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Abstract

We study the access to credit and the propensity to exit the market of firms with no bank debt (the main funding source of Spanish non-listed firms) around the COVID-19 crisis. Our methodology allows us to disentangle credit supply from credit demand, as having no bank debt may be the result of financial constraints or a deliberate strategy. Before the COVID-19 crisis, zero-bank-debt firms, especially risky ones, faced more difficult access to bank loans than firms that had previously held bank debt owing to their lack of credit history. These credit constraints were tightened by the COVID shock, regardless of firms' risk, arguably because of increased information asymmetries during a period of high macroeconomic uncertainty. Zero-bank-debt firms, even those with a low probability of default, were much more likely to leave the market during the COVID-19 crisis than firms with a history of bank debt. Moreover, granting new credit to zero-bank-debt firms reduced their probability of exit, which suggests a causal relationship between the two aforementioned findings. Beyond the specific setting of the pandemic, this paper adds to the broader literature on a better understanding of supply and demand-side constraints for corporate external funding, as crystalised in zero-debt firms.

Keywords: zero-debt firms, credit constraints, information asymmetries, guarantees, market exit.

JEL classification: G30, G32, G21.

Resumen

El presente documento estudia el acceso al crédito y la propensión a salir del mercado de las empresas sin deuda bancaria (la principal fuente de financiación de las empresas españolas no cotizadas) en torno a la crisis del COVID-19. La metodología implementada permite distinguir entre oferta y demanda de crédito, dado que no tener deuda bancaria puede deberse a restricciones financieras o a una estrategia deliberada por parte de las empresas. Antes de la crisis del COVID-19, las empresas sin deuda bancaria tenían mayores dificultades para acceder a los préstamos bancarios que las empresas con deuda bancaria previa, en especial las arriesgadas, debido a carecer de historial crediticio. Estas restricciones crediticias se endurecieron a causa del *shock* del COVID-19, con independencia del riesgo de las empresas, probablemente como consecuencia del incremento de las asimetrías de información durante un período de gran incertidumbre macroeconómica. No obstante, el uso de garantías públicas mitigó las restricciones crediticias a las que se enfrentaban las empresas seguras y sin deuda bancaria. Las empresas sin deuda bancaria, incluso aquellas con una baja probabilidad de impago, también tenían una probabilidad de salir del mercado mucho mayor que las empresas con deuda bancaria previa durante la crisis del COVID-19. Puede existir una relación causal entre los dos resultados, dado que la concesión de nuevo crédito a empresas sin deuda bancaria redujo su probabilidad de salida de mercado. Más allá del contexto específico de la pandemia, este documento contribuye a la literatura que busca una mejor comprensión de las restricciones a la financiación externa de las empresas tanto por el lado de la oferta como por el de la demanda, reflejadas en las empresas sin deuda.

Palabras clave: empresas sin deuda, restricciones al crédito, asimetrías de información, garantías, salidas de mercado.

Códigos JEL: G30, G32, G21.

1. Introduction

The existence of zero-debt firms[1] is a worldwide phenomenon. As traditional theories of capital structure, such as the trade-off theory (Kraus and Litzenberger, 1973) and the pecking order theory (Myers and Majluf, 1984), do not manage to explain why so many firms across countries are debt-free (Bessler et al., 2013), most of the existent literature has focused on developing new hypotheses that can shed some light on the subject. These new theories can be classified as supply- and demand-side because, in imperfect capital markets, a firm's capital structure is determined not only by its demand for capital, but also by its ability to raise funds externally (i.e., the supply side).[2]

In contrast, we study the dynamics of firms with no bank debt (the main funding source of Spanish non-listed firms) in two dimensions, their potential access to credit and their propensity to exit the market, around the Covid-19 crisis, in Spain. The Covid-19 crisis was essentially a transitory negative demand shock that led to large funding deficits for companies from certain productive sectors. As it is a unique event that can be dated very precisely,[3] it constitutes a well-identified shock that enables us to study whether the lack of credit history affects the likelihood of obtaining new bank loans and, as a consequence, the probability of leaving the market during economic crises. The lack of credit history increases information asymmetries between loan applicants and their potential lenders, a phenomenon that may be especially relevant during periods of enhanced information asymmetries, implying that banks might prioritise the provision of credit to their existing customers, on which they have soft information thanks to relationship lending. In addition, banks might also prioritise granting loans to their existing customers to avoid a surge in their NPLs and recording loan loss provisions (i.e., loan evergreening). Therefore, beyond the specific setting of the pandemic, this paper contributes to the broader literature that studies the supply- and demand-side constraints for corporate external funding, as crystalised in zero-debt firms, as well as their effects on the credit and output markets.

With that aim, we assemble a unique dataset that comprises the universe of loans granted to Spanish firms and their loan applications, coupled with firms' balance sheets. This rich dataset allows us to address the main identification challenge, to disentangle credit supply from credit demand, as having no bank debt may be due to financial constraints (i.e., caused by credit supply) or may be a

[1] Throughout this paper we will use the terms "zero-debt firms", "debt-free firms", and "all-equity firms" interchangeably.
[2] For a review of the relevant literature and those theories, see Section 2.
[3] In Spain, the state of alarm, which imposed the confinement of all the population –specifying some exceptions such as the purchase of food and medication or commuting to the workplace- was declared on March 14, 2020, by means of the Royal Decree 463/2020.

deliberate strategy that some firms voluntarily choose (i.e., driven by credit demand). In particular, we control for credit demand with information on loan applications and the fraction of interest-bearing debt maturing in the short run, as firms with a fairly high fraction of such debt are very likely to apply for new loans. This new methodology can be applied to isolate credit supply to firms without previous lending relationships, given that the widely used identification strategy of Khwaja and Mian (2008) cannot be implemented in that context because it relies on firms with multiple bank relationships. In any case, descriptive evidence suggests that credit constraints may play a crucial role, as firms with no bank debt are smaller, younger, have a higher share of liquid assets, more working capital, and a lower share of tangible fixed assets.

While our analysis focuses on the Spanish case because of the richness of our data, the existence of firms with zero bank debt is not a unique phenomenon restricted to Spain, as such firms constitute a sizeable group in many European countries. Figure 1 shows the percentage of firms with zero bank debt across six euro area countries in 2018. With the exception of France, for which the sample of firms in the dataset are generally much larger and thereby less likely to have no bank debt, in the rest of countries those firms account for a fairly large proportion of the total stock of firms, ranging from 49.4% in Belgium to 71.2% in Slovakia.[4] This implies that the results of our study are likely to exhibit external validity, as they can be generalised to other economies.

[Insert Figure 1 here]

Our main analyses deliver the following results. We find that, before the Covid-19 crisis, firms that had no (drawn or undrawn) bank debt in any month over the period 2014 – 2018 (henceforth, zero-bank-debt firms) had a much lower probability of obtaining new credit than firms with previous bank debt, especially the risky ones, as measured by their probability of default (PD). This result suggests that, before the pandemic, risky zero-bank-debt firms faced tighter credit constraints than safe zero-bank-debt firms relative to firms with previous bank debt and the same risk level, arguably because information asymmetries caused by the lack of credit history mattered more when firms were less creditworthy. But, remarkably, the difference in the access to credit between zero-bank-debt firms and firms with previous bank debt increased during the Covid-19 crisis, regardless of their risk, highlighting the enhanced role of information asymmetries during a period of high macroeconomic uncertainty in which it was harder for banks to assess borrowers' risk. This finding suggests that the Covid-19 shock exacerbated pre-existing credit market imperfections. These

[4] This information comes from iBACH (Micro Bank for the Accounts of Companies Harmonized), a dataset that is only available to researchers of the National Central Banks of the six countries that participate in the project: Belgium, Spain, France, Italy, Portugal, and Slovakia.

results are robust to the exclusion of refinanced loans, alternative measures of credit demand, subsamples of firms defined according to their funding structure, and alternative methodologies to construct a balanced sample of treated and control units (zero-bank-debt firms and firms with previous bank debt, respectively).

In addition, we study the access to trade credit by zero-bank-debt firms. We first find that, before the Covid-19 crisis, zero-bank-debt firms had, on average, the same probability of obtaining new trade credit as firms with previous bank debt, implying that the lack of credit history did not hamper the access to this alternative funding source, which is likely to hinge on other factors such as the strength of the relationship of a firm with its providers and the degree of trust between the two parties. We also find that the Covid-19 shock caused zero-bank-debt firms to rely more on trade credit to meet their funding deficits, arguably because, during the pandemic, it was particularly difficult for them to obtain bank credit.[5]

We also analyse the role of guarantees in mitigating the credit constraints faced by safe zero-bank-debt firms compared to safe firms with previous bank debt during the Covid-19 crisis. We focus our analysis on safe firms because of two reasons. First, as banks are unlikely to engage in loan evergreening in the case of safe firms, we can isolate the adverse effect of the lack of credit history on the access to bank credit by zero-bank-debt firms. Second, we are particularly interested in the negative impact of the absence of credit history on the access to bank credit by creditworthy firms because this may lead to important inefficiencies in the allocation of resources. We find that pledging guarantees facilitated the access to credit of zero-bank-debt firms relative to firms with previous bank debt arguably because, as secured credit has expected higher recovery rates than unsecured credit, banks were more willing to provide the former than the latter to new borrowers, on which they did not have soft information thanks to relationship lending.[6] However, we also find that the effectiveness of guarantees in mitigating the credit constraints faced by zero-bank-debt firms during the pandemic was highly heterogeneous and depended on the type of guarantee. In particular, pledging personal guarantees or collateral[7] yielded a modest impact on easing the credit

[5] This finding is in line with Carbó-Valverde et al. (2016), who document that during the global financial crisis credit constrained SMEs used trade credit as an alternative funding source to bank loans in Spain. However, while they focus on firms with problems in access to bank credit, our study analyses in detail the lack of credit history as one of the causes of such problems.

[6] While, in principle, this result could also be driven by secured credit being cheaper than unsecured credit, please note that all our analyses are carried out on a sample of firms that apply for loans or are very likely to do it, which rules out this sort of demand effects.

[7] A personal guarantee refers to the commitment of the guarantor (generally the firm's owner or its partners) to honour the firm's debt with her wealth or personal assets in case of default by the original borrower (i.e., the company). Collateral refers to specific assets (real estate, financial or movable assets, other assets) that can be seized by the lender in case of default by the firm.

constraints faced by zero-bank-debt firms relative to firms with previous bank debt. The rationale behind is that, in the case of personal guarantees, credit is secured with the present and future wealth of the guarantor, which may generate a high degree of uncertainty about credit recovery rates, mainly in the medium- and long-run. Therefore, the very high macroeconomic uncertainty during the pandemic made even harder for banks to assess the creditworthiness of new loan applicants and to estimate the value of the assets pledged as collateral, so that they prioritised lending to their existing customers (on which they had soft information). By contrast, public guarantees were very effective in mitigating the credit constraints faced by zero-bank-debt firms. The reason is that, when banks' skin in the game was much lower thanks to the public guarantees, in which the government covered a large proportion of the potential losses, they were less reluctant to grant credit to zero-bank-debt firms despite their lack of credit history. Nevertheless, as zero-bank-debt firms still had a lower probability of obtaining new secured credit than firms with previous bank debt, this tool did not completely eliminate the obstacles faced by the former.

We then analyse the effect of lending relationships on the propensity to exit the market before and during the Covid-19 crisis. We first find that the probability of leaving the market before the Covid-19 crisis by a zero-bank-debt firm was, on average, roughly the same as the probability of a firm with previous bank debt. But we also find that the Covid-19 shock raised substantially the probability that zero-bank-debt firms exited the market relative to firms with previous bank debt, regardless of their risk, arguably because it also reduced the probability that the former obtained new credit relative to the latter, both in the case of safe and risky firms. In addition, the fact the Covid-19 shock caused zero-bank-debt firms to have both a higher probability of leaving the market and a lower probability of obtaining new credit than firms with previous bank debt in the segment of safe firms suggests that frictions in the credit market may lead to inefficient exits, in the sense of causing creditworthy firms to leave the market.

Finally, the causal link between the access to credit and the propensity to exit the market by zero-bank-debt firms is corroborated by the last finding: granting new credit to a zero-bank-debt firm during the Covid-19 crisis reduced, on average, its probability of exit. This effect was larger for safe zero-bank-debt firms than for their risky counterparts, which may reflect the fact that some risky zero-bank-debt firms may not manage to stay afloat even with additional financial support because their financial condition is too deteriorated. As the provision of new credit may make a larger difference in terms of firm survival for stronger zero-bank-debt firms than for weaker ones, mitigating the financial constraints faced by the former should be a priority from a policy perspective.

Regarding the policy implications of our findings, our study highlights that zero-bank-debt firms may face particularly acute frictions in the credit market vis-á-vis firms with previous bank debt during economic crises, due to increased information asymmetries or banks' lending practices. As this may lead to inefficient market exits, policies that mitigate the financial constraints of those firms such as enhanced financial reporting requirements and public guarantee programmes may be beneficial for the whole economy. In addition, contract enforcement should be improved (e.g., by strengthening creditors' rights[8] and by increasing the efficiency of the competent courts in terms of speed and cost[9]), so that lenders expect a lower probability of moral hazard (i.e., strategic default) and higher recovery rates in the event of default, thereby becoming more willing to provide credit to new corporate borrowers. Facilitating the access of safe zero-bank-debt firms to bank credit would also contribute to a greater diversification of their funding sources because they would not rely exclusively on internal funds and trade credit, which would foster their investment. As these firms do not pose a risk to the banking sector, it would also have positive aggregate effects.

2. Related literature and contribution: why some firms are debt-free

The study of zero-debt firms is relatively new, even though traditional theories of capital structure, such as the trade-off theory (Kraus and Litzenberger, 1973) and the pecking order theory (Myers and Majluf, 1984), cannot generally explain this phenomenon.[10] The theories that aim to explain the existence of zero-debt firms can be classified as supply- and demand-side because, in imperfect capital markets, a firm's capital structure is determined not only by its demand for capital, but also by its ability to raise funds externally (i.e., the supply side). This distinction is crucial for the purpose of our study because we want to isolate the credit constraints faced by zero-bank-debt firms (i.e., supply-side frictions in the credit market) vis-à-vis firms with previous bank debt, and analyse their effect on the propensity to exit the market by the former relative to the latter.

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[8] See, inter alia, La Porta et al. (1997, 1998), Demirgüç-Kunt and Maksimovic (1998), Giannetti (2003), Beck et al. (2005), Djankov et al. (2007), Qian and Strahan (2007), Davydenko and Franks (2008), Araujo et al. (2012), and Rodano et al. (2016).

[9] See, inter alia, Jappelli et al. (2005), Visaria (2009), Fabbri (2010), Chemin (2012), Araujo et al. (2012), and Ponticelli and Alencar (2016).

[10] According to the trade-off theory, a company chooses its optimal level of debt by weighting the advantages and disadvantages of debt finance (the tax benefits of debt and the costs of financial distress, respectively). According to the pecking order theory, the cost of different funding sources increases with asymmetric information, as managers are assumed to know better the true condition of the firm and its future growth prospects than investors. When a firm issues new equity, investors believe that managers think that the firm is overvalued and are taking advantage of this overvaluation. As a result, investors place a lower value to the new equity issuance. By contrast, when a firm issues new debt, investors think that the management of the company is optimistic regarding its future and that the current stock price is undervalued. Consequently, managers base the choice of funding source in an order of preference. They first use retained earnings and, when those are depleted, they issue debt, lastly raising equity as a last resort. Hence, the pecking order theory predicts that, if and only if internal funds are sufficient to meet financing requirements, firms will not issue debt and will be debt-free (Ghose and Kabra, 2016; Huang et al., 2017).

Regarding supply-side theories, the financial constraint hypothesis (Devos et al., 2012; Bessler et al., 2013; Dang, 2013; Byoun and Xu, 2013; Kokoreva and Ivanova, 2016; Meng, 2021) states that, under asymmetric information, a firm may face credit rationing because lenders cannot easily evaluate the quality of the firm and its investments, implying that some firms with positive NPV projects may not have access to external financing (Stiglitz and Weiss, 1981). In addition, in the presence of moral hazard, it is difficult for new firms to borrow directly (i.e., by issuing publicly traded bonds), since their reputation in debt markets is not sufficiently strong yet (Diamond, 1989, 1991). Accordingly, zero-debt firms are smaller[11] and younger than their levered counterparts, have fewer tangible assets that can be pledged as collateral for debt financing (Benmelech and Bergman, 2009), conserve more cash from cash-flow (Almeida et al., 2004), distribute less dividends (Fazzari et al., 1988), and are more likely use lease financing rather than rely on external financing to purchase assets.[12]

By contrast, demand-side theories consider that some firms are debt-free because they voluntarily choose this capital structure. The financial flexibility hypothesis (Graham and Harvey, 2001; Marchica and Mura, 2010; De Jong et al., 2012; Bessler et al., 2013; Dang, 2013; Rapp et al., 2014; Kokoreva and Ivanova, 2016; Meng, 2021) states that, in the presence of market frictions such as adverse selection (Akerlof, 1979) or transaction costs (Leary and Roberts, 2005), high-growth firms eschew debt but accumulate large cash reserves in order to preserve their borrowing capacity for financing future investment opportunities.[13] Those firms are also very profitable, exhibit high growth opportunities and pay higher dividends than their levered counterparts. An alternative theory is the managerial entrenchment hypothesis (Strebulaev and Yang, 2013), which states that the manager's personal preferences differ from those of the shareholders. In particular, if the manager is endowed with substantial stock ownership and is thus underdiversified, he would find debt riskier than shareholders. In addition, if the board of directors is more manager-friendly, he would find it easier to make choices based on his own personal preferences thanks to weak monitoring. Accordingly, the authors find that firms with higher CEO stock ownership are more likely to have zero debt, especially if boards are smaller and less independent.[14] Entrenched managers may also avoid debt issuance either to protect their human capital by reducing their company's probability of default (Fama, 1980) or to consume private benefits by eliminating

[11] According to Berger et al. (2001) and López-Espinosa et al. (2017) small firms are informationally opaque. See also Faulkender and Petersen (2006), who examine the differences between small private firms and publicly traded firms.
[12] Eisfeldt and Rampini (2009) find that constrained firms are more likely to lease their assets rather than use debt financing to purchase them because, in case of insolvency, the U.S. bankruptcy code makes it easier for a lessor to repossess leased assets than for a secured lender to repossess collateral.
[13] See also Graham (2000) and Almeida and Philippon (2007) for the analysis of conservative debt policies.
[14] Agrawal and Nagarajan (1990) also find that managers of all-equity firms have significantly larger stockholdings than managers of similar-sized levered firms in their industry.

interest payments, thereby increasing the resources under their control (Stulz, 1990). These managers may also want to avoid the disciplinary pressures associated with leverage (Jensen, 1986; Hart, 1995), which implies that they will lever up only when there is a threat to their entrenchment and job security (Berger et al., 1997).[15] Finally, some authors also find that family-controlled firms are more likely to be debt-free (Agrawal and Nagarajan, 1990; Strebulaev and Yang, 2013). The rationale behind is that, since family members may be altruistic and derive utility from passing on the family legacy and safeguarding the wellbeing of other family members (Becker, 1981; Bertrand and Schoar, 2006), the desire for long-term survival increases the perceived risk of default associated with debt.[16]

As regards to this study, we contribute to the existing literature by analysing the effects of having no bank debt (the main funding source of Spanish non-listed firms) on two dimensions, access to credit and propensity to exit the market, around the Covid-19 crisis, a well-identified exogenous shock. That is, rather than developing a new theory to explain why many firms in Spain do not hold any bank debt, we analyse the access of zero-bank-debt firms to credit and their propensity to exit the market relative to firms with previous bank debt using the Covid-19 shock for identification. To do so we make use of a granular dataset and develop a rigorous new methodology to control for credit demand with information on loan applications and the fraction of outstanding debt maturing in the short run, which enables us to identify supply effects. With these tools we find that zero-bank-debt firms face important financial constraints due to their lack of credit history, which become particularly acute during periods of high economic uncertainty. This makes them more vulnerable to negative shocks than firms with previous bank debt because they can resort to a lesser extent to bank loans or credit lines to cover their funding deficits and, consequently, more prone to exit the market.

In addition, we contribute to the literature that studies the pros and cons of relationship lending vs. transaction-based lending. In particular, to the extent that relationship lenders have an informational advantage over transaction lenders, this allows them to keep granting credit to their current borrowers in crisis times. Accordingly, Bolton et al. (2016) and Beck et al. (2018) show that, during the Global Financial Crisis, firms that benefitted from ties to relationship lenders, as opposed to transaction-based lenders, were more likely to continue receiving external funding.

[15] However, Devos et al. (2012) reject the hypothesis that zero-leverage policies are driven by entrenched managers attempting to avoid the disciplinary pressures of debt, as their firms do not have weaker internal or external governance mechanisms. In addition, the debt initiation decisions of these firms are not preceded by shocks to their entrenchment, such as takeover threats or the emergence of activist blockholders.
[16] Other studies highlight the role of cultural factors (El Ghoul et al., 2018) and labour protection laws (Boustanifar and Verriest, 2022) in explaining zero-leverage policies.

These results are consistent with those of our paper. However, rather than analysing the impact of the intensity of relationship lending on the credit supply to all firms, our findings provide fresh insights into the exceptional circumstance of firms without any lending relationship. We document that these firms had an even more difficult access to credit during the Covid-19 crisis, regardless of their risk, which is harder to assess for banks during severe crises such as the pandemic because of the enhanced role of information asymmetries during periods of high macroeconomic uncertainty.

Finally, we also contribute to the literature that disentangles credit supply from credit demand in the context of corporate borrowers. In particular, we propose a new methodology to control for credit demand with information on loan applications and the fraction of outstanding debt maturing in the short run which can be implemented by researchers that aim to isolate credit supply to firms without previous lending relationships. An estimation à la Khwaja and Mian (2008) is not feasible in such a context because it relies on firms with multiple bank relationships.

3. Data

3.1. Description of datasets

Our empirical analysis combines three administrative datasets managed by the Banco de España. The first database, the Central Balance Sheet Data Office (CBSDO), contains financial information mandatorily filed by Spanish firms. In addition, it includes, among others, information on the firm's fiscal identifier, sector of activity (NACE code), location of the company's headquarters (zip code), firm's creation date, number of employees, corporative structure (i.e., whether the firm belongs to a group), legal form[17], demographic status (new firm, active firm, inactive firm or exit), and whether it is listed or not. The CBSDO does not include information on sole proprietorships.

The second dataset is the Credit Register of Banco de España (CR). The register records granular information on all the loans (new and outstanding) granted by all monetary financial institutions domiciled in Spain. In particular, since 2016, for each specific loan contract, it contains information on the borrower of the loan (firm fiscal identifier), the bank that grants the loan, and the loan characteristics such as size, maturity, creditworthiness, type of contract[18] and type of guarantee, including whether the loan was granted under a public guarantee scheme.

[17] It includes, among others: i) public limited companies; ii) private limited companies; iii) general partnerships; iv) limited partnerships; v) communities of assets; vi) cooperatives; vii) associations and foundations; viii) local corporations; viii) autonomous organisms; ix) religious congregations; x) temporary joint ventures; xi) permanent establishments of entities that do not reside in Spain.

[18] Financial credit, commercial credit, leasing, and factoring.

The third dataset reports information on loan applications. In particular, it contains all the requests for information on the credit situation of potential customers made by banks to CR. They can be considered as loan applications, at least, for the firms without previous lending relationships with a given bank, as banks receive information from CR about their current customers on a monthly basis.

3.2. Sample selection and variable definitions

We study the access to bank credit by firms before and during the Covid-19 pandemic. As we control for firm characteristics, we make use of the financial statements available at the CBSDO as of December 2018 and December 2019. We use those corresponding to 2019 to define the predetermined characteristics of the firms when we analyse their access to credit from March 2020 to December 2020, whereas those of 2018 are used to define the predetermined characteristics of the firms when we analyse their access to credit from March 2019 to December 2019.

We restrict our sample to firms: i) that do not belong to a business group[19]; ii) with adequate accounting quality (based on the Banco de España's internal classification criteria[20]); iii) that do not operate in the financial sector or in non-market sectors according to the NACE industry classification;[21] iv) that report information on the industry they belong to; v) that are unlisted; and vi) that are profit maximisers.[22] We end up with a sample of 1,317,031 firm-year observations (691,954 observations for the pre-Covid period and 625,077 for the Covid period).

Variables of interest

Our main dependent variables are *New Credit* and *Exit. New Credit* is a dummy variable that equals one if the firm obtained new bank credit (either term loans or credit lines) during our sample period, either before the pandemic (March 2019 – December 2019) or during it (March 2020 – December

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[19] We exclude firms that belong to a business group because, although some of those firms may not hold bank debt, they may receive funds from other firms from their group that hold bank debt, which would contaminate the analysis of access to credit and propensity of exit the market by zero-bank-debt firms vs. firms with previous bank debt.

[20] In particular, we apply two filters provided by the CBSDO: (i) balance sheets with non-reliable monetary units; (ii) firms with inadequate information in their financial statements (with blatant accounting errors, such as large mismatches in balance sheet amounts, negative values in items that should be positive by definition, missing headings, or figures of disproportionate magnitude).

[21] We remove firms from the following sectors: Financial service activities, except insurance and pension funding (64). Insurance, reinsurance and pension funding, except compulsory social security (65). Activities auxiliary to financial services and insurance activities (66). Public administration and defence; compulsory social security (84). Activities of membership organisations (94). Activities of households as employers of domestic personnel (97). Undifferentiated goods- and services-producing activities of private households for own use (98).

[22] We remove state-owned companies, local corporations, non-profit organisations, membership organisations, associations, foundations and religious congregations. We also exclude holding companies because their financials may not be comparable with those of the rest of firms. We only keep Spanish companies because foreign firms are not available in the CBSDO.

2020), and zero otherwise. We include undrawn credit facilities to capture credit supply better, as drawn credit is largely affected by the borrower's need for funds and, consequently, it is also determined by demand shifts. Note also that we exploit information on new credit flows, rather than on outstanding loans, which rules out measurement error in the variable *New Credit.*[23] For some analyses we distinguish between secured and unsecured credit by means of several variables. All of them are dummy variables that equal one if the firm obtained the respective type of credit, and zero if the firm did not receive any new bank credit. *New Credit with any Guarantee* is a dummy variable that equals one if the firm obtained new credit secured by any type of guarantee. *New Credit with Collateral or Personal Guarantee* is a dummy variable that equals one if the firm obtained new credit secured by either collateral or a personal guarantee, or by both of them, but without any additional public guarantee. *New Credit with Public Guarantee* is a dummy variable that equals one if the firm obtained new credit secured by a public guarantee, but without any additional collateral or personal guarantee provided by the firm's owner or partners. *New Credit without Guarantee* is a dummy variable that equals one if the firm obtained new unsecured credit. Finally, *Exit* is a dummy variable that equals one if the firm exits the market. For the sample before the Covid-19 crisis, *Exit* equals one if the firm exited the market or became inactive[24] in the period 2018-2019, and zero otherwise, whereas for the Covid-19 period *Exit* equals one if the firm exited the market or became inactive in the period 2020-2021, and zero otherwise.

Our main explanatory variable of interest is *No Bank Debt*, which is a dummy that denotes whether the firm had any bank debt (either term loans or credit lines) in its most recent history before the beginning of our sample period. Specifically, it equals one if the firm had no (drawn or undrawn) bank debt in any month over the period 2014 – 2018, and zero otherwise. In the former case, we use the term "zero-bank-debt firm". We construct this variable by combining the annual balance sheet information from CSBDO –which only reports the drawn credit at the end of the fiscal year- and the monthly information from CR –which contains both the drawn and undrawn credit commitments. Note that all the analyses are carried out at the firm level, rather than at the bank-firm level, because of three reasons. First, in the latter case, by default, the variable *New Credit* could only increase (i.e., from zero to one) in all the bank-firm pairs associated to new credit

[23] As a robustness test we also exclude refinanced loans to rule out that our main findings are entirely driven by banks rolling over the loans granted to their existing customers.

[24] In Spain the owners of firms that become inactive do not often dissolve them because of the legal costs associated with the procedure. Hence, we consider that being inactive is similar to formally exit the market. According to the CBSDO, inactive firms are those that meet the following two conditions during any of the last two financial years: (i) Assets and Liabilities >0 and (ii) all the items of the profit & loss account=0. While the inclusion of inactive firms may generate some measurement error if some of those firms become active again, it is well known that measurement error in the dependent variable does not lead to biased and inconsistent OLS estimates as long as it is uncorrelated with the explanatory variables –as is often assumed-, only to larger standard errors (Wooldridge, 2003, pp. 302-304).

relationships of zero-bank-debt firms that appear in the credit register by the first time. That would cause a mechanical positive association between firms with zero initial outstanding bank debt and *New Credit.* Also note that an estimation à la Khwaja and Mian (2008) is not feasible in such a context given that it relies on firms with multiple bank relationships. The second reason why we use firm-level data, rather than bank-firm level data, is because we want to analyse the access to credit and the propensity to exit the market by firms that do not have lending relationships with *any* bank. Finally, we lack information on the banks to which a set of firms that are very likely to demand credit (i.e., those with more than 25% of their interest-bearing debt maturing within the next 12 months) apply in case they had prior banking relationships.

In addition, we use firm controls to deal with its size (logarithm of total assets), age (logarithm of years), solvency (share capital to total assets), liquidity (liquid assets to total assets), profitability (return on assets, ROA), collateral availability (tangible fixed assets to total assets), working capital ratio (current assets minus current liabilities to total assets), and paid taxes (corporate taxes over total assets). Finally, we also use industry-location-size-time fixed effects, where industry is measured at the NACE 3-digit level, location at the NUTS-3 level (Spanish provinces), size corresponds to micro, small, medium-sized, or large firms according to the European Commission classification[25], and time refers to year.

Panel A of Table 1 describes the main characteristics of zero-bank-debt firms and firms with previous bank debt and ascertains whether the difference in terms of each characteristic between the two groups of firms is statistically different from zero based on tests on the equality of means. The two groups of firms exhibit significant differences in most of the variables used in our analyses as controls. In particular, the evidence suggests that some firms do not have bank debt because they may be financially constrained, as zero-bank-debt firms are substantially smaller –and small firms are informationally opaque (Berger et al., 2001; López-Espinosa et al., 2017)- and younger (there are less information asymmetries in the case of firms with a long track record), have a much higher share of liquid assets and more working capital (arguably because of precautionary motives, since they cannot draw from credit lines when hit by a liquidity shock), and a lower share of tangible fixed assets (the main assets that can be pledged as collateral to obtain secured credit). In addition, zero-bank-debt firms are less leveraged than firms with previous bank debt (i.e., they have a higher equity ratio), which indicates that they do not fully replace bank debt with other types of debt such as bonds or trade credit. Zero-bank-debt firms also pay more taxes (as a percentage of their total

[25] https://ec.europa.eu/growth/smes/sme-definition_es

assets) than firms with previous bank debt, which suggests that they take less advantage of the tax shield of debt.

As some firms in our initial sample could have voluntarily chosen not to have bank debt, Panel B of Table 1 replicates the previous analysis for the subsample of firms that demand credit or are very likely to do it. We consider that a firm has demanded credit or is expected to do it in two different cases: (i) when a firm applies for a new loan, as proxied by banks' information requests; (ii) when a firm with previous interest-bearing debt (i.e., drawn and undrawn bank credit and other debt obligations) has more than 25%[26] of this debt maturing within the next 12 months. We include the second case to identify those firms that are very likely to apply for a loan because a sizable proportion of its current debt is maturing in the short run. Otherwise, we could not properly identify the demand for credit by firms with previous bank debt because these companies are less likely to appear in the loan application dataset, since banks with prior credit exposures to those firms receive information on their aggregate credit positions and their performing status on a monthly basis. As in Panel A, the two groups of firms exhibit significant differences in most of the variables, suggesting that some zero-bank-debt firms among those that demand credit or are very likely to do it are financially constrained, as they are smaller, younger, have a higher share of liquid assets, more working capital, and a lower share of tangible fixed assets than firms with previous bank debt. Similarly, zero-bank-debt firms are also less leveraged and pay more taxes (as a percentage of their total assets) than firms with previous bank debt. As all these differences could lead to biased and inconsistent estimates in our econometric analyses, we will combine propensity score matching with linear regression to ensure balance, i.e., that treated units (zero-bank-debt firms) and control units (firms with previous bank debt) are very similar in the foregoing characteristics, as it will be explained in detail in the next section.

[Insert Table 1 here]

Finally, in several analyses we split the sample into two groups of firms according to their financial health proxied by their probability of default (PD), which is estimated following the methodology developed by Blanco et al. (2024). Safe (risky) zero-bank-debt firms are those with a PD lower

[26] This figure corresponds to the 75th percentile of the distribution of the interest-bearing debt that matures in the next 12 months, following the methodology of Benetton, Mayordomo and Paravisini (2022). In addition, the percentage of firms with previous interest-bearing debt and with *more* than 25% of this debt maturing in the next 12 months that obtain new credit is substantial, 63%, while the percentage of firms with previous interest-bearing debt and with *less* than 25% of this debt maturing in the next 12 months that obtain new credit drops to 38%. As the percentage of firms with previous interest-bearing debt and with more than 33% of this debt maturing in the next 12 months that obtain new credit is 62%, it seems appropriate to use the 25% threshold for our baseline analysis, relegating the 33% threshold to robustness analyses.

(greater) than the median PD of firms with previous bank debt that obtained new bank credit during the period 2016-2019. Blanco et al. (2024) consider that a firm is in default when it has NPLs during at least three months of a given year. They develop six models for different size-sector combinations. In particular, they consider two size classes (micro-firms vs. small, medium and large firms) and three sectors of activity (manufacturing, construction and other sectors[27]). All the models are estimated by means of a logit regression that includes five accounting ratios (own funds to total assets; financial expenditures to sales; ROA; liquid assets to total assets; sales to total assets or gross value added to total assets) and the growth rate of aggregate credit to NFCs.

4. Methodology and results

4.1. Access of zero-bank-debt firms to credit

Zero-bank-debt firms are expected to have a lower probability of obtaining new credit than firms with previous bank debt due to their lack of credit history, which increases information asymmetries between loan applicants and their potential lenders. This phenomenon may be especially relevant during periods of high macroeconomic uncertainty due to the enhanced role of information asymmetries.

In this sense, the Covid-19 crisis represents a unique well-identified exogenous shock to study how the lack of credit history affected the likelihood of obtaining new bank loans before and during the pandemic. With this aim, we formally analyse whether not having previous bank debt was a particular barrier to obtain a loan after the Covid-19 shock (i.e., since March 2020) based on the following regression:

$$\begin{aligned} NewCredit_{j,t} = {} & \delta NoBankDebt_j + \lambda PostCovid_t x NoBankDebt_j \\ & + \text{TControls}_{j,t-1} + \eta_{i,l,s,t} + \epsilon_{j,t} \end{aligned} \tag{1}$$

where *New Credit* is a dummy variable that indicates whether the firm *j* obtained new bank credit during our sample period, either before or during the pandemic. The subscript *t* denotes the pre-Covid period (March 2019 – December 2019) or the Covid-19 period (March 2020–December 2020) and the dummy variable *Post Covid* equals one for the latter. The subscripts *i*, *l*, and *s* denote industry, location, and size, respectively. We choose a narrow window of time around the Covid-19 shock mainly because of two reasons. First, to avoid the confounding effect of a policy

[27] The category "Other sectors" comprises: Primary sector; Energy; Retail and wholesale trade; Hospitality, restoration and leisure; Transport and storage; Other market services; Motor vehicles.

implemented by the Spanish government in 2021 to improve the financial condition of the firms most affected by the Covid-19 crisis by providing direct aid to repay debts incurred during the pandemic.[28] Second, because the period March 2020–December 2020 was the most acute phase of the pandemic and we want to exploit the magnifying effect of the Covid-19 shock on the information asymmetries in the credit market.

The vector *Controls* comprises a set of firm characteristics potentially associated with the likelihood of demanding bank credit and/or obtaining it: *size*, *age*, *equity ratio*, *ROA*, *liquidity ratio*, *tangibility*, *working capital ratio*, and *tax ratio* (see the Appendix for the definition of these variables). All those variables are lagged one year to mitigate endogeneity concerns. Finally, the use of industry-location-size-time fixed effects ($\eta_{i,l,s,t}$) enables us to analyse the access to credit by firms that operate in the same industry (NACE 3-digit level), are domiciled in the same province (NUTS-3 level), and have a similar size (i.e., they are micro, small, medium-sized, or large firms according to the European Commission classification) in the same period *t*. In particular, it allows us to control for similar patterns of credit demand by firms with those specific characteristics and also by supply shocks that are common to all banks in the economy.

We first estimate a restricted version of equation (1), in which we set λ equal to zero, i.e., we regress the variable *New Credit* on *No Bank Debt*, the vector of lagged firm controls and industry-location-size-time fixed effects. Table 2 reports the estimation results. In addition to assessing the statistical significance of the coefficient of interest, we also discuss the magnitude of the estimated effect to have an idea of its economic significance. For that purpose, we compute the semielasticity associated to each variable of interest, which is defined as the ratio of each coefficient to the unconditional probability in each subsample.[29] Column (1) shows the results with all firms, while column (3) displays the results with the subsample of firms that demand credit or are very likely to do it. According to column (1), a zero-bank-debt firm had, on average, a probability of obtaining new credit that was 24 pp. lower than that of a firm with previous bank debt during the whole period (March 2019–December 2020), which is a large effect with a semielasticity of -0.73 from

[28] Against the backdrop of the Covid-19 crisis, the Spanish government established the "COVID line of direct aid to sole proprietors and companies". The facility, funded with a total of €7 billion, channeled direct aid to firms and sole proprietors whose activity had been most adversely affected by the economic effects of the pandemic for the repayment of debts incurred by firms since March 2020. In particular, it involved specific-end direct aid that allowed for the payment of debts such as payments to suppliers, supplies, wages, rentals and, in the event of any remaining amount, debts with bank creditors, giving priority to the reduction of the publicly-backed debt's face value. The direct aid was granted in 2021. For an evaluation of the programme see Blanco et al. (2024).

[29] The unconditional probability is the proportion of observations in which *New Credit* equals 1. Note that the unconditional probability equals the unconditional mean in the case of Bernoulli random variables such as our dependent variables.

its unconditional probability. The coefficient and the semielasticity of the variable *No Bank Debt* in (3) are much lower than in (1), which suggests that the results using all firms are partly driven by the lower demand for bank loans by zero-bank-debt firms. Nevertheless, column (3) shows that the probability that a zero-bank-debt firm obtained new credit before the Covid-19 crisis was, on average, 11.1 pp. lower than that of a firm with previous bank debt, which is a sizeable effect with a semielasticity of -0.19 from its unconditional probability. This result indicates that zero-bank-debt firms that were willing to take a loan faced important supply restrictions in their access to bank credit relative to firms with previous bank debt and otherwise similar characteristics.

We now estimate equation (1). Table 2 reports the estimation results, with column (2) using all firms and column (4) using the subsample of firms that demand credit or are very likely to do it. The coefficient of the interaction between *No Bank Debt* and *Post Covid* is negative and highly significant both in (2) and (4), and the associated semielasticities are quite similar in the two columns. According to column (2) (column (4)), the Covid-19 shock reduced the probability that zero-bank-debt firms obtained new credit by 1 pp. (0.08 pp.) relative to firms with previous bank debt, implying a semielasticity of -0.03 (-0.01) from its unconditional probability. While this effect is relatively small compared to the large effect of being a zero-bank-debt firm before the Covid-19 crisis, as measured by their corresponding semielasticities, it constitutes a magnifying effect of the latter. Therefore, it indicates that the Covid-19 crisis accentuated the already severe credit supply restrictions faced by zero-bank-debt firms relative to firms with previous bank debt due to their lack of credit history, arguably because of the prevailing role of information asymmetries during the pandemic.

[Insert Table 2 here]

However, based on the evidence reported in Table 1, one might argue that zero-bank-debt firms are very different from firms with previous bank debt and, as a consequence, differences in access to credit between the two groups could be driven by these discrepancies, even if one could control for all firm characteristics, because regression models may violate the common support assumption.[30] To avoid this potential problem, we combine Propensity Score Matching (PSM) with linear regression to ensure balance, i.e., that treated units (zero-bank-debt firms) and control units

[30] As highlighted by Imbens (2004), the estimation of average treatment effects is sensitive to differences in the covariate distribution of treated and control individuals. In particular, regression models may violate the common support assumption (i.e., the probability of receiving treatment for each possible value of the vector of covariates is *strictly* within the unit interval) since covariate cells without both treated and control observations can end up contributing to the estimates by extrapolation. This implies that controlling for firm characteristics may not yield the correct estimates if treated and control firms are *very* different in the observed characteristics, so that there is no overlap in the distributions of those characteristics in treated and control firms.

(firms with previous bank debt) are very similar in their observable characteristics. In particular, we follow Dehejia and Wahba (2002) and implement a two-step approach using the sample of firms that demand credit or are very likely to do it. In a first step, we carry out PSM –in particular, single nearest-neighbour method with replacement- by running a logit regression of *No Bank Debt* on a vector of variables (*size*, *age*, *ROA*, *liquidity ratio*, *equity ratio*, *working capital ratio*, *tangibility*, and *tax ratio*). We select a matching algorithm with replacement because, according to Dehejia and Wahba (2002), it reduces the potential bias of the estimates. The rationale behind is that matching with replacement minimises the propensity-score distance between the matched comparison units and the treatment units because each treatment unit can be matched to the nearest comparison unit, given that a comparison unit may be matched more than once. Similarly, we choose single nearest-neighbour matching to reduce the potential bias. In a second step, we run a weighted regression using the treated and matched control units, with the control units weighted by the number of times that they are matched to a treated unit. Importantly, from now on, all the remaining analyses on the access to credit by zero-bank-debt firms are carried out in the subsample of firms that have demanded bank credit or are very likely to do it and by means of the weighted regressions described above.

We show that the estimation sample is balanced in Table 3, which reports the means of the vector of variables used in the PSM for zero-bank-debt firms and firms with previous bank debt, as well as tests on the equality of means. In most cases the difference between the means of the two groups is not statistically different from zero. While in some cases such difference is statistically significant because of the very large sample size (more than 256,000 observations), it is much lower than in the unbalanced sample (Panel B of Table 1) and quite small. For instance, while the difference in the average liquidity ratios of zero-bank-debt firms and firms with previous bank debt is 2 pp. in the balanced sample (Table 3), the difference in the average liquidity ratios of these two types of firms is 15.7 pp. in the unbalanced sample (Panel B of Table 1). In any case, we control for these small differences by including the same vector of variables in all our weighted regressions.

[Insert Table 3 here]

We now estimate both a restricted version of equation (1) –in which we set λ equal to zero- and the original equation (1) by means of weighted regressions using the sample of firms that demand credit or are very likely to do it. The estimation results, which are reported in columns (1) and (2) of Table 4 (restricted and unrestricted version, respectively) are quite similar to the ones obtained with unweighted regressions (columns (3) and (4) of Table 2, respectively). According to column (1), the probability that a zero-bank-debt firm obtained new credit before the Covid-19 crisis was, on average, 7.8 pp. lower than that of a firm with previous bank debt, which is a sizeable effect with a semielasticity of -0.16 from its unconditional probability. According to column (2), the Covid-19 shock reduced the probability that zero-bank-debt firms received new credit by 2.3 pp. relative to firms with previous bank debt, which is a non-negligible effect with a semielasticity of -0.05 from its unconditional probability.

In addition, we examine whether the access to credit by zero-bank-debt firms compared to firms with previous bank debt before the Covid-19 crisis depended on their risk, as measured by their probability of default (PD), and whether the effect of the Covid-19 shock on the credit constraints faced by zero-bank-debt firms relative to firms with previous bank debt was heterogeneous and also depended on their risk. To address these issues, we estimate equation (1) for two subsamples of firms: (i) those with a PD greater than the median PD of firms with previous bank debt that obtained new bank credit during the period 2016-2019 (henceforth, risky firms) and (ii) those with a PD lower than that median (henceforth, safe firms). The estimation results are reported in columns (3) and (4) of Table 4 (safe and risky firms, respectively). According to column (3), the probability that a safe zero-bank-debt firm obtained new credit before the Covid-19 crisis was, on average, 3.5 pp. lower than that of a safe firm with previous bank debt, which is a small effect with a semielasticity of -0.07 from its unconditional probability. By contrast, according to column (4), the probability that a risky zero-bank-debt firm obtained new credit before the Covid-19 crisis was, on average, 12.1 pp. lower than that of a risky firm with previous bank debt, which is a much larger effect with a semielasticity of -0.23 from its unconditional probability. These results imply that, before the pandemic, risky zero-bank-debt firms faced tighter credit constraints than safe zero-bank-debt firms relative to firms with previous bank debt and the same risk level, arguably because the information asymmetries caused by the lack of credit history mattered more when firms were less creditworthy. Column (3) also shows that the Covid-19 shock reduced the probability that safe zero-bank-debt firms obtained new credit by 2.5 pp. relative to safe firms with previous bank debt, which is a non-negligible effect with a semielasticity of -0.05 from its unconditional probability. In analogous fashion, column (4) shows that the Covid-19 shock decreased the probability that risky zero-bank-debt firms obtained new credit by 1.8 pp. relative to risky firms with previous bank debt, which is an effect of similar magnitude with a semielasticity of -0.04 from its unconditional probability.[31] These results indicate that the Covid-19 shock tightened the credit constraints of all zero-bank-debt firms, regardless of their risk, arguably because of the enhanced role of information asymmetries in an environment of high macroeconomic uncertainty in which it was harder for

[31] As this is a relative effect, we cannot ascertain whether banks restricted their credit supply to both types of firms, but more to zero-bank-debt firms or, by contrast, rolled over their loans to their existing customers (i.e., loan evergreening) while rejecting applications from potential customers.

banks to assess borrowers' risk. This suggests that the Covid-19 shock exacerbated pre-existing credit market imperfections. Also note that, as we compare the access to credit by zero-bank-debt firms relative to firms with previous bank debt and the same level of default risk, the fact that zero-bank-debt firms faced a more difficult access to credit than firms with previous bank debt (before and after the Covid-19 crisis) may be solely attributed to the lack of credit history of the former, leading to higher information asymmetries in the credit market that were amplified by the Covid-19 shock.

[Insert Table 4 here]

4.2. Access to credit by zero-bank-debt firms. Robustness tests and extensions

We conduct several robustness tests and extensions to verify that our two main findings (first, zero-bank-debt firms experienced a more difficult access to bank credit than firms with previous bank debt before the Covid-19 crisis; second, the Covid-19 shock tightened the credit constraints faced by zero-bank-debt firms relative to firms with previous bank debt) still hold when we modify certain parameters of our methodology to control for credit demand or use different estimation samples. We restrict the sample to the segment of safe firms because of two reasons. First, as banks are unlikely to engage in loan evergreening in the case of safe firms, we can isolate the adverse effect of the lack of credit history on the access to bank credit by zero-bank-debt firms relative to firms with previous bank debt. Second, we are particularly interested in the negative impact of the absence of credit history on the access to bank credit by creditworthy firms because this may lead to important inefficiencies in the allocation of resources. The results of those tests are reported in Panel A of Table 5. Column (1) shows the baseline estimates, and it is identical to column (3) of Table 4. In column (2) we exclude refinanced loans to rule out that our main findings are entirely driven by banks rolling over the loans granted to their existing customers. In column (3) we consider an alternative threshold for the fraction of debt maturing within one year (33% instead of 25%). In column (4) we use an alternative measure of credit demand. In particular, loan applications are only considered for zero-bank-debt firms[32] while, for firms with previous debt, we assume that they demand new credit if more than 25% of their interest-bearing debt matures within one year. In column (5) the treated group only comprises zero-bank-debt firms which also have no other types of interest-bearing debt (e.g., bonds). Across columns (1) to (5) the coefficient of *No Bank Debt* is negative, statistically significant and sizeable, and the corresponding semielasticities

[32] Banks with prior credit exposures to firms do not need to check the credit register, as they directly obtain information on those firms on a monthly basis. Therefore, an information request on a firm with previous bank debt necessarily implies that the bank making such request is a new bank, i.e., the extensive margin of credit supply.

are quite similar. In analogous fashion, the coefficient of the interaction between *No Bank Debt* and *Post Covid* is also negative, statistically significant and sizeable, and the corresponding semielasticities are quite similar across all those columns. By contrast, in column (6) we study the dependence on trade credit instead of bank credit. For that purpose, we use the baseline specification but replacing, as the dependent variable, *New Credit* by *New Trade Credit*, a dummy variable that equals 1 if the firm's trade credit increases and 0 otherwise. In this case, the coefficient of *No Bank Debt* is not statistically different from zero, indicating that the lack of credit history does not hamper the access to this alternative funding source, which is likely to depend on other factors such as the strength of the relationship of a firm with its providers and the degree of trust between the two parties (e.g., no previous delayed payments). In addition, the coefficient of the interaction between *No Bank Debt* and *Post Covid* is now *positive* and statistically significant, implying that the Covid-19 shock caused zero-bank-debt firms to rely more on trade credit to meet their funding deficits during the pandemic, as during this period it was particularly difficult for them to obtain bank credit.

We also carry out several robustness tests to ensure that our main results are not driven by the specific choices regarding the methodology of the PSM we have made. The results of those tests are reported in Panel B of Table 5. Column (1) displays again the baseline estimates, and it is identical to column (3) of Table 4. In column (2) we use the single nearest-neighbour method *without* replacement, which means that we perform a one-to-one matching procedure. In column (3) we impose a very narrow caliper[33] (equal to 0.0001). As caliper matching only uses as many control units as are available within the calipers, a very narrow caliper reduces bias, although it may also reduce the precision of the estimates by decreasing sample size. In column (4), to ensure that our regression models satisfy the common support assumption (i.e., the probability of receiving treatment for each possible value of the vector of covariates is *strictly* within the unit interval), we prescreen the sample by means of PSM before running *unweighted* regressions. In particular, we first follow Crump et al. (2009) and only keep firms with a propensity score in the interval (0.1, 0.9). In column (5) we implement the same procedure, but using a stricter criterion: we only keep firms with a propensity score in the interval (0.2, 0.8). Finally, in column (6) we combine Inverse Probability of Treatment Weighting (IPTW) with linear regression. IPTW uses the propensity score to balance the characteristics of treatment units and control units by weighting each unit by the inverse probability of receiving actual treatment (also called "probability of exposure"), which is estimated by the propensity score. Weights are calculated for each unit as (1/propensity score) for

[33] The caliper is the maximum difference between the propensity scores of pairs of treated and untreated units that is allowed in PSM.

the treatment group and 1/(1−propensity score) for the control group.[34] By doing so, treatment units with a lower probability of exposure (and control units with a higher probability of exposure) receive larger weights and therefore their relative influence on the comparison is increased. Subsequent inclusion of the weights in the analysis renders assignment to either the treatment or control group independent of the variables included in the PSM. We then incorporate the weights in the regression model (i.e., weighted linear regression) to obtain estimates adjusted for confounders.[35] Across columns (1) to (6) the coefficient of *No Bank Debt* is negative, statistically significant and sizeable, and the corresponding semielasticities are quite similar. In analogous fashion, the coefficient of the interaction between *No Bank Debt* and *Post Covid* is also negative, statistically significant and sizeable, and the corresponding semielasticities are quite similar across all those columns.

[Insert Table 5 here]

Another robustness test consists of augmenting equation (1) with the interactions between the dummy variable *Post Covid* and other two proxies for asymmetric information, *size* (log of total assets) and *age* (firm age, in logs), as small firms are informationally opaque (Berger et al., 2001; López-Espinosa et al., 2017) and there are more information asymmetries in the case of young firms with a short track record. The augmented regression model is described in equation (2):

$$\begin{aligned} NewCredit_{j,t} &= \delta NoBankDebt_j + \lambda_1 PostCovid_t x NoBankDebt_j \\ &\quad + \lambda_2 PostCovid_t xSize_{jt} + \lambda_3 PostCovid_t xAge_{jt} + \text{TControls}_{j,t-1} \\ &\quad + \eta_{i,l,s,t} + \epsilon_{j,t} \end{aligned} \tag{2}$$

The results are reported in Table 6. Column (1) displays the baseline estimates of equation (1), and they are identical to column (3) of Table 4. Column (2) displays the estimates of a restricted version of equation (2) in which we set λ_3 equal to zero. Column (3) shows the estimates of another restricted version of equation (2) in which we set λ_2 equal to zero. Finally, column (4) displays the estimates of equation (2). The coefficients of *No Bank Debt* and the coefficients of the interaction between *No Bank Debt* and *Post Covid* are almost identical across the four columns, implying that our previous findings were not driven by the variable *No Bank Debt* capturing other sources of

[34] As in the baseline analysis we obtain the propensity score by running a logit regression of *No Bank Debt* on *size*, *age*, *ROA*, *liquidity ratio*, *equity ratio*, *working capital ratio*, *tangibility*, and *tax ratio*.
[35] For an introduction to IPTW see Chesnaye et al. (2022).

asymmetric information. In addition, the coefficient of the interaction between *size* and *Post Covid* is not statistically different from zero neither in column (2) nor in column (4), and the coefficient of the interaction between *age* and *Post Covid,* although significant both in column (3) and (4), implies very small effects. These results also indicate that the estimation sample is balanced, as the differences in *size* and *age* between zero-bank-debt firms and firms with previous bank debt are so small that the effect of the interaction between those variables and *Post Covid* is negligible.

[Insert Table 6 here]

4.3. The role of guarantees

We now analyse the role of guarantees in mitigating the credit constraints faced by safe zero-bank-debt firms. We take into account all types of guarantees, such as personal guarantees, collateral and the public guarantees that were provided by the Spanish government during the Covid-19 crisis.[36] With this aim, we undertake a cross-sectional regression analysis based on the Covid-19 period (March 2020 – December 2020). We restrict the estimation to the Covid-19 period because there was a substantial increase in secured credit due to the public guarantee schemes established by the Spanish government, which accounted for most of the secured credit during such period. This phenomenon would distort an analysis based both on the pre-Covid and the Covid-19 periods. Therefore, we estimate the following weighted regression based on the Covid-19 period and the subsample of safe firms with observed loan applications or very likely to apply for a new loan, given their fraction of interest-bearing debt maturing in the short run:

$$NewCredit_j = \delta Alt1\_NoBankDebt_j + \text{TControls}_j + \eta_{i,l,s} + \epsilon_j \quad (3)$$

where *Alt1 No Bank Debt* is a dummy variable that equals one if the firm had no bank debt (either term loans or credit lines) in any month over the period 2015 – 2019, and 0 otherwise.[37] *New Credit* is a dummy variable that equals one if the firm obtained new bank credit between March 2020 and December 2020, the vector *Controls* is constructed using financial information from 2019, and $\eta_{i,l,s}$ are industry-location-size fixed effects.

[36] Against the backdrop of the Covid-19 crisis, the Spanish government established two public guarantee schemes managed through ICO, Spain's public bank. Under these guarantee schemes, the government covered up to 80% of the potential losses on loans granted by financial institutions (up to 80% in loans to self-employed and SMEs and up to 70% or 60% in loans to large firms depending on whether this financing was composed of new loans or rollovers). For an analysis of those schemes see Martin et al. (2023) and Jiménez et al. (2022).

[37] We use the variable *Alt1 No Bank Debt*, rather than *No Bank Debt*, because this regression analysis excludes the pre-Covid-19 period (March 2019 – December 2019).

We run this regression for five different dependent variables: *New Credit, New Credit without Guarantee*, *New Credit with any Guarantee, New Credit with Collateral or Personal Guarantee,* and *New Credit with Public Guarantee*. All of them are dummy variables that equal one if the firm obtains the respective type of credit, and zero if the firm does not receive any new bank credit. The estimation results are reported in Table 7, in which each column corresponds to a different dependent variable. Comparing columns (2) and (3) *–New Credit without Guarantee* vs. *New Credit with any Guarantee*- we can observe that the lack of credit history especially hinders the access to unsecured credit, as the semielasticity of *Alt1 No Bank Debt* is much larger (in absolute value) in (2) than in (3): -0.24 and -0.14, respectively. The intuition is straightforward: secured credit has higher expected recovery rates than unsecured credit. Therefore, banks were more willing to provide secured credit than unsecured credit to new borrowers, on which they did not have soft information thanks to relationship lending (Petersen and Rajan, 1994; Berger and Udell, 1995). But the fact that the semielasticities of *Alt1 No Bank Debt* in (3) and (1) are very similar (-0.14 and -0.13, respectively) suggests that the effectiveness of guarantees in mitigating the credit constraints faced by zero-bank-debt firms during the pandemic was highly heterogeneous and depended on the type of guarantee. This is exactly what we observe in the last two columns of Table 7. In column (4), where the dependent variable is *New Credit with Collateral or Personal Guarantee,* the semielasticity of *Alt1 No Bank Debt* is -0.23, very similar to the one reported in column (2), where the dependent variable is *New Credit without Guarantee* (i.e., unsecured credit). Importantly, 85% of the loans in which private guarantees were pledged only had personal guarantees, implying that the credit was secured with the present and future wealth of the guarantor, which could generate a high degree of uncertainty about recovery rates, mainly in the medium- and long-run (Mayordomo *et al.*, 2021). This means that, during the most acute phase of the Covid-19 crisis, providing personal guarantees or collateral yielded modest results in alleviating the credit constraints encountered by zero-bank-debt firms as compared to firms with previous bank debt. This is arguably because the very high macroeconomic uncertainty during that period made even harder for banks to assess the creditworthiness of new loan applicants and to estimate the value of the assets pledged as collateral, so that they prioritised lending to their existing customers, on which they had soft information thanks to relationship lending. By contrast, in column (5), where the dependent variable is *New Credit with Public Guarantee,* the semielasticity of *Alt1 No Bank Debt* is, by far, the lowest of the five columns (-0.07). The rationale behind is that, when banks' skin in the game was much lower thanks to the public guarantees, in which the government covered a large proportion of the potential losses, they were less reluctant to grant credit to zero-bank-debt firms despite their lack of credit history. Nevertheless, as the coefficient of *Alt1 No Bank Debt* is negative and significant, and the corresponding semielasticity is non-negligible, we may conclude that the use of public guarantees did not completely eliminate the credit constraints faced by safe zero-bank-debt firms, as they still had a lower probability of obtaining new credit than safe firms with previous bank debt.

[Insert Table 7 here]

5. The survival of zero-bank-debt firms

We now investigate the effect of not having previous bank debt on the probability of market exit before and during the Covid-19 crisis. With this aim, we estimate the following regression model:

$$Exit_{j,t} = \delta Alt2\_NoBankDebt_{j,t} + \lambda PostCovid_t x Alt2\_NoBankDebt_{j,t} + \mathrm{TControls}_{j,t-1} + \eta_{i,l,s,t} + \epsilon_{j,t} \quad (4)$$

We use two sample periods, one before the Covid-19 crisis and another one during that crisis, to estimate equation (4). In the first sample period, *Exit* is a dummy variable that equals 1 if the firm exited the market or became inactive in the period 2018-2019, *Alt2 No Bank Debt* is a dummy variable that equals 1 if the firm had no outstanding bank debt in any month during the period 2013-2017, and the vector *Controls* is constructed using balance sheets from 2017. In the second sample period, *Exit* is a dummy variable that equals 1 if the firm exited the market or became inactive in the period 2020-2021, *Alt2 No Bank Debt* is a dummy variable that equals 1 if the firm had no outstanding bank debt in any month during the period 2015-2019, and the vector *Controls* is constructed using balance sheets from 2019. Finally, *Post Covid* is a dummy variable that equals 1 for the period 2020-2021, and 0 otherwise. Note that, contrary to the baseline analysis, *Alt2 No Bank Debt* is time varying to ensure the comparability between the two samples. In the previous analyses, we used information on whether a firm had bank debt or not in any month during the period 2014-2018 to study firms' access to credit between March 2019 and December 2020, or whether a firm had bank debt or not in any month during the period 2015-2019 to study the role of guarantees in facilitating firms' access to credit between March 2020 and December 2020. However, the use of a time-invariant variable in this new setup to measure firms' reliance on bank credit would lead to the employment of balance-sheet information from the period 2013-2017 to explain their survival during the period 2018-2021, which would imply a large time gap between the measurement of the dependent variable and that of the regressor of interest. For instance, the probability of exit in 2021 would be linked to very outdated financial statements (from four to eight years before the event), which may not reflect firms' reliance of bank credit in current times.

Moreover, the nature of the dependent variables in equations (1) and (4) is very different (new credit vs. exits, respectively) and, in the latter case, the use of a time-invariant variable could generate a survivorship bias that would lead to inconsistent estimates of the parameters of interest. In particular, the companies used in the Covid-19 period would be those that were alive during the seven years prior to 2020 whereas, for the pre-Covid period, the companies used in our regression analysis would be only alive during the five years prior to 2018.

The estimation results are reported in Table 8. Column (1) displays the estimate with the whole sample, while columns (2) and (3) show the estimates with the subsamples of risky and safe firms, respectively. According to column (1), the probability of leaving the market before the Covid-19 crisis by a zero-bank-debt firm was, on average, roughly the same as the probability of a firm with previous bank debt. We support this statement because the coefficient of *Alt2 No Bank Debt* in column (1) is only marginally significant, with a very limited economic significance. In addition, in columns (2) and (3) the economic significance of the coefficients is also very limited.

To examine the impact of the Covid-19 shock, it is necessary to assess the coefficient of the interaction between *Post Covid* and *Alt2 No Bank Debt.* This coefficient is positive and highly significant across the three columns. According to column (1), the Covid-19 shock increased the probability that zero-bank-debt firms exited the market (compared to firms with previous bank debt) by 1 pp., which is a large effect with a semielasticity of 0.44 from its unconditional probability. Similar findings are observed when distinguishing between risky and safe firms. According to column (2), the Covid-19 shock raised the probability that risky zero-bank-debt firms exited the market (relative to risky firms with previous bank debt) by 2 pp., which is a large effect with a semielasticity of 0.62 from its unconditional probability. According to column (3), the Covid-19 shock increased the probability that safe zero-bank-debt firms exited the market (relative to safe firms with previous bank debt) by 0.9 pp., which is also a large effect with a semielasticity of 0.55 from its unconditional probability. These findings imply that the Covid-19 shock raised substantially the probability that zero-bank-debt firms exited the market relative to firms with previous bank debt, regardless of their risk, arguably because it also reduced the probability that the former obtained new credit relative to the latter, both in the case of safe and risky firms, as previously documented (columns (3) and (4) of Table 4). In addition, the fact that the Covid-19 shock caused zero-bank-debt firms to have both a higher probability of leaving the market and a lower probability of obtaining new credit than firms with previous bank debt in the segment of safe firms suggests that frictions in the credit market may lead to inefficient exits, in the sense of causing creditworthy firms to leave the market.

[Insert Table 8 here]

Finally, we study the role of new credit in keeping afloat zero-bank-debt firms during the Covid-19 crisis. For that purpose, we investigate the effect of obtaining new credit on the probability of market exit during the period 2020-2021 for the subsample of zero-bank-debt firms that applied for a loan during the year 2020 by estimating equation (5):

$$Exit_j = \eta NewCredit_j + \mathrm{TControls}_j + \eta_{i,l,s} + \epsilon_j \tag{5}$$

where *Exit* is a dummy variable that equals one if the firm exited the market during the period 2020-2021, *New Credit* is a dummy variable that equals one the firm obtained new credit between March 2020 and December 2020, the vector *Controls* is constructed using the financial statements from 2019, and $\eta_{i,l,s}$ are industry-location-size fixed effects.

The estimation results obtained from this cross-sectional regression are reported in Table 9. Column (1) displays the estimate with the whole sample, while columns (2) and (3) display the estimates with the subsamples of risky and safe firms, respectively. The coefficient of *New Credit* is negative and highly significant across the three columns. According to column (1), granting new credit to a zero-bank-debt firm reduced, on average, its probability of exit in 2020-2021 by 0.5 pp. This result, which suggests a causal link between obtaining new credit and the probability of leaving the market by zero-bank-debt firms, corroborates our previous conjecture, namely that zero-bank-debt firms were more prone to exit the market during the pandemic than firms with previous bank debt because the Covid-19 shock made them more financially constrained. We now turn to the estimates based on the subsamples of risky and safe firms, which show that granting new credit to safe zero-bank-debt firms decreased their probability of exit more than granting it to risky zero-bank-debt firms. In particular, according to column (2), granting new credit to a risky zero-bank-debt firm reduced, on average, its probability of leaving the market by 0.5 pp., which is a sizeable effect with a semielasticity of -0.79 from its unconditional probability. But, according to column (3), granting new credit to a safe zero-bank-debt firm decreased, on average, its probability of leaving the market by 0.4 pp., which is a larger effect with a semielasticity of -1.14. This result may reflect the fact that some zero-bank-debt firms with a high PD (i.e., risky firms) may not manage to stay afloat even with additional financial support because their financial condition is too deteriorated. As granting a bank loan may make a higher difference in terms of firm survival for stronger zero-bank-debt firms than for weaker ones, mitigating the financial constraints faced by the former should be a priority from a policy perspective. This differential effect is not explained by the loans granted to safe zero-bank-debt firms being larger than those granted to risky zero-bank-debt firms, as the average loan obtained by a safe (risky) zero-bank-debt firm was €52,339 (€64,046), which accounted for 22% (24%) of its total assets.

[Insert Table 9 here]

6. Conclusions

As traditional theories of capital structure cannot explain the existence of zero-debt firms all around the world, most of the existent literature has focused on developing new theories that may resolve this puzzle. In contrast, we study the access to credit and the propensity to exit the market of Spanish non-listed firms without prior bank debt around the Covid-19 crisis, a well-identified exogenous shock. For that purpose, we assemble a unique dataset that comprises the universe of loans granted to Spanish firms and their loan applications, coupled with firms' balance sheets, which enables us to control for credit demand, as having no bank debt may be due to financial constraints or may be a deliberate strategy of the firm. In particular, we control for credit demand with information on loan applications and the fraction of interest-bearing debt maturing in the short run, as firms with a fairly high fraction of such debt are very likely to apply for new loans. This new methodology contributes to the literature that disentangles credit supply from credit demand by companies, as it can be applied to isolate credit supply to firms without previous lending relationships, a context in which the identification strategy of Khwaja and Mian (2008) is not feasible because it relies on firms with multiple bank relationships.

We find that zero-bank-debt firms had a much lower probability of obtaining new credit than firms with previous bank debt before the Covid-19 crisis, especially in the segment of risky firms. This result suggests that, before the pandemic, risky zero-bank-debt firms faced tighter credit constraints than safe zero-bank-debt firms relative to firms with previous bank debt and the same risk level, arguably because information asymmetries caused by the lack of credit history mattered more when firms were less creditworthy. This difference increased in 2020, regardless of firms' risk, highlighting the prevailing role of information asymmetries during a period of high macroeconomic uncertainty in which banks found it harder to assess borrowers' risk. The fact that the Covid-19 shock also tightened the credit constraints faced by safe zero-bank-debt firms indicates that it exacerbated pre-existing credit market imperfections. We also study the access to trade credit by zero-bank-debt firms. We first find that, before the Covid-19 crisis, zero-bank-debt firms had, on average, the same probability of obtaining new trade credit as firms with previous bank debt, implying that the lack of credit history did not hamper the access to this alternative funding source. We also find that the Covid-19 shock caused zero-bank-debt firms to rely more on trade credit to meet their funding deficits, arguably because, during the pandemic, it was particularly difficult for them to obtain bank credit.

We also find that pledging guarantees facilitated the access to credit of safe zero-bank-debt firms relative to firms with previous bank debt. The rationale behind is that, as secured credit has higher expected recovery rates than unsecured credit, banks were more willing to provide the former than the latter to new borrowers, on which they did not have soft information thanks to relationship lending. However, we also find that the effectiveness of guarantees in mitigating the credit constraints faced by zero-bank-debt firms during the pandemic was highly heterogeneous and depended on the type of guarantees. In particular, pledging personal guarantees or collateral yielded a modest impact on easing the credit constraints faced by zero-bank-debt firms relative to firms with previous bank debt because the very high macroeconomic uncertainty during the pandemic made even harder for banks to assess the creditworthiness of new loan applicants and to estimate the value of the assets pledged as collateral. By contrast, public guarantees were very effective in mitigating the credit constraints faced by zero-bank-debt firms. The reason is that, when banks' skin in the game was much lower thanks to the public guarantees, in which the government covered a large proportion of the potential losses, they were less reluctant to grant credit to zero-bank-debt firms despite their lack of credit history.

We then study the effect of lending relationships on the propensity to exit the market before and during the Covid-19 crisis. We first find that the probability of leaving the market before the Covid-19 crisis by a zero-bank-debt firm was, on average, roughly the same as the probability of a firm with previous bank debt. But we also find that the Covid-19 shock raised substantially the probability that zero-bank-debt firms exited the market relative to firms with previous bank debt, regardless of their risk, arguably because it also reduced the probability that the former obtained new credit relative to the latter. The fact the Covid-19 shock caused zero-bank-debt firms to have both a higher probability of leaving the market and a lower probability of obtaining new credit than firms with previous bank debt in the segment of safe firms suggests that frictions in the credit market may lead to inefficient exits.

Finally, granting new credit to zero-bank-debt firms reduced their probability of exit, which corroborates a causal link between access to credit and propensity to exit the market for those firms. This effect was larger for safe zero-bank-debt firms than for their risky counterparts. As the provision of new credit may make a higher difference in terms of firm survival for stronger zero-bank-debt firms than for weaker ones, mitigating the financial constraints faced by the former should be a priority from a policy perspective.

All in all, our results highlight that zero-bank-debt firms may face particularly acute frictions in the credit market vis-á-vis firms with previous bank debt during economic crises, due to increased information asymmetries or banks' lending practices. As this may lead to inefficient market exits, policies that mitigate the financial constraints of those firms such as enhanced financial reporting requirements, public guarantee programmes, and the improvement of contract enforcement may be beneficial for the whole economy.

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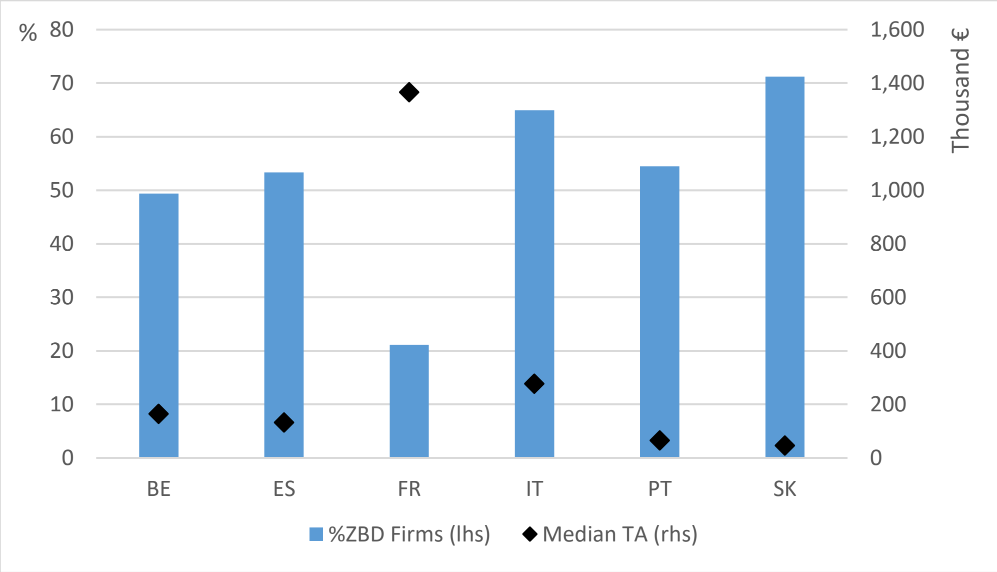
Figure 1: Percentage of firms with zero bank debt and median firm size across selected euro area countries in 2018



Source: Authors' elaboration from iBACH (Micro Bank for the Accounts of Companies Harmonized) for 2018 and the following countries: Belgium (BE), Spain (ES), France (FR), Italy (IT), Portugal (PT), and Slovakia (SK). The blue bars represent the percentage of firms with zero bank debt (ZBD firms) in each country, while the black diamonds indicate the median total assets (TA), in thousand euros, of the distribution of firms' total assets in each country.

Table 1: Descriptive statistics of zero-bank-debt firms and firms with bank debt

This table shows the means of variables during the period 2018-2019 for zero-bank-debt firms (i.e., firms that had no drawn or undrawn bank debt in any month over the period 2014 – 2018) and firms with previous bank debt. In Panel A we study all firms in our sample while in Panel B we focus on firms that demand credit or it is very to do so. In particular, in Panel B we restrict the sample to the following two cases: (i) when a firm applies for a new loan, as proxied by banks' information requests; (ii) when a firm with previous interest-bearing debt (i.e., drawn and undrawn bank credit and other debt obligations) has more than 25% of this debt maturing within the next 12 months. *Size* is the natural logarithm of total assets, in thousand €. *Age* is the natural logarithm of firm age, in years. *ROA* is the ratio of EBITDA to total assets. *Liquidity ratio* is the ratio of liquid assets to total assets, where liquid assets are cash and cash equivalents. *Equity ratio* is the ratio of share capital to total assets. *Working capital ratio* is the ratio of working capital to total assets. *Tangibility* is the ratio of tangible fixed assets to total assets. *Tax ratio* is the ratio of corporate taxes to total assets. All variables have been winsorised at the 2.5th and 97.5th percentiles. The statistical significance of the difference between the means of the two groups has been assessed by running linear regressions of each variable on a dummy variable denoting zero-bank-debt firms and a constant, with standard errors clustered at the firm-level.

Table 1.A: Full sample

		(1) Zero-bank-debt firms		(2) Firms with previous bank debt		Difference means (1)-(2)	p-value
	Units	Mean	Obs	Mean	Obs		
Size	Natural log	4.41	527,168	5.51	764,260	-1.10	0.00
Log(age)	Natural log	1.85	552,265	2.47	764,766	-0.63	0.00
ROA	%	2.73	527,168	5.14	764,260	-2.41	0.00
Liquidity Ratio	%	32.90	527,168	15.83	764,260	17.07	0.00
Equity Ratio	%	33.93	527,168	24.69	764,260	9.24	0.00
Working Capital Ratio	%	17.32	527,168	8.23	764,260	9.09	0.00
Tangibility	%	21.52	527,168	34.14	764,260	-12.62	0.00
Tax Ratio	%	1.28	527,168	0.94	764,260	0.34	0.00

Table 1.B: Subsample of firms that demand credit

		(1) Zero-bank-debt firms		(2) Firms with previous bank debt		Difference means (1)-(2)	p-value
	Units	Mean	Obs	Mean	Obs		
Size	Natural log	4.52	128,032	5.58	431,634	-1.06	0.00
Log(age)	Natural log	1.52	134,998	2.44	431,777	-0.91	0.00
ROA	%	4.28	128,032	5.75	431,634	-1.48	0.00
Liquidity Ratio	%	30.15	128,032	14.50	431,634	15.66	0.00
Equity Ratio	%	31.97	128,032	26.29	431,634	5.68	0.00
Working Capital Ratio	%	14.64	128,032	7.80	431,634	6.84	0.00
Tangibility	%	20.28	128,032	29.27	431,634	-8.99	0.00
Tax Ratio	%	1.50	128,032	1.03	431,634	0.48	0.00

Table 2: Access to new credit by zero-bank-debt firms during the Covid-19 crisis

This table shows the coefficient of the variable No Bank Debt and the coefficient of the interaction between *No Bank Debt* and the variable *Post Covid* in OLS regressions in which the dependent variable (*New Credit*) is a dummy that equals 1 if the firm obtains new bank credit and 0 otherwise. *No Bank Debt* is a dummy variable that equals 1 if the firm had no (drawn or undrawn) bank debt in any month over the period 2014 – 2018. *Post Covid* is a dummy variable that equals 1 for observations from 2020 and 0 otherwise. In columns (1) and (2) we use all firms in our sample, whereas in columns (3) and (4) we use the subsample of firms that demand credit or are very likely to do it. In particular, we restrict the sample to the following two types of firms: (i) firms that apply for a new loan, as proxied by banks' information requests; (ii) firms with previous interest-bearing debt (i.e., drawn and undrawn bank credit and other debt obligations) that have more than 25% of this debt maturing within the next 12 months. All specifications include the following lagged firm controls: *size* (log of total assets), *age* (in logs), *equity ratio* (ratio of share capital to total assets), *working capital ratio* (ratio of working capital to total assets), *liquidity ratio* (ratio of liquid assets to total assets), *ROA* (ratio of EBITDA to total assets), *tangibility* (ratio of tangible fixed assets to total assets), and *tax ratio* (ratio of corporate taxes to total assets). All specifications also include Industry-Location-Size-Time Fixed Effects, where Industry is defined at the 3-digit level according to the NACE classification, Location at the NUTS-3 level (i.e., Spanish provinces), and Size comprises 4 categories according to the EU definition (micro, small, medium-sized, large). The estimation period is 2019-2020. The semielasticity is the ratio of each coefficient to the unconditional probability in each subsample. Robust standard errors in brackets are clustered at the firm-level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Sample	All firms		Firms with credit demand	
Dependent Variable	New Credit	New Credit	New Credit	New Credit
No Bank Debt	-0.240***	-0.236***	-0.111***	-0.107***
	[0.001]	[0.001]	[0.002]	[0.003]
Post Covid x No Bank Debt		-0.010***		-0.008***
		[0.001]		[0.003]
Industry-Location-Size-Year FE	YES	YES	YES	YES
Lagged Firm Controls	YES	YES	YES	YES
Observations	1,282,444	1,282,444	550,705	550,705
R-squared	0.219	0.219	0.150	0.150
Semielasticity of No Bank Debt	-0.726	-0.712	-0.187	-0.18
Semielasticity of Post Covid x No Bank Debt		-0.029		-0.013

Table 3: Descriptive statistics of zero-bank-debt firms and firms with bank debt
Subsample of firms that demand credit, PSM weights

This table shows the means of variables during the period 2018-2019 for zero-bank-debt firms (i.e., firms that had no drawn or undrawn bank debt in any month over the period 2014 – 2018) and firms with previous bank debt. We restrict the sample to firms that demand credit or are very likely to do it. We consider that a firm has demanded credit or is expected to do it in two different cases: (i) when a firm applies for a new loan, as proxied by banks' information requests; (ii) when a firm with previous interest-bearing debt (i.e., drawn and undrawn bank credit and other debt obligations) has more than 25% of this debt maturing within the next 12 months. *Size* is the natural logarithm of total assets, in thousand €. *Age* is the natural logarithm of firm age, in years. *ROA* is the ratio of EBITDA to total assets. *Liquidity ratio* is the ratio of liquid assets to total assets, where liquid assets are cash and cash equivalents. *Equity ratio* is the ratio of share capital to total assets. *Working capital ratio* is the ratio of working capital to total assets. *Tangibility* is the ratio of tangible fixed assets to total assets. *Tax ratio* is the ratio of corporate taxes to total assets. All variables have been winsorised at the 2.5th and 97.5th percentiles. The statistical significance of the difference between the means of the two groups has been assessed by running weighted linear regressions of each variable on a dummy variable denoting zero-bank-debt firms and a constant, with standard errors clustered at the firm-level. The weights come from Propensity Score Matching (PSM) –single nearest-neighbour method with replacement- which it is implemented by running a logit regression of *No Bank Debt* on *size, age, ROA, liquidity ratio, equity ratio, working capital ratio, tangibility,* and *tax ratio.* In these regressions the firms with previous bank debt are weighted by the number of times they are matched to a zero-bank-debt firm.

		(1) Zero-bank debt firms		(2) Firms with bank debt		Difference means (1)-(2)	p-value
	Units	Mean	Obs	Mean	Obs		
Size	Natural log	4.52	128,032	4.53	128,032	-0.01	0.83
Age	Natural log	1.61	128,032	1.67	128,032	-0.07	0.00
ROA	%	4.28	128,032	2.39	128,032	1.89	0.00
Liquidity Ratio	%	30.15	128,032	32.17	128,032	-2.02	0.02
Equity Ratio	%	31.97	128,032	30.89	128,032	1.08	0.23
Working Capital Ratio	%	14.64	128,032	13.72	128,032	0.92	0.41
Tangibility	%	20.28	128,032	19.88	128,032	0.39	0.16
Tax Ratio	%	1.50	128,032	1.49	128,032	0.01	0.77

Table 4: Access to new credit by zero-bank-debt firms during the Covid-19 crisis
Only firms that demand credit, subsamples by firms' probability of default (PD), PSM weights

This table shows the coefficient of the variable *No Bank Debt* and the coefficient of the interaction between *No Bank Debt* and the variable *Post Covid* in weighted linear regressions in which the dependent variable (*New Credit*) is a dummy that equals 1 if the firm obtains new bank credit and 0 otherwise. *No Bank Debt* is a dummy variable that equals 1 if the firm had no (drawn or undrawn) bank debt in any month over the period 2014 – 2018, and zero otherwise. *Post Covid* is a dummy variable that equals 1 for observations from 2020 and 0 otherwise. The weights used in the regressions come from Propensity Score Matching (PSM) –single nearest-neighbour method with replacement- which it is implemented by running a logit regression of *No Bank Debt* on *size, age, ROA, liquidity ratio, equity ratio, working capital ratio, tangibility,* and *tax ratio.* In these regressions the firms with previous bank debt are weighted by the number of times they are matched to a zero-bank-debt firm. In all columns we restrict the sample to firms that demand credit. We consider that a firm has demanded credit or is expected to do it in two different cases: (i) when a firm applies for a new loan, as proxied by banks' information requests; (ii) when a firm with previous interest-bearing debt (i.e., drawn and undrawn bank credit and other debt obligations) has more than 25% of this debt maturing within the next 12 months. Column (3) corresponds to a subsample of firms whose probability of default (PD) is lower than the median PD of firms with bank debt during the estimation period (safe firms), while column (4) corresponds to a subsample of firms whose PD is higher than that median (risky firms). The PD is estimated with the methodology developed by Blanco et al. (2024). All specifications include the following lagged firm controls: *size* (log of total assets), *age* (in logs), *equity ratio* (ratio of share capital to total assets), *working capital ratio* (ratio of working capital to total assets), *liquidity ratio* (ratio of liquid assets to total assets), *ROA* (ratio of EBITDA to total assets), *tangibility* (ratio of tangible fixed assets to total assets), and *tax ratio* (ratio of corporate taxes to total assets). All specifications also include Industry-Location-Size-Time Fixed Effects, where Industry is defined at the 3-digit level according to the NACE classification, Location at the NUTS-3 level (i.e., Spanish provinces), and Size comprises 4 categories according to the EU definition (micro, small, medium-sized, large). The estimation period is 2019-2020. The semielasticity is the ratio of each coefficient to the unconditional probability in each subsample. Robust standard errors in brackets are clustered at the firm-level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Sample	All firms	All firms	Safe firms	Risky firms
Dependent Variable		New Credit		
No Bank Debt	-0.078***	-0.066***	-0.035***	-0.121***
	[0.003]	[0.004]	[0.005]	[0.007]
Post Covid x No Bank Debt		-0.023***	-0.025***	-0.018*
		[0.005]	[0.006]	[0.010]
Only firms that demand credit	YES	YES	YES	YES
Industry-Location-Size-Year FE	YES	YES	YES	YES
Lagged Firm Controls	YES	YES	YES	YES
Observations	249,655	249,655	178,383	67,120
R-squared	0.164	0.164	0.182	0.249
Semielasticity of No Bank Debt	-0.160	-0.136	-0.075	-0.238
Semielasticity of Post Covid x No Bank Debt		-0.048	-0.053	-0.036

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Table 5. Access to new credit by safe zero-bank-debt firms during the Covid-19 crisis
Panel A. Robustness analyses and extensions: alternative definitions or samples

This panel shows the coefficient of the variable *No Bank Debt* and the coefficient of the interaction between *No Bank Debt* and the variable *Post Covid* in weighted linear regressions in which the dependent variable (*New Credit*) is a dummy that equals 1 if the firm obtains new bank credit and 0 otherwise in columns (1) – (5). *No Bank Debt* is a dummy variable that equals 1 if the firm had no (drawn or undrawn) bank debt in any month over the period 2014 – 2018, and 0 otherwise. "Post Covid" is a dummy variable that equals 1 for observations from 2020, and 0 otherwise. The weights used in the regressions come from Propensity Score Matching (PSM) –single nearest-neighbour method with replacement- which it is implemented by running a logit regression of *No Bank Debt* on *size, age, ROA, liquidity ratio, equity ratio, working capital ratio, tangibility,* and *tax ratio*. In these regressions the firms with previous bank debt are weighted by the number of times they are matched to a zero-bank-debt firm. We restrict the sample to safe firms, defined as those firms whose probability of default (PD) is lower than the median PD of firms with bank debt during the estimation period. We also restrict the sample to firms that demand credit. Columns (1), (3) – (6) include all firms that demand credit, while column (2) excludes refinanced loans. In columns (1) – (2) and (5) – (6) we consider that a firm demands credit in two different cases: (i) when a firm applies for a new loan, as proxied by banks' information requests; (ii) when a firm with previous interest-bearing debt (i.e., drawn and undrawn bank credit and other debt obligations) has more than 25% of this debt maturing within the next 12 months. In column (3) we consider an alternative threshold for the fraction of debt maturing within one year (33% instead of 25%), while in column (4) we use an alternative measure of credit demand by considering loan applications only for zero-bank-debt firms. In column (5) the treated group only comprises zero-bank-debt firms which also have no other types of interest-bearing debt. In column (6) we use the baseline specification but replacing, as the dependent variable, *New Credit* by *New Trade Credit*, a dummy variable that equals 1 if the firm's trade credit increases and 0 otherwise. All specifications include lagged firm controls and Industry-Location-Size-Time Fixed Effects. The estimation period is 2019-2020. The semielasticity is the ratio of each coefficient to the unconditional probability in each subsample. Robust standard errors in brackets are clustered at the firm-level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Sample	Baseline	Excluding refinancing loans	Fraction of debt maturing in one year (33%)	Alternative measure of credit demand	Firms with no bank debt and no other interest-bearing debt	New debt with suppliers as dep. var.
Dependent variable	New Credit					New Trade Credit
No Bank Debt	-0.035***	-0.011**	-0.040***	-0.013**	-0.015***	-0.001
	[0.005]	[0.005]	[0.005]	[0.005]	[0.006]	[0.004]
Post Covid x No Bank Debt	-0.025***	-0.032***	-0.024***	-0.026***	-0.022***	0.039***
	[0.006]	[0.006]	[0.006]	[0.007]	[0.008]	[0.006]
Only firms that demand credit	YES	YES	YES	YES	YES	YES
Industry-Location-Size-Year FE	YES	YES	YES	YES	YES	YES
Lagged firm controls	YES	YES	YES	YES	YES	YES
Observations	178,383	167,853	175,354	159,320	100,663	178,383
R-squared	0.182	0.179	0.184	0.185	0.194	0.195
Semielasticity of No Bank Debt	-0.075	-0.024	-0.084	-0.027	-0.033	-0.002
Semielasticity of Post Covid x No Bank Debt	-0.053	-0.073	-0.05	-0.057	-0.048	0.115

Table 5. Panel B. Robustness tests: alternative methodologies

This panel shows the coefficient of the variable *No Bank Debt* and the coefficient of the interaction between *No Bank Debt* and the variable *Post Covid* in linear regressions in which the dependent variable (*New Credit*) is a dummy that equals 1 if the firm obtains new bank credit and 0 otherwise. *No Bank Debt* is a dummy variable that equals 1 if the firm had no (drawn or undrawn) bank debt in any month over the period 2014 – 2018, and 0 otherwise. *Post Covid* is a dummy variable that equals 1 for observations from 2020, and 0 otherwise. In all columns we restrict the sample to firms that demand credit. We consider that a firm has demanded credit or is expected to do it in two different cases: (i) when a firm applies for a new loan, as proxied by banks' information requests; (ii) when a firm with previous interest-bearing debt (i.e., drawn and undrawn bank credit and other debt obligations) has more than 25% of this debt maturing within the next 12 months. Column (1) displays the baseline estimates, obtained by weighted linear regressions. The weights used in these regressions come from Propensity Score Matching (PSM) –single nearest-neighbour method with replacement- which it is implemented by running a logit regression of *No Bank Debt* on *size, age, ROA, liquidity ratio, equity ratio, working capital ratio, tangibility,* and *tax ratio.* In these regressions the firms with previous bank debt are weighted by the number of times they are matched to a zero-bank-debt firm. Columns (2) and (3) also display estimates obtained by weighted linear regressions using PSM, but in column (2) it is implemented without replacement and in column (3) we impose a caliper equal to 0.0001. In columns (4) and (5) we prescreen the sample by means of PSM before running unweighted regressions. In column (4) we follow Crump et al. (2009) and only keep firms with a propensity score in the interval (0.1, 0.9), while in column (5) we only keep firms with a propensity score in the interval (0.2, 0.8). In column (6) we combine Inverse Probability of Treatment Weighting (IPTW) with linear regression. We first estimate the propensity score to compute the weights for each firm -(1/propensity score) for zero-bank-debt firms and 1/(1−propensity score) for firms with previous bank debt- and we then incorporate them in the regression model (i.e., weighted linear regression). All specifications include the same firm controls and Industry-Location-Size-Time Fixed Effects reported in Panel A. The estimation period is 2019-2020. The semielasticity is the ratio of each coefficient to the unconditional probability in each subsample. Robust standard errors in brackets are clustered at the firm-level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Method	Baseline	Without replacement	Caliper=0.0001	PS (0.1, 0.9)	PS (0.2, 0.8)	IPTW
Dependent variable			New Credit			
No Bank Debt	-0.035***	-0.060***	-0.047***	-0.069***	-0.040***	-0.058***
	[0.005]	[0.004]	[0.004]	[0.003]	[0.004]	[0.005]
Post Covid x No Bank Debt	-0.025***	-0.012***	-0.015**	-0.010**	-0.012***	-0.014**
	[0.006]	[0.005]	[0.006]	[0.004]	[0.005]	[0.007]
Observations	178,383	177,643	170,325	263,984	164,258	141,393
R-squared	0.182	0.141	0.176	0.142	0.143	0.194
Only firms that demand credit	YES	YES	YES	YES	YES	YES
Industry-Location-Size-Year FE	YES	YES	YES	YES	YES	YES
Lagged Firm Controls	YES	YES	YES	YES	YES	YES
Semielasticity of No Bank Debt	-0.075	-0.121	-0.097	-0.128	-0.078	-0.129
Semielasticity of Post Covid x No Bank Debt	-0.053	-0.025	-0.032	-0.018	-0.024	-0.032

Table 6: Access to new credit by safe zero-bank-debt firms during the Covid-19 crisis. Robustness analysis including other proxies for asymmetric information

This table shows the coefficient of the variable *No Bank Debt* and the coefficients of the interactions between *No Bank Debt*, *Size* and *Age* and the variable *Post Covid* in weighted linear regressions in which the dependent variable (*New Credit*) is a dummy that equals 1 if the firm obtains new bank credit and 0 otherwise. *No Bank Debt* is a dummy variable that equals 1 if the firm had no (drawn or undrawn) bank debt in any month over the period 2014 – 2018, and 0 otherwise. *Size* is the log of total assets and *Age* is the firm age, in logs. *Post Covid* is a dummy variable that equals 1 for observations from 2020 and 0 otherwise. The weights used in the regressions come from Propensity Score Matching (PSM) –single nearest-neighbour method with replacement- which it is implemented by running a logit regression of *No Bank Debt* on *size, age, ROA, liquidity ratio, equity ratio, working capital ratio, tangibility,* and *tax ratio.* In these regressions the firms with previous bank debt are weighted by the number of times they are matched to a zero-bank-debt firm. We restrict the sample to safe firms, defined as those firms whose probability of default (PD) is lower than the median PD of firms with bank debt during the estimation period. The PD is estimated with the methodology developed by Blanco et al. (2024). We also restrict the sample to firms that demand credit. We consider that a firm has demanded credit or is expected to do it in two different cases: (i) when a firm applies for a new loan, as proxied by banks' information requests; (ii) when a firm with previous interest-bearing debt (i.e., drawn and undrawn bank credit and other debt obligations) has more than 25% of this debt maturing within the next 12 months. All specifications include the following lagged firm controls: *size* (log of total assets), *age* (in logs), *equity ratio* (ratio of share capital to total assets), *working capital ratio* (ratio of working capital to total assets), *liquidity ratio* (ratio of liquid assets to total assets), *ROA* (ratio of EBITDA to total assets), *tangibility* (ratio of tangible fixed assets to total assets), and *tax ratio* (ratio of corporate taxes to total assets). All specifications also include Industry-Location-Size-Time Fixed Effects, where Industry is defined at the 3-digit level according to the NACE classification, Location at the NUTS-3 level (i.e., Spanish provinces), and Size comprises 4 categories according to the EU definition (micro, small, medium-sized, large). The estimation period is 2019-2020. The semielasticity is the ratio of each coefficient to the unconditional probability in each subsample. Robust standard errors in brackets are clustered at the firm-level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) Baseline	(2) Adding Size	(3) Adding Age	(4) Adding Size and Age
Dependent variable			New Credit	
No Bank Debt	-0.035***	-0.035***	-0.035***	-0.035***
	[0.005]	[0.005]	[0.005]	[0.005]
Post Covid x No Bank Debt	-0.025***	-0.025***	-0.026***	-0.026***
	[0.006]	[0.006]	[0.006]	[0.006]
Post Covid x Size		-0.001		0.001
		[0.002]		[0.003]
Post Covid x Age			-0.006*	-0.007**
			[0.003]	[0.003]
Only firms that demand credit	YES	YES	YES	YES
Industry-Location-Size-Year FE	YES	YES	YES	YES
Lagged Firm Controls	YES	YES	YES	YES
Observations	178,383	178,383	178,383	178,383
R-squared	0.182	0.182	0.182	0.182
SE of No Bank Debt	-0.075	-0.074	-0.075	-0.075
SE of Post Covid x No Bank Debt	-0.053	-0.053	-0.056	-0.055
SE of Post Covid x Size		-0.001		0.003
SE of Post Covid x Age			-0.013	-0.014

Table 7. Access to new credit by safe zero-bank-debt firms during the Covid-19 crisis. The role of guarantees

This table shows the coefficients of the variable *Alt1 No Bank Debt* in cross-sectional weighted linear regressions in which there are five different dependent variables. All of them are dummy variables that equal one if the firm obtains the respective type of credit, and zero if the firm does not receive any new bank credit. *New Credit* is a dummy that equals 1 if the firm obtained any new bank credit. *New Credit with any Guarantee* is a dummy variable that equals one if the firm obtained new credit secured by any type of guarantee. *New Credit with Collateral or Personal Guarantee is* a dummy variable that equals one if the firm obtained new credit secured by either collateral or a personal guarantee, or by both of them, but without any additional public guarantee. *New Credit with Public Guarantee* is a dummy variable that equals one if the firm obtained new credit secured by a public guarantee, but without any additional collateral or personal guarantees. *New Credit without Guarantee* is a dummy variable that equals one if the firm obtained new unsecured credit. *Alt1 No Bank Debt* is a dummy variable that equals 1 if the firm had no (drawn or undrawn) bank debt in any month over the period 2014 – 2018, and 0 otherwise. The weights used in the regressions come from Propensity Score Matching (PSM) – single nearest-neighbour method with replacement- which it is implemented by running a logit regression of No *Bank Debt* on *size, age, ROA, liquidity ratio, equity ratio, working capital ratio, tangibility,* and *tax ratio*. In these regressions the firms with previous bank debt are weighted by the number of times they are matched to a zero-bank-debt firm. We restrict the sample to safe firms, defined as those firms whose probability of default (PD) is lower than the median PD of firms with bank debt during the estimation period. The PD is estimated with the methodology developed by Blanco et al. (2024). We also restrict the sample to firms that demand credit. We consider that a firm demands credit in two different cases: (i) when a firm applies for a new loan; (ii) when a firm with previous interest-bearing debt (i.e., drawn and undrawn bank credit and other debt obligations) has more than 25% of this debt maturing within the next 12 months. All specifications include the following firm controls constructed from the financial statements of 2019: *size* (log of total assets), *age* (in logs), *equity ratio* (ratio of share capital to total assets), *working capital ratio* (ratio of working capital to total assets), *liquidity ratio* (ratio of liquid assets to total assets), *ROA* (ratio of EBITDA to total assets), *tangibility* (ratio of tangible fixed assets to total assets), and *tax ratio* (ratio of corporate taxes to total assets). All specifications also include Industry-Location-Size Fixed Effects, where Industry is defined at the 3-digit level according to the NACE classification, Location at the NUTS-3 level (i.e., Spanish provinces), and Size comprises 4 categories according to the EU definition (micro, small, medium-sized, large). The estimation period is 2020. The semielasticity is the ratio of each coefficient to the unconditional probability in each subsample. Robust standard errors in brackets are clustered at the firm-level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Dependent variable	New Credit	New Credit without Guarantee	New Credit with any Guarantee	New Credit with Collateral or Personal Guarantee	New Credit with Public Guarantee
No Bank Debt	-0.067***	-0.023***	-0.072***	-0.029***	-0.034***
	[0.005]	[0.004]	[0.005]	[0.005]	[0.006]
Only firms that demand credit	YES	YES	YES	YES	YES
Industry-Location-Size-Year FE	YES	YES	YES	YES	YES
Lagged Firm Controls	YES	YES	YES	YES	YES
Observations	103,946	55,973	98,983	57,952	83,203
R-squared	0.179	0.178	0.190	0.200	0.211
Semielasticity of No Bank Debt	-0.127	-0.244	-0.144	-0.233	-0.070

Table 8: Effect of lending relationships on the probability of exit before and after the Covid-19 crisis

This table shows the coefficient of the variable *Alt2 No Bank Debt* and the coefficient of the interaction between *Alt2 No Bank Debt* and the variable *Post Covid* in OLS regressions in which the dependent variable (*Exit*) is a dummy variable that equals 1 if the firm exited the market and 0 otherwise. We use two samples, one before the Covid-19 crisis and another one during that crisis. In the first sample, *Exit* is a dummy variable that equals 1 if the firm exited the market or became inactive in the period 2018 – 2019, *Alt2 No Bank Debt* is a dummy variable that equals 1 if the firm had no (drawn or undrawn) bank debt in any month over the period 2013 –2017, and the vector *Controls* is constructed using balance sheets from 2017. In the second sample, *Exit* is a dummy variable that equals 1 if the firm exited the market or became inactive in the period 2020-2021, *Alt2 No Bank Debt* is a dummy variable that equals 1 if the firm had no (drawn or undrawn) bank debt in any month over the period 2015-2019, and the vector *Controls* is constructed using balance sheets from 2019. Finally, *Post Covid* is a dummy variable that equals 1 for the period 2020-2021 and 0 otherwise. Column (1) includes all firms. Column (2) corresponds to a subsample of firms whose probability of default (PD) is greater than the median PD of firms with bank debt during the estimation period (risky firms), while column (3) corresponds to a subsample of firms whose PD is lower than that median (safe firms). The PD is estimated with the methodology developed by Blanco et al. (2024). All specifications include the following lagged firm controls: *size* (log of total assets), *age* (in logs), *equity ratio* (ratio of share capital to total assets), *working capital ratio* (ratio of working capital to total assets), *liquidity ratio* (ratio of liquid assets to total assets), *ROA* (ratio of EBITDA to total assets), *tangibility* (ratio of tangible fixed assets to total assets), and *tax ratio* (ratio of corporate taxes to total assets). All specifications also include Industry-Location-Size-Time Fixed Effects, where Industry is defined at the 3-digit level according to the NACE classification, Location at the NUTS-3 level (i.e., Spanish provinces), and Size comprises 4 categories according to the EU definition (micro, small, medium-sized, large). The estimation period is 2020-2021. The semielasticity is the ratio of each coefficient to the unconditional probability in each subsample. Robust standard errors in brackets are clustered at the firm-level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
Sample	All firms	Risky	Safe
Dependent variable		Exit	
Alt2 No Bank Debt	0.001*	-0.002**	-0.002***
	[0.000]	[0.001]	[0.000]
Post Covid x Alt2 No Bank Debt	0.010***	0.020***	0.009***
	[0.001]	[0.001]	[0.001]
Industry-Location-Size-Year FE	YES	YES	YES
Lagged Firm Controls	YES	YES	YES
Observations	1,271,497	493,569	770,161
R-squared	0.049	0.074	0.049
Semielasticity of Alt2 No Bank Debt	0.030	-0.052	-0.101
Semielasticity of Post Covid x Alt2 No Bank Debt	0.442	0.623	0.546

Table 9. Effect of new credit on the probability of exit by zero-bank-debt firms during the Covid-19 crisis

This table shows the coefficient of the variable *New Credit* in OLS cross-sectional regressions in which the dependent variable (*Exit 2020-2021*) is a dummy variable that equals 1 if the firm exited the market in 2020 or 2021 and 0 otherwise. *New Credit* is a dummy variable that equals 1 if the firm obtains new bank credit between March 2020 and December 2020 and 0 otherwise. We restrict the sample to firms with no (drawn or undrawn) bank debt in any month over the period 2015-2019 that applied for loans to control for firms' demand for credit. Column (1) includes all firms. Column (2) corresponds to a subsample of firms whose probability of default (PD) is greater than the median PD of firms with bank debt during the estimation period (risky firms), while column (3) corresponds to a subsample of firms whose PD is lower than that median (safe firms). The PD is estimated with the methodology developed by Blanco et al. (2024). All specifications include the following firm controls constructed from the financial statements of 2019: *size* (log of total assets), *age* (in logs), *equity ratio* (ratio of share capital to total assets), *working capital ratio* (ratio of working capital to total assets), *liquidity ratio* (ratio of liquid assets to total assets), *ROA* (ratio of EBITDA to total assets), *tangibility* (ratio of tangible fixed assets to total assets), and *tax ratio* (ratio of corporate taxes to total assets). All specifications also include Industry-Location-Size Fixed Effects, where Industry is defined at the 3-digit level according to the NACE classification, Location at the NUTS-3 level (i.e., Spanish provinces), and Size comprises 4 categories according to the EU definition (micro, small, medium-sized, large). The semielasticity is the ratio of each coefficient to the unconditional probability in each subsample. Robust standard errors in brackets are clustered at the firm-level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
Sample	All firms	Risky Firms	Safe Firms
Dependent variable		Exit 2020-2021	
New Credit	-0.005***	-0.005***	-0.004***
	[0.001]	[0.002]	[0.001]
Only firms that demand credit	YES	YES	YES
Industry-Location-Size-Year FE	YES	YES	YES
Lagged Firm Controls	YES	YES	YES
Observations	44,589	9,625	33,489
R-squared	0.069	0.158	0.087
Semielasticity of New Credit	-1.039	-0.789	-1.143

Appendix: definition of variables

Variables	Units	Definition
New Credit	0/1	Dummy variable that equals 1 if the firm has obtained new bank credit (either term loans or credit lines) during the sample period, and 0 otherwise.
No Bank Debt	0/1	Dummy variable that equals 1 if the firm had no (drawn or undrawn) bank debt in any month over the period 2014 – 2018, and 0 otherwise.
Alt1 No Bank Debt	0/1	Dummy variable that equals 1 if the firm had no (drawn or undrawn) bank debt in any month over the period 2015 – 2019, and 0 otherwise.
Alt2 No Bank Debt	0/1	We use two samples, one before the Covid-19 crisis and another one during that crisis, to define this variable. In the first sample, *Alt2 No Bank Debt* is a dummy variable that equals 1 if the firm had no (drawn or undrawn) bank debt in any month over the period 2014 – 2018, and 0 otherwise. In the second sample, *Alt2 No Bank Debt* equals 1 if the firm had no (drawn or undrawn) bank debt in any month over the period 2015 – 2019, and 0 otherwise.
PD	%	Probability of default, estimated with the methodology developed by Blanco et al. (2024). A firm is considered to be in default when it has NPLs during at least three months of a given year.
Exit	0/1	Dummy variable that equals 1 if the firm exits the market or is inactive, and 0 otherwise.
Size	Thousands €	Firm's total assets, in logs.
Age	Years	Firm age, in logs.
ROA	%	Ratio of Earnings Before Interest, Taxes, Depreciation and Amortization (EBITDA) to total assets.
Liquidity ratio	%	Ratio of liquid assets to total assets, where liquid assets are cash and cash equivalents.
Equity ratio	%	Ratio of share capital to total assets.
Working capital ratio	%	Ratio of working capital to total assets.
Tangibility	%	Ratio of tangible fixed assets to total assets.
Tax ratio	%	Ratio of corporate taxes to total assets.

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