Credit allocation and the financial crisis: evidence from Spanish companies

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Received: 5 November 2018 / Accepted: 9 June 2022 / Published online: 18 August 2022
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Abstract
The worldwide financial crisis of 2007–2008 raised serious concerns about the soundness of banks’ activities and about the extent to which banking regulation should supervise banks’ investment decisions. We contribute to this topic by examining the Spanish case, which has been emblematic of the bubble and burst dynamics in the credit market. In particular, we study the allocation of bank credit among Spanish companies from 1999 to 2014, showing that larger companies accumulated greater amounts of bank loans per unit of total assets, thus leading to a notable concentration. We also find that, during the Spanish boom period, bank loans shifted from the manufacturing to the construction industry, and in particular to the largest companies of the latter sector. This happened in spite of the high leverage of large construction firms, which was increasing also due to their growing debt. We argue that the higher operating benefits, reflecting the increase of the housing price during the boom period, overvalued construction firms as potential borrowers. The bankruptcy of several large construction companies during the Spanish crisis supports the need for monitoring and regulation, to avoid an excessive concentration of bank credit to a few large companies, especially if they belong to a specific sector.

Keywords Credit allocation · Financial crisis · Financial leverage · Firm size · Industries and sectors

JEL Classification G21 · L11 · C24

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1 Introduction

It is well known that Spanish companies finance their production and investments mainly through bank loans, suggesting that the channeling of bank loans into the economy is a critical issue that deserves attention. In particular, the financial crises of 2007, triggered by the housing bubble, and the consequent subprime mortgage crises proved that lender–borrower links (both bank-household and bank-firm) in the credit market are very relevant and that the way loans are distributed in the economy may dramatically determine economic fluctuations and downturns.

In this regard, it is crucial to inspect how loans by commercial banks have been allocated to Spanish companies, and to understand whether and how this distribution of credit money might have contributed to the fragility of the economy, and to its final collapse. In this paper, we address this issue by studying the determinants of bank loan allocation to Spanish companies during the boom and crisis periods, and by assessing how these loans affected the economic performance and the financial stability of the companies. Our methodology is based on the “micro” observation of medium-to-large Spanish companies, which hold a significant part of total bank loans. In particular, we observe the evolution, from 1999 to 2014, of the balance sheets entries of these companies, along with other financial statement items.

In order to answer the general question of the paper, we identify three research steps that should help us to better tackle the problem. In the first step, we examine how banks supplied loans to firms, according to their size and economic sector. In particular, we study whether bank credit is concentrated to large companies or to companies that belong to specific sectors, and how this concentration evolves during the observed time span. We find strong evidence of concentration of bank loans in the balance sheets of large companies, i.e., a large amount of bank loans is held by a relatively small number of big firms. This result is in line with other financial statement items of firms, like sales, equity, or total assets, which often follow fat-tailed distributions, but bank loans exhibit the highest concentration level among all these items. These concentration levels are also quite stable and persistent during the examined time span. Moreover, we find a sizable shift in the allocation of bank loans during the Spanish boom, from manufacturing to the construction sector. In 1999, both sectors had a share of around 30% of total bank loans, but a few years later, in 2007, companies in the construction sector held 55% of total bank loans, while companies in the manufacturing sector were left with 15%. At the same time, very large firms in the construction sector accumulated a considerable share of this new debt, showing also a growing leverage ratio.

In the second step, we investigate the economic performance and the financial robustness of companies that have been granted loans throughout the observed period. We find that profitability (measured with return on assets) of companies that received larger amounts of loans has been low, while their cost of debt increased, potentially undermining financial stability. In addition, we estimate that the bankruptcy probability

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1 See, for instance, the recent study “Financial systems in Europe and the United States: Structural differences where banks remain the main source of finance for companies” by the European Savings and Retail Banking Group (ESBG); http://www.wsbi-esbg.org/SiteCollectionDocuments/EU-US.study.ESBG%20May.2016.pdf.

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of companies that received larger amounts of bank loans has been significantly higher, especially after the bubble burst in 2008. This evidence corroborates the idea of a questionable mechanism for allocating bank loans over firms.

The last step focuses on understanding the determinants of the allocation process of bank loans, which contributed to concentrate credit to the balance sheet of large companies. We estimated parametric and semi-parametric models showing that large companies, during the boom period, received new loans in a more than a proportional way with respect to their total assets. This is even more evident for companies belonging to the construction sector and might explain the observed concentration of bank credit. Our analysis also suggests that companies with high financial leverage were still able to attract large amount of loans. Therefore, large companies, especially in the construction sector, became even larger (in terms of total assets) and riskier (in terms of financial leverage).

The paper proceeds as follows: The next section presents the literature review. Section 3 describes the data set. The results of the descriptive and econometric analysis are then discussed in Sects. 4 and 5, respectively. The paper ends with conclusions in Sect. 6.

2 Literature review

As outlined in the introduction, in order to investigate the role that bank loans allocation played in the period of the Spanish financial crisis, the paper addresses multiple research questions. We are not aware of previous papers that address the problem in the same general terms we do, but each one of the research questions we tackle can be connected to different streams of literature. A first stream regards the decision faced by banks on how to allocate credit among borrowers, related in particular to the diversification vs. concentration issue. This literature essentially focuses on banks’ operating practices about loans’ allocation and thus on credit availability for companies. It is connected to our paper because it gives a rationale for why banks should concentrate loans to a smaller set of companies or not. Another stream of literature tries to find a relation between the credit sector activity, business cycles, and economic instability. Apart from the classic macroeconomic literature on the effects of financial shocks, post-Keynesian and agent-based literature explored credit-driven bubble and burst dynamics. Several empirical studies on bank-firms credit links flourished after the financial crisis. However, few of these works focused on the effects of bank loans concentration.

The main body of literature dealing with the allocation of bank loans aims at finding a suitable composition of banks portfolio to achieve an optimal risk/return trade-off. The two main elements in this literature are portfolio diversification, which should decrease the exposure to risk, and information asymmetry between banks and firms, which leads to a higher risk for banks (Persky and Bassett 2006; Artzner et al. 1999; Haugen 2001). The theory advocates that, given asymmetric information in the financial market, the diversification is likely to moderate the cost of financial intermediation (Diamond 1984) and raises the incentive to monitor (Cerasi and Daltung 2000). It also increases profit efficiency, reduces banks’ realized risk, and has a positive impact
on banks’ capitalization (Rossi et al. 2009). However, since financial markets run with frictions due to asymmetric information, the literature on financial intermediation argues that banks can gather expertise and reduce uncertainty if they concentrate lending on particular sectors (Jahn et al. 2013). Lenders also endeavor to build a long-term relationship with their borrowers focusing on a smaller number of companies. This lending strategy, where lenders gather borrowers’ soft information over time, is called relationship lending. The financial literature shows that the relationship lending can generate useful information for lenders, with significant effects on their access to credit and with minor effects on credit price (Petersen and Rajan 1994; Petersen 1999). Moreover, DeYoung and Roland (2001), Stiroh (2004) and Stiroh and Rumble (2006) argue that the higher volatility of non-interest income, induced by the diversified investment portfolio, outweighs diversification benefits. Considering diversification across industries, Acharya et al. (2006) shows that diversification worsens the effectiveness of monitoring, resulting in lower bank returns and riskier loan portfolios for high-risk banks. In our paper, we analyze the balance sheets of borrowing companies, showing that bank loans in Spain have been highly concentrated to large firms during the observed time span. In the boom period, until 2007, loans were mainly given to large firms in the construction sector. This evidence suggests the predominance of relationship lending with respect to diversification. We also show that the economic performance of the firms that obtained large amounts of credit has often been disappointing, therefore increasing the risk borne by banks.

Concerning the economic impact of credit money distribution, classic macroeconomic models did not pay traditionally much attention to financial intermediation, as stated by Stiglitz (2018). After the crisis, one of the main challenges has been to capture the interaction between banking distress and the real economy. A priority for DSGE models has been to better integrate the role of credit institutions and financial frictions (see Gertler and Kiyotaki 2015; Gertler et al. 2016). However, this literature does not address the distributional issues of financial resources raised in our paper. In this respect, we show how the concentration of bank lending to large companies in Spain increased the financial leverage of these companies, potentially undermining the robustness of the banking sector. The work of Acharya et al. (2019) shows how the credit market fails due to the concentration of loans, which, in turn, weakens the effects of unconventional monetary policy. The authors claim that the concentration of bank lending to large companies strengthens their ties, making banks more dependent on their borrowers and more exposed to systemic risk. If the central bank aims to recapitalize the financial sector, the policy may not affect the real economy since lenders will primarily finance existing low-quality borrowers, so-called zombie companies, to avoid bigger losses (too big to fail). In addition, zombie loans are usually extended at a favorable interest rate distorting the market competition and affecting the overall economic performance. In this paper, we observe a concentration of credit money to large firms also during the boom period, as the size of a company turns out to be an important factor for obtaining bank loans. We also show that companies receiving bank loans have been often characterized by low profitability and high leverage, running into bankruptcy with a higher probability, denoting a questionable process of credit allocation. Our paper contributes to this literature, showing that the problem of zombie companies in the aftermath of a crisis might originate before, during good times,
due to an excessive concentration of bank credit. One of the few studies that explores the macroeconomic impact of the concentration of banking markets is Bremus et al. (2018), which investigates the relation between growth fluctuations and bank granularity. They show (in the spirit of Gabaix (2011)) that idiosyncratic shocks to large banks may affect macroeconomic outcomes. Differently from our paper, they analyze the concentration of loans among lenders (banks) and not among borrowers (companies). There is also a large body of literature on heterogeneous agent-based models in macroeconomics, showing the importance of bank credit for business cycles. Raberto et al. (2012) and Erlingsson et al. (2013) show the crucial role of bank loans in driving the business cycle, especially during downturns, when bankruptcy chains occur. Delli Gatti et al. (2005), Dosi et al. (2013) and Dosi et al. (2015) obtain similar results.

We finally contribute to the literature on firm’s size distribution (Stanley et al. 1995; Axtell 2001; Cirillo 2010; Fagiolo et al. 2008; Bottazzi et al. 2015), by examining and comparing the distribution of different financial statement items of companies. We find empirical evidence that a small number of large firms account for a high proportion of the total bank credit in the economy. Bank loans are more concentrated than sales, employees or total assets, which are known to exhibit fat-tailed distributions.

3 Data

All firm-level data are obtained from Bureu Van Dijk (Sabi) database. We collect a large panel of yearly balance sheets and income statements. The panel includes medium and large companies in Spain over the period 1999–2014. The threshold for the medium and large size is defined according to The Consolidated Spanish Companies Law and European Union Legislation. Following this rule, we select the companies with the average book value of total assets greater than €2.85 millions and the average amount of annual sales larger than €5.7 million, which ensures audited financial statements and therefore more reliable data. We focus on medium and large firms since they account for a large part of the activity in the Spanish economy. For instance, in our sample, the value-added of the top 100 firms account for approximately 10% of Spanish GDP and the value-added of the top 2000 firms are more than 20% of GDP, on average over 16 years, as shown in Fig. 1.

We use the four-digit SIC code and classify all firms into six industry groups such as mining & energy, construction & real estate, manufacturing, transportation & communications, wholesale & retail trade, and services. The total sales of the companies in our sample account for 53.3% of the total Spanish gross output, which was €1741 billions on average during the considered time span. The industry distribution of firms, which is considered over the pooled sample and the entire period, reflects that the wholesale & retail trade is the largest sector according to the number of firms (see Table 1). It

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2 Available at: https://sabi.bvdinfo.com/version-2016119/home.serv?product=sabineo.

3 According to The Consolidated Spanish Companies Law, all corporations, except for those authorized to present abridged financial statements, must have their financial statements audited. Moreover, according to the European Union legislation, companies are allowed to have abridged financial statements only if at least two of the following thresholds are fulfilled: (1) total assets of €2.85 million or less; (2) annual revenue of €5.7 million or less; and (3) average number of employees during the year of 50 or fewer.
Table 1  Aggregate values per industry, averaged over years (1999–2014). Shares are computed as percentages with respect to all firms in the sample. Percentages in square brackets are shares of Spanish gross output

| Industries                        | Number of firms | Total assets (billion EUR) | Annual sale (billion EUR) | Employees (thousands) |
|-----------------------------------|-----------------|-----------------------------|---------------------------|-----------------------|
| Mining & energy                   | 170             | 30.4                        | 44.8                      | 26.9                  |
|                                   | 0.8%            | 2.9%                        | 4.9% [2.6%]               | 0.8%                  |
| Construction & real estate        | 4042            | 273.7                       | 98.2                      | 299.5                 |
|                                   | 17.9%           | 26.3%                       | 10.6% [5.6%]              | 9.0%                  |
| Manufacturing                     | 6563            | 265.2                       | 272.8                     | 893.8                 |
|                                   | 29.1%           | 25.5%                       | 29.5% [15.7%]             | 26.54%                |
| Transportation & communication    | 1404            | 130.7                       | 83.1                      | 321.4                 |
|                                   | 6.2%            | 12.6%                       | 9.0% [4.8%]               | 9.7%                  |
| Wholesale & retail trade          | 7526            | 187.9                       | 338.4                     | 887.1                 |
|                                   | 33.4%           | 18.0%                       | 36.6% [19.4%]             | 26.7%                 |
| Services                          | 2863            | 153.3                       | 86.2                      | 893.9                 |
|                                   | 12.7%           | 14.7%                       | 9.3% [4.95%]              | 26.9%                 |
| Total                             | 22,568          | 1041.2                      | 923.5 [53.03%]            | 3322.6                |

has 7526 firms, corresponding to a share of 33.4%, on average. Manufacturing and construction are the second and third industries, having on average 6563 and 4042 firms with a share of 29.1% and 17.9%, respectively.

Table 1 shows that the construction sector is the largest one according to total assets, with a share of 26.3, while the manufacturing and trade sectors have a share of total assets of 25.5 and 18%, respectively. The retail sector is the largest one according to sales, which sum to €338.4 billion. Concerning employment, services and manufacturing together sum to the 53.5% of the total workforce in our sample. Retail,
transportation, and construction sectors have a share of 26.7, 9.7, and 9%, respectively.

We do not consider financial corporations and public administrations because we are interested in the allocation of bank loans to private companies. We also exclude the agricultural sector, both because it holds very limited amounts of bank loans, and to avoid potential distortion due to the relevant role of public subsidies.

Our sample counts on average 22,625 firms per year, over the period 1999–2014, which in total sums up to 362,004 observations.

4 The allocation of bank loans in Spain (1999–2014)

The aim of this section is to provide an overview, from a distributional perspective, of the allocation of bank loans to the Spanish companies described in Sect. 3. Henceforth, we will use “bank debt,” “bank credit,” or “bank loans” as synonyms, indicating the total amount of bank loans in the liability side of the balance sheet of a given company. Concentration refers to the extent to which a small number of firms account for a large portion of an economic variable, such as total sales, assets, or employment. We use the Gini index and the Hill Tail index as measures of concentration (or dispersion) of several economic indicators across firms.4

Figure 2 shows the yearly Gini and Hill Tail indexes of several financial statement items of Spanish companies, from 1999 to 2014. In particular, Hill Tail index in Fig. 2b confirms that many of these items are distributed according to fat-tailed distributions (see Axtell 2001). Table 9 in appendix presents a more detailed analysis of these distributions. The figure indicates that a relatively small number of firms own a large share of employees, sales and total assets; in other words, these quantities are concentrated to a small number of firms. Figure 2a represents the dynamics of this concentration, measured as Gini indexes, during the considered period. It emerges that the concentration of bank debt is persistently higher than any other considered variables. This is especially true for long-term bank debt 5 which is more concentrated than equity and trade credit on the liability side. Finally, bank debt is also much more concentrated than other standard measures of firm size, as total assets, sales, or the number of employees.

All the Gini coefficients that are shown in Fig. 2a are quite stable over the 15 years considered. Only after the crisis, some indexes show a positive trend, particularly sales and number of employees. This positive trend might be explained by the high number of firms’ defaults (or by the strong size contraction of many firms) during the crisis, and by the consequent rise in unemployment. Firms withstanding the crisis have been able in the following years to reinforce their market share, hiring new workers and therefore raising the concentration level of these quantities in the economy, in a sort of survival of the fittest mechanism. This interpretation is in line with the empirical studies of Reint et al. (2017) and Dias and Marques (2020), who observe that the

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4 We also use other measures of dispersion such as the Herfindahl index, relative mean absolute deviation and relative median absolute deviation which confirm our findings, and they are available upon request.

5 The long-term bank debt is the share that is not going to expire within the current accounting year. Therefore, this category includes only loans with a maturity longer than one year.
probability of survival of inefficient firms has been extremely reduced after the crisis. Moreover, Ouyang (2009) shows that young firms, which are generally smaller and not always the least productive, are disproportionately hit by recessions. This might contribute to explain the growth of concentration of employees and sales.

As the time-span under investigation has been designed to include the financial crisis, we can examine how the distribution of financial risk among companies evolves over time. We use bank debt over total assets (or bank debt ratio) as a measure of financial leverage and risk. Figure 3 shows the evolution of firms’ leverage in the period under study, aggregating firms by size according to ten deciles. In the first decile, there are the 10% smallest companies in terms of total assets, while in the last decile there are the 10% largest ones. If bank debt was held by companies in proportion to their total assets, we should observe in Fig. 3 the overlapping of all the deciles lines, whereas we observe that large firms hold more bank debt with respect to their size. Figure 3b, in particular, shows that long-term bank debt to total assets increases regularly with firm size. Figure 3 also indicates that the leverage of companies increased during the boom and decreased after the crisis. Figure 3a, in particular, displays the deleveraging process after the crisis, which led to a more homogeneous balance sheet structure where the ratio of bank debt to total assets converged to a value close to 15%.

For a better understanding of bank loans allocation, we distinguish between different sectors of the economy. Figure 4 shows how total bank loans are distributed among firms in the main economic sectors. At the beginning of the Spanish boom, in 1999, bank credit was mainly owned by companies belonging to the manufacturing and
construction sectors, holding a 30% of total debt each. Wholesale and retail followed with less than a 20%. We observe in Fig. 4 a remarkable crowding-out effect between manufacturing and construction during the boom period, with the former decreasing to almost 15% of total bank loans and the latter increasing to approximately 55%. The other sectors do not exhibit comparable changes. After 2007, we observe a progressive fall in the share of bank debt in the construction industry, which returns to the initial value of 30%, or lower, and weak recovery of the manufacturing share.

Figure 5 shows the information of Fig. 3a, i.e., the distribution of bank debt ratio, for each one of the two considered sectors. The picture gives two main insights. First, the leverage of the construction sector raised during the boom period and declined during the crisis, whereas in the manufacturing industry there is no evidence of a trend. Second, larger firms in the construction sector have a higher bank debt-to-total assets ratio. In particular, large construction firms double this ratio from 0.2 in 1999 to 0.4 in 2008, while in the manufacturing sector the ratio of larger firms is stable over time around 0.2. This means that bank loans to the largest companies in the construction sector increased from 20 to 40% from 1999 to 2008. Summarizing, Figs. 4 and 5
suggest that, during the boom period, construction companies (i) attracted more bank loans and (ii) expanded their financial leverage, especially the large ones.

Empirical evidence shows that financial leverage ratios may vary across industries (see Gitman et al. 2011). For example, the debt-to-equity ratio of the manufacturing sector is generally lower than the one of the construction sector. In this regard, we report in Table 2 the median values of the financial leverage (debt-to-equity ratio) for the companies over industries using the pooled sample, from 1999 to 2014, showing that these results are in line with the previous empirical evidence. We use this median value over all years as an internal benchmark for each industry to identify companies with high financial leverage. For instance, if a company has a higher debt-to-equity ratio than the industry benchmark, we define it as a high-leveraged one.

Figure 6a shows the evolution of the percentage of high-leveraged large companies, i.e., the ones belonging to the last decile in terms of total assets, during the observed period, both in all industries and in the construction sector. During the boom period, the percentage of large firms with high leverage increased, whereas it decreased during the crisis. This is even more evident in the construction sector. Figure 6b shows how the share of total bank loans allocated to large high-leveraged companies increased during the crisis, reaching a peak of 70% in 2007. The fact that a large fraction of bank debt was in the hands of high-leveraged companies can be considered as an indicator of financial fragility of the economic system since from the previous analysis we saw that a decile accounts for 2256 companies on average (see Table 1 in Sect. 3) and that the value-added of the top 2000 companies in our sample account for more than 20% of GDP (see Fig. 1 in Sect. 3).

These figures are consistent with Illueca et al. (2014) and García-Alcober et al. (2020), pointing out that, after 2000, banks lent significantly more to borrowers exhibiting higher loan growth, and lent more to borrowers with lower accounting quality. In retrospect, we could argue that this concentration of bank debt has been harmful to the Spanish economy. The default of several large construction companies contaminated

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### Table 2

| Industries                | Median financial leverage ratio |
|---------------------------|---------------------------------|
| Construction & Real estate| 3.32                            |
| Manufacturing             | 1.49                            |
| Wholesale & retail trade  | 2.04                            |
| Services                  | 1.82                            |
| All industries            | 1.95                            |

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6 We mainly checked information on financial leverage of US companies. Gitman et al. (2011) provides data on financial ratio benchmarks based on the RMA Annual Statement Studies from ValuSource (https://www.valusource.com/). For the construction sector, we also checked the CFMA's Construction Financial Benchmark Online questionnaires, see, e.g., the one of 2017 (https://secureii.com/cfma/reporting/insights.aspx). Other websites facilitate financial ratios, based on the Internal Revenue Service financial information, e.g., BizStats (http://www.bizstats.com/).
(a) The percentage of high leverage (H-L) firms in the top decile of assets

(b) The share of bank loans to high leverage (H-L) firms in the top decile of assets

Fig. 6 The share of large high-leverage (H-L) firms and the share of loans received by large H-L firms over years. Large H-L firms are defined as the ones in the top decile of assets, having a debt over equity ratio higher than the median in the period.

Fig. 7 Return on assets by industry

the whole Spanish banking system, freezing lending for many years, as the post-2008 deleveraging process clearly shows (see Figs. 3, 5).

What is the rationale behind the shift of bank loans from a less leveraged sector (manufacturing) to a more leveraged one (construction)? The expected profitability of the two sectors could have driven this shift as, from the banking sector perspective, a higher profitability of the construction sector might compensate for the higher risk associated with it. Therefore, we examine two standard profitability indicators such as Return On Assets (ROA) and Operating Margin. Figures 7 and 8 present the evolution of these two profitability indicators. During the boom period, we do not observe any variation in the mean ROA of both sectors, while we observe a significant increase in

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7 See, for instance, the report on Spain of the European Construction Sector Observatory of the European Commission, published in March 2016; http://ec.europa.eu/growth/sectors/construction/observatory_en.

8 We prefer ROA to ROE (Return On Equity) because ROA presents a variant of profitability available to both debt and equity investors, while ROE is more specific to equity investors. Operating margin is equivalent to return on sales (ROS).

9 Due to the low share of bank credit in the Mining & Energy sector (see Fig. 4) we remove it from the following plots for the sake of readability and compactness.
the mean operating margin of the construction sector. This sector is characterized by the highest profitability, measured as average operating margin, whereas it shows a similar profitability with respect to the other sectors when considering return on assets. After the crisis, both ROA and operating margin decrease in the construction sector. The contrasting results on the two indicators can give us some useful hints, as they include different information. While operating margin refers to the profits earned from the core operations of the company, ROA is calculated on the actual margin earned after interest payments on debt and tax outflows. In particular, operating margin is defined as \( 1 - \frac{\text{operating expenses}}{\text{sales}} \), increasing when sales grow more than operating expenses (before paying debt) and thus depending on the variation of the final goods prices. Moreover, operating margin in the construction sector can be related to the price of collateral (housing unit price), potentially capturing a financial accelerator mechanism (see Kiyotaki and Moore 1997), which can be described as follows: the rise in the housing unit price increased the value of borrowers’ collateral and the amount of loans issued to both households and construction companies, which further stimulated spending and price growth. Differently from operating margin, ROA considers also financial costs.

Comparing Figs. 7 and 8, the observed comovement between loan provision and operating margin in the construction sector, together with the weak relation between loans and ROA, suggest that banks have overvalued the price signal and undervalued the expected financial costs of companies, included in the ROA indicator. In other words, the allocation process of bank loans has been more sensitive to an indicator that did not include the cost of debt, therefore contributing to increase the leverage of the construction sector, as observed in Figs. 5 and 6. Under this perspective, the peculiar banks’ capacity of affecting both the supply and the demand side in the housing market might have played a primary role in the crisis. The positive feedback linked to the housing price has been interrupted when the lack of demand pushed the
price level down, making large firms unable to repay their loans since they already were over-indebted.\(^{10}\)

In the next sections, we use regressions to quantify some of the evidence emerged in the previous descriptive analysis. In particular, we want to understand both the effects of bank loans on companies’ economic performance, and the main attributes needed by a firm to obtain bank loans. Section 4.1 explores the impact of bank loans on companies’ profitability and cost of debt. Section 5.1 examines which are the key features that allows a company to receive bank loans. Finally, Sect. 5.3 studies if the received amount of loans affects firms’ bankruptcy probability.

4.1 Effects of bank loans on ROA and cost of debt

We present two econometric models. The dependent variable of the model in Eq. (1) is the interest bill to debt ratio of company \(i\) at time \(t\), which represents a proxy for the average interest rate paid on the current debt. The dependent variable of the model in Eq. (2) is the return on assets of company \(i\) at time \(t\), which is an indicator of firm’s profitability. Both models include four explanatory variables: \textit{new loan}, \textit{operating margin}, dummies for each \textit{industry}, a dummy for crisis 2008 and their interactions.\(^{11}\)

\[
\text{Interest Bill To Debt Ratio}_{it} = \beta_0 + \beta_1 \cdot \log(\text{New Loan}_i)_{t-1} + \text{InteractionTerms}\theta + \beta_2 \cdot \text{Operating Margin}_{it} + \beta_3 \cdot \log(\text{New Loan}_i)_{t-1} \times \text{Operating Margin}_{it} + \text{InteractionTerms}\delta + \text{InteractionTerms}\lambda + \beta_4 \cdot \text{After Crisis 2008}_t + \epsilon_{it}, \tag{1}
\]

\[
\text{ROA}_{it} = \beta_0 + \beta_1 \cdot \log(\text{New Loan}_i)_{t-1} + \text{InteractionTerms}\theta + \beta_2 \cdot \text{Operating Margin}_{it} + \beta_3 \cdot \log(\text{New Loan}_i)_{t-1} \times \text{Operating Margin}_{it} + \text{InteractionTerms}\delta + \text{InteractionTerms}\lambda + \beta_4 \cdot \text{After Crisis 2008}_t + \epsilon_{it}. \tag{2}
\]

Coefficient \(\beta_1\) shows how new loans at time \(t-1\) explain the average interest rate on current debt [Eq. (1)] as well as firm profitability [Eq. (2)]. New loans are calculated for each company as a positive difference of total bank debt between year \(t\) and \(t-1\), thus corresponding to the net balance between new injections and expired credit.\(^{12}\) The

\(^{10}\) See Marzal-Martínez et al. (2014) and Ortega and Peñalosa (2012), or the Eurofound (http://www.eurofound.europa.eu/) case study on the collapse of Martinsa–Fadesa (the country’s leading real estate company): “Insolvency and restructuring in the Spanish real estate and construction sector: Martinsa-Fadesa”.

\(^{11}\) We provide in appendix summary statistics (Table 10) as well as a pairwise correlation matrix (Table 11) of all variables used in the models in Sects. 4 and 5.

\(^{12}\) The variable \textit{new loan} is calculated as: \textit{New Loan}_\(t\) = max(\textit{\Delta Total Bank Debt}_\(t\), 0), where \textit{\Delta Total Bank Debt}_\(t\) = \textit{Total Bank Debt}_\(t\) – \textit{Total Bank Debt}_\(t-1\). While positive amounts of \textit{new loan} always indicate new loan inflow for a company, zero amounts of \textit{new loan} can correspond to the following outcomes: (i) no new loans; (ii) new loans are opened up at time \(t\), but in an amount smaller than the amount
regressions further include the interaction terms new loan-industries represented by a vector of coefficients \( \theta \). The impact of operating margin is measured by coefficient \( \beta_2 \), while \( \beta_3 \) captures the interaction new loan-operating margin. The interactions new loan-operating margin-industries estimate a vector of coefficients \( \delta \). Therefore, coefficients \( \beta_1 + \theta s + \beta_3 + \delta s \) are our main coefficients of interest in explaining the average interest rate and firm profitability. The last set of interactions operating margin-industries estimate a vector of coefficients \( \lambda \). Both equations include dummy variable AfterCrisis2008 that takes value 1 if the year is greater than or equal to 2008, and zero otherwise. In addition, the models include the industry-year fixed effects for all five corresponding industries and all years, where the reference industry is the wholesale and retail trade sector, while the reference year is the last considered year in the sample.

We estimate the models from Eqs. (1) and (2) providing the results in Tables 3 and 4, respectively. In both tables, model (1) represents a reduced specification of the equations including only \( \log(\text{NewLoan}_{it-1}) \) and InteractionTerms\( \theta \); model (2) in the tables represents the exact specifications given in the equations estimated over the entire time span; while models (3) and (4) are the equations estimated separately for the period before and after the crisis, respectively, thus omitting dummy AfterCrisis2008. All the models are estimated using the fixed effect (FE) panel data estimator upon the suggestion of the Hausman test, and using robust and clustered standard errors at the firm level. Thus, the fixed-effect coefficients on our key predictors tell us the common slope of the predictors averaged across the firms. In the following, we examine the results in the tables below.

Table 3 indicates that new loans taken in period \( t - 1 \) explain the present interest bill per unit of total debt. The coefficient of new loan \( \beta_1 \) is positive and significant in all considered models, suggesting that companies receiving a higher amount of new loans at time \( t - 1 \) increase the interest rate paid on debt at time \( t \), on average. This effect varies over industries and depends also on the operating margins of companies, as shown in models (2)–(4). In particular, in the construction and services sectors’ model (2) finds that higher companies’ operating margins amplify the effect of new loans on financial costs. Examining periods before and after 2008 separately, models (3) and (4) confirm the positive effect of new loan on financial costs in all industries.

Table 4 suggests that companies that received loans during the previous year experience significantly lower ROA, as shown by coefficient \( \beta_1 = -0.00160^{***} \) in model (1). This effect is related to the result of Eq. (1), showing that new loans trigger higher financial costs and, therefore, lower return on assets. In addition, model (2) introduces operating margin, showing its significant and positive relation with ROA in all industries, as expected since they are both profitability indicators. However, the interaction term new loan-operating margin is negative, meaning that for any additional unit of new loans taken by companies this relation becomes weaker. This can be explained, again, by noting that companies with higher operating margins tend to get more loans (see Sect. 5 for more details), thus increasing financial costs and negatively affecting...
Table 3 The coefficient estimates are from the fixed-effect (FE) panel data model, which is chosen according to Hausman test. Each regression includes industry-year-afterCrisis2008 fixed effects.

|                                | FE within model (1) int. bill-to-debt ratio | FE within model (2) int. bill to debt ratio | FE within < 2008 model (3) int. bill-to-debt ratio | FE within ≥ 2008 model (4) int. bill-to-debt ratio |
|--------------------------------|--------------------------------------------|--------------------------------------------|-------------------------------------------------|-------------------------------------------------|
| log(New Loan_{i,t-1})         | 0.000869**                                | 0.000991***                               | 0.000415*                                       | 0.00102**                                       |
|                                | (8.58)                                     | (8.33)                                     | (1.79)                                          | (9.29)                                          |
| log(New Loan_{i,t-1} × ManufacturingIndustry_{i,t}) | -0.000136                                 | -0.000848                                 | 0.000270                                        | -0.000147                                       |
|                                | (-1.02)                                    | (-0.55)                                    | (1.04)                                          | (-1.01)                                         |
| log(New Loan_{i,t-1} × ConstructionIndustry_{i,t}) | 0.000135                                  | 0.000141                                 | 0.000470*                                       | -0.000421**                                     |
|                                | (0.84)                                     | (0.08)                                     | (1.80)                                          | (-2.23)                                         |
| log(New Loan_{i,t-1} × ServicesIndustry_{i,t}) | 0.0000747                                 | -0.000878                                 | 0.000454                                        | -0.000461**                                     |
|                                | (0.45)                                     | (-0.49)                                    | (1.42)                                          | (-2.22)                                         |
| log(New Loan_{i,t-1} × Trans&Com.Industry_{i,t}) | 0.0000629                                 | -0.000480                                 | 0.000520*                                       | -0.000188                                       |
|                                | (0.32)                                     | (-0.24)                                    | (1.77)                                          | (-0.83)                                         |
| OperatingMargin_{it}           | 0.0348**                                   | 0.00776                                   | 0.0243*                                         | 0.0243*                                         |
|                                | (2.33)                                     | (0.26)                                     | (1.78)                                          | (1.78)                                          |
| log(New Loan_{i,t-1} × OperatingMargin_{it}) | -0.00435**                                | 0.000470                                 | -0.00282                                        | -0.00282                                        |
|                                | (-2.29)                                    | (0.11)                                     | (-1.54)                                         | (-1.54)                                         |
| log(New Loan_{i,t-1} × ManufacturingIndustry_{i,t} × OperatingMargin_{it}) | -0.0000430                                 | -0.00297                                 | 0.00222                                         | 0.00222                                         |
|                                | (-0.02)                                    | (-0.65)                                    | (1.10)                                          | (1.10)                                          |
| log(New Loan_{i,t-1} × ConstructionIndustry_{i,t} × OperatingMargin_{it}) | 0.00465**                                 | 0.000298                                 | 0.00303*                                        | 0.00303*                                        |
|                                | (2.43)                                     | (0.01)                                     | (1.65)                                          | (1.65)                                          |
|                                      | \( FE_{within} \) model (1) | \( FE_{within} \) model (2) | \( FE_{within} \) model (3) < 2008 | \( FE_{within} \) model (4) \( \geq 2008 \) |
|--------------------------------------|------------------------------|-----------------------------|-----------------------------------|-----------------------------------|
| int. bill-to-debt ratio              | int. bill to debt ratio      | int. bill-to-debt ratio     | int. bill-to-debt ratio           | int. bill-to-debt ratio           |
| \( \log(\text{New Loan}_i)_{t-1} \times \text{Services Industry}_i \times \text{Operating Margin}_i \) | 0.00491**                    | -0.00339                   | 0.00338*                         |                                   |
|                                      | (2.50)                       | (-0.08)                    | (1.75)                            |                                   |
| \( \log(\text{New Loan}_i)_{t-1} \times \text{Trans&Com. Industry}_i \times \text{Operating Margin}_i \) | 0.00416**                    | -0.00166                   | 0.00263                          |                                   |
|                                      | (2.15)                       | (-0.40)                    | (1.29)                            |                                   |
| \( \text{Operating Margin}_i \times \text{Manufacturing Industry}_i \) | -0.00395                     | 0.00850                    | -0.0269*                         |                                   |
|                                      | (-0.23)                      | (0.26)                     | (-1.84)                           |                                   |
| \( \text{Operating Margin}_i \times \text{Construction Industry}_i \) | -0.0390***                   | -0.0134                    | -0.0265*                         |                                   |
|                                      | (-2.58)                      | (-0.44)                    | (-1.92)                           |                                   |
| \( \text{Operating Margin}_i \times \text{Services Industry}_i \) | -0.0406**                    | -0.00899                   | -0.0293**                        |                                   |
|                                      | (-2.56)                      | (-0.29)                    | (-1.97)                           |                                   |
| \( \text{Operating Margin}_i \times \text{Trans&Com. Industry}_i \) | -0.0341**                    | 0.009998                   | -0.0235                          |                                   |
|                                      | (-2.19)                      | (0.03)                     | (-1.59)                           |                                   |
| \( \text{AfterCrisis2008}_i \)     | -0.00739***                  | -0.00732***                |                                   |                                   |
|                                      | (-16.16)                     | (-16.17)                   |                                   |                                   |
| \( \text{Constant} \)              | 0.0273***                    | 0.0265***                  | 0.0282***                        | 0.0204***                        |
|                                      | (63.08)                      | (57.24)                    | (44.26)                           | (46.09)                           |
| \( N \)                             | 86,399                       | 86,225                     | 47,582                            | 38,643                            |

\( t \) statistics in parentheses

* \( p < 0.10 \)

** \( p < 0.05 \)

*** \( p < 0.01 \)
Table 4  The coefficient estimates are from the fixed-effect (FE) panel data model which is chosen according to Hausman test. Each regression includes industry-year-afterCrisis2008 fixed effects

|                         | FE within model (1) ROA | FE within model (2) ROA | FE within < 2008 model (3) ROA | FE within ≥ 2008 model (4) ROA |
|-------------------------|-------------------------|-------------------------|---------------------------------|---------------------------------|
| log(New Loan\textsubscript{i})\textsubscript{t−1} | −0.00160*** (−5.20)    | −0.000232 (−0.38)        | 0.000319 (0.55)                 | −0.000452 (−0.60)               |
| log(New Loan\textsubscript{i})\textsubscript{t−1} \times ManufacturingIndustry\textsubscript{i} | −0.00157*** (−3.07)    | 0.000911 (0.86)          | 0.000437 (0.52)                 | 0.000297 (0.25)                 |
| log(New Loan\textsubscript{i})\textsubscript{t−1} \times ConstructionIndustry\textsubscript{i} | 0.000767 (1.25)        | −0.0000784 (−0.07)       | 0.00351*** (2.19)               | 0.00180 (1.46)                  |
| log(New Loan\textsubscript{i})\textsubscript{t−1} \times ServicesIndustry\textsubscript{i} | 0.0000225 (0.03)       | 0.00202* (1.67)          | 0.00173 (1.33)                  | 0.00303* (1.85)                 |
| log(New Loan\textsubscript{i})\textsubscript{t−1} \times Trans&Com.Industry\textsubscript{i} | −0.000292 (−0.32)      | 0.000245 (0.16)          | 0.00304* (1.78)                 | −0.000677 (−0.52)               |
| OperatingMargin\textsubscript{it} | 1.171*** (11.19)        | 1.454*** (14.28)         | 1.090*** (7.69)                 |                                 |
| log(New Loan\textsubscript{i})\textsubscript{t−1} \times OperatingMargin\textsubscript{it} | −0.0550*** (−2.89)     | −0.0518*** (−3.41)       | −0.0645*** (−2.67)             |                                 |
| log(New Loan\textsubscript{i})\textsubscript{t−1} \times ManufacturingIndustry\textsubscript{i} \times OperatingMargin\textsubscript{it} | −0.0229 (−0.78)        | 0.00577 (0.31)           | −0.0204 (−0.63)                 |                                 |
| log(New Loan\textsubscript{i})\textsubscript{t−1} \times ConstructionIndustry\textsubscript{i} \times OperatingMargin\textsubscript{it} | 0.0420** (2.05)        | −0.00101 (−0.06)         | 0.0597** (2.41)                 |                                 |
|                        | FE within model (1) ROA | FE within model (2) ROA | FE within ROA < 2008 | FE within ROA ≥ 2008 |
|------------------------|-------------------------|-------------------------|----------------------|----------------------|
| `log(New Loan_{it-1} \times ServicesIndustry_{it} \times OperatingMargin_{it})` | 0.000729 (0.03) | -0.0314* (-1.68) | 0.0268 (1.00) |                   |
| `log(New Loan_{it-1} \times Trans&Com.Industry_{it} \times OperatingMargin_{it})` | 0.00755 (0.32) | -0.0163 (-0.68) | 0.0495* (1.79) |                   |
| `OperatingMargin_{it} \times ManufacturingIndustry_{it}` | -0.0966 (-0.69) | -0.292** (-2.39) | -0.0726 (-0.43) |                   |
| `OperatingMargin_{it} \times ConstructionIndustry_{it}` | -0.994*** (-7.81) | -0.858*** (-5.92) | -1.003*** (-6.65) |                   |
| `OperatingMargin_{it} \times ServicesIndustry_{it}` | -0.584*** (-3.81) | -0.557*** (-3.56) | -0.666*** (-3.58) |                   |
| `OperatingMargin_{it} \times Trans&Com.Industry_{it}` | -0.487*** (-2.73) | -0.513*** (-2.17) | -0.687*** (-3.60) |                   |
| `AfterCrisis2008_{it}` | -0.0470*** (-25.70) | -0.0269*** (-14.82) |                   |                   |
| `Constant`             | 0.0743*** (45.01)    | 0.0299*** (12.13)  | 0.00626* (1.94)    | 0.00626** (2.14)   |
| `N`                    | 86,678                | 86,501                | 47,668              | 38,833              |

t statistics in parentheses

* $p < 0.10$

** $p < 0.05$

*** $p < 0.01$
ROA. The interaction terms new loan-operating margin-industries differentiate this effect across sectors. The size of the coefficient for the reference sector is given by the interaction term new loan-operating margin $\beta_3$, while the size of the coefficient for all other sectors is presented by $\delta$ coefficients (new loan-operating margin-industries interactions). Dummy after-crisis2008 clearly shows that companies are characterized by lower return on assets after the crisis, while models (3) and (4) consider periods before and after 2008, separately. Both models confirm the negative sign of the interaction between new loan and operating margin, along with a negative effect of new loan on ROA in both periods.

Finally, these econometric exercises corroborate the main findings emerged from the descriptive analysis of Sect. 4. In particular, they show that profitability (ROA) is related to operating margin but also depends on financial costs, which are increasing for higher amounts of new loans. In this respect, Sect. 5.3 explores the potential consequences of this mechanism, estimating the effect of new loans on bankruptcy probability.

5 Determinants of bank loans allocation

In this section, we investigate the determinants of bank credit allocation, and in particular, we estimate the impact of firm’s size on the amount of new loans provided by banks. Our main aim is to explore whether companies receive credit more than proportionally with respect to their size, which could explain why we observe a high level of credit concentration. The size of companies is measured as the book value of total assets, while the amount of new loans is defined as in the previous section, i.e., it corresponds to the positive net balance between new injections and expired credits. While the previous section provides an overview of credit distribution in the Spanish economy, including almost all industries, this section focuses on the three most important sectors: wholesale and retail trade, manufacturing, and construction. We focus our analysis mainly on manufacturing and construction, since the most interesting information and trade-off emerging from the descriptive analysis regard these two industries. In addition, we use wholesale and retail trade as a reference industry in our regression analysis, since it is the largest industry in terms of the number of companies and annual sales, and it exhibits a stable share of bank debt over the years (see Table 1 and Fig. 4).

Our design follows the model of determinants of firm’s debt ratio described in Petersen and Rajan (1994). While the authors measure the availability of credit regressing firms’ debt-to-total-assets-ratio on the characteristics of the firms, we estimate the logarithm of new loans granted to firms, using a similar set of explanatory variables. We focus on the flow of new loans and not on the credit stock because we want to understand the allocation mechanism. In particular, we regress the logarithm of new loans on the logarithm of the book value of total assets and on other firms’ characteristics, which we are going to describe in detail below. The coefficient of interest represents the elasticity between the distribution of new loans and firms’ total assets. It indicates the percentage change in the amount of new loans granted to firms with respect to the percentage change in firms’ assets.
Since the dependent variable new loans is censored to zero,\textsuperscript{13} we first follow Petersen and Rajan (1994) using an one-sided Tobit model\textsuperscript{14} to estimate the coefficients. Applying the Tobit model, we treat the observations of new loans for those firms who did not get new credit as zero values. However, regressions with firms’ new loans as a dependent variable suffer from a simultaneous equation bias since the amount of new loans is simultaneously determined from both demand and supply sides. For instance, firms can be rationed on the credit market (a supply effect) or they can have enough internal resources and less need for external funds (a demand effect).

To account for the demand- and supply-side effects, we use a sample selection estimation strategy. We find the rationale for this approach in the Keynesian theory of the matching mechanism on the credit market (see Gertler 1988). The Keynesian “state of confidence” theory explains the credit market matching classifying two states: the first state is about “borrower’s beliefs” in profitable investments, where firms decide (select themselves) whether to apply for new loans; the second state is “the state of credit,” where lenders decide whether to finance (select) borrowers. Accordingly, we consider loan allocation as a selection process that leads us to use selection models. Therefore, besides the one-sided Tobit model, we also employ a standard Heckman sample selection procedure to estimate our empirical model. In addition, we use a semi-parametric selection model (see Ahn and Powell 1993; Engberg et al. 1996) to check the robustness of our result. There might be also other estimation methodologies available, for instance, quantile regression; however, we do not use it mainly because companies may change quantiles over time and the estimations can be misleading as a result of the inter-quantile movements. The standard Heckman selection procedure follows a two-step estimation approach. In the first step, Probit model estimates a probability that firms will demand and receive new loans and calculate the inverse Mills ratio using the estimated probabilities. In the second step, the main equation is estimated including in the regression the inverse Mills ratio to correct for the selection bias.

5.1 Parametric estimation: models and variable choice

Following Petersen and Rajan (1994), our empirical model of the determinants of new credit provision is given as:

\[
\log(\text{New Loans}_i) = \beta_0 + \beta_1 \cdot \log(\text{Total Assets}_i)_{t-1} + \text{InteractionTerms}_\theta \\
+ \beta_2 \cdot \log(\text{Equity}_i)_{t-1} + \beta_3 \cdot \text{Return On Assets}_i(t-1) \\
+ \beta_4 \cdot \text{Operating Margin}_i(t-1) + \text{InteractionTerms}_\gamma \\
+ \beta_5 \cdot \text{Market Power}_i(t-1) + \beta_6 \cdot \text{High Leverage Firm}_i(t-1) \\
+ \beta_7 \cdot \text{Age}_i + \epsilon_{it}. \tag{3}
\]

\textsuperscript{13} See summary statistics in Table 10 in appendix.
\textsuperscript{14} The dependent variable new loans can be either zero for those companies who do not have new loans at time $t$, or any positive amount of new loans. Since we estimate our model taking the logarithm of the dependent variable, we first replace all zero values with 0.001 and then take the logarithmic transformation, where all values lower than one become negative. Then, we apply the one-sided Tobit model, where all negative observations are censored to zero.
The dependent variable is the logarithm of new loans that is given to a company \( i \) at time \( t \). Our coefficients of interest \( \beta_1 + \theta s \) measure the impact of firm’s assets on the allocation of new loans for each industry. The impact is given in terms of elasticity suggesting how many percents would the amount of new loans increase if firm assets augment one percent. \( \beta_1 \) is the coefficient associated with the logarithm of the book-value-of-total-assets at time \( t - 1 \). \( \theta s \) are the coefficients related to the interaction terms of the book-value-of-total-assets with industry and AfterCrisis2008 dummies, which allow us to trace out the coefficient \( \beta_1 \) over industries and in periods before and after the crisis. The interaction terms are given as: (i) \( \log(\text{Total Assets}) \times \text{Industry} \); (ii) \( \log(\text{Total Assets}) \times \text{Industry} \times \text{AfterCrisis2008} \); (iii) \( \log(\text{Total Assets}) \times \text{AfterCrisis2008} \); they estimate a vector of elasticity coefficients \( \theta \). We also examine whether firms’ financial stability and profitability have any predictive power for the allocation of bank credit. For instance, Petersen and Rajan (1994) show that credit availability is higher for less profitable firms and it is greater for large firms and those in sectors with high average earnings. However, it is worth remarking that they use the debt-to-assets ratio as a proxy for credit availability, which is a standard measure of firm financial leverage. Therefore, their results can be also interpreted as if larger firms were relatively riskier in terms of the level of leverage. Moreover, they include only small enterprises in the analysis, where the credit availability can be affected through the transparency channel since larger firms are more transparent and able to reveal more information to their lenders. Here we rule out the impact of firms’ transparency on credit provision, including only medium and large companies that are all audited. Moreover, we use the flow of new loans as the dependent variable to clearly define the impact of firms’ assets on credit provision, while we consider debt-to-assets ratio exclusively as a measure of firms’ financial leverage.

To explore the predictive power of firms’ financial stability and profitability, we include the logarithm of equity to examine whether the net worth of firm \( i \) at time \( t - 1 \) significantly explains the new loan allocation (coefficient \( \beta_2 \)). To measure the predictive power of firms’ profitability, we include return on assets at time \( t - 1 \) (coefficient \( \beta_3 \)) and also Operating Margin at time \( t - 1 \) (coefficient \( \beta_4 \)). We also include interaction terms of Operating Margin with industry and AfterCrisis2008 dummies to estimate the coefficient \( \beta_4 \) over industries and in periods before and after the crisis. The interaction terms are given as: (i) \( \text{Operating Margin} \times \text{Industry} \); (ii) \( \text{Operating Margin} \times \text{Industry} \times \text{AfterCrisis2008} \); (iii) \( \text{Operating Margin} \times \text{AfterCrisis2008} \); they estimate a vector of coefficients \( \gamma \). We define Market Power as the ratio of firm’s sales to total industry sales (\( \beta_5 \)). Following Sect. 4, we create a dummy variable for high-leverage firms (dummy high-leverage firm), which indicates if the leverage ratio of the firms is above the industry-specific threshold. The coefficient \( \beta_6 \), associated with this dummy, shows whether banks allocate loans toward high-leverage companies. We also include firm age and the average standard deviation of return on assets in the last four years. Firm age (\( \beta_7 \)) is a proxy for the unobservable firm relation with banks where older companies should have a higher probability of getting new loans and better conditions. However, firm age is also known to be a driver of firm performance; thus, older

\[ \text{AfterCrisis2008} = 1 \text{ if Year} \geq 2008, \text{ and 0 otherwise}. \]
companies may have lower demand for new credit. The standard deviation of return on assets indicates risk and should decrease the probability of obtaining new loans. Nevertheless, the volatility is not a significant determinant of the provision of credit, as shown by Petersen and Rajan (1994). Therefore, following this line of thinking, we assume an exclusion restriction for the standard deviation of return on assets in the parametric sample selection model, considering that it significantly predicts only the probability of getting new loans, but it does not determine the amount of new loans that are granted to companies. Note that using the semi-parametric sample selection model, we release the exclusion restriction assumption and we include this variable in the main equation as well.

Table 5 shows the output of the Tobit model in column (1), while the columns (2)–(4) present the outputs of the Heckman selection model. The models in column (1) and (2) include the same set of variables except for the exclusion restriction for the Heckman model. The model in column (3) includes the interaction term Operating Margin × AfterCrisis2008, while the model in column (4) includes all interactions of Operating Margin presented above (estimating the vector of coefficients γ). In addition, we present the results of the Probit estimation in Table 6, which is the first stage of the Heckman model given in Table 5—column (2).

The estimation results indicate that the firm’s total assets significantly explain the allocation of new loans since the coefficient β1 is always significant and positive. The interaction terms associated with the vector of parameters θ, in addition, capture the average difference of the coefficient among industries and over the periods before and after the crisis in 2008 and show that the magnitude of the coefficient of firm’s assets varies over the industries and the periods. We summarize results in Fig. 9, focusing on the outputs of columns (1) and (4). Note that columns (2)–(4) of the Heckman model provide almost identical results.

The left part of each panel in Fig. 9 summarizes the impact of firms’ total assets over industries in the boom period of the Spanish economy, while the right part of each panel presents the impacts after 2008. We remind that the reported values predict the percentage change in the amount of new loans granted to firms if their total asset changes by one percent. Figure 9a shows a larger elasticity coefficient in the construction sector in the pre-crisis period, where the Tobit model indicates elasticity of 1.761. In the post-crisis period, the coefficient drops to 0.703. On the other hand,
Table 5 The coefficient estimates are from the one-sided (censored at zero) Tobit model and the Heckman selection MLE model. Each regression includes industry-year-afterCrisis2008 fixed effects. Heckman estimations also contain selection term. The selection equation additionally includes the average standard deviation of return-on-assets in the last four years (see Table 6).

| Term | Tobit (1) log(\text{New Loan}) | Tobit (2) log(\text{New Loan}) | Tobit (3) log(\text{New Loan}) | Tobit (4) log(\text{New Loan}) |
|------|---------------------------------|---------------------------------|---------------------------------|---------------------------------|
| \log(\text{Total Assets}_i)_{t-1} | 1.253*** | 0.908*** | 0.909*** | 0.907*** |
| | (15.75) | (33.96) | (33.97) | (33.82) |
| \log(\text{Total Assets}_i)_{t-1} \times \text{Manufacturing Industry}_i | -0.400*** | -0.0785*** | -0.0785*** | -0.0751*** |
| | (-5.13) | (-2.87) | (-2.88) | (-2.75) |
| \log(\text{Total Assets}_i)_{t-1} \times \text{Construction Industry}_i | 0.508*** | 0.246*** | 0.243*** | 0.244*** |
| | (6.00) | (9.15) | (8.71) | (8.50) |
| \log(\text{Total Assets}_i)_{t-1} \times \text{Manufacturing Industry}_i \times \text{AfterCrisis2008}_t | 0.669*** | 0.101*** | 0.101*** | 0.0980*** |
| | (6.51) | (2.97) | (2.98) | (2.87) |
| \log(\text{Total Assets}_i)_{t-1} \times \text{Construction Industry}_i \times \text{AfterCrisis2008}_t | -0.169 | -0.0871** | -0.0835** | -0.0806** |
| | (-1.36) | (-2.43) | (-2.29) | (-2.16) |
| \log(\text{Total Assets}_i)_{t-1} \times \text{AfterCrisis2008}_t | -0.889*** | -0.0369 | -0.0361 | -0.0365 |
| | (-11.41) | (-1.50) | (-1.47) | (-1.47) |
| \log(\text{Equity}_i)_{t-1} | -0.514*** | -0.193*** | -0.194*** | -0.194*** |
| | (-9.58) | (-10.50) | (-10.51) | (-10.55) |
| \text{ReturnOnAssets}_i(t-1) | -0.846*** | -0.323** | -0.326** | -0.445*** |
| | (-2.71) | (-2.46) | (-2.32) | (-2.81) |
| \text{Operating Margin}_i(t-1) | 0.363** | 0.398*** | 0.489** | 0.994** |
| | (2.22) | (4.25) | (2.23) | (2.38) |
| \text{Operating Margin}_i(t-1) \times \text{Manufacturing Industry}_i | | | -0.740* | |
| | | | (-1.70) | |
| \text{Operating Margin}_i(t-1) \times \text{Construction Industry}_i | | | -0.470 | |
| | | | (-1.02) | |
Table 5 continued

| Term                                                                 | Tobit (1) \(\log(\text{New Loan})\) | Heckman (2) \(\log(\text{New Loan})\) | Heckman (3) \(\log(\text{New Loan})\) | Heckman (4) \(\log(\text{New Loan})\) |
|---------------------------------------------------------------------|--------------------------------------|----------------------------------------|----------------------------------------|----------------------------------------|
| \(\text{OperatingMargin}_{i(t-1)} \times \text{ManufacturingIndustry}_i \times \text{AfterCrisis}_{2008,i}\) | 0.556 (1.02)                         | –0.131 (–0.24)                         | –0.131 (–0.28)                         |                                        |
| \(\text{OperatingMargin}_{i(t-1)} \times \text{ConstructionIndustry}_i \times \text{AfterCrisis}_{2008,i}\) | –0.154 (–0.71)                       | –0.131 (–0.24)                         |                                        |                                        |
| \(\text{MarketPower}_{i(t-1)}\)                                      | –0.503 (–1.35)                        | –0.565*** (–3.47)                      | –0.563*** (–3.46)                      | –0.555*** (–3.41)                      |
| \(\text{DummyHigh} - \text{LeverageFirm}_{i(t-1)}\)                  | 0.630*** (8.91)                       | 0.181*** (8.51)                        | 0.181*** (8.51)                        | 0.179*** (8.44)                        |
| \(\text{Firm age}_i\)                                                | –0.00153 (–0.77)                      | –0.00572*** (–8.80)                    | –0.00571*** (–8.78)                    | –0.00568*** (–8.74)                    |
| \(\sigma(\text{return on assets})_{t} \text{ over the last 4 years}\) | –10.55*** (–12.86)                    |                                        |                                        |                                        |
| \(\lambda\)                                                          | –1.515*** (–164.362)                  | –1.515*** (–164.355)                   | –1.516*** (–164.728)                   |                                        |
| \(\text{Constant}\)                                                 | –7.909*** (–14.73)                    | –0.471*** (–2.67)                      | –0.471*** (–2.67)                      | –0.459*** (–2.60)                      |
| \(N\)                                                               | 168,524                              | 168,524                                | 168,524                                | 168,524                                |

* \(t\) or \(z\) statistics in parentheses
* * \(p < 0.10\)
* ** \(p < 0.05\)
* *** \(p < 0.01\)
Table 6  The coefficient estimates are from the Probit model. Depended variable Dummy New Loan is equal to one if a firm raises new loans at time $t$ and zero otherwise. Each regression includes industry-year-afterCrisis2008 fixed effects. The marginal effects are calculated at means.

| Term                                      | $log(Total\ Assets_{it})_{t-1}$ | $log(Total\ Assets_{it})_{t-1} \times ManufacturingIndustry_{it}$ | $log(Total\ Assets_{it})_{t-1} \times ConstructionIndustry_{it}$ | $log(Equity_{it})_{t-1}$ | $ReturnOnAssets_{it(t-1)}$ | $OperatingMargin_{it(t-1)}$ | $Market\ Power_{it(t-1)}$ | $DummyHigh - LeverageFirm_{it(t-1)}$ | $\sigma(\text{return on assets})_{i \text{ over the last 4 years}}$ | $Firm\ age_{it}$ | $Constant$ | $N$          |
|-------------------------------------------|---------------------------------|---------------------------------------------------------------------|---------------------------------------------------------------------|--------------------------|----------------------------|-------------------------------|--------------------------|--------------------------------------|---------------------------------------|--------------------------|--------------|--------------|
|                                           |                                 |                                                                     |                                                                     |                          |                            |                               |                          |                                      |                                        |                          |              |              |
|                                           | $0.119^{***}$                   | $-0.0625^{***}$                                                     | $0.0458^{***}$                                                      | $-0.0601^{***}$          | $-0.206^{***}$             | $0.0285$                       | $-0.0144$                | $0.0810^{***}$                      | $-1.570^{***}$                        | $0.000289$               | $-0.856^{***}$ | $168,524$   |
|                                           | $(9.69)$                        | $(5.29)$                                                            | $(3.43)$                                                            | $(7.14)$                 | $(4.33)$                   | $(1.25)$                       | $(0.29)$                  | $(7.30)$                                                            | $(12.56)$                                                            | $(0.96)$                  | $(10.52)$    |              |
|                                           |                                 |                                                                     |                                                                     |                          |                            |                               |                          |                                      |                                        |                          |              |              |
|                                           | $0.0457^{***}$                  | $-0.0240^{***}$                                                     | $0.0176^{***}$                                                      | $-0.0231^{***}$          | $-0.0793^{***}$            | $0.0110$                       | $-0.00556$               | $0.0312^{***}$                      | $-0.604^{***}$                        | $0.000111$               |                          |              |
|                                           | $(9.69)$                        | $(5.29)$                                                            | $(3.43)$                                                            | $(7.14)$                 | $(4.33)$                   | $(1.25)$                       | $(0.29)$                  | $(7.30)$                                                            | $(12.57)$                                                            | $(0.96)$                  |              |              |
|                                           |                                 |                                                                     |                                                                     |                          |                            |                               |                          |                                      |                                        |                          |              |              |
|                                           | $z$ statistics in parentheses   |                                                                     |                                                                     |                          |                            |                               |                          |                                      |                                        |                          |              |              |
|                                           | * $p < 0.10$                    |                                                                     |                                                                     |                          |                            |                               |                          |                                      |                                        |                          |              |              |
|                                           | ** $p < 0.05$                   |                                                                     |                                                                     |                          |                            |                               |                          |                                      |                                        |                          |              |              |
|                                           | *** $p < 0.01$                  |                                                                     |                                                                     |                          |                            |                               |                          |                                      |                                        |                          |              |              |

Fig. 9b summarizes the output of the Heckman model, confirming a higher elasticity in the construction sector and indicating a credit allocation mechanism that favors large companies. This is especially evident in the pre-crisis period where the model estimates an elasticity of 1.151 versus 1.07 in the period after 2008. In the manufacturing industry, we find a significantly lower and more stable coefficient over periods. The coefficient of the trade sector is similar to the manufacturing one.
Results in Table 5 show the negative coefficients of equity and return-on-assets, indicating that banks allocated credit toward firms with lower equity and profitability. A notable difference between Tobit and Heckman estimations confirms the existence of a selection mechanism. The former model overestimates the effects since it does not take into account that the companies who receive loans are actually the ones with the lower return on assets who demand more funds. On the other hand, the latter estimation controls for this (self)selection process. The coefficients of Operating margin suggest that credit allocation follows a positive price signal. This result is stable over the years since the interaction term of Operating margin with dummy AfterCrisis2008 is not significant [see the model in column (3)]. In addition, we examine it over industries including all interaction terms in column (4) and find that the coefficient of price signal is much lower in manufacturing than in construction. This finding suggests that the credit provision is more sensitive to the change in price (or expected price) of collateral in the construction sector, which is mainly represented by the housing units owned by construction companies. Decomposing total assets into non-current and current assets, we find a greater explanatory power of current assets (see Table 7), where these housing units are stored in firms’ balance sheet as they are expected to be sold in a relatively short amount of time, i.e., within one year. The negative impact of market power in Table 5 indicates that companies with lower sales, relative to the total industry sales in the previous year, rely more on external loans to finance their costs. The high-leverage dummy shows that firms with a financial leverage ratio above the industry median obtain greater amounts of new loans on average. Finally, we find a marginal but significant and negative coefficient of age, which is in line with previous findings of Petersen and Rajan (1994).

So far we have used a parametric selection model approach to deal with the simultaneous equation bias in the regressions with firms’ new loans as the dependent variable. However, using the parametric sample selection models requires strong assumptions that may not always hold. In particular, to use the Heckman sample selection model we have to assume: (1) a particular functional form of the selection term (see Kyriazidou, 1997 for the discussion) and (2) the exclusion restriction for $\sigma(return\ on\ assets)$. To enhance our results with a more comprehensive analysis and to check the robustness of our findings, in the following we use a semi-parametric selection model which allows us to release the above-mentioned assumptions. In addition, we perform a semi-parametric analysis for each industry, and each year separately, showing the evolution of coefficients over industries and years.

5.2 Semi-parametric estimator: robustness check

To build a semi-parametric estimator, we use a two-step matching approach following Ahn and Powell (1993) and Engberg et al. (1996). The main goal of this method is to eliminate unobservable effects that can create estimation bias without depending on strong assumptions. In our study, we use this approach for two reasons: (i) to deal with the selection processes on the credit market without assuming a particular functional form of the selection term or an exclusion restriction and (ii) to cancel out any unobservable industry or year-fixed effects. The main idea is to match two similar
Table 7  Robustness check. The coefficient estimates are from the one-sided (censored at zero) *Tobit* model and the *Heckman selection MLE* model. Each regression includes industry-year-afterCrisis2008 fixed effects. Heckman estimations also contain selection term. The selection equation additionally includes the average standard deviation of *return-on-assets* in the last four years

| Term                                                                 | Tobit (1) | Heckman (2) |
|----------------------------------------------------------------------|-----------|-------------|
| log(C.Assets)](t-1)                                                 | 0.905***  | 0.432***    |
| log(C.Assets)](t-1) × ManufacturingIndustryi                        | -0.227**  | -0.119***   |
| log(C.Assets)](t-1) × ConstructionIndustryi                         | 0.667***  | 0.279***    |
| log(C.Assets)](t-1) × ManufacturingIndustryi × AfterCrisis2008      | 0.599***  | 0.0525      |
| log(C.Assets)](t-1) × ConstructionIndustry × AfterCrisis2008        | -0.160    | -0.229***   |
| log(C.Assets)](t-1) × AfterCrisis2008                               | -0.679*** | 0.0350      |
| log(NC.Assets)](t-1)                                                | 0.653***  | 0.222***    |
| log(NC.Assets)](t-1) × ManufacturingIndustryi                       | -0.169*** | 0.0431*     |
| log(NC.Assets)](t-1) × ConstructionIndustryi                        | -0.132**  | -0.0352     |
| log(NC.Assets)](t-1) × ManufacturingIndustryi × AfterCrisis2008     | 0.104     | 0.0505      |
| log(NC.Assets)](t-1) × ConstructionIndustry × AfterCrisis2008       | 0.0116    | 0.102***    |
| log(NC.Assets)](t-1) × AfterCrisis2008                              | -0.211*** | -0.0599***  |
| log(Equity)](t-1)                                                   | -0.796*** | 0.0274      |
| ReturnOnAssets)](t-1)                                               | -0.807**  | -0.759***   |
| OperatingMargin)](t-1)                                              | 0.470***  | 0.513***    |
| MarketPower)](t-1)                                                  | -0.684*   | -0.363**    |
| DummyHigh − LeverageFirm)](t-1)                                     | 0.312***  | 0.393***    |
| σ(return on assets), over the last 4 years                           | -9.454*** |             |
companies and to discover which factors explain the difference in the amount of new loans between them. The factors that should explain the difference are the explanatory variables of the following model:

\[
\log(\text{New Loans}_{ig})_t = \beta_0 + \beta_1 \cdot \log(\text{Total Assets}_{ig})_{t-1} + \beta_2 \cdot \log(\text{Equity}_{ig})_{t-1} \\
+ \beta_3 \cdot \text{Return On Assets}_{ig(t-1)} + \beta_4 \cdot \text{Operating Margin}_{ig(t-1)} \\
+ \beta_5 \cdot \text{Market Power}_{ig(t-1)} + \beta_6 \cdot \text{High Leverage Firm}_{ig(t-1)} \\
+ \beta_7 \cdot \text{Age}_{igt} + \beta_8 \cdot \sigma(\text{return on assets}_{ig})_t + \epsilon_{igt},
\]

Note that this is the model given in Eq. (3), but we are including the standard deviation of return on asset without assuming any exclusion restriction as well as we excluded all interaction terms since we will estimate the model for each industry and each year separately.

We say that two companies are similar if they have the same (or similar) probability of obtaining new loans. Therefore, we calculate the probability of having new loans for each company \(i\) in industry \(g\) at time \(t\) using a Probit model including the set of explanatory variables given in Eq. (4). Note that this is the first step of the Heckman selection model. Once we have calculated the probabilities, we are matching similar companies based on these estimated values.

In practice, we create all possible pairs of companies obtaining \(M = \binom{n}{2}\) pairs of firms. Then, we take the difference between each pair \(\Delta_{ij}\), ending up with a sample of \(M = \binom{n}{2}\) observations. Hence, our model becomes:

\[
\Delta_{ij} \log(\text{New Loans}_{mg})_t = \beta_1 \cdot \Delta_{ij} \log(\text{Total Assets}_{mg})_{t-1} \\
+ \beta_2 \cdot \Delta_{ij} \log(\text{Equity}_{mg})_{t-1} \\
+ \beta_3 \cdot \Delta_{ij} \text{Return On Assets}_{mg(t-1)} \\
+ \beta_4 \cdot \Delta_{ij} \text{Operating Margin}_{mg(t-1)} \\
+ \beta_5 \cdot \Delta_{ij} \text{Market Power}_{mg(t-1)} \\
+ \beta_6 \cdot \Delta_{ij} \text{High Leverage Firm}_{mg(t-1)}
\]
where $m$ identifies each pair of companies, $g$ stands for industry and $t$ indicates years.

Then we use the estimated probabilities of having new loans for firm $i$ and firm $j$ to calculate kernel weights $K(\cdot)_m$ which will be assigned to each pair of companies $m$. If each pair $m$ consists of firms $i$ and $j$, we use the estimated probabilities $P_i$ and $P_j$ and calculate the kernel weight $K(\Delta_{ij} P)_m$, where $\Delta_{ij} P = |P_i - P_j|$, such that: $\lim_{\Delta_{ij} P \to 0} K(\Delta_{ij} P)_m = 1$ and $\lim_{\Delta_{ij} P \to 1} K(\Delta_{ij} P)_m = 0$. In words, higher weights are associated with the pairs of companies with closer probabilities of having new loans. Finally, we run a weighting regression on $M = \binom{n}{2}$ observations applying the kernel weights to each corresponding observation $m$.

The detailed outputs for the three industries that are considered in the parametric estimation are provided in Tables 12, 13, and 14 in appendix, while the results of our coefficient of interest $\beta_1$, which is the elasticity between new loans and firm size (total assets), is summarized and given in Fig. 10.

Figure 10 suggests that the elasticity coefficient in the construction industry was increasing up to 2006 reaching its maximum value close to 1.3, while it was declining in the following years attaining its minimum of 0.658 in 2010. A couple of important findings should be remarked. First, the large amount of bank loans assigned to the construction sector before the crisis (see Fig. 4) is mainly allocated to large companies. Also in the other sectors banks were lending to larger companies, but the allocation was more balanced than in the construction sector since the elasticity coefficient is mostly below 1. During the Spanish crisis, when less loans were available, we observe that new loans were distributed in more uniformly. However, in the recapitalization period of the Spanish economy, when banks were allocating higher amounts of credit, we find again an allocation bias toward large companies, not only in the construction but also in other sectors. After 2013, the elasticity of the manufacturing sector became greater than one and larger than in the other two considered sectors. Recalling Fig. 4, we remind that in the post-crisis period there was a re-balancing process of banks’ loan

\[ + \beta_7 \cdot \Delta_{ij} \text{Age}_{mgt} + \beta_8 \cdot \Delta_{ij} \text{\sigma(return on assets}_{mgt})_t \]
\[ + \Delta_{ij} \text{\varepsilon}_{mgt}. \]
Table 8  The coefficient estimates are from the fixed-effect (within) logit model. Depended variable Dummy default is equal to one if a firm defaults at time \( t \), and zero otherwise. The regression includes industry-year-afterCrisis2008 fixed effects and constant. The marginal effects are calculated at means.

|                  | Logit \( \frac{dy}{dx} \) model (1) dummy default | Logit \( \frac{dy}{dx} \) model (2) dummy default | Logit \( \frac{dy}{dx} \) model (3) dummy default |
|------------------|--------------------------------------------------|--------------------------------------------------|--------------------------------------------------|
| log(\( New \ Loan_i \)\(_{t-1}\))          | -0.000191 (-0.41)                                |                                                 |                                                 |
| log(\( New \ Loan_i \)\(_{t-2}\))          |                                                 | 0.00107** (2.07)                                 |                                                 |
| log(\( New \ Loan_i \)\(_{t-3}\))          |                                                 |                                                 | 0.00155*** (2.80)                                |
| \( AfterCrisis2008_t \)                      | 0.0675*** (29.01)                                | 0.0696*** (28.83)                                | 0.0777*** (28.87)                                |
| \( N \)                                        | 86,564                                          | 77,862                                          | 69,776                                          |

*\( t \) statistics in parentheses
*\( p < 0.10 \)
**\( p < 0.05 \)
***\( p < 0.01 \)

portfolio from the construction sector toward the manufacturing and trade industries. The two sectors together accounted for a share of 40% of total bank loans (20% each) at the end of 2014, while the construction sector decreased its share to 30%. Acharya et al. (2019), showing that in the post-crisis period (when the European Central Bank aimed to re-capitalize the financial sector of the European economies) lenders were primarily financing existing low-quality borrowers, so-called zombie companies, to avoid bigger losses (too big to fail). This is in line with our observed distribution of loans, biased toward the largest companies in the post-crisis period.

5.3 Bankruptcy probability of firms receiving loans

We aim at assessing the financial fragility of companies that received bank loans. To do this, we design a firm default model where we estimate whether the amount of new loans taken in the preceding one, two, or three years has any predictive power on the firm’s default. The model is:

\[
DummyDefault_{it} = \beta_0 + \beta_k \cdot \log(\text{New Loans}_i)_{t-k} + \text{IndustryDummy}_i \lambda + \alpha \cdot \text{AfterCrisis2008}_t + \text{YearDummy}_t \theta + \epsilon_{it},
\]

where the dependent variable is a dummy that is equal to one if a company defaults\(^{16}\) at time \( t \), and zero otherwise. \( \beta_k \) is our coefficient of interests which is associated

\(^{16}\) We define the default as an interruption of the economic activity of a company for any reason linked to financial issues. This is captured by the following values of the “status” variable: bankruptcy; dissolution; inactive; insolvency proceedings; official deregistration; provisional deregistration; provisional deregistration according to Art. 3781 RRMM*; provisional deregistration: financial statements not filed in; suspension of payments proceedings; and winding up.
with the *new loans* that had been received in periods \( t - k \), where \( k \in \{1, 2, 3\} \). In practice, we estimate three separate models including the amount of received loans in periods \( t - 1 \), \( t - 2 \), and \( t - 3 \), and we obtain the correspondent \( \beta \)'s in models (1)–(3), respectively. The models also include industry-year and after-crisis fixed effects, and they are estimated with the fixed-effect (FE) logistic panel data model upon the suggestion of the Hausman test using robust and clustered standard errors at the firm level. Note that, due to the FE estimator all firm-specific time-invariant variables, such as industry fixed effects are finally dropped from the model.

The results of the estimated model provided in Table 6 show that a higher amount of received loans (*new loans*) in the past two or three years increases the probability of default for firms (\( \beta \)'s in models (2) and (3) is significant and positive). In addition, the results indicate that the probability of default is significantly higher after the crisis, captured by the corresponding dummy variable (Table 8).

### 6 Conclusions

This paper studied the allocation of bank loans in Spain from 1999 to 2014. We found empirical evidence that a small number of large firms account for a high proportion of the total bank loans in the economy. Bank loans are more concentrated, across firms, than sales, employees or assets, which are known to exhibit fat-tailed distributions. We also found that companies in the construction sector have been able to raise more loans during the boom period, at the expense of the manufacturing sector. We study the rationale of this reallocation of loans from manufacturing to construction, finding that it has been mainly driven by the housing price bubble, which determined a comparative increase in the operating margins of construction companies. On the other hand, profitability indicators were not favorable in the construction sector, while financial fragility indicators, as debt over assets and equity over assets ratios, were considerably higher. This scenario signals a questionable allocation of bank loans in Spain, during the observed period. In this respect, we found that the default probability of companies who had received more loans in previous years turns out to be higher.

Concerning the determinants of bank credit allocation, we estimated parametric and semi-parametric models that confirm the foregoing analysis. Large companies, during the boom period, received new loans in a more than a proportional way with respect to their total assets. This is even more evident for companies belonging to the construction sector and might explain the observed accumulation of bank credit.

Therefore, large companies, especially in the construction sector, became even larger (in terms of total assets) and riskier (in terms of financial leverage). When the crisis started, several ones went bankrupt, with severe repercussions on the macroeconomic stability and on the performance of the country.

According to some authors, this situation has been possible because of controversial governance on risk-taking in the financial industry which favored large, already indebted companies. This has been particularly critical in the construction sector, where the price expansion in the housing market created apparent investment opportunities, attracting massive amounts of loans.
Finally, banks’ credit allocation is a crucial issue in modern capitalistic economies, and the implications of concentrating credit to few large firms in terms of GDP fluctuations should be investigated in depth. The Spanish case under study suggest the need to design incentives and/or regulations in order to prevent the excessive concentration of bank loans and to foster economic stability.

Future developments include the repetition of the analysis with data sets of other countries, in order to check the international consistency of our results. We also plan to explore and design a set of statistical equilibrium models describing the loan allocation process, in order to investigate the determinants of the observed empirical distributions. In this respect, a hypothesis we want to test is if the allocation mechanism of bank loans could be, at least in part, responsible for the fat-tailed distribution of firms’ assets.

**Funding** This work was supported by the EU STREP Project SYMPHONY (FP7-ICT-2013- 10, Grant Agreement 611875) and by the EU STREP project FinMaP (FP7-SSH-2013-2, Grant Agreement 612955).

**Declarations**

**Conflict of interest** The authors declare that they have no conflict of interest.

**Appendix**

**Power law analysis and Hill tail index estimation**

We estimate the Hill Tail index (a scaling parameter) presented in Fig. 2b using the Hill Tail estimator as suggested by Bottazzi et al. (2015), and following the procedure given by Clauset et al. (2009) we examine whether economic indicators follow a power low distribution. The index typically lies in the range of $2 < \alpha < 3$, and the lower the tail index, the thicker the tails (see Danielsson (2011) for details). If the index is smaller than 2, a variable has theoretically an infinite variance, which is the case of non-current bank debt, total assets, total bank debt, equity and total sales. The detailed estimations are given in Table 9 confirming that the distributions of all firm size proxies, such as total assets, annual sales, and number of employees, have heavy tails and also appear visually to follow a power law. Upon more careful analysis, a power law distribution is not ruled out, but log-normal distribution sometimes may offer better fit to the data, which is in line with findings of Bottazzi et al. (2015) (Tables 10, 11).
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Table 9 Tests of power law behavior in the data sets. For each data set (each variable in each year), we estimate cutoff values $X_{min}$ together with a scaling parameter (tail index) $\alpha$ and perform the goodness-of-fit test providing p-values ($p^{GoF}$) for the fit to the power law model. The test quantifies the plausibility of the hypothesis, $H_0$: data follow a power law; $H_A$: data do not follow a power law. Following Clauset et al. (2009), we set the rejection rule to $p < 0.1$. In addition, we provide likelihood ratios for the alternatives—log-normal, Poisson and exponential distributions, $LR^{LN}$, $LR^{POIS}$, $LR^{EXP}$, respectively. The likelihood-ratio test quantifies the plausibility of the hypothesis, $H_0$: both distributions are equally far from the true distribution; $H_A$: one of the test distributions is closer to the true distribution. We also present $p^{LR}$, $p^{POIS}$, and $p^{EXP}$ for each alternative. If we reject $H_0$ meaning that $p < 0.1$ then the $LR$ values indicate which distribution is favorable. Positive values of the log-likelihood ratios $LR > 0$ indicate that a power law distribution is favored over the alternative.

| Year | $X_{min}$ | $\alpha$ | $p^{GoF}$ | $LR^{LN}$ | $p^{LR}$ | $LR^{POIS}$ | $p^{LR}$ | $LR^{EXP}$ | $p^{LR}$ |
|------|-----------|----------|-----------|-----------|---------|-------------|---------|-----------|---------|
| 1999 | 3648      | 1.806    | 0.248     | -8.995    | 0.000   | 6.009       | 0.000   | 10.986    | 0.000   |
| 2000 | 3732      | 1.780    | 0.441     | -9.656    | 0.000   | 7.227       | 0.000   | 12.196    | 0.000   |
| 2001 | 3779      | 1.765    | 0.542     | -11.021   | 0.000   | 7.584       | 0.000   | 12.303    | 0.000   |
| 2002 | 4122      | 1.769    | 0.408     | -13.485   | 0.000   | 8.493       | 0.000   | 13.664    | 0.000   |
| 2003 | 4112      | 1.748    | 0.451     | -15.326   | 0.000   | 9.436       | 0.000   | 14.636    | 0.000   |
| 2004 | 4494      | 1.747    | 0.503     | -17.074   | 0.000   | 9.655       | 0.000   | 14.936    | 0.000   |
| 2005 | 4583      | 1.729    | 0.545     | -14.492   | 0.000   | 9.253       | 0.000   | 14.210    | 0.000   |
| 2006 | 5396      | 1.738    | 0.506     | -11.900   | 0.000   | 10.176      | 0.000   | 15.436    | 0.000   |
| 2007 | 5553      | 1.720    | 0.484     | -9.683    | 0.000   | 12.202      | 0.000   | 17.401    | 0.000   |
| 2008 | 5324      | 1.711    | 0.488     | -11.937   | 0.000   | 9.732       | 0.000   | 15.076    | 0.000   |
| 2009 | 4913      | 1.698    | 0.548     | -12.995   | 0.000   | 9.709       | 0.000   | 14.783    | 0.000   |
| 2010 | 4884      | 1.694    | 0.419     | -12.778   | 0.000   | 9.432       | 0.000   | 14.346    | 0.000   |
| 2011 | 4868      | 1.694    | 0.476     | -11.894   | 0.000   | 10.689      | 0.000   | 15.059    | 0.000   |
| 2012 | 4547      | 1.685    | 0.484     | -12.484   | 0.000   | 10.514      | 0.000   | 14.607    | 0.000   |
| 2013 | 4529      | 1.685    | 0.499     | -12.181   | 0.000   | 10.212      | 0.000   | 14.139    | 0.000   |
| 2014 | 4956      | 1.705    | 0.351     | -5.443    | 0.000   | 8.655       | 0.000   | 11.623    | 0.000   |

| Year | $X_{min}$ | $\alpha$ | $p^{GoF}$ | $LR^{LN}$ | $p^{LR}$ | $LR^{POIS}$ | $p^{LR}$ | $LR^{EXP}$ | $p^{LR}$ |
|------|-----------|----------|-----------|-----------|---------|-------------|---------|-----------|---------|
| 1999 | 5553      | 1.955    | 0.348     | -6.661    | 0.000   | 8.128       | 0.000   | 11.372    | 0.000   |
| 2000 | 5379      | 1.916    | 0.146     | 15.350    | 0.000   | 7.957       | 0.000   | 10.949    | 0.000   |
| 2001 | 5587      | 1.913    | 0.368     | -10.895   | 0.000   | 8.686       | 0.000   | 11.681    | 0.000   |
| 2002 | 5810      | 1.922    | 0.390     | -8.743    | 0.000   | 9.132       | 0.000   | 12.154    | 0.000   |
| 2003 | 6470      | 1.942    | 0.514     | -6.158    | 0.000   | 9.126       | 0.000   | 12.207    | 0.000   |
| 2004 | 7013      | 1.949    | 0.536     | -4.508    | 0.000   | 8.988       | 0.000   | 12.043    | 0.000   |
| 2005 | 7018      | 1.931    | 0.472     | -6.038    | 0.000   | 8.452       | 0.000   | 11.376    | 0.000   |
| 2006 | 7127      | 1.910    | 0.369     | -11.432   | 0.000   | 8.452       | 0.000   | 11.300    | 0.000   |
| 2007 | 7913      | 1.915    | 0.356     | -7.879    | 0.000   | 8.916       | 0.000   | 11.920    | 0.000   |
| 2008 | 7247      | 1.888    | 0.391     | -10.210   | 0.000   | 8.466       | 0.000   | 11.595    | 0.000   |
| 2009 | 6788      | 1.907    | 0.390     | -5.708    | 0.000   | 8.900       | 0.000   | 12.199    | 0.000   |
Table 9 continued

| Year | $X_{min}$ | $\alpha$ | $p^{GoF}$ | $LR^{LN}$ | $p^{LR}$ | $LR^{POIS}$ | $p^{LR}$ | $LR^{EXP}$ | $p^{LR}$ |
|------|-----------|-----------|------------|-----------|---------|-------------|---------|------------|---------|
| 2010 | 6774      | 1.893     | 0.488      | -7.912    | 0.000   | 8.470       | 0.000   | 11.750     | 0.000   |
| 2011 | 6991      | 1.879     | 0.532      | -5.994    | 0.000   | 7.602       | 0.000   | 10.875     | 0.000   |
| 2012 | 6573      | 1.849     | 0.487      | -7.774    | 0.000   | 6.870       | 0.000   | 10.112     | 0.000   |
| 2013 | 7001      | 1.855     | 0.319      | -5.461    | 0.000   | 7.064       | 0.000   | 10.249     | 0.000   |
| 2014 | 6869      | 1.826     | 0.512      | -5.007    | 0.000   | 6.296       | 0.000   | 8.514      | 0.000   |

| Year | $X_{min}$ | $\alpha$ | $p^{GoF}$ | $LR^{LN}$ | $p^{LR}$ | $LR^{POIS}$ | $p^{LR}$ | $LR^{EXP}$ | $p^{LR}$ |
|------|-----------|-----------|------------|-----------|---------|-------------|---------|------------|---------|
| 1999 | 300       | 2.267     | 0.570      | 1.443     | 0.149   | 282.346     | 0.000   | 9.997      | 0.000   |
| 2000 | 217       | 2.253     | 0.505      | 1.784     | 0.074   | 399.834     | 0.000   | 11.393     | 0.000   |
| 2001 | 215       | 2.242     | 0.473      | 0.333     | 0.739   | 506.329     | 0.000   | 10.877     | 0.000   |
| 2002 | 240       | 2.254     | 0.217      | 0.835     | 0.404   | 471.940     | 0.000   | 10.694     | 0.000   |
| 2003 | 311       | 2.275     | 0.721      | 1.314     | 0.189   | 326.952     | 0.000   | 10.505     | 0.000   |
| 2004 | 159       | 2.213     | 0.054      | -0.720    | 0.471   | 698.461     | 0.000   | 12.043     | 0.000   |
| 2005 | 183       | 2.226     | 0.753      | 0.247     | 0.805   | 634.823     | 0.000   | 11.873     | 0.000   |
| 2006 | 153       | 2.213     | 0.768      | -0.304    | 0.761   | 799.288     | 0.000   | 12.610     | 0.000   |
| 2007 | 202       | 2.218     | 0.199      | -0.253    | 0.800   | 622.203     | 0.000   | 12.713     | 0.000   |
| 2008 | 217       | 2.193     | 0.533      | -0.661    | 0.509   | 635.026     | 0.000   | 11.904     | 0.000   |
| 2009 | 175       | 2.166     | 0.620      | -0.566    | 0.571   | 654.144     | 0.000   | 12.285     | 0.000   |
| 2010 | 241       | 2.176     | 0.954      | 0.626     | 0.532   | 442.530     | 0.000   | 11.851     | 0.000   |
| 2011 | 222       | 2.163     | 0.769      | 0.457     | 0.648   | 475.585     | 0.000   | 11.835     | 0.000   |
| 2012 | 219       | 2.145     | 0.327      | -0.579    | 0.563   | 450.017     | 0.000   | 11.443     | 0.000   |
| 2013 | 219       | 2.146     | 0.289      | 0.733     | 0.464   | 495.486     | 0.000   | 11.068     | 0.000   |
| 2014 | 205       | 2.102     | 0.937      | 0.486     | 0.627   | 376.739     | 0.000   | 9.626      | 0.000   |

Statistically significant $p$-values are denoted in bold

Semi-parametric estimator and results

To implement the semi-parametric estimator, we first define our main model such as:

$$y_{igt} = X_{igt} \beta_{gt} + \varepsilon_{igt}, \quad (7)$$

where $y$ is new bank loans, and $X$ is a vector of explanatory variables given in Eq. (4). We assume $d_{igt} = 1\{x_{igt} \gamma_{gt} + \upsilon_{igt} > 0\}$, $y_{igt} = y_{igt} \cdot d_{igt}$, and that $f(\varepsilon_{igt}, \upsilon_{igt})$ is independent of $x_{igt}$. Since we do not want to assume a particular distribution $f$, in the first step we run a Probit model and estimate the probabilities that firms obtain new loans such as:

$$d_{igt} = Z_{igt} \gamma_{gt} + \upsilon_{igt}, \quad (8)$$
### Table 10 Descriptive statistics

|                          | Obs. | Mean  | SD    | Min  | p1    | p25   | p50   | p75   | p99   | Max  |
|--------------------------|------|-------|-------|------|-------|-------|-------|-------|-------|------|
| Int. bill-to-debt ratio  | 345,266 | 0.024 | 0.029 | 0    | 0     | 0.009 | 0.020 | 0.032 | 0.111 | 0.987 |
| ΔBank debt ≥ 0           | 206,717 | 2026.5 | 26,562.4 | 0    | 0     | 0     | 638   | 27,622 | 4,056,695 |
| log(New Loan)            | 97,952 | 6.493 | 1.846 | 0    | 1.386 | 5.451 | 6.565 | 7.616 | 10.900 | 15.216 |
| Operating Margin         | 350,111 | 0.049 | 0.576 | −282.341 | −0.398 | 0.011 | 0.036 | 0.082 | 0.564 | 47.539 |
| ROA                      | 357,957 | 0.054 | 0.347 | −5.438 | −0.216 | 0.005 | 0.034 | 0.088 | 0.438 | 192.875 |
| Default                  | 357,573 | 0.031 | 0.174 | 0    | 0     | 0     | 0     | 1     | 1     | 1    |
| Total Assets             | 358,366 | 45127.4 | 300,970.7 | 500  | 1160  | 5312  | 10,403 | 24,695 | 574,076 | 34,100,000 |
| log(TotalAssets)         | 358,366 | 9.438 | 1.258 | 6.215 | 7.056 | 8.578 | 9.250 | 10.114 | 13.261 | 17.345 |
| Equity                   | 358,349 | 16,706.7 | 138,639 | 0    | 61    | 1363  | 3417  | 8904  | 223,470 | 21,300,000 |
| log(Equity)              | 358,349 | 8.158 | 1.596 | −6.908 | 4.111 | 7.217 | 8.137 | 9.094 | 12.317 | 16.876 |
| Market power             | 348,992 | 0.500 | 0.500 | 0    | 0     | 0     | 0     | 0     | 0     | 0.012 |
| High – leverage firms    | 358,366 | 0.500 | 0.500 | 0    | 0     | 0     | 0     | 1     | 1     | 1    |
| Age                      | 358,366 | 20.343 | 15.119 | 0    | 1     | 10    | 18    | 27    | 75    | 159   |
| σ(return on assets)_{t} (last 4 years) | 208,693 | 0.043 | 0.055 | 0    | 0.002 | 0.015 | 0.029 | 0.053 | 0.225 | 5.848 |
| Non – Current Assets     | 358,366 | 22,946.7 | 230,513 | 0.001 | 1     | 783   | 2478  | 7745  | 332,685 | 31,600,000 |
| log(Non – Current Assets)| 358,366 | 7.677 | 2.403 | −6.908 | 0     | 6.663 | 7.815 | 8.955 | 12.715 | 17.269 |
| Current Assets           | 358,366 | 22,178.4 | 109,946.5 | 0.001 | 525   | 3379  | 6522  | 14,876 | 260,749 | 10,800,000 |
| log(Current Assets)      | 358,366 | 8.918 | 1.266 | −6.908 | 6.263 | 8.125 | 8.783 | 9.608 | 12.471 | 16.197 |
| Variables            | $Int. bill_t$ | log($New Loan)_t$ | $Op. M. $ | $Op. M_{t-1} $ | $ROA$ | $ROA_{t-1}$ |
|---------------------|---------------|-------------------|----------|----------------|-------|-----------|
| Int. bill to debt ratio$_t$ | 1             |                   |          |                |       |           |
| log($New Loan)_t$   | 0.036***      | 1                 |          |                |       |           |
| Operating Margin$_t$ | 0.003*        | 0.018***          | 1        |                |       |           |
| Operating Margin$_{t-1}$ | 0.005***    | 0.068***          | 0.225*** | 1              |       |           |
| $ROA$               | $-0.053^{***}$ | $-0.077^{***}$    | $0.182^{***}$ | $0.107^{***}$ | 1     |           |
| $ROA_{t-1}$         | $-0.059^{***}$ | $-0.026^{***}$    | $0.109^{***}$ | $0.164^{***}$ | $0.218^{***}$ | 1      |
| Default             | 0.040***      | 0.027***          | $-0.022^{***}$ | $-0.008^{***}$ | $-0.030^{***}$ | $-0.053^{***}$ |
| log($Total Assets)_{t-1}$ | 0.002       | 0.515***          | $0.007^{***}$ | $0.017^{***}$ | $-0.022^{***}$ | $-0.072^{***}$ |
| log($Equity)_{t-1}$ | $-0.028^{***}$ | 0.359***          | $0.014^{***}$ | $0.030^{***}$ | $0.010^{***}$ |           |
| MarketPower$_{(t-1)}$ | $-0.019^{***}$ | 0.140***          | $0.003*$ | $0.004^{**}$ | $0.008^{***}$ | $0.010^{***}$ |
| High — LeverageFirm$_{(t-1)}$ | 0.074*** | 0.091***          | $-0.020^{***}$ | $-0.031^{***}$ | $-0.049^{***}$ | $-0.215^{***}$ |
| Age$_t$             | $-0.014^{***}$ | 0.013***          | $-0.007^{***}$ | $-0.004^{**}$ | $-0.017^{***}$ | $-0.043^{***}$ |
Table 11 continued

| Variables                          | $\text{Int. bill}_t$ | $\log(\text{New Loan})_t$ | $\text{Op. M.}_t$ | $\text{Op. M}_{t-1}$ | $\text{ROA}_t$ | $\text{ROA}_{t-1}$ |
|-----------------------------------|----------------------|----------------------------|--------------------|----------------------|----------------|-------------------|
| $\sigma(\text{return on assets})_t$ | $-0.007^{***}$       | $-0.040^{***}$             | $-0.002$           | $-0.006^{***}$       | $0.194^{***}$ | $0.236^{***}$     |
| $\log(\text{Non - Current Assets})_{t-1}$ | $0.037^{***}$       | $0.358^{***}$             | $-0.005^{***}$     | $0$                  | $-0.035^{***}$ | $-0.111^{***}$   |
| $\log(\text{Current Assets})_{t-1}$ | $-0.038^{***}$       | $0.464^{***}$             | $-0.001$           | $0.011^{***}$        | $-0.014^{***}$ | $-0.017^{***}$   |

| Variables                          | $\text{Default}$ | $\log(\text{TA})_{t-1}$ | $\log(\text{Eq.})_{t-1}$ | $\text{M. P.}_{(t-1)}$ | $\text{HL. Firm}_{(t-1)}$ | $\text{Age}_t$ | $\sigma(\text{ROA})_t$ | $\log(\text{NC. A.)}_{t-1}$ | $\log(\text{C. A.)}_{t-1}$ |
|-----------------------------------|------------------|--------------------------|--------------------------|-------------------------|---------------------------|---------------|-------------------------|-------------------------------|-----------------------------|
| $\text{Int. bill to debt ratio}_t$ | $1$              |                          |                          |                         |                           |               |                         |                               |                             |
| $\log(\text{New Loan})_t$         |                  |                          |                          |                         |                           |               |                         |                               |                             |
| $\text{Operating Margin}$         |                  |                          |                          |                         |                           |               |                         |                               |                             |
| $\text{Operating Margin}_{t-1}$   |                  |                          |                          |                         |                           |               |                         |                               |                             |
| $\text{ROA}$                      |                  |                          |                          |                         |                           |               |                         |                               |                             |
| $\text{ROA}_{t-1}$                |                  |                          |                          |                         |                           |               |                         |                               |                             |
| $\text{Default}$                  | $1$              |                          |                          |                         |                           |               |                         |                               |                             |
| $\log(\text{Total Assets})_{t-1}$ |                  | $0.030^{***}$            | $1$                     |                         |                           |               |                         |                               |                             |
| $\log(\text{Equity})_{t-1}$       | $-0.023^{***}$   | $0.823^{***}$            | $1$                     |                         |                           |               |                         |                               |                             |
| $\text{MarketPower}_{(t-1)}$      | $-0.003^{*}$     | $0.280^{***}$            | $0.213^{***}$          | $1$                     |                           |               |                         |                               |                             |
| $\text{High - Leverage Firm}_{(t-1)}$ | $0.056^{***}$   | $-0.046^{***}$           | $-0.438^{***}$         | $0.018^{***}$           | $1$                       |               |                         |                               |                             |
| $\text{Age}_t$                    | $-0.025^{***}$   | $0.227^{***}$            | $0.338^{***}$          | $0.042^{***}$           | $-0.209^{***}$           | $1$           |                         |                               |                             |
| $\sigma(\text{return on assets})_t$ | $0.027^{***}$   | $-0.045^{***}$           | $0.019^{***}$          | $-0.009^{***}$          | $-0.106^{***}$           | $-0.046^{***}$ | $1$                     |                               |                             |
| $\log(\text{Non - Current Assets})_{t-1}$ | $-0.016^{***}$ | $0.645^{***}$            | $0.638^{***}$          | $0.171^{***}$           | $-0.108^{***}$           | $0.244^{***}$ | $-0.066^{***}$ | $1$                             |                             |
| $\log(\text{Current Assets})_{t-1}$ | $0.035^{***}$   | $0.861^{***}$            | $0.674^{***}$          | $0.274^{***}$           | $0.003^{*}$              | $0.215^{***}$ | $-0.038^{***}$ | $0.381^{***}$       | $1$                         |

*p < 0.10

**p < 0.05

***p < 0.01
where \( d \) is an indicator equal to 1 if a firm gets new bank loans at time \( t \); \( Z \) is a vector of explanatory variables in the first-step selection equation.\(^{17}\)

In the second step, we choose firm \( i \) and \( j \) in industry \( g \) at time \( t \) such that from equations (8) we have the equality \( Z_{igt} \hat{\gamma}_{gt} = Z_{jgt} \hat{\gamma}_{gt} \), i.e., we match firm \( i \) and firm \( j \) within an industry and year with the same probability of receiving new bank loans and subtract one firm from another. In particular using Eq. (7), we do the following transformation:

\[
y_{igt} - y_{jgt} = (X_{igt} - X_{jgt})\beta_{gt} + \hat{\lambda}_{gt}(Z_{igt} \hat{\gamma}_{gt}) - \hat{\lambda}_{gt}(Z_{jgt} \hat{\gamma}_{gt}) = (X_{igt} - X_{jgt})\beta_{gt}.
\]

(9)

In practice, we assume a second-order Gaussian kernel function. We calculate and assign the kernel weights to each possible pair of companies within the industry and year, i.e., we use an estimator such as:

\[
\begin{bmatrix}
\sum K\left(\frac{(Z_{igt} - Z_{jgt})\hat{\gamma}_{gt}}{n}\right)(X_{igt} - X_{jgt})(X_{igt} - X_{jgt})'
\sum K\left(\frac{(Z_{igt} - Z_{jgt})\hat{\gamma}_{gt}}{n}\right)(X_{igt} - X_{jgt})(Y_{igt} - Y_{jgt})'
\end{bmatrix}^{-1} \times
\begin{bmatrix}
\sum K\left(\frac{(Z_{igt} - Z_{jgt})\hat{\gamma}_{gt}}{n}\right)(X_{igt} - X_{jgt})(X_{igt} - X_{jgt})'
\sum K\left(\frac{(Z_{igt} - Z_{jgt})\hat{\gamma}_{gt}}{n}\right)(X_{igt} - X_{jgt})(Y_{igt} - Y_{jgt})'
\end{bmatrix}
\]

(10)

The data-dependent bandwidths are chosen by generalized cross-validation over a crude grid of possible values. Using the same approach, we also recover the intercept terms from the main models that were lost due to the transformation (Tables 12, 13, 14).

\(^{17}\) Note that in our case the set of explanatory variables \( Z_{igt} = X_{igt} \) and it is given in Eq. (4), while the estimation results are provided in Table 6.
Table 12  The dependent variable is the logarithm of new loans that is taken by firms in the current year. The coefficient estimates are from a semi-parametric selection model, for the construction industry and for each year separately.

| Independent variable                  | 2004     | 2005     | 2006     | 2007     | 2008     |
|---------------------------------------|----------|----------|----------|----------|----------|
| ln(total assets_{it})_{t-1}           | 1.156*** | 1.238*** | 1.291*** | 1.114*** | 0.994*** |
|                                       | (3376.483) | (1400.632) | (1825.345) | (4034.592) | (1970.384) |
| DummyHigh – LeverageFirm_{it(t-1)}    | 0.205*** | 0.128*** | 0.007*** | 0.281*** | 0.092*** |
|                                       | (1650.404) | (408.010) | (26.981) | (2751.920) | (495.617) |
| Return on assets_{it(t-1)}            | -0.345*** | -0.814*** | -1.234*** | -0.290*** | -2.829*** |
|                                       | (-17,009.784) | (-15,110.405) | (-28,768.673) | (-15,277.493) | (-98,905.523) |
| ln(equity_{it(t-1)})                  | -0.228*** | -0.290*** | -0.268*** | -0.148*** | -0.142*** |
|                                       | (-568.287) | (-279.563) | (-330.299) | (-454.404) | (-237.296) |
| Firm age_{it}                         | -0.012*** | -0.053    | -0.014**  | -0.005**  | -0.054    |
|                                       | (-3.963)   | (-0.701)  | (-2.347)  | (-2.273)  | (-1.146)  |
| Market power_{it(t-1)}                | -1.301*** | -1.638*** | -1.392*** | -0.249*** | -1.173*** |
|                                       | (-67,815.923) | (-35,861.793) | (-22,774.335) | (-15,327.516) | (-30,763.985) |
| σ(return on assets_{it}) over the last 4 years | 2.540*** | 0.821*** | 0.715*** | 0.511*** | 3.773*** |
|                                       | (269,348.903) | (18,626.864) | (34,019.527) | (53,341.648) | (243,863.390) |
| Independent variable | 2004 | 2005 | 2006 | 2007 | 2008 |
|----------------------|------|------|------|------|------|
| Operating margin\(_{i(t-1)}\) | 1.289*** (21,152.629) | 0.814*** (4626.032) | 1.086*** (6694.351) | 0.146*** (2674.902) | 0.470*** (3817.053) |
|\(N\) | 1368 | 1583 | 1773 | 1734 | 1307 |

| Independent variable | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 |
|----------------------|------|------|------|------|------|------|
| \(\ln(\text{total assets}_t)_{i-1}\) | 0.830*** (1542.699) | 0.658*** (1653.985) | 0.789*** (583.539) | 1.040*** (1182.287) | 1.091*** (1260.691) | 1.033*** (844.601) |
| DummyHigh – LeverageFirm\(_{i(t-1)}\) | 0.073*** (386.095) | 0.244*** (1720.980) | 0.107*** (232.135) | 0.098*** (366.915) | -0.739*** (-2627.831) | -0.296*** (-919.299) |
| Return on assets\(_{i(t-1)}\) | -1.536*** (-48,527.047) | 0.155*** (7387.861) | -1.636*** (-19,607.557) | 0.187*** (-4555.698) | -0.590*** (-9622.622) | -0.574*** (-6975.634) |
| \(\ln(\text{equity}_t)_{i-1}\) | 0.053*** (92.844) | 0.163*** (371.247) | 0.041*** (28.442) | -0.154*** (-160.368) | -0.456*** (-496.566) | -0.414*** (-314.084) |
| Firm age\(_t\) | -0.064 (-1.411) | -0.023 (-0.626) | -0.018 (-0.142) | 0.00004 (0.005) | 0.0008 (0.095) | -0.005 (-0.481) |
| Market power\(_{i(t-1)}\) | -0.189*** (-2623.960) | -0.253*** (-7236.625) | 0.181*** (944.625) | 0.126*** (915.655) | 0.548*** (5456.646) | 1.552*** (13,368.133) |
| \(\sigma(\text{return on assets}_t)_{i}\) | -0.751*** (-2623.960) | -1.389*** (-7236.625) | -2.122*** (944.625) | 0.398*** (915.655) | -2.074*** (5456.646) | -1.118*** (-30,209.472) |
| over the last 4 years | (-40,951.539) | (-101,474.756) | (-43,310.670) | (16,027.942) | (-74,449.679) | (-30,209.472) |
| Operating margin\(_{i(t-1)}\) | 0.136*** (882.028) | 0.106*** (1080.980) | -0.061*** (-110.201) | -0.065*** (-160.210) | 0.264*** (979.897) | 0.091*** (209.829) |
|\(N\) | 850 | 855 | 718 | 421 | 409 | 341 |

\(t\)-statistics in parentheses

\(\ast \) \(p < 0.10\)

\(\ast\ast \) \(p < 0.05\)

\(\ast\ast\ast \) \(p < 0.01\)
Table 13  The dependent variable is the logarithm of *new loans* that is taken by firms in the current year. The coefficient estimates are from a semi-parametric selection model, for the manufacturing industry and for each year separately.

| Independent variable | 2004        | 2005        | 2006        | 2007        | 2008        |
|----------------------|-------------|-------------|-------------|-------------|-------------|
| ln(total assets)_{t-1} | 0.976***    | 0.997***    | 0.938***    | 0.907***    | 1.079***    |
|                      | (2040.172)  | (5103.071)  | (4878.067)  | (1884.518)  | (3571.845)  |
| DummyHigh - LeverageFirm_{i(t-1)} | 0.159***    | 0.256***    | 0.229***    | 0.312***    | 0.196***    |
|                      | (758.952)   | (3064.025)  | (2837.921)  | (1546.492)  | (1657.419)  |
| Return on asset_{i(t-1)} | −0.321***   | −0.392***   | −0.028***   | 0.334***    | −0.906***   |
|                      | (−9204.389) | (−26,722.264) | (−1747.612) | (9277.571)  | (−42,696.811) |
| ln(equity)_{i(t-1)} | −0.352***   | −0.300***   | −0.260***   | −0.223***   | −0.351***   |
|                      | (−613.588)  | (−1283.246) | (−1152.980) | (−404.413)  | (−1014.128) |
| Firm age_{i} | −0.010      | −0.007**    | −0.003      | −0.002      | −0.005      |
|                      | (−1.357)    | (−2.518)    | (−1.308)    | (−0.315)    | (−1.379)    |
| Market power_{i(t-1)} | −0.928***   | −2.009***   | −1.020***   | −1.715***   | −0.830***   |
|                      | (−27,290.523) | (−120,122.366) | (−105,505.907) | (−50,912.266) | (−36,592.525) |
| σ(return on assets)_{i(t-1)} over the last 4 years | −1.576***   | −2.255***   | −1.839***   | −0.598***   | −0.484***   |
|                      | (−113,236.520) | (−420,898.127) | (−27,6727.919) | (−39,513.907) | (−59,519.187) |
Table 13 continued

| Independent variable | 2004       | 2005       | 2006       | 2007       | 2008       | 2009       | 2010       | 2011       | 2012       | 2013       | 2014       |
|----------------------|------------|------------|------------|------------|------------|------------|------------|------------|------------|------------|------------|
| Operating margin\_i(t−1) | −0.038***  | −0.516***  | −0.620***  | −0.394***  | 0.319***   |            |            |            |            |            |            |
|                      | (−1220.331)| (−39,899.695) | (−49,049.806) | (−12,414.796) | (12,091.448) |            |            |            |            |            |            |
| N                   | 2674       | 2776       | 2870       | 2823       | 2469       |            |            |            |            |            |            |
|\ln(total assets\_i)\_{t−1} |            |            |            |            |            | 0.976***   | 1.028***   | 0.941***   | 0.971***   | 1.231***   | 1.255***   |
|                      |            |            |            |            |            | (2928.033) | (1608.790) | (3761.216) | (3084.530) | (2472.882) | (3688.651) |
| DummyHigh − Leverage\_i(t−1) | 0.034***   | 0.017***   | 0.235***   | 0.167***   | −0.039***  | 0.034***   | 0.104***   |            |            |            |            |
|                      | (258.750)  | (65.932)   | (2227.104) | (1386.537) | (−201.110) | (788.593)  |            |            |            |            |            |
| Return on assets\_i(t−1) |            |            |            |            |            | −0.265***  | −0.344***  | −0.183***  | −0.226***  | −0.474***  | −0.546***  |
|                      |            |            |            |            |            | (−733.913) | (−472.815) | (−652.729) | (−643.313) | (−865.879) | (−1442.629) |
| Firm age\_i |            |            |            |            |            | −0.002     | 0.001      | −0.003     | −0.001     | −0.007     | −0.001     |
|                      |            |            |            |            |            | (−0.361)   | (0.155)    | (−0.675)   | (−0.285)   | (−1.000)   | (−0.262)   |
| Market power\_i(t−1) | −1.576***  | −1.304***  | −1.688***  | −1.809***  | −0.957***  | −1.549***  |            |            |            |            |            |
|                      | (−57,973.351) | (−30,409.846) | (−120,739.252) | (−100,396.169) | (−25,028.602) | (−26,567.893) |            |            |            |            |            |
|\sigma(\text{return on assets}_i)_{t} over the last 4 years | −0.225***  | −1.488***  | −0.238***  | −1.107***  | −5.048***  | −4.410***  |            |            |            |            |            |
|                      | (−17,891.554) | (−61,200.754) | (−19,509.514) | (−90,709.073) | (−264,839.608) | (−320,234.593) |            |            |            |            |            |
| Operating margin\_i(t−1) | −0.668***  | −0.017***  | −0.469***  | 0.118***   | −0.831***  | 0.108***   |            |            |            |            |            |
|                      | (−16,537.075) | (−336,538) | (−23,167.781) | (4039.017) | (−19,898.128) | (3174.040) |            |            |            |            |            |
| N                   | 1647       | 1933       | 1756       | 1458       | 1501       | 1245       |            |            |            |            |            |

\(t\)-statistics in parentheses

\* \(p < 0.10\)

\*\* \(p < 0.05\)

\*\*\* \(p < 0.01\)
Table 14 The dependent variable is the logarithm of new loans that is taken by firms in the current year. The coefficient estimates are from a semi-parametric selection model, for the wholesale and retail trade industry and for each year separately.

| Independent variable | 2004     | 2005     | 2006     | 2007     | 2008     |
|----------------------|----------|----------|----------|----------|----------|
| ln(total assets$_{i-1}$) | 0.878*** | 0.772*** | 1.030*** | 1.037*** | 0.888*** |
| (848.383)            | (5046.432) | (3621.775) | (601.1887) | (4144.114) |
| DummyHigh – LeverageFirm$_{i(t-1)}$ | 0.098*** | 0.356*** | 0.068*** | 0.241*** | 0.143*** |
| (200.932)            | (4458.133) | (532.518) | (3049.847) | (1580.409) |
| Return on assets$_{i(t-1)}$ | 0.003*** | -0.828*** | -0.241*** | -0.220*** | -1.016*** |
| (32.795)             | (-56.336.184) | (-10.416.243) | (-16.501.270) | (-63.173.467) |
| ln(equity$_{i(t-1)}$) | -0.261*** | -0.031*** | -0.323*** | -0.194*** | -0.188*** |
| (-206.250)           | (-155.437) | (-932.855) | (-914.201) | (-743.395) |
| Firm age$_{i}$       | -0.009   | -0.010*** | -0.008**  | -0.009*** | -0.006*** |
| (-0.660)             | (-5.199) | (-2.268) | (-4.217) | (-2.640) |
| Market power$_{i(t-1)}$ | -1.104*** | -0.518*** | -0.191*** | -1.879*** | 0.047*** |
| (-19.915.156)        | (-42.823.305) | (-6414.106) | (-266.265.623) | (1845.299) |
| $\sigma$ (return on assets$_{i}$)$_{t}$ | 0.009*** | 0.171*** | 0.379*** | -0.826*** | 0.935*** |
| (256.556)            | (29.833.902) | (36.649.139) | (-123.727.806) | (104.752.320) |
| over the last 4 years |          |          |          |          |          |
### Table 14 continued

| Independent variable | 2004     | 2005     | 2006     | 2007     | 2008     |
|----------------------|----------|----------|----------|----------|----------|
| Operating margin$_{i(t-1)}$ | 0.768*** | 0.073*** | 0.725*** | 0.527*** | 0.798*** |
|                      | (16,567.023) | (8442.894) | (54,390.089) | (51,610.375) | (44,422.216) |
| N                    | 2771     | 2953     | 3133     | 3053     | 2630     |

| Independent variable | 2009     | 2010     | 2011     | 2012     | 2013     | 2014     |
|----------------------|----------|----------|----------|----------|----------|----------|
| ln(total assets$_{i})_{t-1}$ | 0.637*** | 0.732*** | 0.711*** | 0.714*** | 0.634*** | 0.951*** |
|                      | (2435.436) | (1111.437) | (2277.627) | (2463.0167) | (1470.686) | (2071.760) |
| DummyHigh - LeverageFirm$_{i(t-1)}$ | 0.171*** | 0.269*** | 0.256*** | 0.197*** | 0.331*** | -0.020*** |
|                      | (1578.448) | (960.648) | (1902.392) | (1848.842) | (1932.626) | (-113.406) |
| Return on assets$_{i(t-1)}$ | -1.064*** | -0.146*** | 1.286*** | -0.784*** | 0.452*** | 0.924*** |
|                      | (-47.152.795) | (-2932.454) | (57,448.117) | (-35, 200.570) | (15,693.766) | (31,976.623) |
| ln(equity$_{i})_{(t-1)}$ | -0.015*** | -0.016*** | -0.062*** | -0.169*** | -0.006*** | -0.387*** |
|                      | (-47.419) | (-20.331) | (-167.133) | (-524.642) | (-11.105) | (-72.302) |
| Firm age$_{i}$ | 0.0001     | -0.002     | -0.004     | -0.007**   | -0.009* | -0.006    |
|                      | (0.049)   | (-0.238)   | (-0.929)   | (-2.228)   | (-1.843) | (-1.261)  |
| Market power$_{i(t-1)}$ | -0.442*** | -0.781*** | 0.240***  | -0.076***  | 1.047*** | -0.056*** |
|                      | (-236, 15.571) | (-12, 743.955) | (5619.551) | (-2086.180) | (44,671.884) | (-1688.471) |
| σ(return on assets$_{i(t-1)}$) over the last 4 years | -0.484*** | 1.465*** | -2.597*** | 0.306*** | -1.227*** | -3.067*** |
|                      | (-49, 698.364) | (59,710.086) | (-219, 157.732) | (30,287.983) | (-85, 165.365) | (-252, 856.709) |
| Operating margin$_{i(t-1)}$ | 0.019*** | -1.492*** | -0.470*** | 0.828*** | -0.284*** | -0.390*** |
|                      | (967.229) | (-40, 192.789) | (-24, 276.952) | (50,195.685) | (-9950.889) | (-16,825.808) |
| N                    | 1864     | 2320     | 2107     | 1790     | 1794     | 1628     |

$t$-statistics in parentheses  
* $p < 0.10$  
** $p < 0.05$, *** $p < 0.01$
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