Navigating credit dynamics: Does it matter for firm-level investment? Evidence from AnaCredit*

Serkan Kocabaş[1,3] and Lorena Saiz[2,4]

[1]University Carlos III de Madrid

[2]European Central Bank

[3]skocabas@eco.uc3m.es

[4]lorena.saiz@ecb.europa.eu

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Abstract

This study investigates how credit supply shocks impact firm-level investment across the euro area using the novel AnaCredit database. Employing the methodology developed by Amiti and Weinstein (2018), we decompose loan growth rates into four components: bank-specific, firm-specific, industry-specific, and common shocks. Our findings show that idiosyncratic bank supply shocks significantly affect firm-level investment, particularly among firms that are highly dependent on bank loans. Furthermore, these granular bank-specific shocks explain most of the aggregate loan dynamics. We also find that the effects of bank shocks vary depending on firm characteristics, such as firm size, loan portfolio composition, and reliance on external financing. These results underscore the critical role banks play in shaping investment dynamics, especially under varying economic conditions.

Keywords: AnaCredit, investment, bank credit, credit supply, real effects

JEL Classification: E22, E50, G21, G31

Non-technical summary

This study investigates how changes in bank lending influence firms' investment decisions in the euro area. Using detailed loan information from the AnaCredit database and the methodology proposed by Amiti and Weinstein (2018), we decompose loan growth into four types of shocks: firm-specific, bank-specific, industry-level, and common shocks.

The findings highlight that idiosyncratic bank shocks (i.e., changes unique to individual banks) play a significant role in shaping firms' investment behaviour, particularly for smaller firms that rely heavily on bank loans. Smaller and younger firms are more vulnerable to these shocks because they often lack alternative funding sources, such as bonds or internal cash reserves. In contrast, larger firms with diversified financial resources are less affected. Moreover, firms with a higher reliance on short-term debt are more vulnerable due to the continuous need for refinancing debt. For firms, loans from multiple lenders can amplify the positive effects of bank and firm shocks. Firms in the manufacturing sector and those in Italy and Spain are more vulnerable to bank supply shocks. The effects of bank and firm shocks are highly asymmetric, with negative shocks having a larger negative impact on investment, particularly for bank supply shocks. Intangible investment is relatively unaffected by bank supply shocks because firms must rely on internal financing, given the non-collateralizable nature of these assets.

At the macroeconomic level, the study shows that firm-specific and bank-specific shocks are key drivers of aggregate credit fluctuations, whereas investment decisions at a broader level are more influenced by industry-wide trends and firm-level credit demand shocks. This underscores the interconnectedness of micro-level shocks with macroeconomic outcomes, supporting the "financial accelerator" theory, which states that disruptions in credit markets can amplify economic fluctuations.

1 Introduction

Credit dynamics is generally considered an important driver of business cycle fluctuations. The literature emphasizes the critical role of financial frictions, particularly credit constraints. These constraints play a pivotal role in amplifying economic shocks and influencing monetary policy transmission. Seminal works by Bernanke et al. (1999) and Holmstrom and Tirole (1997) highlight how developments in credit markets can amplify and propagate shocks to the real economy. This is the so-called ”financial accelerator”.

Distinguishing between credit supply and demand shocks remains a significant challenge. The difficulty arises, in part, due to the endogenous connection between firm performance and changes in outstanding credit. More specifically, banks are more likely to reduce credit supply during periods when firms' demand for credit is also likely to decline, such as during economic crises. Furthermore, the matching between firms and banks is often not random. For instance, weakly performing firms may preferentially seek loans from banks that are less stringent in their screening processes than others. In addition, credit supply shocks can stem from various factors, including unexpected changes in credit standards at individual banks, systemic events such as financial crises, and policy shifts such as changes in the monetary policy stance.

Empirical studies have used instrumental variables or information from bank surveys to identify bank supply shocks. Over time, as matched bank-firm loans from credit registries became available, several econometric approaches were proposed. Khwaja and Mian (2008) (KM) identified bank credit supply shocks comparing loan growth across banks for the same firm. Firm-time fixed effects absorb all firm-specific demand shocks and riskiness, while bank-time fixed effects can be interpreted as credit supply shocks (i.e., willingness or ability of banks to lend). The key requirement for identification is that firms must borrow from at least two banks so that demand is constant across lenders, and differences capture supply. KM examined the impact of liquidity shocks by exploiting the cross-bank liquidity variation induced by unanticipated nuclear tests in Pakistan. They showed that banks pass their liquidity shocks on to the firms. Amiti and Weinstein (2018) (AW) extended and generalized the KM approach. In addition to identifying supply shocks, as in KM, this methodology builds a statistical bridge between micro-identification (i.e., granular shocks) and macro-aggregates. Using a variance decomposition framework, they showed how much those supply shocks matter for the aggregate economy. AW found that bank-level supply shocks explain between 30-40% of aggregate loan and investment fluctuations in Japan. They also showed that the results hold outside crises, not just in liquidity shock events. The identification uses within-firm, across-bank variation, and therefore needs multi-bank firms (i.e., firms borrow from multiple banks), and typically single-bank firms are excluded.

Degryse et al. (2019) extended the AW methodology to contexts with fewer multi-bank firms by using firm grouping. Instead of relying only on multi-bank variation, firms are grouped by industry, location, size and time (ILST). These firm-group ILST fixed effects absorb the demand variation. Therefore, this methodology can handle environments where most firms borrow from a single bank (e.g., developing countries). However, one limitation of this methodology is the strong assumption that firms in the same ILST cell share identical demand shocks.

Essentially, KM and AW compare banks within one firm to identify credit supply shocks, while Degryse et al. (2019) compare banks across similar firms. These methodologies have subsequently been implemented in various empirical contexts. Volk (2023) applied KM approach to Slovenian firm-bank loans and showed that the results were similar when using ILST (Degryse et al. (2019)) instead. Amador and Nagengast (2016) applied AW methodology to Portuguese firm-bank loans and argued that the AW decomposition can also be used in the presence of small firms with a single banking relationship as long as they account for only a small share of the total loan volume of their banks. Rivadeneira et al. (2024) examined how bank credit supply shocks estimated using ILST approach affected employment, wages and survival of firms in Mexico during the COVID-19 pandemic.

Regarding the real effects of credit supply shocks, previous research has focused on the global financial crisis, concluding that such shocks are more critical in times of tighter liquidity constraints and heightened uncertainty, such as during recessions. Specifically, credit supply contractions can negatively impact the real economy, particularly when borrowers lack access to alternative funding sources. Moreover, negative credit supply shocks can propagate through the economy via supply linkages or downstream effects (Alfaro et al. (2021)). Credit supply contractions are generally associated with declines in firm investment and employment, although the impact on employment tends to be more moderate because firms typically reduce investment before cutting employment. While the adverse effects of credit supply contractions are well documented, the effects of credit supply expansions remain less conclusive (see Güler et al. (2021) for a review). Some studies suggest that loose credit conditions can promote investment and growth, while others caution against possible misallocation of resources during periods of excessive credit availability.

Existing research has highlighted the significant heterogeneity in the effects of credit supply shocks across firms and countries. Firm-specific factors such as size, sector, age, and reliance on bank loans play a crucial role in determining their sensitivity to bank shocks. However, less attention has been paid to how the impact of idiosyncratic bank supply shocks varies across countries depending on the degree of bank concentration, number of borrowing/lending relationships, and firm-specific characteristics. This study reexamines these dynamics using the novel AnaCredit database, which provides detailed, matched bank-firm loan data across the euro area.

The primary contribution of this study lies in applying the Amiti and Weinstein (2018) (AW) methodology to the AnaCredit dataset to investigate the impact of bank supply shocks on both firm-level and aggregate investment in the euro area. This approach enables the identification of credit supply shocks without the need for instrumental variables, providing a comprehensive decomposition of loan growth rates into bank-specific, firm-specific, industry-specific, and common shocks.[1] This decomposition offers valuable insights into how granular bank-supply shocks propagate and contribute to changes in aggregate lending.

This work examines the effects of credit shocks on firm investment in the euro area, focusing on the four largest euro area economies over the period 2019-2023. It addresses three key research questions: (i) To what extent are credit supply shocks the drivers of both granular and aggregate investment in the euro area economy? (ii) Are the effects of credit supply shocks heterogeneous across firms of different types? (iii) Did the COVID-19 pandemic alter the impact of credit supply shocks on investment?

The remainder of this paper is organized as follows. Section 2 outlines the methodology for disentangling credit supply and demand shocks. Section 3 offers an overview of the dataset and assesses the external validity of the identified bank supply and demand shocks. Section 4 presents the main results, analyzing the impact of these shocks on firm-level investment in both tangible and intangible assets, while exploring the role of loan maturity, the number of lending relationships, and potential asymmetric effects. Section 5 investigates heterogeneous impacts, including the effects of the COVID-19 pandemic, and evaluates how bank shocks influence aggregate investments. Section 6 provides some robustness checks, and Section 7 concludes.

[1] Some studies, such as Ivashina et al. (2022), have shown that credit dynamics vary across loan types (e.g., cash flow loans versus asset-based loans). However, this aspect is beyond the scope of our work.

2 Methodology

Estimation of credit supply and demand shocks. AW developed a method to distinguish between borrowing shocks specific to firms and supply shocks unique to banks for publicly traded companies in Japan. They presented the following model to break down credit growth from credit institution b to firm f:

$$\frac{L_{fbt} - L_{fbt-1}}{L_{fbt-1}} = \alpha_{ft} + \beta_{bt} + \epsilon_{fbt} \tag{1}$$

In this context, α_{ft} denotes the firm-borrowing channel, encompassing all firm-specific elements that impact borrowing, such as productivity shocks at the firm level, shifts in investment opportunities, the availability of alternative financing sources, or variations in creditworthiness. Meanwhile, β_{bt} captures the bank lending channel, which includes all bank-specific factors that affect a bank's lending practices over time. The term ϵ_{fbt} represents the error component.

In principle, α_{ft} and β_{bt} can be determined by utilizing an extensive array of time-varying fixed effects for both banks and firms. However, this strategy is inefficient and biased because it fails to consider the equilibrium interactions that influence the outcomes in the loan market. For instance, banks can only extend more loans if there is demand from firms, and firms can only seek additional loans if at least one bank is willing to provide them. Overlooking these constraints can lead to bank lending estimates that significantly deviate from actual loan growth rates.

AW introduced the idea of employing a series of adding-up constraints to capture the equilibrium relationships between banks and firms within the loan market. On the lender's side, by taking Equation (1) and multiplying both sides by the lagged proportion of loans to firm f, denoted as $\phi_{fb,t-1}$, and then summing across all firms, the bank's loan growth can be depicted as its credit supply shock for that period, combined with the weighted average of the credit demand shocks from all its clients:

$$D_{bt}^{B} \equiv \sum_{f} \left(\frac{L_{fbt} - L_{f,bt-1}}{L_{fb,t-1}} \right) \frac{L_{fb,t-1}}{\sum_f L_{fb,t-1}} = \beta_{bt} + \sum_{f} \phi_{fb,t-1} \alpha_{ft} + \sum_{f} \phi_{fb,t-1} \epsilon_{fbt} \tag{2}$$

where $\phi_{fb,t-1} \equiv \frac{L_{fb,t-1}}{\sum_f L_{fb,t-1}}$, and D_{bt}^{B} represents the rate at which bank b increases its lending to all its customers.

Similarly, on the borrower's side, by multiplying both sides of equation (1) by the previous period's proportion of borrowing from bank b, $\theta_{fb,t-1}$, and summing over all banks, the firm's loan growth can be described as its credit demand shock plus the weighted average of the credit supply shocks from all its lenders,

$$D^F_{ft} \equiv \sum_b \left(\frac{L_{fbt} - L_{f,bt-1}}{L_{fb,t-1}} \right) \frac{L_{fb,t-1}}{\sum_b L_{fb,t-1}} = \alpha_{ft} + \sum_b \theta_{fb,t-1}\beta_{bt} + \sum_b \theta_{fb,t-1}\epsilon_{fbt} \tag{3}$$

where $\theta_{fb,t-1} \equiv \frac{L_{fb,t-1}}{\sum_b L_{fb,t-1}}$, and D^F_{ft} equals the growth rate of borrowing by firm f from all its banks.

It is important to recognize that both $\phi_{fb,t-1}$ and $\theta_{fb,t-1}$ are predetermined variables, which enables us to apply the following moment conditions to the data:

$$E\left[\sum_f \phi_{fb,t-1}\epsilon_{fbt}\right] = \sum_f \phi_{fb,t-1} E[\epsilon_{fbt}] = 0; \tag{4}$$

and

$$E\left[\sum_b \theta_{fb,t-1}\epsilon_{fbt}\right] = \sum_b \theta_{fb,t-1} E[\epsilon_{fbt}] = 0; \tag{5}$$

This results in the following interconnected equations that the parameters α_{fbt} and β_{fbt} must satisfy:

$$D^B_{bt} = \beta_{bt} + \sum_f \phi_{fb,t-1}\alpha_{ft} \tag{6}$$

and

$$D^F_{ft} = \alpha_{ft} + \sum_b \theta_{fb,t-1}\beta_{bt} \tag{7}$$

For each year, Equations (6) and (7) establish a system consisting of $F + B$ linear equations and $F + B$ unknowns, which initially implies a unique solution to the problem. Nevertheless, because the loan shares sum to one, the system becomes under-determined, leading to an infinite number of solutions. By introducing an additional constraint, standard techniques for solving linear equations can be employed to derive a solution.[2]

To obtain parameters that are economically meaningful, we adopt AW's method by expressing

[2] AW express all equations related to the loan growth rates of firms relative to firm number one and all equations related to the loan growth rates of banks relative to bank number one.

α_{ft} and β_{bt} in terms of their respective medians for each year. Consequently, the overall lending of each bank can be divided into four components:

$$D_t^B = (\overline{A}_t + \overline{B}_t)1_B + \Phi_{t-1}N_t + \Phi_{t-1}\tilde{A}_t + \tilde{B}_t \tag{8}$$

The initial term, referred to as "common shocks," represents changes in lending that are uniform across all lending pairs, such as fluctuations in interest rates. This is estimated as the median of firm and bank shocks for a given year t. The subsequent term, referred to as the "industry shock," is a bank-specific weighted average of industry-level shocks affecting the bank's clients. Each industry shock is defined as the median firm-level shock within the industry and is then aggregated across industries using loan exposures as weights.

The third component is the "firm borrowing shock," which reflects variations in a bank's lending due to unique changes in the borrowing needs of clients that are unrelated to shifts in the bank's loan supply. This is calculated as the firm shock in year t minus the median firm shock within the industry for the same year. The fourth component is the "bank shock," which assesses alterations in a bank's loan supply that are independent of influences from firms, industries, or widespread economic shocks. It is determined by subtracting the median bank shock in year t from the bank shock in that year.

3 The Data

3.1 AnaCredit

AnaCredit, the Eurosystem's "Analytical Credit Database," is a comprehensive dataset that contains detailed and standardized information on individual bank loans across all euro area member states. For this study, we use monthly bank-firm loan data from AnaCredit, spanning September 2018 to December 2023 for the four largest euro area countries (i.e., Germany, France, Italy, and Spain). The dataset includes loans exceeding €25,000, granted to non-financial corporations in the euro area. We exclude loans to firms operating in financial and insurance activities (NACE section K), activities of households as employers (NACE section T), and activities of extraterritorial organizations and bodies (NACE section U).

AnaCredit provides extensive information on loan purpose, loan type, interest rate type, collateralization or loan protection, maturity, interest rate spreads for floating-rate loans, firm size and sector, renegotiation status, default status, and non-performing status. The number of debtor-creditor pairs varies between 6 and 17 million annually and differs across countries. We further enriched the dataset by merging it with the ORBIS database to obtain firm-level financial information, such as tangible and intangible investments, firm size, age, total assets, sales growth, cash flow, leverage ratio, liquidity ratio, and other relevant variables.

As a benchmark, we compare the volume of data extracted and cleaned from AnaCredit with the Balance Sheet Item (BSI) Statistics, which has a broader coverage. The total outstanding amount of loans captured by AnaCredit alone accounts for approximately 70% of the BSI total, on average, as shown in Figures 9 and 10 in the Appendix. This coverage varies by country, with the highest in Italy (80.5% of BSI) and the lowest in France (50.3% of BSI).

Our matched bank-firm loan dataset from AnaCredit differs significantly from that used by Amiti and Weinstein (AW), who focused exclusively on firms listed on the Japanese stock market. In our dataset, the distribution of borrowing relationships per firm is strongly right-skewed (Figures 3 and 4, left panels, in the Appendix). Approximately 85% of firms in France borrow from only one bank, compared to 70% in Germany and 60% in Spain and Italy. In contrast, this ratio in AW was as low as 2%. This skewness arises due to the prevalence of small and medium-sized enterprises (SMEs), whose borrowing requirements typically do not justify the cost of maintaining multiple banking relationships.

The high proportion of firms with a single banking relationship poses a challenge for estimating bank shocks, which rely mainly on the variation in loan growth rates across banks and firms. However, the total loan volume is less concentrated among these single-relationship firms (Figures 3 and 4, right panels in the Appendix). This characteristic enables us to directly apply the decomposition framework proposed by AW, as shown in Amador and Nagengast (2016).[3]

In our sample, the distribution of firms per bank reveals that many banks lend to a relatively small number of firms (Figures 5 and 6, left panels in the Appendix). More than half of the banks have lending relationships with fewer than 500 firms—specifically, 77% in Germany, 68% in Spain, and 52% in France, while in Italy, this figure is approximately 33%. However, these banks represent a relatively small share of total lending volumes: approximately 28% in Germany, 11% in France, 8% in Spain, and 6% in Italy (Figures 5 and 6, right panels, in the Appendix).

The concentration of the banking sector significantly influences the macroeconomic impact of bank-specific shocks. When a few banks dominate the market, their idiosyncratic shocks can substantially affect aggregate lending and investment rates rather than averaging out. Throughout the sample period, the market share of the largest institutions remained substantial: approximately 41% for the 24 largest banks in Germany, 46% for the 36 largest banks in France, 69% for the 23 largest banks in Italy, and 81% for the 18 largest banks in Spain (Figures 7 and 8 in the Appendix).

3.2 ORBIS

To examine the effects of shocks identified using the methodology of Amiti and Weinstein (2018), we utilize granular annual financial data for non-financial corporations in Germany, France, Italy, and Spain from the ORBIS database (Bureau Van Dijk). This comprehensive dataset includes balance sheet and income statement details across nearly all corporate sectors, covering almost 900,000 firms (approximately two million observations) after data are cleaned. A key advantage is the inclusion of both listed and unlisted companies, particularly smaller firms, thereby providing greater statistical power than studies that exclusively use large, listed firms (e.g., U.S. studies relying on Compustat).

We exclude firms in the financial sector, agriculture, mining, and those with significant

[3] We use standard growth rates rather than the mid-point growth definition employed by Barbieri et al. (2022). Although mid-point growth rates are more robust to outliers and to firm entry and exit, their use modifies the distribution of firm- and bank-level credit shocks. Furthermore, because we are also interested in aggregate shocks, standard growth rates provide a more natural choice, as they ensure that micro-level shocks aggregate consistently to the macro level. This consideration was also a key reason why we opted to use the AW methodology to identify credit supply and demand shocks.

government ownership. The remaining sectors comprise manufacturing (NACE section C), construction (F), wholesale and retail trade (G), transportation and storage (H), accommodation and food services (I), information, communication and R&D (J, M), and other business activities (M, N). Following Kalemli-Özcan et al. (2015), we clean the data by removing firm-year observations with invalid values, such as negative or zero total assets, negative employment, employment exceeding two million, negative sales, negative or missing fixed assets, and inconsistencies in the balance sheet.

Our primary measure of investment is the tangible investment ratio, which is defined as net investment in tangible assets divided by the previous year's net capital stock. To mitigate the influence of outliers, all ratios derived from balance sheet variables are winsorized by country at the top and bottom two percent, consistent with Kalemli-Özcan et al. (2018). As firms report their financial accounts in different months, we align the shock series with each firm's reporting date by merging the shock and ORBIS datasets based on each firm's reporting month. This approach effectively captures the temporal variations in shock exposure. The extensive coverage of small and medium-sized enterprises (SMEs) in the dataset is especially valuable for analyzing the underlying mechanisms.

3.3 Descriptive analysis

Figures 1 and 2 show the decomposition of total credit growth in the four largest euro area economies into aggregated idiosyncratic firm credit demand and bank credit supply shocks, industry-specific demand shocks, and common shocks, as derived using the AW approach. Negative common shocks played a significant role during this period, suggesting that credit flows were subdued for most firms and banks in the study sample.

As discussed in Barbieri et al. (2022), aggregated idiosyncratic bank credit supply and firm credit demand shocks provide valuable insights into the behavior of the tails of the bank and firm credit shock distributions.

Across all countries, the firm credit demand component remained positive for most of the period, indicating credit expansion within a subset of firms.

In Italy, Spain, and France, positive bank credit supply shocks were more prevalent during the early part of the sample period. However, following the monetary policy tightening at the end of 2022, negative bank credit supply shocks became increasingly apparent. Although this pattern was less pronounced in Germany, bank credit supply shocks played a significant role in

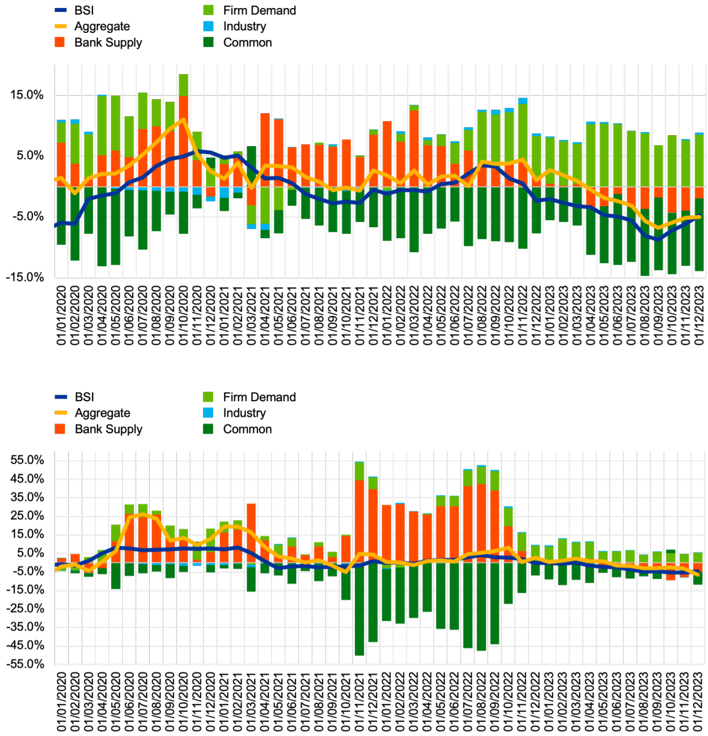

Figure 1: Annual growth (percentages) - Italy and Spain

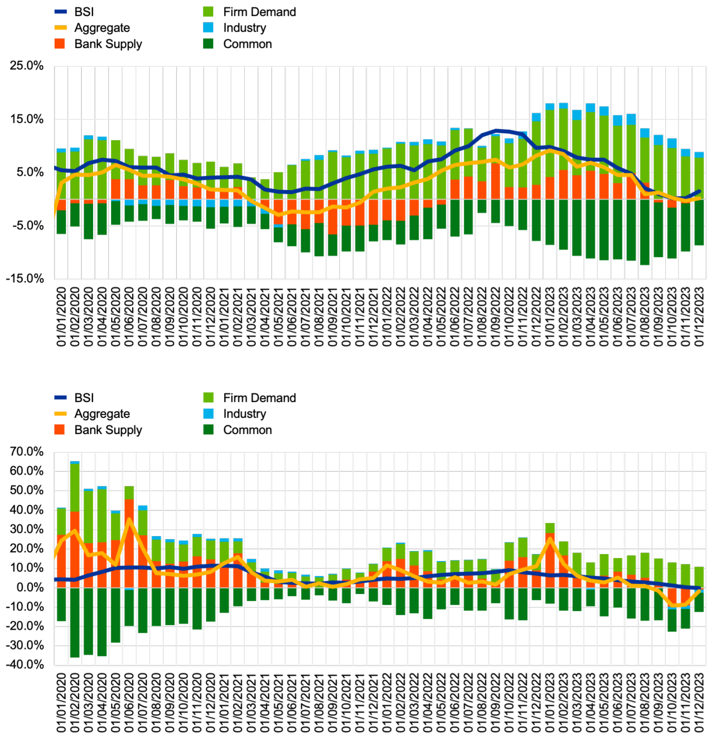

Figure 2: Annual growth (percentages) - Germany and France

moderating total credit growth during the monetary policy tightening period.

Table 1 presents descriptive statistics for our identified shocks after matching them with firm-level data. As firms' closing dates vary across countries, the average values of the identified shocks also differ across countries. In the pooled dataset covering all countries, the average bank supply shock is 4.38 basis points, with a standard deviation of 33.63, while the average firm demand shock is 29.44 basis points, with a standard deviation of 112.10. The average industry shock amounts to 2.04 basis points, with a standard deviation of 6.39. Finally, the average common shock is -9.27 basis points, with a standard deviation of 11.24.

Table 1: Descriptive statistics of the shocks (basis points)

	DE	ES	FR	IT	Pooled
Bank supply shocks					
mean	-5.49	12.90	1.43	3.02	4.38
sd	28.59	35.56	44.41	24.77	33.63
Firm demand shock					
mean	32.63	24.59	40.92	26.15	29.44
sd	119.76	105.69	135.31	99.62	112.10
Industry shock					
mean	0.40	1.23	7.02	0.80	2.04
sd	4.90	3.53	11.70	2.21	6.39
Common shock					
mean	-4.64	-14.92	-11.39	-5.49	-9.27
sd	1.45	17.87	6.03	4.12	11.24

Table 2 presents the summary statistics for our main variables of interest. The average net tangible investment is 18.44 percent with a standard deviation of 97.42. The average firm age is 20 years, with a standard deviation of 16. As typically observed in firm-level datasets, there is considerable variation, highlighting firms' heterogeneous nature. The average figures for investment, firm size, leverage ratio, and age appear to differ across countries.

Table 2: Descriptive statistics of the firm level dataset from ORBIS

	DE	ES	FR	IT	Pooled
			Net investment in tangibles (percent)		
mean	11.06	12.73	18.85	25.52	18.44
sd	68.27	79.56	103.48	115.02	97.42
min	-72.67	-90.75	-92.08	-73.61	-92.08
max	507.63	498.86	693.57	719.67	719.67
			Total assets (log euros)		
mean	15.75	13.55	14.00	13.99	14.12
sd	3.76	1.41	1.25	1.44	2.05
min	9.91	9.30	9.51	9.81	9.30
max	24.57	16.76	16.80	17.16	24.57
			Age (years)		
mean	29	18	19	20	20
sd	27	11	15	14	16
min	1	1	1	1	1
max	776	152	123	159	776
			Financial leverage (percent)		
mean	31.26	36.88	23.71	15.00	25.19
sd	29.12	25.41	18.35	16.68	23.61
min	0.00	0.00	0.00	0.00	0.00
max	144.15	134.87	77.13	58.97	144.15
Obs.	291,336	579,003	277,337	755,900	1,903,576

3.4 External validity

In this section, we evaluate the external validity of bank supply and firm demand shocks identified through the decomposition of loan growth rates using the AW methodology. Specifically, the objective is to determine whether the estimated shocks are significantly correlated with the proxy variables previously used in the literature.

Starting with bank credit supply shocks, we explore their relationship with changes in banks' Tier 1 capital, since banks with substantial capital increases are likely to experience more favorable bank shocks, as capital injections enhance lending capacity (Shimizutani and Montgomery (2009)). Furthermore, AW used the decline in banks' market-to-book values as a sign of reduced bank lending. Since only a few banks in the AnaCredit dataset are publicly traded, we focus on analyzing banks' return on assets (ROA) and return on equity (ROE) instead of market-to-book value fluctuations. We anticipate that banks showing poor performance in these two metrics will face more adverse bank shocks, as reduced profitability often forces banks to limit lending (Peek and Rosengren (1997), Peek and Rosengren (2000), Amiti and Weinstein (2018)).

We divide our sample into four quartiles for each variable, identifying low-performing banks as those in the lowest quartile of $ROA_{b,t}$ and $ROE_{b,t}$ and banks with substantial capital increases as those in the top quartile of the Tier 1 capital growth rate. Subsequently, we regress the identified bank supply shock on each indicator separately, incorporating country $\times$ year fixed effects. The primary explanatory variables for each regression are dummy indicators set to one if a bank falls into the lowest quartile of $ROA_{b,t}$ or $ROE_{b,t}$ or the top quartile of the Tier 1 capital growth rate. The standard errors are clustered at the bank level.

As shown in Table 3, the estimated bank supply shocks align with the anticipated relationship across all three proxies. On average, banks in the lowest ROA quartile experience supply shocks that are 8.5 pp lower than those of other banks. Similarly, those in the lowest ROE quartile show supply shocks that are 8.1 pp lower, confirming that financially distressed institutions tend to contract credit. In contrast, banks undergoing significant capital increases exhibit supply shocks that are 8.9 pp higher than their peers, supporting the notion that recapitalizations help alleviate credit constraints. These findings are consistent with the mechanisms highlighted in the banking literature (e.g., Khwaja and Mian (2008), Amiti and Weinstein (2018)).

Table 3: External Validity - Bank Supply - Full Sample

Dependent Variable: *Bank Shocks*$_{b,t}$	(1)	(2)	(3)
Low Return on Asset$_{b,t}$	-0.0850***		
	(0.0229)		
Low Return on Equity$_{b,t}$		-0.0809***	
		(0.0235)	
Large Capital Increase$_{b,t}$			0.0892**
			(0.0358)
R^2	0.155	0.155	0.155
Observations	3,276	3,276	3,276

Standard errors, reported in parentheses, are clustered at the bank level.

All regressions include country × year fixed effects.

We winsorize each variable at the country level by replacing the top and bottom 2 percent of the distribution.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

We employ a similar quartile-splitting method for firm-level characteristics to validate firm credit demand shocks. Specifically, we categorize younger firms as those in the lowest quartile of firm age and highly indebted firms as those in the highest quartile of the leverage ratio. These firms are expected to show stronger loan demand driven by growth needs or refinancing pressures (Hubbard et al. (2002); Khwaja and Mian (2008)). Conversely, more profitable firms are identified as those in the highest quartile of profitability, and high liquidity firms are identified as those in the highest quartile of liquidity, with these firms likely requiring less external finance (Chodorow-Reich (2014)). We then regress the identified firm demand shock on each indicator separately, incorporating country × sector × year fixed effects and clustering standard errors at the firm level.

As illustrated in Table 4, younger firms experience demand shocks that are 7.6 pp higher than those of other firms, aligning with their increased dependence on external financing. Firms with high levels of debt exhibit demand shocks that are 7.5 pp higher, indicating the need for rollovers or precautionary borrowing. Conversely, firms with substantial liquidity face demand shocks that are 1.97 pp lower, consistent with their reduced dependence on credit. More profitable firms show a 7.6 pp decrease in demand, suggesting that internal funds serve as a substitute for external borrowing. These findings support standard financing hierarchy theories and underscore that demand shocks derived from the AW decomposition capture significant variations in credit demand across different types of firms.

Overall, these tests confirm the external validity of our shock measurement. Bank supply shocks effectively capture the financial health specific to each institution, whereas firm demand shocks reflect the diversity in borrowing needs, both of which align with established economic mechanisms.

Table 4: External Validity - Firm Demand - Full Sample

Dependent Variable: $Firm\ Shocks_{f,t}$	(1)	(2)	(3)	(4)
$Younger\ Firms_{f,t}$	0.0757***			
	(0.00176)			
$More\ Profitable\ Firms_{f,t}$		-0.0760***		
		(0.00191)		
$High\ Debted\ Firms_{f,t}$			0.0750***	
			(0.00184)	
$High\ Liquidity\ Firms_{f,t}$				-0.0197***
				(0.00186)
R^2	0.016	0.016	0.016	0.016
Observations	2,105,525	2,105,525	2,105,525	2,105,525

Standard errors, reported in parentheses, are clustered at the firm level.

All regressions include country × sector × year fixed effects.

We winsorize each variable at the country level by replacing the top and bottom 2 percent of the distribution.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4 Results

4.1 Bank supply shocks, firm demand shocks and firm-level characteristics

By decomposing loan growth rates, we can create a time-varying measure of *firm-specific bank supply shocks.* This is achieved by weighting the bank-level shocks according to each bank's share in a firm's loan portfolio:

$$\text{Bank Shock}_{f,t} = \sum_{b} \theta_{fb,t-1}\, \tilde{\beta}_{b,t} \tag{9}$$

In this section, we explore whether firm credit demand shocks and firm-specific bank supply shocks systematically differ among firms with varying characteristics. We concentrate on two aspects of the loan portfolio: (i) the proportion of loans with short-term maturities (less than one year) and (ii) profitability ratios. In addition, we consider two measures of firm size: (i) the number of employees and (ii) total sales of the firm. To evaluate how shocks vary across firms, we calculate the time-averaged values of both shocks and firm characteristics over the sample period and conduct a series of simple linear regressions. Our aim is not to establish causality but to determine whether firms with specific characteristics tend to experience systematically larger or smaller shocks than the average firm.

Table 5 presents the co-variation between bank shocks, loan portfolio characteristics and firm size. The analysis of firm-specific bank supply shocks shows systematic patterns across various firm types. Firms that depend more heavily on short-term loans encounter more pronounced negative shocks, indicating greater vulnerability to credit supply contractions when loan rollover risk is high (Diamond (1991)). Larger firms, measured by either employee count or total sales, also experience significantly smaller negative shocks, probably because of their greater bargaining power and access to alternative financing (Khwaja and Mian (2008)). Higher profitability further mitigates the severity of shocks, consistent with theories that internal funds can buffer against external financing friction (Almeida et al. (2004)). The multivariate specification (column 5) confirms that these relationships remain robust after controlling for interdependencies among characteristics (i.e., the sign of the regression coefficients does not change), although the estimated effect sizes are slightly reduced.

Table 5: Firm-specific Bank Shocks and Firm-level Characteristics

Dependent variable: $Mean\ Bank\ Shock_f$	(1)	(2)	(3)	(4)	(5)
$Mean\ share\ of\ short\ term\ Loans_f$	-0.039***				-0.086***
	(0.001)				(0.001)
$Mean\ profitability\ ratio_f$		-0.082***			-0.028***
		(0.003)			(0.004)
$Mean\ log\ of\ employees_f$			-0.028***		-0.009***
			(0.000)		(0.000)
$Mean\ log\ of\ sales_f$				-0.018***	-0.010***
				(0.000)	(0.000)
R^2	0.002	0.001	0.023	0.020	0.037
N	715,497	634,652	654,399	669,797	421,058

Robust standard errors reported in parantheses.

We winsorize each variable at the country level by replacing the top and bottom 2 percent of the distribution.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6 presents the results of the same analysis for the firm borrowing channel. A higher share of short-term loans is positively associated with demand shocks, suggesting that firms with temporal financing needs may encounter more volatile demand cycles. Larger firms, whether measured by the number of employees or sales, experience significantly stronger positive demand shocks, consistent with the advantages of economies of scale in terms of market access.

In contrast, higher profitability is associated with more negative demand shocks, potentially reflecting profit-driven competitive pressures or mean-reversion dynamics (Fama and French (2000)). In the multivariate specification (column 5), these associations persist after accounting for interdependencies among the characteristics (i.e., the sign of the regression coefficients does not change), although the magnitudes are somewhat smaller.

Table 6: Firm Shocks and Firm-level Characteristics

Dependent variable: *Mean Firm Shock$_f$*	(1)	(2)	(3)	(4)	(5)
Mean share of short term Loans$_f$	0.116***				0.069***
	(0.004)				(0.004)
Mean profitability ratio$_f$		-0.057***			-0.158***
		(0.009)			(0.012)
Mean log of employees$_f$			0.061***		0.037***
			(0.001)		(0.001)
Mean log of sales$_f$				0.050***	0.020***
				(0.001)	(0.001)
R^2	0.002	0.000	0.011	0.017	0.015
N	715,497	634,652	654,399	669,797	421,058

Robust standard errors reported in parantheses.

We winsorize each variable at the country level by replacing the top and bottom 2 percent of the distribution.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.2 Do credit shocks matter for firm investment?

Our main analysis quantifies the effects of bank supply, firm demand, and industry shocks on tangible investment using a firm-level panel-regression framework. The sample covers firms in Germany, France, Italy and Spain from September 2019 to December 2023. All specifications include firm and year fixed effects to absorb time-invariant firm characteristics (e.g., management quality, industry affiliation) and common macroeconomic shocks (e.g., the COVID-19 pandemic). Standard errors are clustered at the bank level to account for residual correlations across firms sharing the same lender.

The baseline model follows the investment literature by including two core controls: cash flow scaled by lagged capital (Cash Flow$_{f,t}$ / Capital$_{f,t-1}$) to capture internal financing constraints (Fazzari et al. (1988); Kaplan and Zingales (1997)) and lagged sales growth (Sales Growth$_{f,t-1}$) as a proxy for investment opportunities, in the spirit of Tobin's Q for unlisted firms (Whited

(2006); Bloom et al. (2007)). We progressively introduce decomposed credit shocks at the industry, bank, and firm levels, following the methodologies in Amiti and Weinstein (2018) and Chodorow-Reich (2014) and interact them with measures of loan dependence to explore heterogeneous effects.

Table 7 presents the results. Column (1) confirms well-established investment dynamics: cash flow is positive and highly significant, indicating that firms invest more when internal funds are abundant, consistent with the financing constraint channel. Lagged sales growth is also positive and significant, reflecting that firms expand capital in response to growth opportunities in the future.

In column (2), we introduce industry shocks that capture sector credit or demand changes (e.g., energy price shocks and regulatory adjustments). The coefficient is negative and significant (-0.242), implying that adverse conditions affecting an industry can reduce investment, likely through sector-wide financing constraints or lower demand (see Banerjee et al. (2020)). For example, manufacturing firms may cut capital expenditures during supply chain disruptions.

Column (3) adds idiosyncratic bank and firm shocks to the model. The results show that both bank-specific credit supply shocks and firm-specific credit demand shocks significantly influence investments. Positive bank shocks, reflecting improved credit supply from lenders, are associated with increased investment, whereas negative shocks constrain capital expenditures. This supports the view that external financing conditions critically affect real investment, consistent with the bank lending channel literature (Khwaja and Mian (2008), Jiménez et al. (2012)). In addition, firm-specific shocks positively impact investment, as firms with stronger fundamentals (e.g., higher product demand, profitability, and growth opportunities) invest more in tangible assets. These shocks, often linked to improved investment opportunities or higher borrowing needs, are intuitive and align with the theory that firms invest more when they anticipate stronger growth prospects or internal productivity improvements. The strong positive effect of firm shocks (0.111) highlights how improved fundamentals, such as higher collateral values, boost capital expenditures.

Column (4) examines how the sensitivity of investment to shocks varies with firms' reliance on bank financing, measured by the mean loan-to-assets ratio. The results reveal that bank-dependent firms are especially vulnerable to negative bank shocks, with those relying heavily on bank loans experiencing sharper declines in their investments. This is reflected in the positive and significant interaction term between bank shocks and loan dependence, suggesting that firms with fewer alternative financing options are more affected by credit supply contraction. This is consistent with prior research, such as Amiti and Weinstein (2018) who found that even among listed firms with equity market access, investment sensitivity to bank shocks was higher for those more loan-dependent. The interaction term (0.044) indicates that a one standard deviation increase in bank shocks boosts investment by 22% more for highly loan-dependent firms. Similarly, firm-specific shocks have a stronger impact on investment for loan-dependent firms (interaction term: 0.127), likely because such shocks directly influence their credit access.

Finally, column (5) replaces the continuous interaction with binned loan dependence to capture the nonlinearities. We divide loan dependence (mean loan-to-assets ratio) into three bins that interact with bank shocks. The first (high) bin includes all firms with mean loan-to-assets ratios above 67th percentile, bin 2 (medium) with those between 33th and 67th percentile, and bin 3 (low) with those less than 33th percentile. All interactions are positive and significant, with declining coefficients from Bin-1 (highest dependence) to Bin-3, indicating diminishing marginal effects. Firms in the highest dependence category react most strongly to bank shocks, while the firm-shock interaction remains robust, reinforcing the heterogeneous effects documented in Column (4).

These results highlight that idiosyncratic shocks matter for investment, but their impact is amplified among firms with a greater dependence on bank financing, consistent with the heterogeneous credit channel emphasized in the post-financial crisis literature (Jiménez et al. (2012); Acharya et al. (2018); Amiti and Weinstein (2018)). It is also worth noting that the model's explanatory power increases once both shocks are included, indicating that these idiosyncratic shocks capture investment variation across firms.

Table 7: Effect of Shocks on Tangible Investment

Dependent variable: $Investment_{f,t}/Capital_{f,t-1}$	(1)	(2)	(3)	(4)	(5)
$Cash\ Flow_{f,t}/Capital_{f,t-1}$	0.0753***	0.0752***	0.0754***	0.0760***	0.0760***
	(0.000791)	(0.000791)	(0.000787)	(0.000796)	(0.000796)
$Sales\ Growth_{f,t-1}$	0.0271***	0.0284***	0.0236***	0.0230***	0.0230***
	(0.00282)	(0.00283)	(0.00281)	(0.00283)	(0.00283)
$Industry\ Shock_{f,t}$		-0.347***	-0.431***	-0.441***	-0.441***
		(0.0272)	(0.0271)	(0.0272)	(0.0272)
$Bank\ Shock_{f,t}$			0.0671***	0.0586***	
			(0.00359)	(0.00559)	
$Firm\ Shock_{f,t}$			0.111***	0.0861***	0.0861***
			(0.00141)	(0.00213)	(0.00211)
$Bank\ Shock_{f,t} \times (Loan\ Dependence_f)$				0.0442***	
				(0.0160)	
$Firm\ Shock_{f,t} \times (Loan\ Dependence_f)$				0.127***	0.127***
				(0.00793)	(0.00782)
$Bank\ Shock_{f,t} \times (Bin-1_f)$					0.0903***
					(0.00675)
$Bank\ Shock_{f,t} \times (Bin-2_f)$					0.0670***
					(0.00566)
$Bank\ Shock_{f,t} \times (Bin-3_f)$					0.0563***
					(0.00554)
Year-fixed effects	Yes	Yes	Yes	Yes	Yes
Firm-fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	1,157,473	1,157,473	1,157,473	1,146,626	1,146,626
R^2	0.390	0.390	0.399	0.399	0.399

Standard errors, reported in parentheses, are clustered at the firm level.

All regressions include firm and year fixed effects.

We winsorize each variable at the country level by replacing the top and bottom 2 percent of the distribution.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.3 Role of loan maturity and number of lending relationships

Table 8 presents evidence of the role of loan maturity and the number of lending relationships in moderating the impact of shocks on firm investment. The results in column (3) establish a baseline: a positive Bank Shock ($Bank\ Shock_{f,t}$ coefficient of 0.0671) and a positive Firm Shock ($Firm\ Shock_{f,t}$ coefficient of 0.111) significantly boost investment, consistent with the theoretical framework of credit supply and firm-level shocks. However, the subsequent columns provide a more granular analysis.

The results in column (4) for the interaction terms are particularly illuminating and show that the negative and highly significant coefficient on $Bank\ Shock_{f,t} \times (Less\ than\ one\ year_{f,t})$ (-0.0912) indicates that for firms with a high proportion of short-term debt, the positive impact of a favorable bank shock is significantly reduced. Similarly, the negative and significant coefficient on $Firm\ Shock_{f,t} \times (Less\ than\ one\ year_{f,t})$ (-0.0902) shows that even when a firm experiences a positive idiosyncratic shock, the presence of short-term debt curtails its investment response. This finding appears to contradict the conventional view that firms use short-term debt to minimize borrowing costs. Although potentially cheaper upfront, short-term debt introduces a continuous need for refinancing, creating a significant rollover risk. During a period of positive bank or firm shocks, a firm with a long-term debt structure has a stable financing foundation that allows it to confidently undertake new investment projects to capitalize on improved conditions. In stark contrast, a firm with a high proportion of short-term debt is preoccupied with servicing or rolling over its immediate financial obligations. Thus, short-term debt acts as a significant constraint, preventing the firm from fully translating favorable conditions into new investments.

The results in column (5) reinforce the importance of a firm's financial network. The positive and significant interaction terms for multiple banking relationships ($Bank\ Shock_{f,t} \times (More\ than\ one\ bank_{f,t})$ at 0.0320 and $Firm\ Shock_{f,t} \times (More\ than\ one\ bank_{f,t})$ at 0.0155) reveal that having more than one bank relationship amplifies the positive effects of bank and firm shocks on investment. This is consistent with the literature on relationship banking, which suggests that a diverse set of lenders provides firms with access to more capital and a buffer against shocks affecting individual banks.

Table 8: Role of Loan Maturity and Number of Lending Relationships

Dependent variable: $Investment_{f,t}/Capital_{f,t-1}$	(1)	(2)	(3)	(4)	(5)
$Cash\ Flow_{f,t}/Capital_{f,t-1}$	0.0753***	0.0752***	0.0754***	0.0743***	0.0754***
	(0.000791)	(0.000791)	(0.000787)	(0.000929)	(0.000787)
$Sales\ Growth_{f,t-1}$	0.0271***	0.0284***	0.0236***	0.0207***	0.0236***
	(0.00282)	(0.00283)	(0.00281)	(0.00306)	(0.00281)
$Industry\ Shock_{f,t}$		-0.347***	-0.431***	-0.339***	-0.435***
		(0.0272)	(0.0271)	(0.0276)	(0.0271)
$Bank\ Shock_{f,t}$			0.0671***	0.0897***	0.0506***
			(0.00359)	(0.00517)	(0.00509)
$Firm\ Shock_{f,t}$			0.111***	0.138***	0.102***
			(0.00141)	(0.00224)	(0.00223)
$Bank\ Shock_{f,t} \times (Less\ than\ one\ year_{f,t})$				-0.0912***	
				(0.0124)	
$Firm\ Shock_{f,t} \times (Less\ than\ one\ year_{f,t})$				-0.0902***	
				(0.00443)	
$BankShock_{f,t} \times (More\ than\ one\ bank_{f,t})$					0.0320***
					(0.00684)
$Firm\ Shock_{f,t} \times (More\ than\ one\ bank_{f,t})$					0.0155***
					(0.00289)
Year-fixed effects	Yes	Yes	Yes	Yes	Yes
Firm-fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	1,157,473	1,157,473	1,157,473	906,989	1,157,473
R^2	0.390	0.390	0.399	0.407	0.399

Standard errors, reported in parentheses, are clustered at the firm level.

All regressions include firm and year fixed effects.

We winsorize each variable at the country level by replacing the top and bottom 2 percent of the distribution.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.4 Asymmetric effects on tangible investment

Next, we aim to address whether negative shocks (such as credit tightening or adverse firm-specific events) have an equal and opposite effect compared to positive shocks (such as credit expansion or favorable firm-specific developments). The emerging consensus, supported by our findings, suggests that these effects are highly asymmetric.

In practice, negative credit supply shocks tend to have a much larger impact on investment than do positive shocks of a similar magnitude. For instance, when a bank sharply reduces lending (due to a capital shortfall or financial crisis), constrained firms may be forced to cancel projects, sell assets, or exit the market. This can lead to a sharp decline in investments and potentially long-lasting economic losses. Conversely, when a bank becomes more generous in its lending, firms do increase investment, but the uptick is often more modest – a healthy firm will not invest in unprofitable projects just because credit is abundant.

As shown in Table 9, the coefficient on $Negative\ Bank\ Shock_{f,t}$ (-0.146) is substantially larger in magnitude than that of $Positive\ Bank\ Shock_{f,t}$ (0.0225), confirming powerful asymmetry. However, for firm demand shocks, investment responds in a broadly symmetric way, with negative shocks reducing investment by -0.0686 and positive shocks increasing it by 0.0884, indicating that firm fundamentals drive investment both downward and upward with similar magnitudes.

This asymmetry is a direct consequence of information frictions in financial markets. A negative bank shock, such as credit contraction, is a clear and unambiguous signal of a deteriorating environment. Lenders, facing heightened risk and potential bankruptcy costs, respond swiftly and sharply by raising the lending rates and restricting the credit supply. This decisive response leads to a significant and immediate decline in investment, as reflected by the large negative coefficient. In contrast, a positive bank shock, such as a credit-easing event, is a more ambiguous signal. Lenders may learn about the improved conditions slowly and gradually, leading to a much more cautious and tempered increase in credit availability than expected. This "slow recovery" phenomenon means that while financial frictions can quickly seize up investment in a downturn, the same mechanisms do not necessarily stimulate it with equal force in an upturn.

Table 9: Effect of Shocks on Tangible Investment - Asymmetric effects

Dependent variable: $Investment_{f,t}/Capital_{f,t-1}$	(1)	(2)	(3)
$Cash\ Flow_{f,t}/Capital_{f,t-1}$	0.0760***	0.0760***	0.0760***
	(0.000796)	(0.000796)	(0.000796)
$Sales\ Growth_{f,t-1}$	0.0230***	0.0230***	0.0229***
	(0.00283)	(0.00283)	(0.00283)
$Industry\ Shock_{f,t}$	-0.441***	-0.426***	-0.444***
	(0.0272)	(0.0272)	(0.0272)
$Bank\ Shock_{f,t}$	0.0586***		0.0504***
	(0.00559)		(0.00621)
$Firm\ Shock_{f,t}$	0.0861***	0.0869***	
	(0.00213)	(0.00213)	
$Bank\ Shock_{f,t} \times (Loan\ Dependence_f)$	0.0442***	0.0600***	0.0473***
	(0.0160)	(0.0160)	(0.0160)
$Firm\ Shock_{f,t} \times (Loan\ Dependence_f)$	0.127***	0.127***	0.126***
	(0.00793)	(0.00793)	(0.00793)
$Negative\ Bank\ Shock_{f,t}$		-0.146***	
		(0.0108)	
$Positive\ Bank\ Shock_{f,t}$		0.0225***	
		(0.00653)	
$Negative\ Firm\ Shock_{f,t}$			-0.0686***
			(0.00553)
$Positive\ Firm\ Shock_{f,t}$			0.0884***
			(0.00232)
Year-fixed effects	Yes	Yes	Yes
Firm-fixed effects	Yes	Yes	Yes
Observations	1,146,626	1,146,626	1,146,626
R^2	0.399	0.400	0.399

Standard errors, reported in parentheses, are clustered at the firm level.

All regressions include firm and year fixed effects.

Negative bank shocks (credit tightening) enter as positive values multiplied by -1.

We winsorize each variable at the country level by replacing the top and bottom 2 percent of the distribution.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.5 Effect of shocks on intangible investment

The findings in Table 10 demonstrate that intangible investments exhibit different financing sensitivities compared to tangible investments. The coefficient for $Cash\ Flow_{f,t}/Capital_{f,t-1}$ is notably large (0.254–0.265) and statistically significant, indicating a stronger reliance on internal financing for intangible than for tangible investments. This suggests that companies tend to finance projects when they have cash available.

In contrast, the impact of external financing was less pronounced. The coefficient of $Bank\ Shock_{f,t}$ is small and lacks statistical significance across different models; its interaction with $Loan\ Dependence_f$ (0.258) is not precisely estimated and remains insignificant, despite being positive. This contrasts starkly with tangible investments, where bank shocks and loan dependence have clear effects. Similarly, the interaction between firm shocks and loan dependence (-0.0248) is not significant, indicating that reliance on banks does not influence firms' adjustment of their spending on intangibles.

Interestingly, firm-specific demand shocks are significant: the coefficients of $Firm\ Shock_{f,t}$ are positive (0.078 and 0.082) and highly statistically significant, suggesting that when firms experience positive fundamentals, they allocate resources to intangibles. This is logical because these investments are forward-looking bets on growth opportunities pursued when demand prospects are favorable.

Overall, the evidence highlights that intangibles are inherently more challenging to finance in debt markets. The lack of collateral, high uncertainty, and information asymmetry diminish the effectiveness of traditional bank credit. Instead, they rely heavily on internal cash flow and firm fundamentals. This difference in financing channels explains why bank shocks have a more substantial impact on tangible investments than on intangible investments.

Table 10: Effect of Shocks on Intangible Investment

Dependent variable: $Intangible\ Investment_{f,t}/Capital_{f,t-1}$	(1)	(2)	(3)
$Cash\ Flow_{f,t}/Capital_{f,t-1}$	0.254^{**}	0.265^{**}	0.265^{**}
	(0.125)	(0.125)	(0.126)
$Sales\ Growth_{f,t-1}$	-0.00225	-0.00382	-0.00357
	(0.0231)	(0.0233)	(0.0233)
$Industry\ Shock_{f,t}$		-0.632^{**}	-0.602^{**}
		(0.273)	(0.273)
$Bank\ Shock_{f,t}$		0.0134	-0.0476
		(0.0359)	(0.0644)
$Firm\ Shock_{f,t}$		0.0776^{***}	0.0824^{***}
		(0.00921)	(0.0145)
$Bank\ Shock_{f,t} \times (Loan\ Dependence_f)$			0.258
			(0.166)
$Firm\ Shock_{f,t} \times (Loan\ Dependence_f)$			-0.0248
			(0.0348)
Year-fixed effects	Yes	Yes	Yes
Firm-fixed effects	Yes	Yes	Yes
Observations	722,945	722,945	720,078
R^2	0.375	0.375	0.372

Standard errors, reported in parentheses, are clustered at the firm level.

All regressions include firm and year fixed effects.

We winsorize each variable at the country level by replacing the top and bottom 2 percent of the distribution.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5 Heterogeneous effects

In this section, we extend our baseline analysis to examine which firms are most affected by shocks. The impact of bank and firm shocks on investment varies according to firms' financing options and characteristics. Factors such as size and age are significant in determining both bank dependence and cash reserves. Sectors differ in terms of their capital requirements and collateral availability. Countries vary in the extent to which their systems are bank-based or market-based. Consequently, we re-estimated the baseline model by firm size, age, sector, country, and the COVID-19 period. This approach enables us to determine where shocks have the greatest impact, whether firms with alternative funding sources are less vulnerable, and how the pandemic has altered these dynamics. The objective is to examine the mechanisms behind the average results and highlight the groups for which investment is most sensitive.

5.1 Role of firm size

Table 11 breaks down the investment response by firm size in terms of the number of employees. We established four distinct firm size categories: micro firms with fewer than 10 employees, small firms with between 10 and 49 employees, medium firms with between 50 and 249 employees, and large firms with 250 or more employees. The results indicate that the coefficients for both $Bank\ Shock_{f,t}$ and $Firm\ Shock_{f,t}$ are the largest and most significant for micro (0.092 and 0.116) and small (0.042 and 0.078) firms. These coefficients gradually decrease as firm size increases, becoming small and statistically insignificant for large firms (0.002 and 0.009), a finding that aligns with the analysis in Amiti and Weinstein (2018). As noted by Amador and Nagengast (2016), small firms are particularly vulnerable to adverse bank shocks because "small firms are almost entirely bank-dependent and therefore feel the full brunt of disruptions to their banks' credit supply." In contrast, larger firms often have diverse funding sources, such as bond issuances and internal funds, which help to cushion the impact of shocks. This Portuguese study found that large firms reduced investment significantly less than small firms during similar bank credit shocks, attributing this to their diversified capital structure and access to alternative financing. Our findings align with this: investment contractions are most severe for micro, small, and medium-sized enterprises, whereas larger firms with multiple financing options are less affected. This highlights a key point from the literature: bank shocks disproportionately impact smaller, bank-dependent firms that lack the financial flexibility.

Table 11: Results by Firm Size

Dependent variable: $Investment_{f,t}/Capital_{f,t-1}$	(1)	(2)	(3)	(4)
	Micro	Small	Medium	Large
$Cash\ Flow_{f,t}/Capital_{f,t-1}$	0.077***	0.088***	0.078***	0.060***
	(0.001)	(0.002)	(0.005)	(0.019)
$Sales\ Growth_{f,t-1}$	0.026***	0.019***	-0.017	-0.011
	(0.004)	(0.005)	(0.014)	(0.046)
$Industry\ Shock_{f,t}$	-0.422***	-0.656***	-0.501***	-0.055
	(0.055)	(0.049)	(0.064)	(0.048)
$Bank\ Shock_{f,t}$	0.092***	0.042***	0.025	0.002
	(0.008)	(0.012)	(0.019)	(0.019)
$Firm\ Shock_{f,t}$	0.116***	0.078***	0.030***	0.009*
	(0.004)	(0.006)	(0.005)	(0.005)
$Bank\ Shock_{f,t} \times (Loan\ Dependence_f)$	0.012	0.030	0.002	0.091
	(0.018)	(0.046)	(0.068)	(0.077)
$Firm\ Shock_{f,t} \times (Loan\ Dependence_f)$	0.087***	0.105***	0.101***	0.022
	(0.015)	(0.026)	(0.024)	(0.021)
Year-fixed effects	Yes	Yes	Yes	Yes
Firm-fixed effects	Yes	Yes	Yes	Yes
R^2	0.412	0.394	0.397	0.414
N	533,216	358,505	69,536	19,664

Standard errors, reported in parentheses, are clustered at the firm level.

All regressions include firm and year fixed effects.

We winsorize each variable at the country level by replacing the top and bottom 2 percent of the distribution.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.2 Role of firm age

Table 12 presents a breakdown of investment sensitivity by firm age, revealing a pattern that is both similar to and distinct from the others. We classify firms as young if they are less than 10 years old, mature if their age is between 10 and 20 years, and old if they are more than 20 years old. The coefficients for $Bank\ Shock_{f,t}$ and $Firm\ Shock_{f,t}$ are highest for young firms (0.118 and 0.149) and gradually decrease for mature (0.076 and 0.104) and old firms (0.022 and 0.059). Investment in younger firms is more adversely affected by shocks than in older, more established firms. Similar to the firm size effect, Table 12 illustrates the life-cycle pattern of investment sensitivity. Start-ups and young firms, such as those under a certain age or lacking a long credit history, tend to significantly reduce their investment when confronted with negative shocks or tighter credit, whereas mature firms exhibit a more moderate response. The coefficients indicate that economic or financial shocks lead to a much greater reduction in the investment-to-capital ratios for young firms than for older ones. These findings align with the notion that young companies are generally more financially constrained and reliant on banks than older companies. Our results are consistent with recent research suggesting that firm age is inversely related to financial constraints; smaller and younger firms encounter the most severe financial frictions and thus display the greatest sensitivity of investment and growth to credit conditions.

Table 12: Results by Firm Age

Dependent variable: $Investment_{f,t}/Capital_{f,t-1}$	(1)	(2)	(3)
	Young	Mature	Old
$Cash\ Flow_{f,t}/Capital_{f,t-1}$	0.082***	0.076***	0.070***
	(0.001)	(0.002)	(0.001)
$Sales\ Growth_{f,t-1}$	0.036***	0.024***	0.006*
	(0.006)	(0.006)	(0.004)
$Industry\ Shock_{f,t}$	-0.280***	-0.254***	-0.536***
	(0.071)	(0.057)	(0.034)
$Bank\ Shock_{f,t}$	0.118***	0.076***	0.022***
	(0.012)	(0.013)	(0.007)
$Firm\ Shock_{f,t}$	0.149***	0.104***	0.059***
	(0.005)	(0.006)	(0.003)
$Bank\ Shock_{f,t} \times (Loan\ Dependence_f)$	-0.037	0.027	0.046**
	(0.025)	(0.038)	(0.021)
$Firm\ Shock_{f,t} \times (Loan\ Dependence_f)$	0.068***	0.073***	0.082***
	(0.017)	(0.024)	(0.011)
Year-fixed effects	Yes	Yes	Yes
Firm-fixed effects	Yes	Yes	Yes
R^2	0.451	0.410	0.364
N	298,674	274,782	528,142

Standard errors, reported in parentheses, are clustered at the firm level.

All regressions include firm and year fixed effects.

We winsorize each variable at the country level by replacing the top and bottom 2 percent of the distribution.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.3 Role of sector

Sectoral analysis reveals notable differences in investment sensitivities. As illustrated in Table 13, service companies exhibit the greatest sensitivity to $Bank\ Shock_{f,t}$ (0.072), followed by manufacturing (0.062) and construction (0.038). Regarding $Firm\ Shock_{f,t}$, the service sector again shows the highest responsiveness (0.100), while construction and manufacturing show nearly identical coefficients (0.081 and 0.080, respectively).

When considering loan dependence, manufacturing firms are particularly notable: the interaction $Firm\ Shock_{f,t} \times (Loan\ Dependence_f)$ is most pronounced in manufacturing (0.178), compared to construction (0.113), and services (0.073). For the $Bank\ Shock_{f,t} \times (Loan\ Dependence_f)$ interaction, only manufacturing exhibits a statistically significant effect (0.063), whereas construction and services do not show significant effects.

These trends indicate that manufacturing firms are most vulnerable when shocks are combined with their dependence on bank financing, while service firms are most directly affected by general bank and firm-level shocks. Overall, construction firms displayed more moderate sensitivities.

These differences correspond to the characteristics of each sector. Manufacturing, being highly capital-intensive, relies heavily on tangible assets and external financing, which explains the large coefficients when loan dependence is included. Service firms, although less capital-intensive, might rely more on relationship-based lending and short-term financing, making them quickly responsive to both bank and firm shocks. Despite being capital-intensive, construction firms often use project-specific or syndicated financing structures, which may reduce their sensitivity to overall bank shocks.

Table 13: Results by Firm Sector

Dependent variable: $Investment_{f,t}/Capital_{f,t-1}$	(1) Construction	(2) Manufacturing	(3) Services
$Cash\ Flow_{f,t}/Capital_{f,t-1}$	0.093***	0.095***	0.068***
	(0.002)	(0.002)	(0.001)
$Sales\ Growth_{f,t-1}$	0.008	0.034***	0.028***
	(0.006)	(0.007)	(0.004)
$Industry\ Shock_{f,t}$	-0.254***	-0.632***	-0.177***
	(0.066)	(0.046)	(0.041)
$Bank\ Shock_{f,t}$	0.038***	0.062***	0.072***
	(0.014)	(0.010)	(0.007)
$Firm\ Shock_{f,t}$	0.081***	0.080***	0.100***
	(0.005)	(0.004)	(0.004)
$Bank\ Shock_{f,t} \times (Loan\ Dependence_f)$	0.032	0.063**	0.022
	(0.046)	(0.031)	(0.017)
$Firm\ Shock_{f,t} \times (Loan\ Dependence_f)$	0.113***	0.178***	0.073***
	(0.019)	(0.017)	(0.014)
Year-fixed effects	Yes	Yes	Yes
Firm-fixed effects	Yes	Yes	Yes
R^2	0.419	0.377	0.403
N	178,699	328,841	639,086

Standard errors, reported in parentheses, are clustered at the firm level.

All regressions include firm and year fixed effects.

We winsorize each variable at the country level by replacing the top and bottom 2 percent of the distribution.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The comprehensive sectoral analysis presented in Table 14 highlights significant diversity in how firms' investments react to industry-wide shocks, those specific to banks, or unique to firms, offering a more detailed perspective than the aggregate analysis.

Industry shocks exhibit the greatest variation, with values ranging from 0.265 in the Food sector to a notably negative −1.942 in Textiles. Significant negative impacts are observed in capital-intensive manufacturing sectors, such as Basic Metals (−1.434) and Machinery (−1.544), where investments are particularly vulnerable to economic downturns. In contrast, sectors such as Construction (−0.254) show more moderate reactions, aligning with their project-based financing models that provide some protection against industry-wide fluctuations.

The bank lending channel is influential in both the manufacturing and services sectors. Manufacturing subsectors, such as Food (0.107) and Fabricated Metals (0.084), demonstrate strong positive responses to bank shocks, while service sectors, such as ICT (0.140) and Transport (0.074), are also heavily depend on bank financing.

The interaction terms reveal significant differences in financing methods. The interaction of Bank Shock × Loan Dependence is positive and significant in sectors such as Paper (0.702), Pharma (0.561), Professional, Scientific & Technical (0.115), and Transport (0.162), indicating that reliance on loans magnifies the impact of changes in the credit supply. However, this interaction is negative for ICT (−0.255), reflecting the sector's dependence on intangible assets that are less suitable as collateral. In this scenario, greater bank dependence may increase ICT firms' vulnerability when credit conditions become restrictive.

Finally, the interaction of Firm Shock × Loan Dependence is generally positive and significant across various industries (e.g., Food 0.143, Apparel 0.213, Machinery 0.319, Construction 0.113, Transport 0.209). This trend suggests that firms reliant on banks tend to amplify their response to firm-specific fundamentals, expanding investments significantly during favorable times but contracting more sharply when conditions worsen.

Overall, these findings emphasize that idiosyncratic shocks do not uniformly affect all sectors. Factors such as capital intensity, collateralizability, and financing structures influence how industries translate both financial and real shocks into their investment outcomes.

Table 14: Sectoral Results - Detailed

Dependent variable: $Investment_{f,t}/Capital_{f,t-1}$	(1) C10	(2) C11	(3) C13	(4) C14	(5) C15	(6) C16	(7) C17	(8) C18	(9) C19	(10) C20	(11) C21
$Cash\ Flow_{f,t}/Capital_{f,t-1}$	0.106***	0.120***	0.079***	0.068***	0.098***	0.096***	0.114***	0.089***	0.030	0.107***	0.070***
	(0.013)	(0.029)	(0.011)	(0.007)	(0.012)	(0.014)	(0.035)	(0.012)	(0.039)	(0.015)	(0.015)
$Sales\ Growth_{f,t-1}$	0.034**	0.041	0.171***	0.072*	0.041	0.018	-0.052	0.032	-0.257	0.033	0.155
	(0.016)	(0.029)	(0.039)	(0.044)	(0.037)	(0.033)	(0.081)	(0.034)	(0.284)	(0.035)	(0.139)
$Industry\ Shock_{f,t}$	0.265**	0.388	-1.942***	0.432	-0.517	-0.349	-0.873***	-1.044***	-0.038	-0.597**	-0.623*
	(0.109)	(0.244)	(0.386)	(0.528)	(0.567)	(0.335)	(0.224)	(0.235)	(0.097)	(0.249)	(0.361)
$Bank\ Shock_{f,t}$	0.107***	0.044	0.018	0.158**	-0.012	0.120***	-0.083	0.068	-0.157	0.076	-0.044
	(0.024)	(0.041)	(0.050)	(0.068)	(0.057)	(0.043)	(0.087)	(0.048)	(0.150)	(0.046)	(0.095)
$Firm\ Shock_{f,t}$	0.073***	0.057**	0.112***	0.053***	0.053***	0.139***	0.068**	0.087***	0.129	0.040**	0.033
	(0.011)	(0.023)	(0.020)	(0.017)	(0.019)	(0.018)	(0.027)	(0.021)	(0.086)	(0.017)	(0.035)
$Bank\ Shock_{f,t} \times (Loan\ Dependence_f)$	-0.033	-0.072	0.216	-0.132	0.286	-0.089	0.702**	0.079	0.904	-0.038	0.561**
	(0.066)	(0.095)	(0.149)	(0.202)	(0.224)	(0.123)	(0.316)	(0.123)	(0.686)	(0.159)	(0.225)
$Firm\ Shock_{f,t} \times (Loan\ Dependence_f)$	0.143***	0.079	0.086	0.213***	0.118	0.022	0.277**	0.195***	-0.240	0.195**	0.150
	(0.041)	(0.066)	(0.082)	(0.080)	(0.080)	(0.067)	(0.135)	(0.073)	(0.337)	(0.092)	(0.118)
R^2	0.410	0.427	0.381	0.381	0.388	0.381	0.368	0.383	0.292	0.382	0.420
N	34,911	7,617	11,099	10,120	8,820	12,249	6,226	13,912	418	10,658	1,433

Dependent variable: $Investment_{f,t}/Capital_{f,t-1}$	(1) C22	(2) C23	(3) C24	(4) C25	(5) C26	(6) C27	(7) C28	(8) C29	(9) C30	(10) C31	(11) C32
$Cash\ Flow_{f,t}/Capital_{f,t-1}$	0.141***	0.101***	0.096***	0.130***	0.075***	0.092***	0.082***	0.111***	0.066***	0.095***	0.080***
	(0.017)	(0.013)	(0.030)	(0.006)	(0.011)	(0.011)	(0.006)	(0.023)	(0.021)	(0.010)	(0.010)
$Sales\ Growth_{f,t-1}$	0.109**	0.073**	-0.042	0.044***	-0.032	-0.136***	-0.016	0.090*	0.047	0.040	0.054
	(0.043)	(0.030)	(0.050)	(0.016)	(0.046)	(0.039)	(0.019)	(0.053)	(0.041)	(0.036)	(0.037)
$Industry\ Shock_{f,t}$	-0.029	-0.258	-1.434***	-1.254***	-0.668*	-1.190***	-1.544***	-0.516*	-0.498	0.313	-0.360
	(0.175)	(0.313)	(0.262)	(0.102)	(0.368)	(0.283)	(0.193)	(0.285)	(0.488)	(0.344)	(0.499)
$Bank\ Shock_{f,t}$	0.029	0.056	-0.005	0.084***	0.011	0.020	0.058	0.002	0.199	0.090*	0.100
	(0.032)	(0.042)	(0.083)	(0.021)	(0.068)	(0.063)	(0.037)	(0.062)	(0.125)	(0.050)	(0.064)
$Firm\ Shock_{f,t}$	0.063***	0.076***	0.037	0.097***	0.053***	0.058***	0.068***	0.050**	0.076*	0.100***	0.086***
	(0.015)	(0.018)	(0.024)	(0.008)	(0.020)	(0.017)	(0.012)	(0.020)	(0.046)	(0.020)	(0.022)
$Bank\ Shock_{f,t} \times (Loan\ Dependence_f)$	-0.019	0.040	0.116	0.050	0.170	0.202	0.236	0.024	-0.236	0.063	-0.073
	(0.115)	(0.132)	(0.236)	(0.077)	(0.316)	(0.226)	(0.157)	(0.215)	(0.341)	(0.129)	(0.204)
$Firm\ Shock_{f,t} \times (Loan\ Dependence_f)$	0.231***	0.208***	0.158*	0.230***	0.207*	0.088	0.319***	0.140	0.004	0.093	0.121
	(0.078)	(0.079)	(0.093)	(0.038)	(0.111)	(0.082)	(0.068)	(0.085)	(0.167)	(0.074)	(0.094)
R^2	0.393	0.399	0.355	0.385	0.359	0.350	0.349	0.380	0.384	0.377	0.387
N	17,728	15,556	6,217	73,047	7,689	9,795	33,017	4,843	2,823	12,980	10,332

Dependent variable: $Investment_{f,t}/Capital_{f,t-1}$	(1) C33	(2) F	(3) J	(4) K	(5) N	(6) T	(7) H	(8) I	(9) G
$Cash\ Flow_{f,t}/Capital_{f,t-1}$	0.090***	0.093***	0.043***	0.055***	0.059***	0.065***	0.090***	0.063***	0.073***
	(0.008)	(0.002)	(0.005)	(0.003)	(0.002)	(0.008)	(0.004)	(0.004)	(0.001)
$Sales\ Growth_{f,t-1}$	0.066**	0.008	0.032	0.030	0.030***	0.049**	0.039***	0.005	0.035***
	(0.029)	(0.006)	(0.025)	(0.020)	(0.010)	(0.024)	(0.010)	(0.006)	(0.007)
$Industry\ Shock_{f,t}$	-0.191	-0.254***	0.827*	-0.268	0.121	-0.199	-0.368***	0.113	-0.385***
	(0.272)	(0.066)	(0.456)	(0.389)	(0.159)	(0.373)	(0.084)	(0.076)	(0.085)
$Bank\ Shock_{f,t}$	0.013	0.038***	-0.010	0.140***	0.033*	0.107**	0.074***	0.055***	0.079***
	(0.047)	(0.014)	(0.050)	(0.036)	(0.019)	(0.043)	(0.021)	(0.014)	(0.010)
$Firm\ Shock_{f,t}$	0.088***	0.081***	0.091***	0.109***	0.094***	0.140***	0.098***	0.089***	0.092***
	(0.017)	(0.005)	(0.016)	(0.012)	(0.008)	(0.020)	(0.008)	(0.007)	(0.004)
$Bank\ Shock_{f,t} \times (Loan\ Dependence_f)$	0.252	0.032	0.034	-0.255**	0.115**	-0.040	0.162***	0.016	0.029
	(0.167)	(0.046)	(0.057)	(0.112)	(0.048)	(0.106)	(0.053)	(0.023)	(0.027)
$Firm\ Shock_{f,t} \times (Loan\ Dependence_f)$	0.274***	0.113***	-0.008	0.032	0.062**	0.047	0.209***	0.056***	0.108***
	(0.082)	(0.019)	(0.019)	(0.044)	(0.027)	(0.051)	(0.028)	(0.016)	(0.016)
R^2	0.388	0.419	0.387	0.394	0.418	0.424	0.416	0.430	0.395
N	17,298	178,699	8,988	35,939	87,559	15,787	76,771	97,545	316,497

Standard errors, reported in parentheses, are clustered at the firm level.

All regressions include firm and year fixed effects.

We winsorize each variable at the country level by replacing the top and bottom 2 percent of the distribution.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Each column corresponds to a NACE sector. The following manufacturing activities are included: C10: food, C11: beverages, C13: textiles, C14: apparel, C15: leather, C16: wood, C17: paper, C18: printing, C19: coke & petroleum, C20: chemicals, C21: pharmaceuticals, C22: rubber & plastic, C23: non-metal minerals, C24: basic metals, C25: fabricated metals, C26: computers, C27: electrical equiment, C28: machinery and equipment, C29: motor vehicles, C30: other transport equiment, C31: furniture, C32: other manufacturing. Construction is sector F. The following services activities are included: C33: repair & maintainance of machinery, J: publishing, K: ICT, N: professional, scientific & technical services, T: other services, H: transportation & storage, I: accommodation and food services, G: wholesale & retail trade.

5.4 Role of country

The cross-country analysis in Table 15 provides an empirical demonstration of how institutional and financial system differences shape the transmission of shocks to firm investments. The results reveal striking heterogeneity across the four euro area countries examined.

The data show that investment in Italy and Spain is highly sensitive to both bank-specific and firm-specific shocks. The coefficients for $Bank\ Shock_{f,t}$ are large and highly significant in Italy (0.103) and Spain (0.068), as are the coefficients for $Firm\ Shock_{f,t}$ (0.093 and 0.072, respectively). This is consistent with these countries' historically bank-based financial systems, given the high prevalence of very small firms that are heavily reliant on bank lending for external financing. In such a system, a contraction in credit from the banking sector can profoundly impact corporate investment because firms have limited alternative funding sources. This strong relationship is further amplified by the significant and positive interaction terms with Loan Dependence, particularly for Italy (0.201 for bank shocks and 0.269 for firm shocks) and Spain (0.037 and 0.086, respectively), indicating that firms highly reliant on bank credit are more vulnerable to these shocks.

In stark contrast, Germany and France exhibit much lower or statistically insignificant sensitivities to bank shocks than the other countries. The coefficient for $Bank\ Shock_{f,t}$ is insignificant for both Germany (-0.021) and France (0.006), suggesting that firms in these economies are more buffered from disruptions in the banking system. This finding is consistent with the literature on diversified financial systems. The coefficients for firm shocks ($Firm\ Shock_{f,t}$), however, remain significant for France (0.048), indicating that even in a more diversified system, firm-specific performance is a key driver of investments.

Overall, the empirical evidence confirms that both the structure of the financial system and the composition of the economy, such as the prevalence of very small firms or sectoral concentration, are crucial determinants of how shocks are transmitted to the real economy. The high investment sensitivity in Italy and Spain and the relative resilience of German firms directly reflect the long-standing differences in their financial architecture, reliance on bank financing, and underlying economic structure.

Table 15: Results by Country

Dependent variable: $Investment_{f,t}/Capital_{f,t-1}$	(1) Germany	(2) Spain	(3) Italy	(4) France
$Cash\ Flow_{f,t}/Capital_{f,t-1}$	0.028***	0.061***	0.085***	0.063***
	(0.006)	(0.001)	(0.001)	(0.002)
$Sales\ Growth_{f,t-1}$	-0.012	0.021***	0.026***	-0.004
	(0.028)	(0.003)	(0.004)	(0.017)
$Industry\ Shock_{f,t}$	-0.050	0.001	-0.945***	0.021
	(0.113)	(0.034)	(0.072)	(0.056)
$Bank\ Shock_{f,t}$	-0.021	0.068***	0.103***	0.006
	(0.035)	(0.007)	(0.011)	(0.016)
$Firm\ Shock_{f,t}$	0.003	0.072***	0.093***	0.048***
	(0.012)	(0.006)	(0.003)	(0.007)
$Bank\ Shock_{f,t} \times (Loan\ Dependence_f)$	0.359*	0.037**	0.201***	0.190***
	(0.216)	(0.017)	(0.058)	(0.065)
$Firm\ Shock_{f,t} \times (Loan\ Dependence_f)$	0.141*	0.086***	0.269***	0.266***
	(0.079)	(0.018)	(0.021)	(0.035)
Year-fixed effects	Yes	Yes	Yes	Yes
Firm-fixed effects	Yes	Yes	Yes	Yes
R^2	0.433	0.415	0.389	0.470
N	12,547	426,550	633,515	74,014

Standard errors, reported in parentheses, are clustered at the firm level.

All regressions include firm and year fixed effects.

We winsorize each variable at the country level by replacing the top and bottom 2 percent of the distribution.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.5 Impact of the pandemic

Corporate investment declined sharply during the COVID-19 pandemic, exacerbating vulnerabilities in financially fragile firms. At the same time, during the pandemic, much of the credit provided —especially through state-guaranteed loans and other government support programs— was aimed at helping firms maintain solvency and survive the economic disruptions. The primary goal of these measures was to ensure that firms had access to liquidity to meet their existing obligations, such as paying employees, covering fixed costs, and servicing debt rather than financing new investments or capital expenditures. This would mean that the relationship between credit and investment changed during the pandemic. To assess the impact of the pandemic, we included a COVID-19 crisis dummy variable in the regressions, assigning a value of one for 2020 and 2021 and zero otherwise. This dummy variable is interacted with the bank and firm shock variables to capture the differential effects during the pandemic period.

Table 16 quantifies the effect of the pandemic on tangible investment by including a COVID-19 crisis dummy and interactions with shocks and loan dependence. The coefficients for crisis-specific variables are particularly telling. The negative and highly significant coefficient on $Crisis \times Firm\ Shock_{f,t}$ (-0.0321) indicates that firms, even those experiencing favorable firm-specific shocks, significantly curtailed their tangible investments during the pandemic. This effect was further amplified for firms that had a high dependence on bank loans, as evidenced by the large negative coefficient on the interaction term $Crisis \times Firm\ Shock_{f,t} \times (Loan\ Dependence_f)$ (-0.131). This finding is consistent with the literature that shows that firms prioritize cash hoarding and preserving liquidity to navigate the high uncertainty of the crisis rather than undertaking new investment projects.

Furthermore, the results of the COVID-19 Crisis Bank Shock present a nuanced picture. The coefficient on $Crisis \times\ Bank\ Shock_{f,t}$ is statistically insignificant, suggesting that the effect of a bank shock on firm investment was not significantly different during the crisis period compared to the rest of the sample. However, the interaction term $Crisis \times\ Bank\ Shock_{f,t} \times (Loan\ Dependence_f)$ is positive and significant (0.0794), suggesting some amplification effects of bank shocks for bank-dependent firms. While in normal times a bank shock might directly spur investment, during the pandemic, credit was primarily used by highly bank-dependent firms to maintain solvency and service existing obligations and not to finance new capital expenditures.

Table 16: Effect of Shocks on Tangible Investment - Impact of the Pandemic

Dependent variable: $Tangible\ Investment_{f,t}/Capital_{f,t-1}$	(1)	(2)	(3)
$Cash\ Flow_{f,t}/Capital_{f,t-1}$	0.0760***	0.0760***	0.0759***
	(0.000796)	(0.000796)	(0.000796)
$Sales\ Growth_{f,t-1}$	0.0230***	0.0231***	0.0238***
	(0.00283)	(0.00283)	(0.00283)
$Industry\ Shock_{f,t}$	-0.441***	-0.440***	-0.404***
	(0.0272)	(0.0272)	(0.0272)
$Bank\ Shock_{f,t}$	0.0586***	0.0611***	0.0625***
	(0.00559)	(0.00877)	(0.00561)
$Firm\ Shock_{f,t}$	0.0861***	0.0862***	0.106***
	(0.00213)	(0.00213)	(0.00347)
$Bank\ Shock_{f,t} \times (Loan\ Dependence_f)$	0.0442***	-0.0154	0.0335**
	(0.0160)	(0.0306)	(0.0161)
$Firm\ Shock_{f,t} \times (Loan\ Dependence_f)$	0.127***	0.127***	0.207***
	(0.00793)	(0.00793)	(0.0133)
$Crisis \times\ BankShock_{f,t}$		-0.000888	
		(0.0110)	
$Crisis \times\ Bank\ Shock_{f,t} \times (Loan\ Dependence_f)$		0.0794**	
		(0.0360)	
$Crisis \times\ Firm\ Shock_{f,t}$			-0.0321***
			(0.00425)
$Crisis \times\ Firm\ Shock_{f,t} \times (Loan\ Dependence_f)$			-0.131***
			(0.0159)
Year-fixed effects	Yes	Yes	Yes
Firm-fixed effects	Yes	Yes	Yes
Observations	1,146,626	1,146,626	1,146,626
R^2	0.399	0.399	0.400

Standard errors, reported in parentheses, are clustered at the firm level.

All regressions include firm and year fixed effects.

We winsorize each variable at the country level by replacing the top and bottom 2 percent of the distribution.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.6 Do these shocks matter for aggregate credit and investment?

The empirical results from the aggregate-level analysis provide a crucial link between micro-level shocks and their macroeconomic consequences. In the aggregate regressions, we incorporate monthly loan growth data from the BSI and monthly-interpolated quarterly aggregate investment data measured as gross fixed capital formation from the quarterly sectoral accounts of non-financial corporations, with the overall investment rate encompassing both tangible and intangible assets. Table 17 shows that shocks originating at the firm, bank, and industry levels are not simply idiosyncratic noise; rather, they are significant drivers of aggregate fluctuations in both loan growth and investment. A Shapley-Owen R-squared decomposition is used to quantify the contribution of each shock type to the model's overall explanatory power. The findings are consistent with the "granular hypothesis," which posits that large idiosyncratic shocks to individual firms or institutions can have a non-trivial impact on the aggregate economy.

For aggregate loan growth, the decomposition reveals that firm-specific shocks (24.92%) and bank-specific shocks (22.21%) are the primary drivers of fluctuations, collectively explaining nearly half of the total variation. This strongly supports the financial accelerator and credit channel theories, which argue that disruptions originating from individual firm balance sheets or the banking system can profoundly impact credit supply. A key finding from the literature confirms that granular bank shocks alone can account for a sizable portion of aggregate loans and investment fluctuations. In contrast, the results for aggregate investment show that industry shocks (42.70%) and firm-specific shocks (20.00%) are the dominant explanatory factors.

Comparing aggregate-level results for investment with the previous firm-level findings, the differences in the signs and magnitudes of the coefficients for bank supply, firm demand, and industry shocks can be attributed to three factors: (i) composition effects: aggregate investment includes intangibles, which have a weak connection to bank credit but a strong one to internal cash, so combining tangibles and intangibles can dilute or reverse bank-shock coefficients; (ii) crisis timing (2020–2021): credit often increased (due to guarantees/liquidity draws) while investment decreased, leading to a negative macro-level association even if the effects within firms were positive; and (iii) sign conventions/aggregation: firm-level analyses distinguish between positive and negative shocks and adjust signs, whereas the aggregate analysis employs single standardized shocks, along with differences in weighting, measurement (such as the capitalization of intellectual property products), and coverage. Moreover, the sample size for the aggregate analysis (5 years) is relatively short. Overall, this is a notable distinction, as it suggests that while financial and firm-level shocks are vital for explaining credit supply dynamics, the ultimate decisions to invest at the macro level are more heavily influenced by industry-wide trends and the collective behavior of individual firms.

Table 17: Effect of Shocks on Aggregate Loan Growth and Investment Rate

	Loan Growth$_t$			**Aggregate Investment Rate**$_t$		
	(1)	(2)	(3)	(1)	(2)	(3)
Common Shock$_t$	-0.0127	0.300***	0.572***	-0.0653	-0.356***	-0.353***
	(0.0284)	(0.0542)	(0.103)	(0.0738)	(0.118)	(0.117)
Industry Shock$_t$	-0.321	0.287	0.0504	4.695***	4.131***	0.378***
	(0.402)	(0.268)	(0.0470)	(0.860)	(0.776)	(0.0709)
Firm Shock$_t$	0.0655	0.286***	0.280***	-0.914***	-1.118***	-0.570***
	(0.0615)	(0.0725)	(0.0709)	(0.131)	(0.146)	(0.0744)
Bank Shock$_t$		0.281***	0.705***		-0.261***	-0.341***
		(0.0524)	(0.132)		(0.0901)	(0.118)
Standardized variables	No	No	Yes	No	No	Yes
Country-fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	208	208	208	208	208	208
R^2	0.448	0.627	0.627	0.284	0.326	0.326
Shapley-Owen R-squared decomposition						
Common Shock$_t$			12.43%			3.41%
Industry Shock$_t$			2.83%			42,70%
Firm Shock$_t$			24.92%			20.00%
Bank Shock$_t$			22.21%			4.44%

We winsorize each variable at the country level by replacing the top and bottom 2 percent of the distribution. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

6 Robustness checks

The robustness checks presented in Table 18 provide further insight into the factors that influence firm investment. The inclusion of additional control variables, such as a lagged firm shock ($Firm\ Shock_{f,t-1}$), liquidity ratio ($Liquidity\ ratio_{f,t-1}$), and cash holdings ($Cash\ Holdings_{f,t-1}$), confirms that the core relationships observed in the previous analyses remain stable.

The results show that firms with higher cash holdings and greater liquidity are better positioned to sustain investments, even during periods of external stress. This finding aligns with the theory of liquidity preference, which states that firms emphasize short-term financial stability and liquidity in response to economic shocks. The fact that these internal liquidity measures maintain their significance alongside external factors such as bank and firm shocks underscores the importance of a firm's financial discipline in its investment decisions.

Table 18: Robustness checks

Dependent variable: $Investment_{f,t}/Capital_{f,t-1}$	(1)	(2)	(3)
$Cash\ Flow_{f,t}/Capital_{f,t-1}$	0.0774***	0.0761***	0.0764***
	(0.00110)	(0.000797)	(0.000814)
$Sales\ Growth_{f,t-1}$	0.0130***	0.0247***	0.00876***
	(0.00365)	(0.00284)	(0.00290)
$Industry\ Shock_{f,t}$	-0.526***	-0.438***	-0.451***
	(0.0341)	(0.0272)	(0.0278)
$Bank\ Shock_{f,t}$	0.0635***	0.0589***	0.0619***
	(0.00773)	(0.00560)	(0.00573)
$Firm\ Shock_{f,t}$	0.0898***	0.0860***	0.0892***
	(0.00281)	(0.00213)	(0.00215)
$Bank\ Shock_{f,t} \times (LoanDependence_f)$	0.0484**	0.0410**	0.0324*
	(0.0206)	(0.0161)	(0.0166)
$Firm\ Shock_{f,t} \times (LoanDependence_f)$	0.0729***	0.127***	0.123***
	(0.00957)	(0.00796)	(0.00813)
$Firm\ Shock_{f,t-1}$	0.0196***		
	(0.00147)		
$Liquidity\ ratio_{f,t-1}$		0.00670***	
		(0.000418)	
$Cash\ Holdings_{f,t-1}$			1.255***
			(0.0199)
Year-fixed effects	Yes	Yes	Yes
Firm-fixed effects	Yes	Yes	Yes
Observations	695,011	1,144,315	1,105,622
R^2	0.432	0.400	0.406

Standard errors, reported in parentheses, are clustered at the firm level.

All regressions include firm and year fixed effects.

We winsorize each variable at the country level by replacing the top and bottom 2 percent of the distribution.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

7 Conclusions

This study shows that bank supply shocks significantly affect firm-level investment within the euro area. Using novel loan-level data from AnaCredit and the framework of Amiti and Weinstein (2018), we decompose loan growth into four components: bank-specific, firm-specific, industry-specific, and common shocks, and link these shocks to firm-level tangible investment. This analysis provides a coherent bridge between micro-level identification to macro-level implications, enabling a comprehensive analysis of how lender-specific disruptions shape firm-level investment and, therefore, the overall economic dynamics.

At the micro level, bank supply shocks have substantial and consistent effects on firm-level tangible investment. These effects vary with firm characteristics: smaller and younger firms, firms more dependent on bank financing, and firms with a larger share of short-term debt are particularly vulnerable. In contrast, investment in intangible assets appears relatively unaffected by bank supply shocks, consistent with the greater reliance on internal funding and limited collateral value of intangibles. Sectoral composition also matters: service and manufacturing firms and firms in countries where bank intermediation is central to corporate finance exhibit greater sensitivity to credit supply shocks than others. At the macro level, the granular shocks we estimate account for a large share of aggregate credit fluctuations, whereas movements in aggregate investment reflect an interplay between these bank-driven forces, broader industry trends, and firm-level credit demand. This pattern is consistent with a financial accelerator mechanism: disruptions in the supply of bank credit can compress investment at scale, particularly when borrowers have limited access to alternative funding sources.

Our analysis highlights meaningful cross-country differences, such as higher sensitivities in Italy and Spain, underscoring the roles of banking market structure, the maturity mix of credit, and firms' outside options in shaping the transmission of such shocks. This study demonstrates that the Amiti and Weinstein (2018) methodology is well-suited to multi-country credit data, which includes the four largest euro area economies over 2019–2023, a period that includes the COVID-19 pandemic, the Russia-Ukraine war and the subsequent tightening of financial conditions.

These findings have clear policy implications. First, it is essential to monitor not only the level but also the distribution of bank credit supply, as idiosyncratic shocks at major intermediaries can significantly affect the aggregate. Second, policies that enhance borrowers' resilience, such as promoting lender diversification where feasible, strengthening liquidity buffers, and extending debt maturities, can mitigate the real effects of adverse bank supply shocks. Third, because intangible-driven growth is inherently under-collateralized, supporting bank financing with scalable alternatives can protect innovative investments throughout the cycle. Overall, in financial systems centered around banks, lender-specific disturbances significantly impact firm-level investment and, through aggregation, can affect the real economy.

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Appendix A Charts

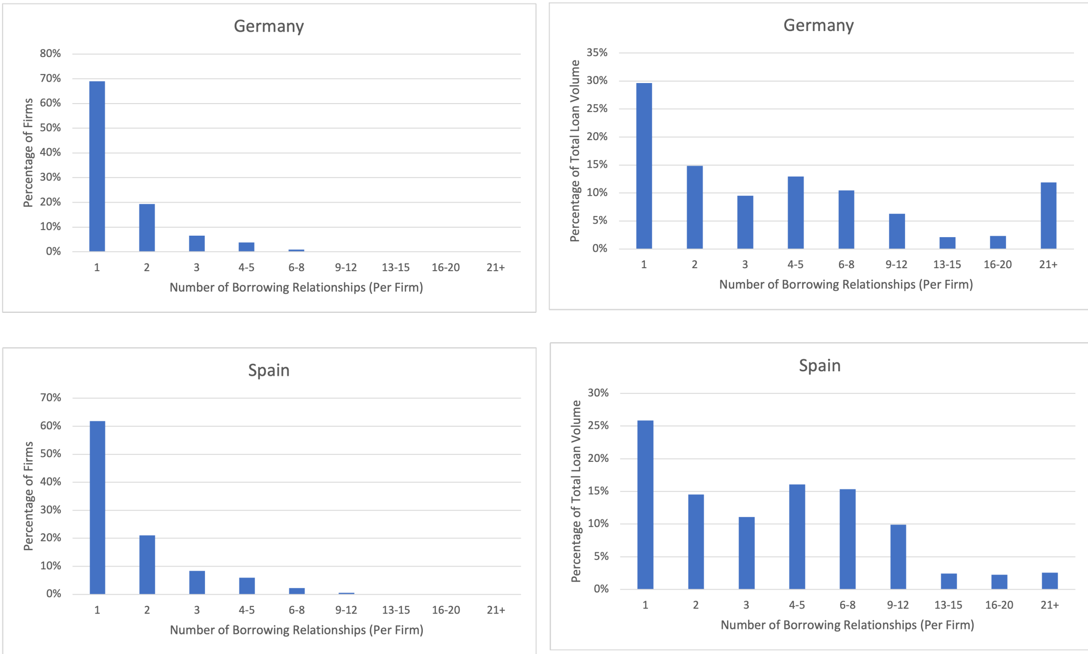


Figure 3: Number of borrowing relationship per firm - Germany and Spain

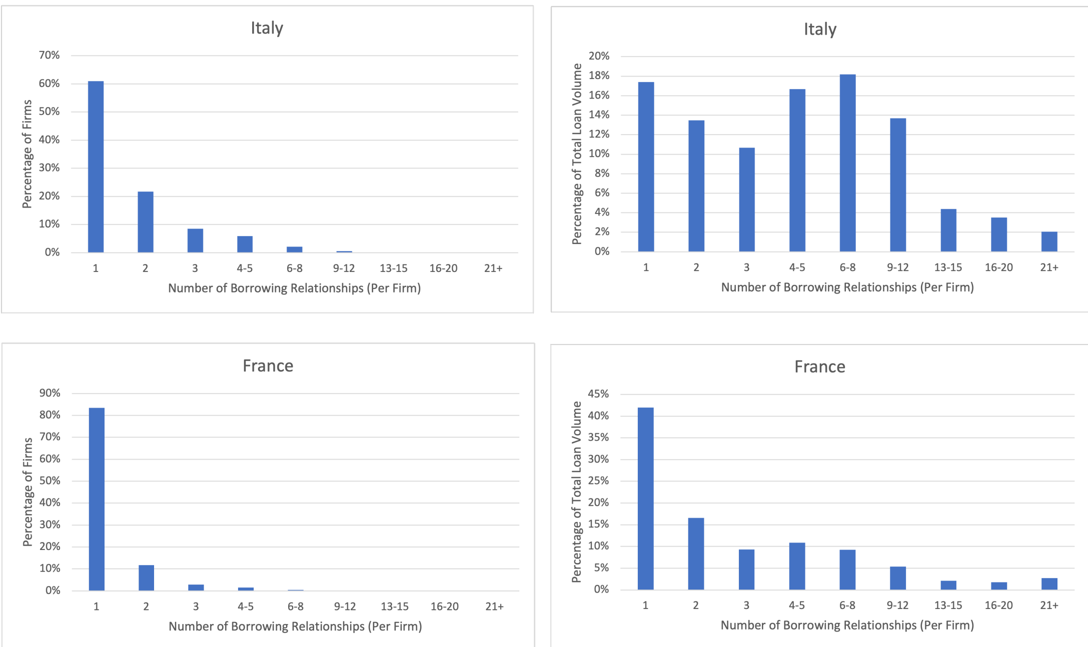


Figure 4: Number of borrowing relationship per firm - Italy and France

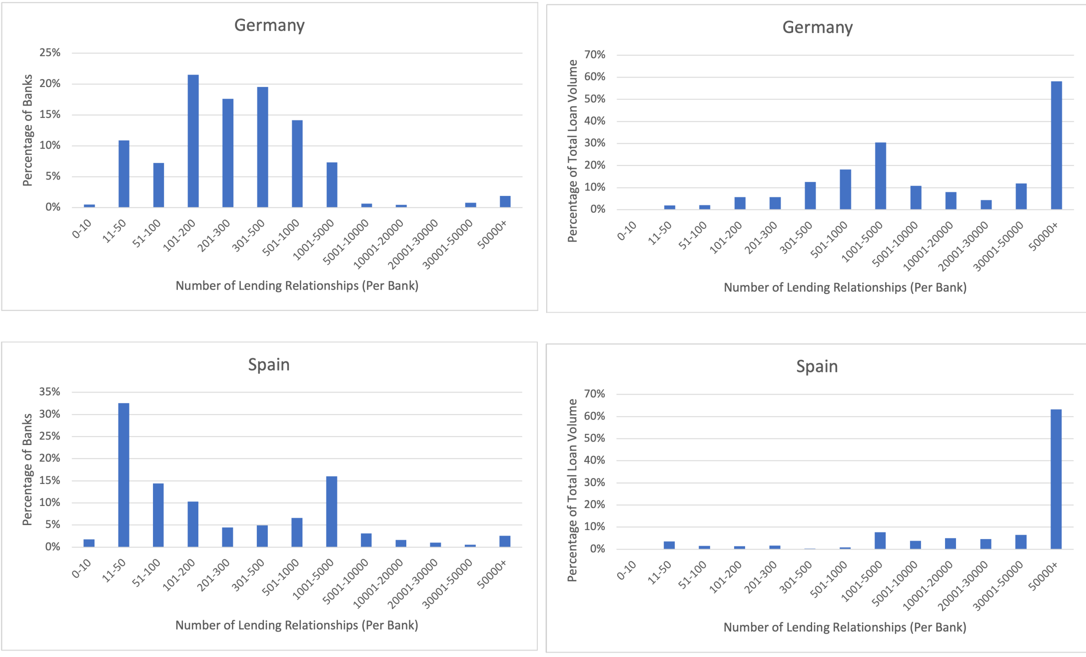


Figure 5: Number of lending relationship per bank - Germany and Spain

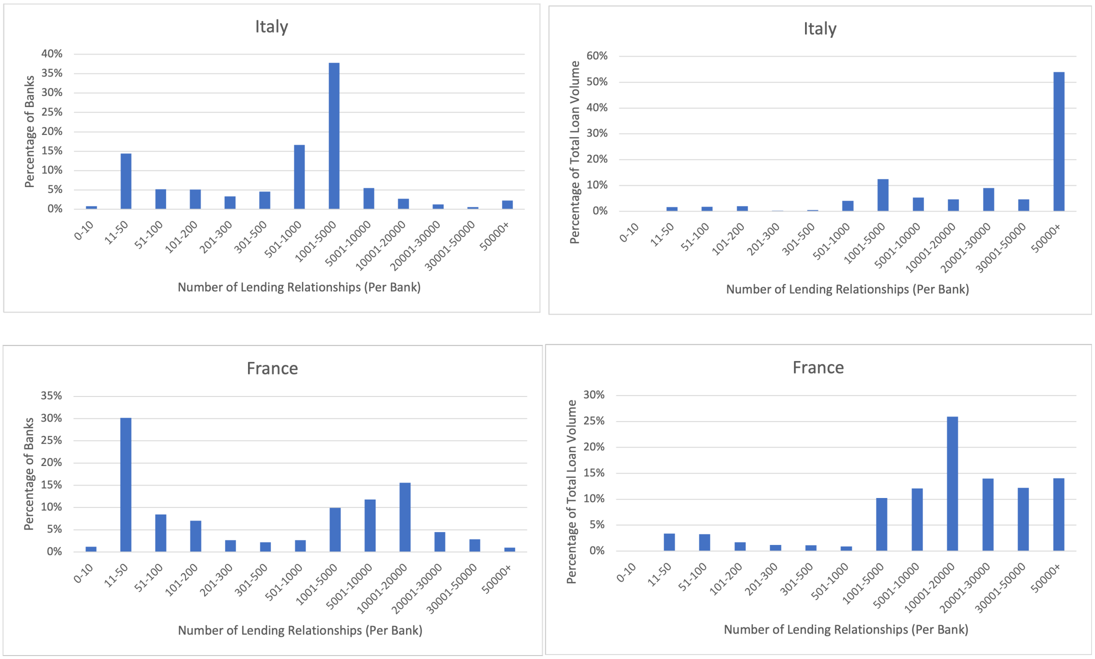
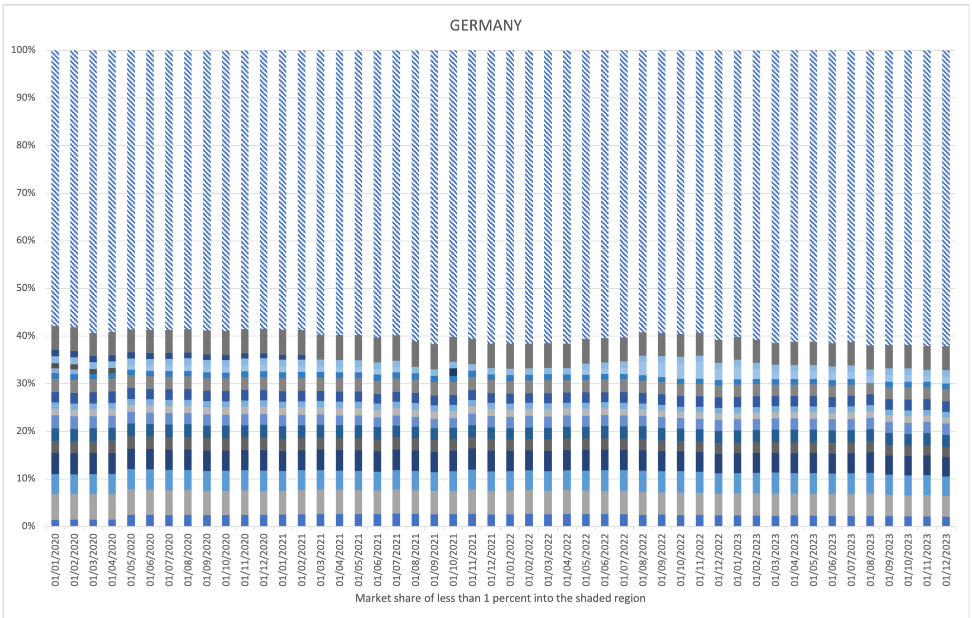


Figure 6: Number of lending relationship per bank - Italy and France



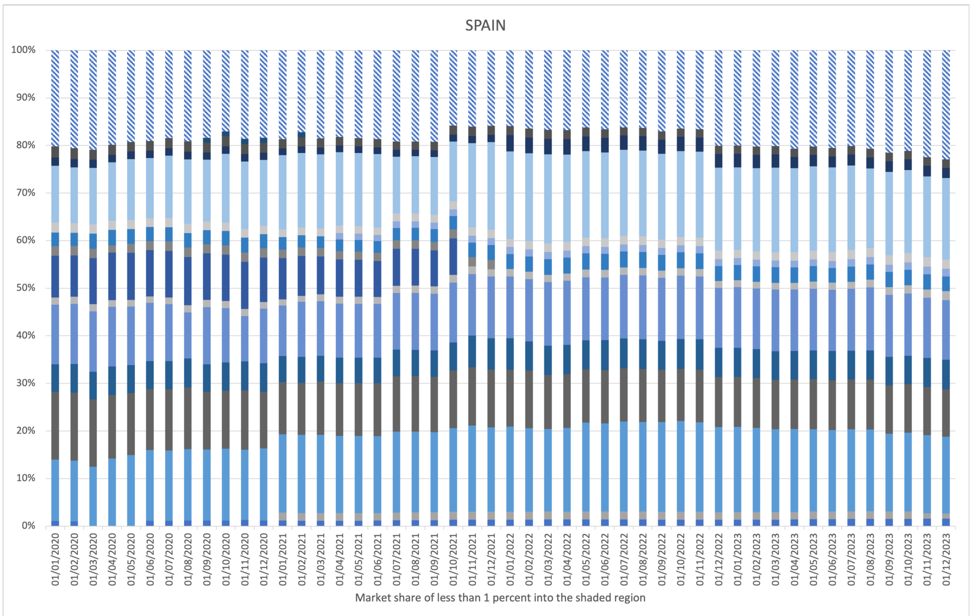
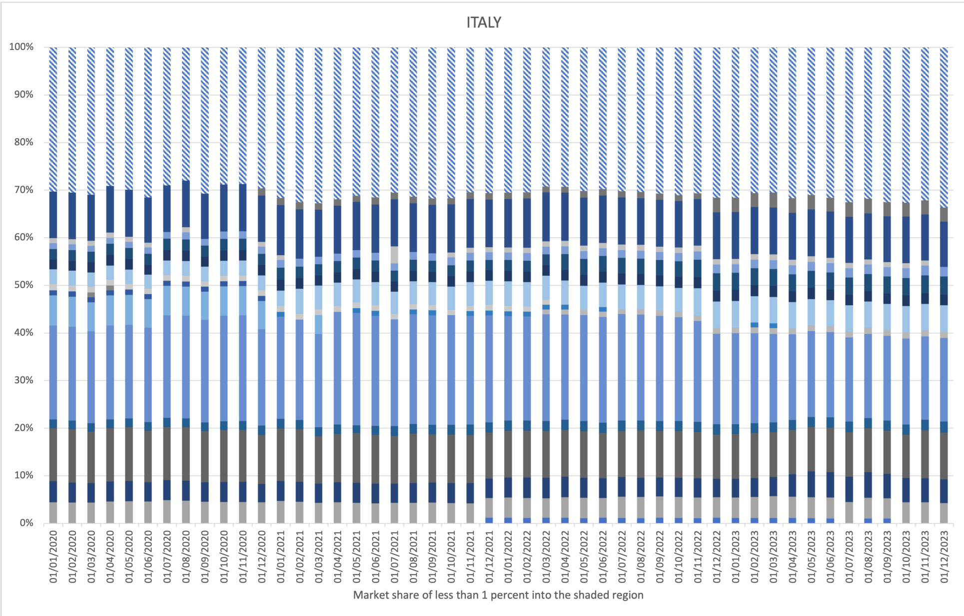


Figure 7: Bank concentration - Germany and Spain



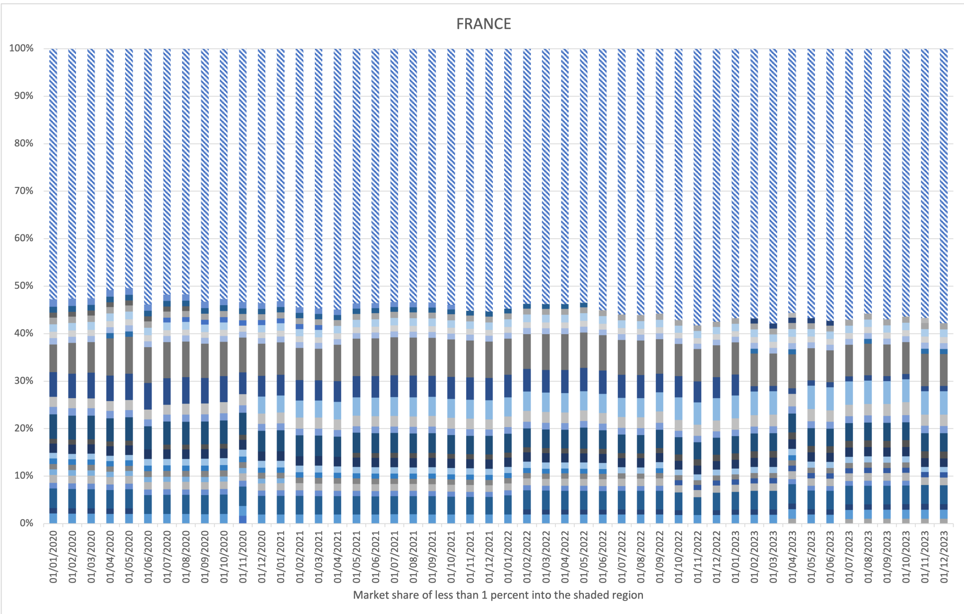
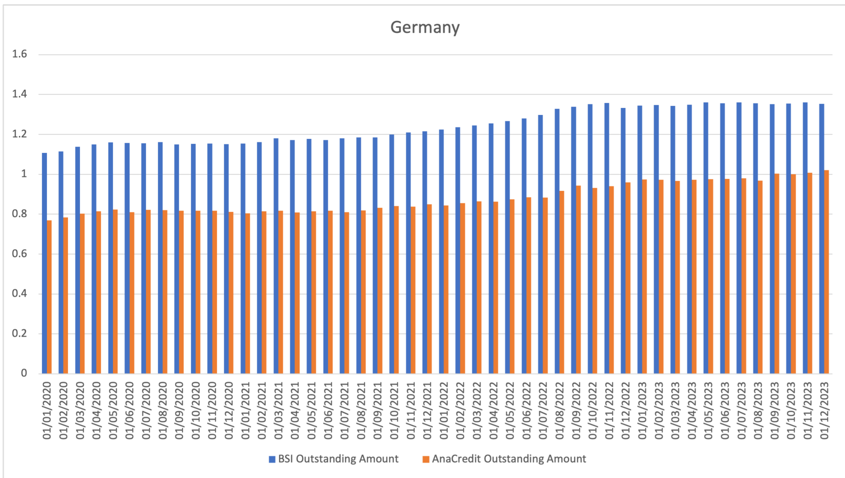


Figure 8: Bank concentration - Italy and France



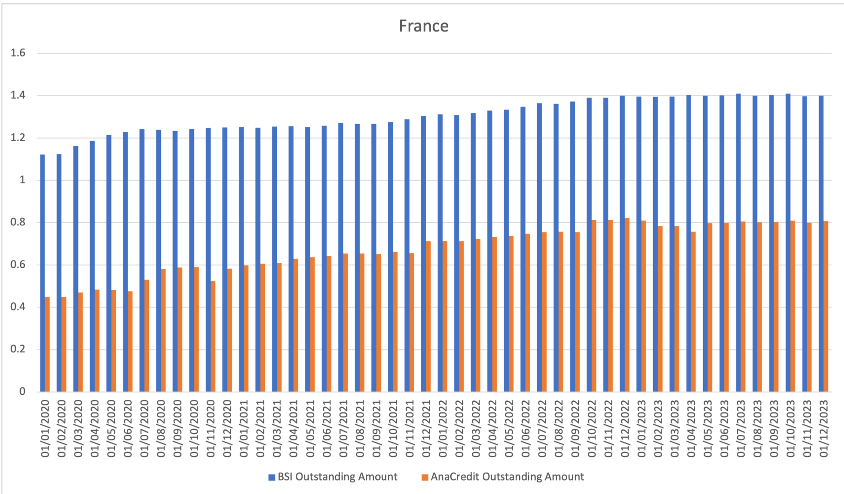


Figure 9: Outstanding amount of credit (trillion Euros) - Germany and France

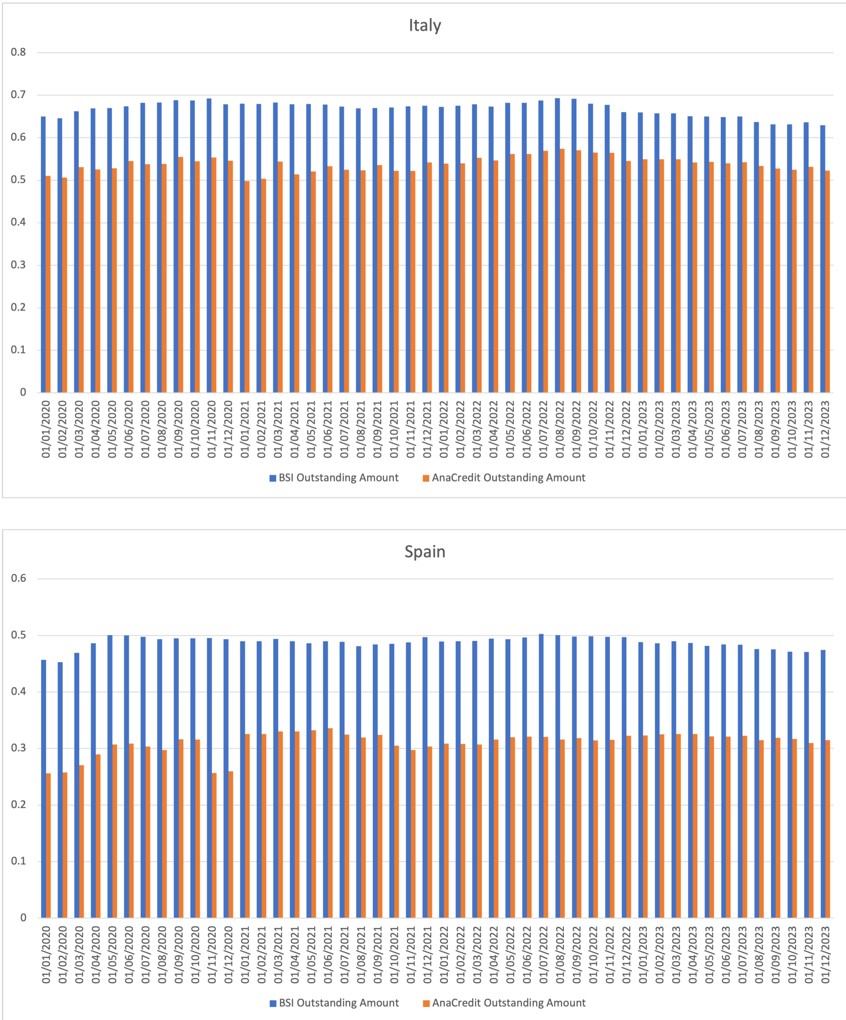


Figure 10: Outstanding amount of credit (trillion Euros) - Italy and Spain

Appendix B Tables

Table 19: External Validity - Bank Supply - Germany

Dependent Variable: *Bank Shocks*$_{b,t}$	(1)	(2)	(3)
Low Return on Asset$_{b,t}$	-0.0434***		
	(0.0152)		
Low Return on Equity$_{b,t}$		-0.0417***	
		(0.0159)	
Large Capital Increase$_{b,t}$			0.0271
			(0.0198)
R^2	0.005	0.004	0.003
Observations	2,816	2,816	2,816

Standard errors, reported in parentheses, are clustered at the bank level.
All regressions include year fixed effects.
We winsorize each variable at the country level by replacing the top and bottom 2 percent of the distribution.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 20: External Validity - Bank Supply - France

Dependent Variable: *Bank Shocks*$_{b,t}$	(1)	(2)	(3)
Low Return on Asset$_{b,t}$	0.0151		
	(0.151)		
Low Return on Equity$_{b,t}$		-0.0459	
		(0.131)	
Large Capital Increase$_{b,t}$			-0.249
			(0.205)
R^2	0.052	0.052	0.056
Observations	44	44	44

Standard errors, reported in parentheses, are clustered at the bank level.
All regressions include year fixed effects.
We winsorize each variable at the country level by replacing the top and bottom 2 percent of the distribution.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 21: External Validity - Bank Supply - Italy

Dependent Variable: *Bank Shocks*$_{b,t}$	(1)	(2)	(3)
Low Return on Asset$_{b,t}$	-0.372**		
	(0.146)		
Low Return on Equity$_{b,t}$		-0.551***	
		(0.176)	
Large Capital Increase$_{b,t}$			0.193
			(0.334)
R^2	0.097	0.157	0.047
Observations	63	63	63

Standard errors, reported in parentheses, are clustered at the bank level.
All regressions include year fixed effects.
We winsorize each variable at the country level by replacing the top and bottom 2 percent of the distribution.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 22: External Validity - Bank Supply - Spain

Dependent Variable: *Bank Shocks*$_{b,t}$	(1)	(2)	(3)
Low Return on Asset$_{b,t}$	-0.495**		
	(0.202)		
Low Return on Equity$_{b,t}$		-0.360*	
		(0.209)	
Large Capital Increase$_{b,t}$			0.181
			(0.206)
R^2	0.234	0.230	0.227
Observations	353	353	353

Standard errors, reported in parentheses, are clustered at the bank level.
All regressions include year fixed effects.
We winsorize each variable at the country level by replacing the top and bottom 2 percent of the distribution.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 23: External Validity - Firm Demand - Germany

Dependent Variable: *Firm Shocks*$_{f,t}$	(1)	(2)	(3)	(4)
Younger Firms$_{f,t}$	0.0902***			
	(0.00507)			
More Profitable Firms$_{f,t}$		-0.0220*		
		(0.0122)		
High Debted Firms$_{f,t}$			0.103***	
			(0.00519)	
High Liquidity] = *Firms*$_{f,t}$				-0.0686***
				(0.00529)
R^2	0.006	0.005	0.006	0.006
Observations	309,641	309,641	309,641	309,641

Standard errors, reported in parentheses, are clustered at the firm level.
All regressions include sector × year fixed effects.
We winsorize each variable at the country level by replacing the top and bottom 2 percent of the distribution.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 24: External Validity - Firm Demand - Spain

Dependent Variable: *Firm Shocks*$_{f,t}$	(1)	(2)	(3)	(4)
Younger Firms$_{f,t}$	0.159***			
	(0.00308)			
More Profitable Firms$_{f,t}$		-0.0696***		
		(0.00308)		
High Debted Firms$_{f,t}$			0.0438***	
			(0.00301)	
High Liquidity Firms$_{f,t}$				-0.0415***
				(0.00314)
R^2	0.012	0.008	0.008	0.008
Observations	621,185	621,185	621,185	621,185

SStandard errors, reported in parentheses, are clustered at the firm level.
All regressions include sector × year fixed effects.
We winsorize each variable at the country level by replacing the top and bottom 2 percent of the distribution.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 25: External Validity - Firm Demand - Italy

Dependent Variable: *Firm Shocks*$_{f,t}$	(1)	(2)	(3)	(4)
Younger Firms$_{f,t}$	0.135***			
	(0.00270)			
More Profitable Firms$_{f,t}$		-0.0532***		
		(0.00268)		
High Debted Firms$_{f,t}$			0.102***	
			(0.00254)	
High Liquidity Firms$_{f,t}$				0.0209***
				(0.00273)
R^2	0.013	0.010	0.011	0.009
Observations	776,002	776,002	776,002	776,002

Standard errors, reported in parentheses, are clustered at the firm level.
All regressions include sector × year fixed effects.
We winsorize each variable at the country level by replacing the top and bottom 2 percent of the distribution.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 26: External Validity - Firm Demand - France

Dependent Variable: *Firm Shocks*$_{f,t}$	(1)	(2)	(3)	(4)
Younger Firms$_{f,t}$	-0.181***			
	(0.00451)			
More Profitable Firms$_{f,t}$		-0.162***		
		(0.00585)		
High Debted Firms$_{f,t}$			0.0243***	
			(0.00493)	
High Liquidity Firms$_{f,t}$				-0.0148***
				(0.00505)
R^2	0.029	0.028	0.026	0.026
Observations	398,697	398,697	398,697	398,697

Standard errors, reported in parentheses, are clustered at the firm level.
All regressions include sector × year fixed effects.
We winsorize each variable at the country level by replacing the top and bottom 2 percent of the distribution.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 27: Effect of Shocks on Aggregate Loan Growth and Investment Rate: Italy

	Loan Growth$_t$			**Aggregate Investment Rate**$_t$		
	(1)	(2)	(3)	(1)	(2)	(3)
Common Shock$_t$	0.456***	1.049***	0.992***	1.073**	1.205**	0.402**
	(0.162)	(0.128)	(0.121)	(0.498)	(0.476)	(0.159)
Industry Shock$_t$	-2.317**	-0.622	-0.0897	14.61***	14.99***	0.761***
	(0.960)	(0.671)	(0.0966)	(2.577)	(2.759)	(0.140)
Firm Shock$_t$	0.0860	0.827***	0.840***	-1.540***	-1.375***	-0.493***
	(0.117)	(0.125)	(0.127)	(0.275)	(0.412)	(0.147)
Bank Shock$_t$		0.722***	0.858***		0.161	0.0675
		(0.0748)	(0.0890)		(0.272)	(0.114)
Standardized variables	No	No	Yes	No	No	Yes
Observations	52	52	52	52	52	52
R-squared	0.408	0.740	0.740	0.581	0.583	0.583
Shapley-Owen R-squared decomposition						
Common Shock$_t$			37.8%			15.89%
Industry Shock$_t$			20.08%			44.21%
Firm Shock$_t$			13.41%			34.24%
Bank Shock$_t$			28.71%			5.66%

We winsorize each variable at the country level by replacing the top and bottom 2 percent of the distribution.
Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 28: Effect of Shocks on Aggregate Loan Growth and Investment Rate: Germany

	Loan Growth$_t$			**Aggregate Investment Rate$_t$**		
	(1)	(2)	(3)	(1)	(2)	(3)
Common Shock$_t$	0.402	1.080***	0.962***	0.740	0.943**	0.401**
	(0.305)	(0.286)	(0.255)	(0.448)	(0.452)	(0.193)
Industry Shock$_t$	0.0184	0.907	0.293	5.736***	6.002***	0.928***
	(1.380)	(0.982)	(0.318)	(1.906)	(1.749)	(0.271)
Firm Shock$_t$	0.712*	1.046***	0.796***	-0.237	-0.137	-0.0498
	(0.400)	(0.222)	(0.169)	(0.595)	(0.620)	(0.225)
Bank Shock$_t$		0.550***	0.758***		0.165	0.109
		(0.142)	(0.195)		(0.185)	(0.122)
Standardized variables	No	No	Yes	No	No	Yes
Observations	52	52	52	52	52	52
R-squared	0.174	0.602	0.602	0.345	0.353	0.353
Shapley-Owen R-squared decomposition						
Common Shock$_t$			19.24%			18.11%
Industry Shock$_t$			7.54%			59.75%
Firm Shock$_t$			28.14%			20.95%
Bank Shock$_t$			45.08%			1.19%

We winsorize each variable at the country level by replacing the top and bottom 2 percent of the distribution. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 29: Effect of Shocks on Aggregate Loan Growth and Investment Rate: Spain

	Loan Growth$_t$			**Aggregate Investment Rate$_t$**		
	(1)	(2)	(3)	(1)	(2)	(3)
Common Shock$_t$	-0.117***	0.0737	0.261	-0.132**	-0.372*	-0.580*
	(0.0361)	(0.104)	(0.367)	(0.0511)	(0.203)	(0.317)
Industry Shock$_t$	-4.880***	-2.978***	-0.479***	8.951***	6.549***	0.465***
	(0.549)	(0.830)	(0.133)	(1.316)	(1.938)	(0.137)
Firm Shock$_t$	0.397***	0.419***	0.441***	-0.524**	-0.551***	-0.256***
	(0.0788)	(0.0716)	(0.0754)	(0.196)	(0.188)	(0.0873)
Bank Shock$_t$		0.154*	0.648*		-0.194	-0.361
		(0.0896)	(0.378)		(0.165)	(0.307)
Standardized variables	No	No	Yes	No	No	Yes
Observations	52	52	52	52	52	52
R-squared	0.520	0.617	0.617	0.551	0.581	0.581
Shapley-Owen R-squared decomposition						
Common Shock$_t$			10.09%			31.39%
Industry Shock$_t$			36.06%			54.15%
Firm Shock$_t$			22.78%			6.05%
Bank Shock$_t$			31.06%			8.42%

We winsorize each variable at the country level by replacing the top and bottom 2 percent of the distribution. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 30: Effect of Shocks on Aggregate Loan Growth and Investment Rate: France

	Loan Growth$_t$			**Aggregate Investment Rate$_t$**		
	(1)	(2)	(3)	(1)	(2)	(3)
Common Shock$_t$	-0.243**	-0.128	-0.325	1.022***	0.850**	0.796**
	(0.104)	(0.132)	(0.336)	(0.283)	(0.319)	(0.299)
Industry Shock$_t$	1.458***	1.486***	0.449***	1.620	1.579	0.176
	(0.437)	(0.393)	(0.119)	(1.309)	(1.256)	(0.140)
Firm Shock$_t$	-0.289**	-0.176	-0.305	0.399	0.230	0.147
	(0.121)	(0.158)	(0.275)	(0.311)	(0.352)	(0.225)
Bank Shock$_t$		0.0541	0.214		-0.0808	-0.118
		(0.0510)	(0.202)		(0.130)	(0.189)
Standardized variables	No	No	Yes	No	No	Yes
Observations	52	52	52	52	52	52
R-squared	0.435	0.450	0.450	0.523	0.527	0.527
Shapley-Owen R-squared decomposition						
Common Shock$_t$			16.57%			50.53%
Industry Shock$_t$			51.33%			3.00%
Firm Shock$_t$			6.25%			20.54%
Bank Shock$_t$			25.84%			25.92%

We winsorize each variable at the country level by replacing the top and bottom 2 percent of the distribution. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.