribution of each predictor to the model’s output by measuring its marginal impact on individual predictions. SHAP values are used solely for interpretation and do not affect variable selection. Note that while the net income-to-assets ratio has a low SHAP value, we nonetheless include it in our predictive model because it improves the AUC (by 0.01). Figure B.37 shows the AUC of this parsimonious logistic regression model, which is around 0.72, indicating acceptable predictive performance (i.e. can reasonably distinguish between firms with loans that become overdue and those that do not).

**Figure B.36:** SHAP values of top five predictors



*Notes:* This figure shows the SHAP values of the top five predictors selected via LASSO. The analysis uses the merged CBI and CIR data from 2000 to 2019.

**Figure B.37:** ROC curve of the logit model



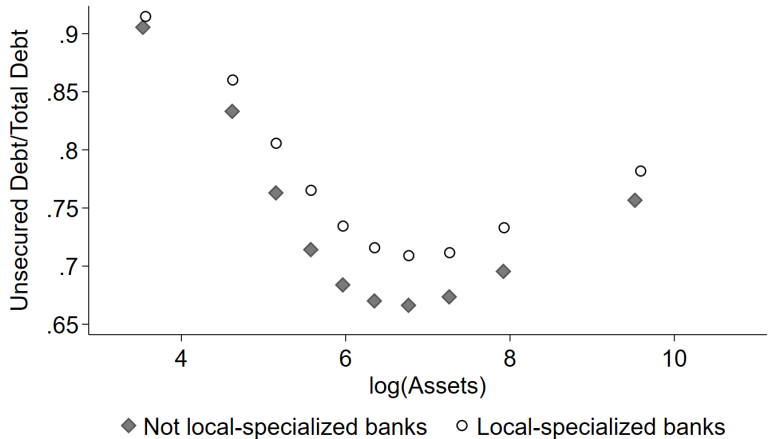
*Notes:* This figure shows the ROC curve for the logit model estimating the expected probability of default, illustrating the trade-off between the true positive rate (sensitivity) against the false positive rate (1 – specificity). The area under the curve (AUC) of 0.7194 indicates a good level of predictive accuracy, showing the model has acceptable discriminating capacity. The analysis uses the merged CBI and CIR data from 2000 to 2019.

Given substantial heterogeneity in the data, we follow Blanco et al. (2023) in estimating the

model separately across different firm groups. Specifically, we divide the sample into groups by size (Eurostat definition) – micro or small/medium/large, and by sector – manufacturing or other sectors. For each group, we verify that the AUC remains at a reasonable level, with values of at least 0.70. We use these size- and sector-specific estimated probabilities of default for the binscatter plot in [Figure 14](#).

**B.10.3 The Role of Bank Lending Specialization**

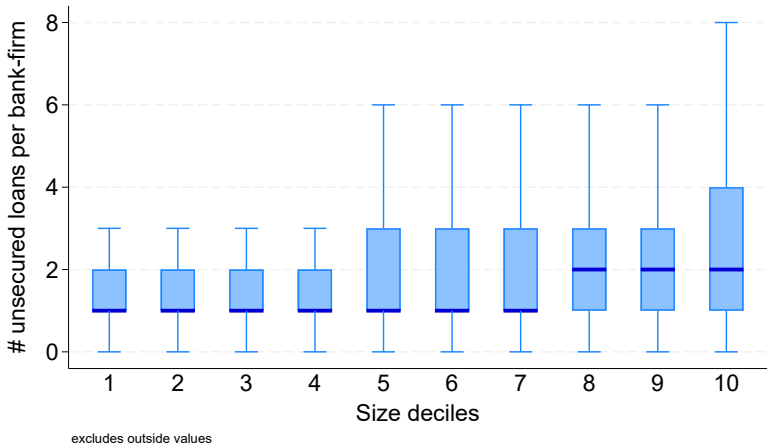
**Figure B.38:** Unsecured Debt Across Firm Size: Local-Specialized vs. Non-Specialized Banks



*Notes:* This figure shows a binscatter plot of the shared of unsecured debt in total debt within equal-sized bins of log(Assets), a measure of firm size. The plot compares unsecured debt of firms borrowing from local-specialized banks versus those borrowing from non-local-specialized banks. The analysis controls for age, sector FE and year FE, and uses the merged CBI and CIR data from 2000 to 2019.

**B.10.4 Other**

**Figure B.39:** Number of Loans That a Bank Extends to a Firm, by Size Decile

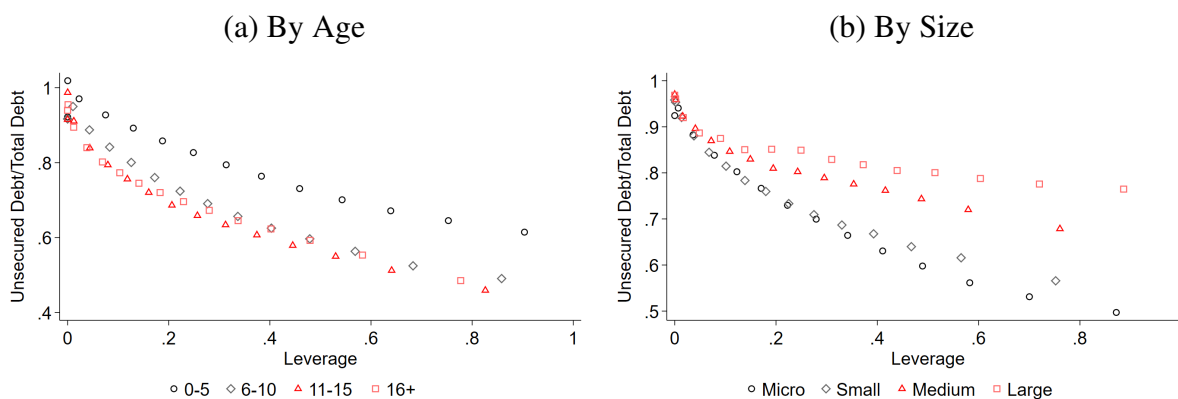


*Notes:* This figure shows a box plot of the number of loans a bank extends to a firm, by size decile. The analysis uses the merged CBI and *new* CIR data from 2018 to 2019.

## B.11 Revisiting Evidence on Debt Composition and Firm Characteristics

**Kermani and Ma (2022)** In this paper, the authors document a pecking order of borrowing, in which the debt composition within a firm portfolio varies with the amount borrowed. They show that firms borrow secured (asset-based) for their initial borrowing, followed by the use of unsecured (cash flow-based) debt with light monitoring (bonds) for medium amount borrowed and unsecured (cash flow-based) debt with heavy monitoring (loans) for high amounts borrowed. This means that secured (asset-based) borrowing is tied to lower leverage whereas unsecured (cash flow-based) borrowing is tied to higher levels of leverage. In our setting, exploring heterogeneity in the cross-section of firms, we instead find that the initial borrowing of firms is unsecured (cash flow-based) debt, not secured (asset-based) debt as they find in their paper (see **Figure B.40**). The difference in result likely stems from the nature of the sample used in the respective analyses – they use Compustat firms and hence publicly-listed firms only, whereas almost the entirety of our sample is composed of private firms.

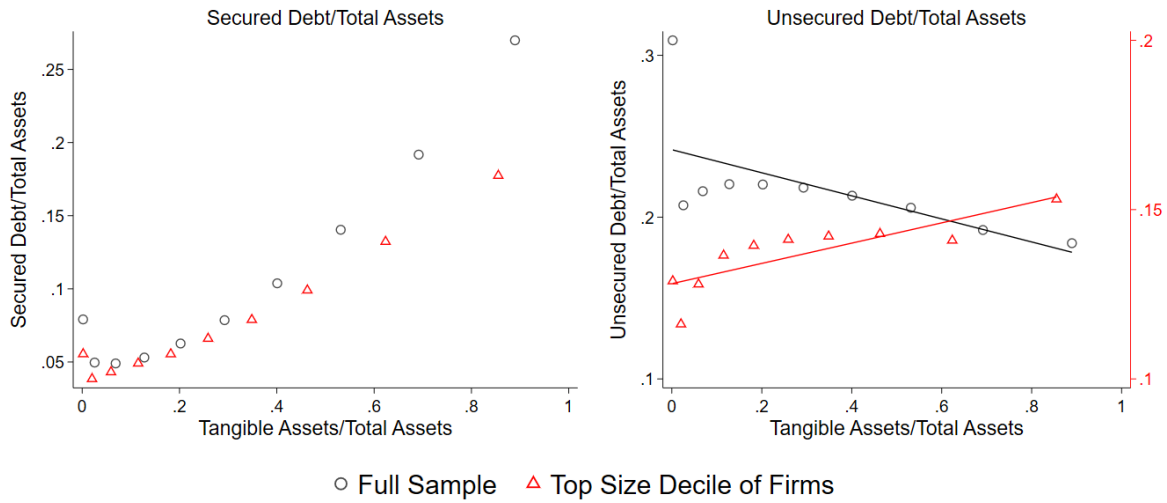
**Figure B.40: Debt Composition and Borrowing Amount**



*Notes:* This figure shows binscatter plots of the share of unsecured debt in total debt within equal-sized bins of leverage, controlling for sector FE and year FE, across firms of different age and size groups, using the merged CBI and CIR data from 2000 to 2019.

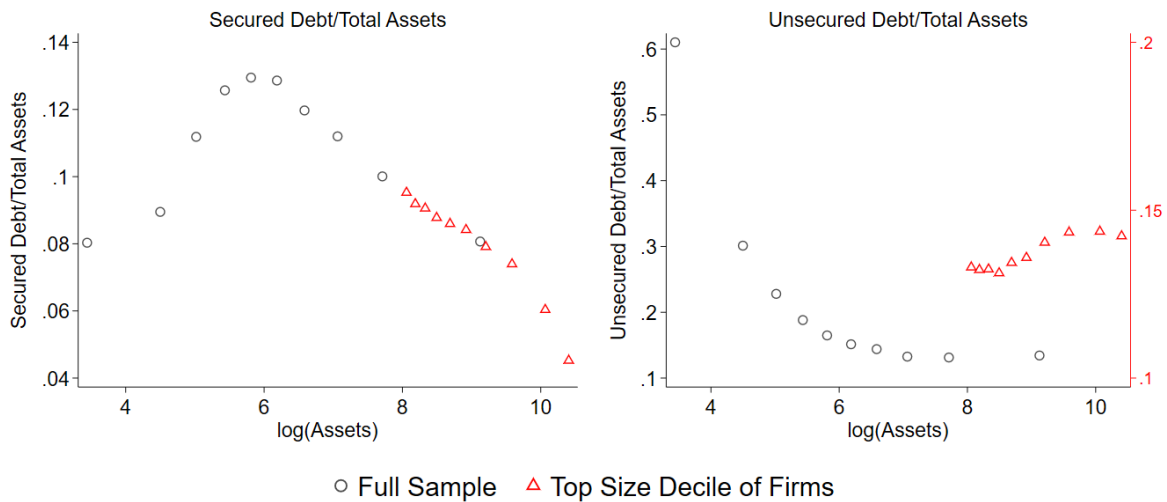
**Rampini and Viswanathan (2025)**. In this paper, the authors suggest that (1) secured debt is explicitly collateralized while unsecured debt is implicitly collateralized, due to the latter being a claim on all *unencumbered* assets of firms; and (2) only the most financially-constrained firms (proxied by firm size as measured by book value of assets) borrow secured. In their setting, tangible assets, being the only type of asset that can be pledged as collateral, serves to restrict both secured and unsecured debt. They provide empirical support by showing a positive correlation between the tangible share in total assets and both secured and unsecured leverage. In addition, they show that unsecured leverage follows a U-shaped pattern along the firm size distribution. In our data, we do not find a robust positive correlation between unsecured leverage and the tangible share in total assets, except among the largest firms (see **Figure B.41**). Furthermore, we find that unsecured leverage decreases with firm size, apart from the largest firms (**Figure B.42**).

**Figure B.41: Secured and Unsecured Debt Leverage Across the Fixed Asset Distribution**



*Notes:* This figure shows binscatter plots of secured leverage (left panel) and unsecured leverage (right panel) across the tangibility distribution, for the full sample and for the top size decile of firms. The analysis controls for age, sector FE and year FE, using the merged CBI and CIR data from 2000 to 2019.

**Figure B.42: Secured and Unsecured Debt Leverage Across the Asset Distribution**



*Notes:* This figure shows binscatter plots of secured leverage (left panel) and unsecured leverage (right panel) across the asset (size) distribution, for the full sample and for the top size decile of firms. The analysis controls for age, sector FE and year FE, using the merged CBI and CIR data from 2000 to 2019.

While we do not find strong empirical support for implicit collateralization of unsecured debt based on this measure (in terms of more tangible capital improving unsecured borrowing capacity), it is still nonetheless a relevant point, in terms of what creditors can recover when a firm defaults on its debts. As [Benmelech et al. \(2025\)](#) note, secured debt not only encumbers assets but may also trigger a collateral rat race among unsecured creditors that will start demanding collateral as well (see [Donaldson et al. \(2020\)](#) for more details). These dynamics can weaken the observable correlation between unsecured debt and asset tangibility.

**Benmelech et al. (2025).** In this paper, the authors highlight the importance of corporate assets in supporting firms' borrowing capacity, presenting a range of empirical exercises to support this argument. A central idea is that assets can support unsecured debt only when they are *unencumbered*, that is, not already pledged as collateral. To illustrate this point, they examine (1) how the correlation between unsecured debt and asset tangibility varies across levels of secured debt usage, and (2) the relationship between unsecured leverage and unpledged tangibility.

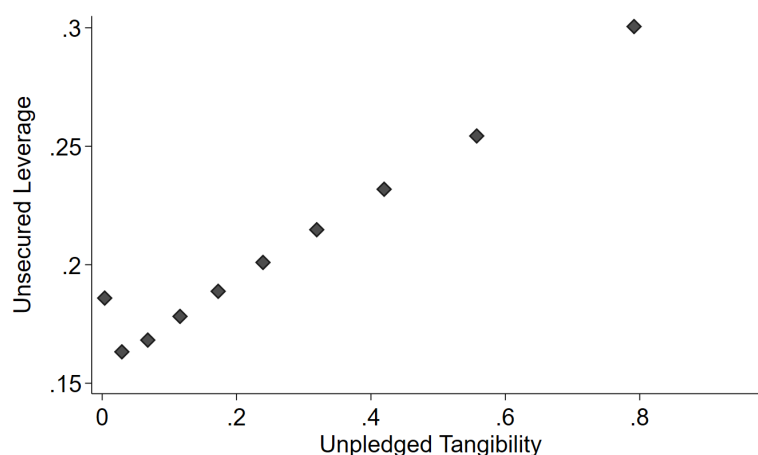
**Table B27** presents the results on the association between unsecured debt and asset tangibility for varying levels of secured debt. In column (1), we find a statistically significant positive correlation between unsecured leverage and tangibility when the level of secured debt is zero. In column (2), we find a smaller, but still statistically significant estimate for firms with positive but below median secured leverage. Finally, in column (3), we find no statistically significant correlation for firms with above median secured leverage. Taken together, these results, which are qualitatively similar to **Benmelech et al. (2025)**, imply that encumbering assets weakens the link between tangibility and unsecured debt.

**Table B27:** Tangibility and Unsecured Leverage for Different Levels of Secured Debt

	(1) Secured Lev. = 0	(2) Secured Lev. >0 & Secured Lev. ≤ p50	(3) Secured Lev. > p50
L.Tangibility	0.039*** (0.002)	0.020*** (0.002)	-0.002 (0.002)
Firm Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	2,363,735	719,549	658,413
R-squared	0.717	0.772	0.652

*Notes:* Standard errors clustered at the firm level in parentheses. \*\*\*p<0.01, \*\*p<0.05, \*p<0.1. Firm controls include log(Assets), log(age), and profitability. This part uses the merged CBI and CIR data from 2000–2019.

**Figure B.43:** Unsecured Leverage and Unpledged Tangibility



*Notes:* This figure shows a binscatter plot of unsecured leverage within equal-sized bins of unpledged tangibility, controlling for log(Assets), log(age), profitability, firm FE and year FE, using the merged CBI and CIR data from 2000 to 2019.