The poor, the rich, and the credit channel of monetary policy *

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Abstract

We examine the nexus between monetary policy, credit supply decisions, and the private wealth of entrepreneurs, using unique data on loan applications of small firms. We find that monetary policy affects loan application outcomes significantly more if entrepreneurs have less private wealth. We further show that loan application outcomes significantly affect entrepreneurs' capacity to generate more income and wealth in the medium term. This implies that the credit channel of monetary policy can have redistributive effects. Additionally, survey data from 19 euro area countries on loan applications by small and medium-sized firms supports these findings, and shows that the effects transmit especially via weakly capitalized and less liquid banks.

Keywords: Monetary policy, bank credit, business loans, entrepreneurs' private wealth

JEL Codes: E51, E52, D63

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1 Introduction

Are the poor affected differently by monetary policy compared to the wealthy, and what role does credit play in this configuration? Recent studies show that monetary policy can affect economic inequality through heterogeneity in households' exposure to three channels: salary income (households' labor market participation), business profits (households' entrepreneurial activities), and the revaluation of assets and liabilities (households' investment portfolio, mortgage rates, etc.). The key premise is that household heterogeneity and nominal rigidities create differential responses to monetary policy innovations, so that the marginal propensity to consume, save, and invest affects households' income and wealth. Despite the burgeoning literature on the interplay between monetary policy and private wealth, we know very little about the role of the credit channel of monetary policy in the (re)distribution of private wealth among entrepreneurs.

In this paper, we hypothesize and empirically establish that monetary policy has a significantly larger effect on the supply of credit to poor business owners than to wealthy business owners. Focusing on business owners (entrepreneurs) is important because small and medium sized enterprises (SMEs) rely heavily on banks for external financing and recent evidence suggests that most earnings disparities arise from differences between firms as opposed to differences within firms (Song et al., 2019). This implies that the credit channel of monetary policy can have redistributive effects if it differentially affects poorer and richer business owners.

Theoretically, consider two types of business owners with different levels of private wealth but with comparable businesses (in terms of balance sheet strength, investment opportunities, etc.). If banks consider private wealth as pledgeable collateral, it might be optimal for them to ration credit to firms with poorer owners due to moral hazard problems in the presence of information asymmetry (Holmstrom and Tirole, 1997). Private wealth can be legally seen as collateral for firms with unlimited liability but, even for limited liability firms, banks might see private wealth as pledgeable collateral, especially for SMEs that form strong relationships with their bank. Therefore, we generally expect banks to be less likely to grant loans to firms with poorer owners, all else being equal. However, during periods of expansionary monetary policy, characterized by low interest rates and ample liquidity, banks are more inclined to search for yield and increase risk-taking, such as by relaxing (implicit) collateral requirements. Therefore, during these periods, banks are relatively more likely to grant loans to firms with poorer owners. This is consistent with the risk-taking channel of monetary policy (Ioannidou et al., 2014; Jiménez et al., 2014), but it also highlights that the potency of the risk-taking channel varies asymmetrically between poorer and richer entrepreneurs seeking credit.

We test our hypothesis using two confidential data sets, both including unique information on SMEs. The first data set includes more than 130,000 loan applications of SMEs to a large systemic euro area bank between 2002 and 2018, together with information on the private wealth of the majority owner of these firms (other than the value of their business). In our panel, the firm's owner is always the top manager and the one who applies for credit to the bank. We also have detailed information about the loans (such as the amount granted, loan spread, maturity, securitization, etc.), as well as information about the firms themselves (such as balance sheets, income statements, employment levels, etc.). Importantly, we know the credit score that the firms were given at the time of their loan application, and thus know the creditworthiness of these firms as estimated by the bank (as in e.g., Berg (2018)). The credit score perfectly predicts the bank's origination decision and creates a known cutoff point, above which the loan is originated and below which the loan is rejected. Using several external sources of data, we show that our sample from this large euro area bank is fully representative of European averages across several dimensions (bank characteristics, firm characteristics, loan rejection rates, bank-firm relationships, etc.).

Observing the credit score constitutes an important element in our identification method. The fact that owners' private wealth mostly originates from their firm's profits (Smith et al., 2019), not only establishes a link between credit supply and wealth, but also poses an identification challenge. While successful businesses are more likely to generate wealth for their owners, successful businesses are also more likely to be considered creditworthy by banks. However, the granularity of our data and the information on the credit score – encompassing both hard and soft information known to the bank – enable us to disentangle the effect of owners' private wealth on monetary policy transmission from the effect of the firms' net worth and the quality of the investment projects on monetary policy transmission. Formally, in much of the empirical analysis, we control for the firm's credit score (thereby holding it constant), or limit the analysis to observations within a narrow bandwidth around the credit score cutoff point (for loan origination versus rejection). Within this bandwidth, almost all observed applicant and firm characteristics are statistically equal. Furthermore, having information on actual loan applications (rather than balance sheet information on the stock of loans) allows us to disentangle credit supply from credit demand. This limits omitted-variable bias in our estimates.

Our empirical results from the analysis around the credit score cutoff point indicate that expansionary monetary policy – measured either by the shadow rate or by exogenous monetary policy shocks (index by Altavilla et al., 2019, to account for potentially endogenous monetary policy) – is associated with higher loan approval rates. A one standard deviation increase in the shadow rate (equal to 3.3 percentage points) is associated with an decrease in the loan approval rate by 2.3 percentage points. Importantly, this effect varies significantly based on the private wealth of business owners. For business owners at the 25th percentile of the wealth distribution (poorer owners), a one standard deviation increase in the shadow rate is associated with a 4.3 percentage points lower probability of the bank granting a loan. Compared to the unconditional approval probability of 84.5%, this is an economically meaningful effect of monetary policy. In contrast, for business owners at the 75th percentile of the wealth distribution (richer owners), the marginal effect of the shadow rate on loan approval is essentially zero. These results survive in a large battery of robustness tests, including the use of a Heckman model to alleviate possible concerns on selection bias.

Given these findings, we next examine the future income and wealth of the loan applicants. For identification, we use a sharp regression discontinuity design (RDD), which compares the effect of the bank's loan decision (approved versus rejected applicants) based on the known cutoff point on the credit score. We find strong evidence that loan origination (as opposed to loan rejection) increases the business owners' income and wealth three years onward by 7.2% and 5.3%, respectively.

We also find that the role of owners' private wealth in the transmission of monetary policy is slightly stronger for firms with unlimited liability than for limited liability firms. Moreover, owners' private wealth significantly reduces the probability of the firm's future loan default (holding the firm's credit score constant), and again slightly more so for owners of unlimited liability firms than for owners of limited liability firms. Thus, our evidence suggests that banks seeing private wealth as collateral is an important channel of our baseline results.

We confirm the external validity of the results from the first data set, using a confidential survey of nearly 10,000 family-owned firms from 19 euro area countries from 2009 to 2020. This survey links loan applications with information on the characteristics of the firms' main bank, as well as with their balance sheet and income statements. Although empirical identification in this setup is less sharp than in the first panel (we do not observe firms' credit scores at the time of their loan application and we infer business owners' private wealth from past dividends), analyzing the external validity of our baseline results across the euro area has obvious merit. Moreover, by observing several different banks, we can analyze the role of supply-side bank characteristics (e.g., liquidity and capital) in the transmission of the effect of monetary policy to wealth inequality via the credit channel.

Our findings from the survey data are consistent with our baseline, showing a larger effect of monetary policy on loan approval for those in the lower part of the wealth distribution. Moreover, we show that the effect of private wealth on the transmission of monetary policy is significantly stronger for banks with lower liquidity and capital ratios. In contrast, we find no evidence that firm-level characteristics affect the role of private wealth in the credit channel of monetary policy. The important role of bank characteristics, as opposed to firm characteristics, is fully consistent with the supply-side theoretical arguments and empirical findings using data from the single bank (as opposed to a demand-side explanation).[1]

Our study's key contribution is to analyze wealth effects within the literature on the credit channel of monetary policy (Bernanke and Blinder, 1992; Ciccarelli et al., 2015; De Graeve

[1]Our empirical settings allow us to abstract from the possibility that the quality of the banking and credit market could be especially poor in more unequal areas. Rajan and Ramcharan (2011), for example, provide evidence that in the 1930s the wealthy may have contributed to keeping banking markets underdeveloped in the U.S counties so as to maintain their grip on power.

et al., 2007; Heider et al., 2019; Hülsewig et al., 2006; Ioannidou et al., 2014; Jiménez et al., 2014; Kashyap and Stein, 2000; Kishan and Opiela, 2000; Maddaloni and Peydró, 2011). Our finding that monetary policy has stronger effects on loan approval likelihoods of business owners with lower private wealth implies that the credit channel of monetary policy has distributional effects. The direction of our findings suggests that, through relative changes in business owners' loan approval likelihood and future income and wealth, contractionary (expansionary) monetary policy mainly reduces (increases) the future wealth of business owners at the lower end of the wealth distribution.

Our paper is also related to the emerging literature on the effect of monetary policy on economic inequality (Amberg et al., 2021; Andersen et al., 2021; Auclert, 2019; Coibion et al., 2017; Holm et al., 2021; Kaplan et al., 2018; Mumtaz and Theophilopoulou, 2017). This literature highlights several economic channels via which monetary policy innovations can affect the income and wealth distribution of households. McKay and Wolf (2023) suggest that the end effect of monetary policy on inequality can be neutral. Evidently, none of these studies examine the role of the credit channel in the nexus between monetary policy and the distribution of wealth/income.

Another related and voluminous strand of literature examines the role of loan approval on firm outcomes. For example, Berg (2018) shows that loan rejections have important real effects on small firms due to precautionary savings motives, leading to significant losses in employment and investment. Delis et al. (2023) show that the bank's decision to accept or reject business loans has important effects on the future income and wealth of entrepreneurs. Banerjee and Duflo (2014)use directed credit in India and show that in previously credit-constrained firms, the marginal rate of return to capital was very high. Several other studies show how the existence or the relaxation of credit constraints might have redistributive effects for the affected firms and the real economy (e.g., Levine (2021); references therein).

The remainder of our paper is structured as follows. In section 2, we discuss the data and methodology used to empirically test our hypothesis. In sections 3 and 4, we discuss the results from the first and second data set, respectively. We conclude in section 5.

2 Data

To examine the relation between the credit channel of monetary policy and the wealth of business owners, we use two data sets. First, we use detailed confidential information from a large systemic euro area bank on loan applications from small firms. Second, we use less detailed but more general survey-based information on loan applications by firms to several banks in 19 euro area countries.

2.1 Small firms obtaining credit from a large European bank

Using data from a single bank is common practice when detailed data are required, especially for empirical identification purposes (Berg, 2018; Delis et al., 2023; Iyer and Puri, 2012, e.g.). Our data set contains such information on small European firms with a majority owner, who applied for a loan to our systemic euro area bank. The firm's owner is also the top manager (decision-maker) of the firm and the one who files the credit application. We have a balanced firm-year panel of 265,676 firm-year observations, corresponding to 15,628 firms from 2002 to 2018. The firms are based in nine European countries, with approximately half of them based in the country where the bank is headquartered. The number of loan applications is 137,321.

Our sample includes detailed information on the loan application and its prospect, the majority owner, and the firm. We know when the loan application was filed and all loan characteristics. We know the *Owner gender*, along with *Owner education*, *Owner age*, *Owner marital status*, number of *Owner dependents*, the owner's private *Wealth* and annual *Income*. Importantly, we have information on the firm's *Credit score*, which is the assessment by the bank on the firm's financial soundness and the loan's prospects, encompassing both hard information (on paper from financial statements) and soft information (e.g., the bank's understanding of the loan applicant talents, the bank-firm relationship, etc.). We also have access to the firms' financial statements. Table 1 provides detailed information on our data and defines the variables used in our empirical analysis. Tables 2 and 3 report summary statistics.

[Insert Tables 1 to 3 about here]

We focus on majority owners of small firms because these owners are almost uniquely tied to their firms, allowing us to study the impact of their private wealth on loan application outcomes during periods of changes in monetary policy. We find that this choice does not introduce sample selection into the main variables of our analysis. Using data from Orbis on small firms (same average size with our panel) from selected euro area countries (Austria, Belgium, Denmark, France, Germany, and the Netherlands), we find that the average leverage and profitability ratios are very similar to the ones in our panel. Specifically, on average, the firms in our sample have an only 0.4% lower leverage ratio and a 0.16% higher ROA. Other firm ratios (reflecting operating expenses, capital expenses, etc.) are also at very similar levels with the firms in our panel.

Moreover, our bank, which operates on a global scale and provides credit to all business types, is representative in terms of key characteristics when compared to other banks. Data from Compustat on 32 other European systemic banks suggests that the annual averages of important bank characteristics like the ratio of liquid assets to total assets, the market to book value, and return on assets are at very similar levels and significantly correlated with the respective ratios of our bank over the years in our sample (correlation coefficients equal to 0.52, 0.67, and 0.75, respectively). Also, data from the Survey on Access to Finance of Enterprises (SAFE) shows that the average annual euro area loan rejection rate is very strongly correlated with the equivalent from our bank (the correlation coefficient is 0.86). The acceptance rate of 84.2% in our sample is slightly higher than the equivalent reported in SAFE. However, although SAFE additionally includes a sample of relatively safer medium-sized firms, it also includes firms from South European countries, where banks were hit harder by the global financial and sovereign debt crises. In a nutshell, the business model of our bank is very similar to the European average, which is also documented in Delis et al. (2023).[2] Using formal econometric techniques (a Heckman model), we further safeguard our analysis against selection bias.

A key variable in our analysis is our measure of the owners' private wealth. *Wealth* includes

[2]Our sample is also fully representative across firm characteristics, such as firm size, profitability, and leverage (based on European data from SAFE), as well as the level of the exclusive relationship between small firms and banks Degryse et al. (2019). We further discuss this issue in the next section, comparing this first data set with the SAFE data that are fully representative of European averages.

the applicants' self-reported wealth which could be seen by the bank as collateral (for firms incorporated under unlimited liability) or seen as source for capital injections in case of distress (presuming the bank can persuade the owners' of firms incorporated under limited liability). It includes all movable assets, e.g. financial assets in bank accounts, stocks, bonds, etc., minus any debt the owner might have. We believe this measure of wealth is relevant for at least two reasons. First, these assets are liquid and they can be quickly injected into the company when needed. Second, for limited liability firms, it is more likely that the bank will be able to persuade an owner to sell some of his/her movable assets and inject them into the company than to sell less liquid assets such as houses and cars.

Besides the tight link between an entrepreneur's wealth and her/his firm, another advantage of focusing on small firms is that most applicants have an exclusive relationship with our bank (Degryse et al., 2019). This not only makes asymmetric information between the two parties as regards our wealth measure (and associated measurement error) unlikely, but also makes the moral persuasion from the side of the bank towards the owner to use his/her private savings in times corporate stress more likely. Importantly, the bank continues to observe applicants' wealth after the loan origination by exerting monitoring effort or because the applicant applies for another loan in a future period.

2.2 Euro area SMEs obtaining credit from different banks

The starting point of our second data set is the SAFE database. This database is the result of a biannual questionnaire organized by the European Central Bank (ECB), which is run since 2009 and covers a six-month reference period for every survey round.[3]

The questionnaire includes qualitative questions about the funding and activities of European firms. The selection of participating firms is done so that the database contains information from a representative sample of European firms. Many firms participate only once or a limited number of times in the survey. The reason for this is simply that the company responsible for running the survey randomly contacts firms from a representative sample. Although the survey covers all European countries, we only consider countries that are part of the euro area

[3]See https://www.ecb.europa.eu/stats/ecb_surveys/safe/html/index.en.html

so that monetary policy is common. Moreover, we consider only private, profit-oriented firms that make independent financial decisions. Hence, subsidiaries and branches of other enterprises are excluded from our sample. Last, we focus on family-owned firms in this data set. This closely resembles the type of enterprises that we observe in our first data set.

Next, we extend the SAFE database with the respondents' financial data, using information from Orbis, provided by Bureau van Dijk.[4] We have financial information up to 10 years before the reference period of the corresponding survey wave. With these data, we measure firm-specific financial characteristics and approximate the private wealth of the business owner.

To measure this private wealth, our starting point is the firm's past dividend payments. Given that most companies in our data set are SMEs, the shareholders, managers, and the loan applicant will likely be part of the same family and often even be the same person. Hence, as the distributed dividends are directly part of the shareholder's private wealth, the owner's private wealth can be measured quite accurately by the evolution of past dividend payments. Indeed, Smith et al. (2019) show that business income is the most important source of income for the top-income households in the U.S., and argue that for tax reasons this is likely to be paid out in dividends rather than wages. Therefore, we approximate business owners' wealth by the accumulation of dividends in the past 10 years. As we have both small and medium-sized firms in this second data set, and the business owners' private wealth and size of the requested loan will be correlated with the size of the firm, we consider the accumulation of dividends relative to the firm's total assets. The accumulated dividends are on average 1.25 million euros, but with large differences between firms (roughly half of the firms are not distributing dividends). More relevant is the relative wealth proxy. For the average business owner, these accumulated dividends equaled 11.5% of last year's total assets. Again, this percentage is similar to that in the first data set.

Next, by exploiting the fact that firms report the names of their main bank, we augment the data set with bank information obtained from BankFocus.[5] This allows using bank-specific characteristics in our empirical analysis, such as the banks' liquidity ratio or CET1 ratio.

[4] See `https://www.bvdinfo.com/en-gb/our-products/data/international/orbis`

[5] See https://www.bvdinfo.com/en-us/our-products/data/international/bankfocus

Overall, we enrich the first part of our analysis, which relates to the behaviour of a single bank, and thus the representativeness of our findings (albeit without the more detailed information on applicant characteristics/the bank's credit score). We provide a detailed explanation of our variables of interest from this second data set in Table 1 and summary statistics in Tables 2 and 3.

In the SAFE questionnaire, firms are asked whether they applied for a bank loan during the reference period of the survey round and, if so, if their application was successful. We use those replies to construct various measures for the loan application success. *Granted* is again a dummy variable with value 1 if the loan application was granted (fully or at least 75% of the requested loan amounted) and 0 if the loan was not granted, or if the firm refused the offer because the costs were too high. Very similar to our first data set, on average 82% of firms that applied for a bank loan were successful. For details, Appendix A reports all the questions we used to assess loan application success.

We control for several financial characteristics of the firms and banks that are important for the outcome of loan applications (see Table 1 for exact definitions). We include firms' profitability (*Firm ROE*), firms' current leverage (*Firm equity ratio*) and firms' ability to pay back loans (*Firm cash flow ratio*). We also consider firm size, by including the natural logarithm of total assets (*Firm size*). On the firms' main bank side, we consider the liquidity (*Bank liquidity ratio*) and capitalization (*Bank capital ratio*) of the bank. As shown in the last two rows of Table 2, the average firm's main bank has a liquidity ratio of 26% and a capital ratio of 6%. As a caveat, we cannot know for sure that the firms' main bank is the one where the firm applied for the loan that they report in the survey. However, as Degryse et al. (2019) show, most firms (more than 85%) borrow from only one bank, so it is quite likely that the main bank is the bank where the firm applied for the loan, and especially so for SMEs.

2.3 Monetary policy

Our main measure of monetary policy is the *Shadow rate* [6] as defined by Wu and Xia (2016). Alternatively, we use the euro area monetary policy shocks by Altavilla et al. (2019). The two

[6] Available via: https://sites.google.com/view/jingcynthiawu/shadow-rates

measures are not strictly comparable and we view them as complements rather than substitutes. The advantage of the shadow rate is its simplicity and comparability with the central bank interest rate. The reflection of exogenous shocks is the main advantage of the measure of Altavilla et al. (2019). In particular, we use what Jarociński and Karadi (2020) call the poor man's sign restrictions series. This takes the value of the changes in the 3-month EONIA swaps if the stock price surprises had the opposite sign to the high-frequency EONIA swaps changes, and zero otherwise. For instance, a contractionary monetary policy announcement moving both equity prices and interest rates in the same direction, would mean markets recognize that the central bank expects the economy to overheat and is hence not recognized as a shock. By contrast, a true surprise tightening would tend to raise interest rates and reduce equity prices.

The average shadow rate is 0.17%, with a minimum value of -6.40% and a maximum of 4.28% in the large bank data set. In the SAFE data set, the average shadow rate is lower than in the large North European bank data set. This is explained by differences in the time span that affect mostly the positive values of the shadow rate and correspond to the period 2002-2009 which is before the start of the SAFE data set. Indeed in the SAFE data set the maximum value of the shadow rate reaches only 0.98%. Concerning the monetary policy shocks, the average value is around 1% in the period 2002-2018, and the series reaches a minimum of -16.75% in June 2006 and a maximum of 15.75% in January 2009.

3 Results from the sample of the single bank

3.1 Monetary policy and probability of loan origination

The starting point of our empirical analysis is the estimation of the following empirical model:

$$\begin{aligned} Granted_{iftcb} = {} & \beta_0 + \beta_1\ Wealth_{it} + \beta_2\ Monetary\ Policy_t + \beta_3\ Monetary\ Policy_t \times Wealth_{it} + \\ & \beta_4\ X_{ift-1}(+\gamma_c + \rho_t + \delta_f) + \epsilon_{iftcb} \end{aligned} \tag{1}$$

Equation 1 is common for the respective analysis of both data sets, except for the dimensions of the samples. $Granted_{iftcb}$ is a binary variable, taking the value 1 if a loan of firm f with owner i is granted in time period t, and 0 if the loan application is rejected. The main difference between the analysis of the two data sets, is that the frequency t in the single bank is quarterly and in SAFE data biannual, while in the latter there are also country c and bank b dimensions. Granted is regressed on our measures of $Wealth$ and $Monetary\ Policy$, which are interacted to examine the heterogeneous effect of monetary policy due to owners' private wealth. We also add a set X_{ift-1} of control variables, reflecting owner (i) or firm (f) characteristics. For the SAFE data set, the control variables X_{ift-1} are all at firm-level. The model is estimated with different combinations of fixed effects at country level γ_c , firm-level δ_f, and time-level ρ_t, which help with empirical identification. ϵ_{iftcb} is the error term.[7]

We expect β_1 to be positive, consistent with previous studies noting the importance of wealth for loan applications (e.g., Frid et al. (2016)) and with the visual inspection of the data. We expect β_2 to be negative: a monetary policy tightening will pass-through to higher deposit rates and higher funding costs for banks, which imply a reduction in the probability of loan applications being approved. Our main coefficient is β_3: a negative coefficient means that loan applications from businesses with wealthier owners are affected more by changes in monetary policy, while a positive coefficient means that loan applications from businesses with wealthier owners are affected less by changes in monetary policy.

The availability of information on loan applications (as opposed to only approved loans) as well as information on the credit score is the basis of our identification method in the estimation of equation 1. First, observing loan applications is important to distinguish between loan supply and loan demand and is instrumental in identifying who gets credit following a monetary policy innovation. In addition, the credit score is de facto a loan supply characteristic, especially as borrowers cannot manipulate it (we provide evidence on this below). Moreover, the credit score limits any potential omitted-variable bias in our estimates for at least two reasons. First, the bank has a long-term repeated interaction with these borrowers, thus any asymmetric information between the borrowers and the lenders must be very low (statistically insignificant). Second, the credit score provides a cutoff point, known to the bank but not the borrower, above which the loan is always originated and below which the loan is always rejected. We extensively use

[7] We can also augment equation (1) to include asymmetric effects between periods of monetary expansion and monetary contraction or between periods of particularly low interest rates (e.g., the zero-lower bound) and periods of positive interest rates. Exploratory analyses show that there are no significant asymmetries in our results.

this cutoff in all stages of our empirical analysis.

Essentially, all the observed applicant characteristics are part of the credit score and the difference in characteristics between accepted and rejected applicants should be approximately zero within a narrow bandwidth around the cutoff point. We indeed find that comparing accepted and rejected applicants within the window -0.3 to 0.3 (around the 0 cutoff point), all the differences in the observed applicant and firm characteristics between the two groups are statistically insignificant. Most notably, *Wealth* at the time of the loan application has a mean value of 11.48 for the rejected applicants in the [-0.3,0] window and a mean value of 11.50 for the accepted applicants in the [0,0.3] window (which is a small, statistically insignificant difference).

Apparently, what determines the loan origination decision in that window is mostly soft information that is obtained or determined by the bank, and is fully encompassed in the credit score (given that the credit score fully determines loan origination or not). Phrased differently, any soft information that shapes the bank's loan origination decision (given that hard information including private wealth is approximately equal between the rejected and accepted groups) should not be correlated with applicants' private wealth around the cutoff point, but rather should correlate with the project's net present value as perceived by the bank. Thus, an empirical analysis of observations around the known cutoff (or even simply controlling for the credit score) allows us to disentangle the effect of owners' private wealth on monetary policy transmission from other confounding effects (for similar intuition and empirical modeling, see e.g., Dagher and Kazimov (2015); Loutskina and Strahan (2009)).

We report our baseline results from our first data set in Table 4. As a reference point, we begin with a specification including all available observations and the control variables in Table 1 (*Owner education, Owner age, Owner dependents, Firm size, Firm ROA, Firm cash holdings, Number of applications, Credit score*). In specification 2, we use only the observations from firms with a credit score in the narrow [-0.3, 0.3] bandwidth. In that specification, the control variables are statistically insignificant, consistent with our expectations and discussion above (the t-tests of the equality of means for almost all of these variables are also statistically insignificant). This finding, along with the consistency of the results across the first two columns regarding the main variables of interest (i.e., *Wealth*, the *Shadow rate*, and their interaction term), implies that our inferences on these variables hold the quality and repayment prospects of the firms constant (i.e., our results are unlikely to be affected by unobserved factors that also determine the loan origination decision). In fact, given the similarity of the estimates, simply controlling for the credit score in the first specification can be sufficient to identify the model; however, we mostly base our inferences on the most restrictive specification in column 2.

[Insert Table 4 about here]

In line with our expectations, it can be seen in the first two columns that β_1 is positive, implying that owners with more private wealth are more likely to have their loan application approved. Also in line with expectations, it can be seen that β_2 is negative, implying that tighter monetary policy correlates with a lower probability of loan approval. Finally, it can be seen that our main coefficient β_3 is positive, meaning that the effect of monetary policy on the probability of loan origination is mitigated by higher private wealth.

To examine the economic relevance of the effect, we consider individuals at the 25th and 75th percentiles on the wealth distribution. This corresponds to a reported private wealth, excluding the value of the firm, of EUR 120,000 and EUR 270,000, respectively. Expressed in natural logarithm of wealth this equals 11.68 and 12.50, respectively. For a loan applicant on the 75th percentile of the wealth distribution, the marginal effect of the *Shadow rate* on *Granted* approximately equals 0 (= -0.212 + 0.017×12.50). For a loan applicant on the 25th percentile of the wealth distribution, the marginal effect of the *Shadow rate* on *Granted* equals -0.013 (= -0.212 + 0.017×11.68); that is for every percentage point increase in the shadow rate, there is 1.3 percentage points lower probability of the bank granting the loan, all else equal. For a one standard deviation increase in the shadow rate (equal to 3.3) this implies a 4.3 percentage points lower loan approval probability. The difference between the effect in the two groups is statistically significant at the 1% level. Moreover, this difference is considerably larger if we would compare loan applicants on the 75th percentile of the wealth distribution to loan applicants on the 10th or 5th percentile of the wealth distribution.

One potential reason for why banks transmit monetary policy less to firms with wealthier owners could be that banks earn more nonlending-related income from these owners (e.g., fees on private asset management) and are therefore more reluctant to pass-through monetary policy. Another potential reason could be that banks have a legal claim on the owner's wealth if the firm does not repay the loan, and therefore are more protected against default and hence less likely to pass-through monetary policy. In columns 3 and 4 of Table 4, we shed light on this issue by separately analyzing the effect of private wealth on the transmission of monetary policy to loan approval for firms with respectively limited and unlimited liability. While the private wealth of owners of firms with limited liability might be protected against default (at least partially), the private wealth of owners of firms with unlimited liability is not. As can be seen, an increase in the shadow rate reduces the likelihood of loan approval less if the owner has more private wealth for both types of firms, but the marginal effect is stronger for firms with unlimited liability. This suggests that the effect is at least partly driven by the bank's legal claim on the private wealth of owners who are fully liable for their firm. However, it could be that banks do not need the legal claim to the owners' private wealth in order to persuade owners to appeal to their private wealth for the loan repayment not to be compromised (and hence the effect continues to be significant even under limited liability). We revisit the role of limited liability when examining the probability of loan default.

In column 5, we include the interaction term *Shadow rate* $\times$ *Credit score* to examine whether the interaction term *Shadow rate* $\times$ *Wealth* erroneously captures the effect of some component of the credit score. This is a powerful test because the credit score controls for both hard and soft information guiding the loan origination decision and this is evident by the significant increase in the adjusted R-squared (we cannot include the main term of the credit score because it perfectly predicts *Granted*). Essentially, the modeling framework of specification 5 assumes that the impact of *Shadow rate* $\times$ *Wealth* is extracted from the larger umbrella effect of *Shadow rate* $\times$ *Credit score*. Consistent with expectations, the interaction term on *Shadow rate* $\times$ *Credit score* is positive and statistically significant, showing that the effect of the shadow rate on the probability of loan origination is weaker for applicants with a higher credit score. Despite the inclusion of this term, the interaction term *Shadow rate* $\times$ *Wealth* retains its statistical and economic significance, further reinforcing the argument that it is indeed soft information that mainly drives the bank's loan origination decision around the cut-off point and that soft information is not correlated with private wealth.

In column 6, we include year:quarter fixed effects, which cause the main term of the shadow rate to drop out. These fixed effects control for time-varying unobserved characteristics, including changes in the macroeconomic environment. In unreported specifications, we additionally include year:quarter × industry and year:quarter × region × industry fixed effects. The estimate on our main interaction term remains largely unaffected, while adding these fixed effects does not significantly increase the adjusted R-squared.

In specifications 7 and 8 of Table 4, we use Heckman models to account for any selection bias, aside from that discussed in section 2.1. In the first stage of specification 7, we estimate the probability that the owner applies for a loan in a specific year of our sample. Note that all these firms have applied for one or more loans during our sample period (we do not observe firms that never applied to the bank). Thus, in this specification we aim to account for self-selection into a loan application during a specific year (as opposed to no application during that year). The first stage of the model includes all available observations (both years in which a specific entrepreneur applies for a loan and years in which she/he does not apply) and the *Owner gender* as an additional control variable. Delis et al. (2022) show that an applicant's gender is a statistically significant determinant of a loan application, with male entrepreneurs displaying a higher application probability. In contrast, the same study finds no evidence for a significant effect of gender on the bank originating or rejecting the loan. Thus, the exclusion condition must be satisfied. Consistent with this evidence, the first-stage results show that male entrepreneurs have an approximately 1% higher probability to apply for credit. Economically, this estimate may not be considered to be very large, but the coefficient is actually statistically significant at the 1% level, satisfying the relevance condition. Importantly, our second-stage results show that the coefficient on *Shadow rate* × *Wealth* remains unaffected, while the insignificant value of Heckman's lambda shows that our data are consistent with no selection bias.

In specification 8, we estimate a second Heckman model, further expanding the observations in the first stage with information on the universe of similarly-sized firms in the nine countries where the bank issues loans. These firms are not included in the sample used so far and information on them comes from Orbis. This test aims at accounting for selection of specific firms in our sample by the specific bank, or self-selection to the bank by the specific firms. The first-stage covariates include *Firm size*, *Firm ROA*, *Firm leverage*, and *Firm cash holdings*, as well as the ratio of interest income to total income of our bank (if the firm applies to our bank) versus the mean of the same ratio of the other major banks in the country. The sample size is 675,327 observations.

The idea for the exclusion condition in this model comes from a similar analysis of Dass and Massa (2011) on the probability of firm-bank association in the syndicated loan market. In the first-stage probit, we select a very similar toolkit of instruments,[8] which are an interaction of the firm's age and a dummy that equals 1 if the firm's location is in the same country with the bank's headquarters; an interaction of the firm's size and the same dummy; concentration of the firm's local banking market (measured by the lagged Herfindahl Index and obtained from the world bank); and regulatory differences in capital requirements between the firm's country and the bank's country. We find that all these variables significantly explain the probability that a firm associates with our bank, whereas their correlation with loan outcomes in our original sample is statistically equal to zero. The results in specification 8 again show that Heckman's lambda is statistically insignificant, implying that our data are consistent with no selection bias, while the second-stage results are similar to those of column 2 of Table 4.

In the results of column 9, we further tighten the window around the cutoff point from -0.1 to 0.1, with the aim of using even more homogeneous groups of rejected versus accepted loan applicants / firms. The results are again similar to the baseline. We note that we conduct several robustness tests on the bandwidth around the cutoff, including restricting the number of observations of the two groups to be equal, using cross-validation methods to determine an "optimal" window, etc.

A last important robustness test in this section is to measure monetary policy with exogenous

[8]The two instruments we do not use compared to Dass and Massa are the number of segments in which a firm operates and the physical distance between the banks' branches and the firm. We do not find the first variable to be a significant correlate in our first-stage probit. For the second variable, we find that it has a significant and negative correlation with loan orogination, which implies that the exclusion condition might not be satisfied.

monetary policy shocks à la Altavilla et al. (2019), instead of the shadow rate (Wu and Xia, 2016). This test ensures that our results are not driven by any endogeneity of the shadow rate that is not accounted for by our previous models. Our results in Table 5 are very similar to our baseline. Moreover, untabulated regressions show that all our robustness tests hold when using monetary policy shocks.

[Insert Table 5 about here]

3.2 Transmission to loan amounts and loan spreads

In this section, we reestimate equation 1 using loan amounts and prices (loan spreads) as the outcome variables. In these specifications, we can fully control for the credit score (it obviously does not perfectly predict these outcome variables) and thus mitigate the omitted-variables bias. The results in the first two specifications of Table 6 show that tighter monetary policy is associated with smaller loans. We further show that wealth appears to have a rather modest effect on the loan amount. In line with our baseline results, we find that wealth mitigates the effect of monetary policy on loan amounts. Tighter monetary policy thus relates to lower loan amounts, especially for business owners with less private wealth.

The results on loan spreads in specifications 3 and 4 are also consistent with an important role for private wealth in the credit channel. Specifically, we find a negative marginal effect of wealth, which at the mean *Shadow rate* equals 6.5 basis points. This implies that corporate loans to poorer business owners have higher spreads. The negative interaction term suggests that this negative effect is stronger when monetary policy is tightening (conversely, the negative effect is weaker in periods when monetary policy is expansionary).

[Insert Table 6 about here]

3.3 Loan approval and future wealth and income

Berg (2018) shows that loan approval has important real effects. He finds that, when comparable firms apply for a loan, those that are not granted the loan invest significantly less and grow significantly slower. If this impacts the firms' capacity to generate profits, it will affect the owners' capacity to accumulate wealth. Given that we have just shown that the transmission of monetary policy through the credit channel is heterogeneous conditional on the private wealth of business owners, monetary policy might contribute to the business owners' future income & wealth through this channel.

In Table 7 we examine whether loan approval has a significant effect on income and wealth accumulation in the medium term, i.e., three years after approval / rejection. Specifically, we regress the owners' annual income as reported at the bank in year t+3 on our indicator *Granted* at time t, holding constant the owners' current wealth and the firms' credit score at time t. We also examine the same model using the owners' accumulated private wealth registered at the bank in year t+3 as dependent variable.

[Insert Table 7 about here]

To identify the effect of the loan decision on the loan applicant's future wealth and income, we follow Berg (2018), who uses an RDD model. In our setting, we have a sharp RDD generated by the credit score around the 0 cutoff, given that the loan is always originated for a credit score greater than 0 and is always rejected for a credit score lower than 0. The functional form of our RDD model is:

$$y_{it+n} = \alpha_0 + \alpha_1 \; Granted_{it} + \alpha_2 \; (x_{it} - \overline{x}) + \alpha_3 \; Granted_{it} \times (x_{it} - \overline{x}) + \alpha_4 \; x'_{it-1} + \nu_{it} \qquad (2)$$

In equation (2), y is the outcome variable (natural logarithm of private wealth or annual income) in year $t{+}n$ and $(x_{it} - \overline{x})$ is the distance of the credit score from its cutoff point $\overline{x}$ (note that this equivalent to the credit score itself given that the cutoff value is equal to 0). The control variables are as in equation (1).

We examine all the tests for the internal validity of the RDD as in Berg (2018) and Delis et al. (2023). We first conduct a manipulation test of Cattaneo et al. (2018), which easily rejects the hypothesis of loan applicants (i.e., business owners) being able to manipulate their credit scores (p-value equal to 0.381 and graphical representation in Figure 1). Such manipulation of their credit score by small firms applying to a large systemic bank is theoretically unlikely (otherwise the bank's business model would be questioned). On the same line, conducting the manipulation test for the subsample of applicants with very strong ties with the bank (e.g., more than 3 loans during our sample period) yields similar results. Second, we report in Figure 2 the sensitivity analysis of our estimates, following Cattaneo et al. (2016). This figure reports the results from a test statistic of the null hypothesis of no treatment effect in the horizontal axis against windows of different length around the cutoff in the vertical axis. The p-value of no treatment effect is easily rejected for all windows (this would be indicated in red color).

Third, we show the relevant figure of our estimates (Figure 3), which has one single clear and sharp cutoff, ruling against falsified cutoff points affecting our inferences. Fourth, the rest of the control variables do not significantly jump at the cutoff point (as also discussed under the estimation of equation 1). In fact, removing all the controls from our empirical analysis, yields almost the same estimates. Fifth, using a nonparametric RDD again yields very similar coefficient estimates.

[Insert Figures 1 to 4 about here]

In line with our expectations, we find that loan approval allows business owners to increase their future income and wealth. The RDD results show that for owners of comparable firms with similar levels of private wealth who apply for a loan, those that get their application approved have increased their annual income by on average 7.2% more (column 2 of Table 7) three years after the loan application compared to those that get their application rejected, allowing them to accumulate on average 5.3% more wealth over this period (column 1 of Table 7).

As monetary policy has a heterogeneous impact on the probability of getting a loan granted (conditional on owners' private wealth), monetary policy also heterogeneously affects owners' future wealth accumulation. Indeed, for owners at the 25th percentile of the wealth distribution, an increase in the shadow rate reduces their likelihood of loan approval and hence also their future wealth accumulation. In contrast, for owners at the 75th percentile of the wealth distribution, an increase in the shadow rate does not affect their likelihood of loan approval and hence also not their future wealth accumulation. We show this explicitly in Figure 4. As such, contractionary monetary policy is likely to widen the distribution of wealth among entrepreneurs in the medium term, while expansionary monetary policy is likely to have the opposite effect.

In columns 3 and 4, we pinpoint the effect via the heterogeneous credit channel of monetary policy, where we use the partial fitted values of *Granted* with respect to *Shadow rate* and *Shadow rate* $\times$ *Wealth* from specification 1 of Table 4, and obtain $\widehat{Granted}$. These specifications estimate how the precise relation between the interaction of monetary policy with wealth and the probability of loan origination (as identified in our baseline results) affects entrepreneurs' capabilities to generate more income and wealth in the medium term.

Re-estimating equation 2 with this new measure of $\widehat{Granted}$, we find that the part of loan approval stemming from changes in monetary policy increases the future wealth of approved loan applicants by 3.8% compared to those that get their application rejected. The equivalent effect on future income equals (4.1%). Thus, we find a potent credit channel of monetary policy that differentially affects entrepreneurs' income and wealth in the medium term (based on the bank's loan origination decision and via initial levels of wealth).

3.4 Wealth and loan default

As discussed in section 3.1, one potential reason why private wealth might matter for banks' decision to grant a loan could be that banks see the owners' private wealth as collateral for loan repayment when the firm's cash flows would be insufficient. This could either be because the bank is legally entitled to the owner's assets in case the owner defaults on his repayment obligation (e.g., when the owner is fully liable for the firm) or because the bank believes that it could persuade the owner into injecting his/her private wealth into the firm (e.g., through a subordinated loan or additional equity) to fulfil the firm's repayment obligations. If so, we would expect the owner's private wealth to be negatively related to loan default.

For firms with granted loan applications, we look at the probability that they will have defaulted on their loan, one year or three years after loan origination (results in Table 8). More specifically, we construct an indicator that equals 1 if the firm defaulted on the loan within one year after origination, and 0 otherwise; and do the same for an indicator three years after loan origination.

We then regress these default indicators on the owner's private wealth at the time of loan origination and the firm's credit score at the time of origination.

[Insert Table 8 about here]

According to the results in columns 1 and 2, firms with a higher credit score are significantly less likely to default on their loan within one year of origination (column 1) and within three years of origination (column 2). Economically, a one standard deviation higher credit score (equal to 0.44 in this sample) is associated with a 2.1 percentage points lower probability of defaulting. As the unconditional probability to default within the year is only 2 percentage points, the credit score is an economically significant predictor. The same holds for private wealth: a one standard deviation higher wealth (0.45 in this sample) is associated with a 1.3 percentage points lower probability of defaulting. Importantly, owners' private wealth seems to matter significantly for the firms' probability to repay a loan, even after fully controlling for the firms' credit score, and hence also the firms' quality and repayment prospects.

In columns 3 and 4 of Table 8, we examine whether this effect is driven entirely by firms with unlimited liability or not. While the effect of owners' private wealth seems to be a bit stronger for unlimited liability firms, the effect does not disappear for limited liability firms. Owners that have more private wealth are less likely to default on their loan, irrespective of whether they are liable with their private wealth for their firm or not. This suggests that owners will appeal to their private wealth to fulfill their repayment obligations (possibly after being persuaded by the bank to do so).

4 Results from the sample of multiple banks

In this section, we report the results from the SAFE data set, with a twofold aim. First, we analyze whether our baseline result holds in a different, international sample of firms and banks (but admittedly using a weaker identification method and measure of wealth). Second, we assess how this result might be affected by bank characteristics to provide further evidence in line with the traditional transmission mechanisms of monetary policy.

4.1 Baseline results

Table 9 reports different specifications from the estimation of equation 1, which vary depending on the set of control variables and fixed effects. In all specifications, we double cluster the standard errors at the survey wave and firm levels. The first specification considers as explanatory variables only *Wealth*, the *Shadow rate*, and their interaction term, without including any fixed effects or control variables. As expected, wealth is positively correlated with loan approval, while the shadow rate is negatively correlated. The estimated coefficient on the interaction term is positive and significant, indicating that the negative effect of monetary policy on loan approval weakens as owner's wealth increases. These findings are fully consistent with our analysis in Section 3.

These results also hold when we add control variables (*Firm ROE, Firm equity ratio, Firm cash flow ratio, and Firm size*) in column 2. As expected, larger and more profitable firms, and those with a stronger capital structure and higher cash flows, are positively correlated with approval rates. In columns 3 and 4, we add country fixed effects and survey wave fixed effects respectively, while in column 5 we include both to control for unobserved country-specific and time-specific effects. Note that the direct effect of the *Shadow rate* is absorbed by the survey wave fixed effects. Moreover, in columns 7 and 8, we add firm fixed effects. Although the panel component of the database is not as strong (the number of firms decreases from 9,158 in column 2 to 3,087), the coefficient on the interaction term remains positive and statistically significant.

[Insert Table 9 about here]

To examine the economic relevance of our hypothesis, we focus on the results of the third column and calculate the impact of monetary policy for individuals with different levels of wealth. In detail, we consider individuals at the 25th, 75th, and 95th percentiles on the wealth distribution, which correspond to distributed dividends over the past 10 years equal to 0%, 11%, and 59% of total assets in the year prior to the loan application. For the individuals at the bottom of the distribution, the marginal effect of the *Shadow rate* on *Granted* equals -0.0154 (= -0.0154 + 0.022$\times$0); that is for every point increase in the shadow rate, there is 1.5% lower probability of the bank granting a loan to an applicant on the 25th percentile of the wealth distribution.

The equivalent effect from a one standard deviation increase in the shadow rate (equal to 2.4 in the SAFE data set) is 3.7%. For loan applicants on the 75th percentile, the marginal effect of a one standard deviation increase in the shadow rate is smaller but still 3.1% (= [-0.0154 + 0.022×0.11]*2.4). For loan applicants on the 95th percentile however, the marginal effect of a one standard deviation increase the shadow rate is 0.6% and hence getting close to zero (= [-0.0154 + 0.022×0.59]*2.4).

Interestingly, despite being a completely different data set with a different computation of wealth, these results are very close to the ones obtained with the first data set. This finding further reinforces the external validity of our results in the previous section.

4.2 The role of bank liquidity and capital

An advantage of the SAFE data set is that we can exploit the cross-section of bank characteristics to better understand the interplay between business owners' wealth and banks' strength in the transmission mechanism of monetary policy. Moreover, examining the robustness of our results for banks with differential characteristics further strengthens the argument that we observe changes in loan supply, as opposed to changes in loan demand (Jiménez et al., 2014; Kashyap and Stein, 2000).

First, we consider banks' *Liquidity ratio* and we split our sample using the average *Liquidity ratio* of the respondent's main bank. In panel A of Table 10, we show the results for the subsample of firms borrowing from banks having above average liquidity ratios. Although the coefficients of the interaction term between wealth and monetary policy are still positive, the impact is less outspoken compared to our baseline analysis. Also, the statistical significance levels of the coefficients is below that of the baseline analysis and becomes insignificant once firm fixed effects are included. In panel B of Table 10, we repeat the analysis with the least liquid banks. Here, we clearly find positive and significant coefficients on *Shadow rate*× *Wealth* and, moreover, the magnitude is larger than those in the other subsample. This confirms that wealth is an important factor in the transmission of monetary policy especially for firms borrowing from banks that are more sensitive to changes in the monetary policy stance.

[Insert Table 10 about here]

Another important characteristic of banks in the response to monetary policy changes is their level of capitalization (Jiménez et al., 2014; Maddaloni and Peydró, 2011, e.g.,). We repeat the previous analysis by using the CET1 ratio as a proxy for bank capitalization. Again, we split our sample by considering banks with capitalization ratios above and below the sample average. As shown in Table 11, the results are similar to those in Table 10. The *Shadow rate*$\times$*Wealth* coefficients are statistically insignificant in panel A (i.e. for banks with above average CET1), while they are significantly positive in panel B (i.e. for banks with below average CET1). Thus, the evidence supports the premise that wealth is an important factor in the transmission of monetary policy especially for firms borrowing from weakly capitalized banks which are more sensitive to changes in the monetary policy stance.

[Insert Table 11 about here]

4.3 The role of firm balance sheet characteristics

A potential criticism of our findings in this section might be that our results are correlated with other firm characteristics that may affect the transmission of monetary policy to credit supply. To address this concern, we add additional interaction terms between selected firms' financial ratios and the monetary policy variable. In principle, and consistent with our empirical identification arguments developed in the previous sections,[9] we expect a limited role for firm characteristics if the identified results are mainly driven by supply-side forces (the demand-side forces being controlled for).

In Table 12, we add in the baseline specification four additional interaction terms with the *Shadow rate*: *Firm ROE*, *Firm equity ratio*, *Firm cash flow ratio*, and *firm size*. We find that none of the new interaction terms are significantly correlated with *Granted*, while the coefficients on *Shadow rate*$\times$*Wealth* and their significance remain very similar to our baseline results. Thus,

[9] To recall, the observation of loan applications and rejections, the Heckman regressions against sample selection bias, the differential effects for banks with different liquidity and capital ratios, and of course the observation of the credit score)

our results are unlikely to be driven by balance sheet channels, despite the significance of the main terms of these variables on the probability to grant the loan.

[Insert Table 12 about here]

5 Conclusion

We hypothesize and empirically establish that business owners' private wealth plays an important role in the transmission of monetary policy through the credit channel. This is a relevant research question. If monetary policy decisions affect business loan approval rates, amounts, and spreads in a heterogeneous way due to their owners' private wealth, then the credit channel might disproportionally affect the future wealth of richer and poorer entrepreneurs. This especially holds for small firms because their owner's wealth most usually comes from the income accumulation derived from their business profits.

Our empirical analysis involves two separate data sets with unique information on loan applications, firms' owners, and firm and bank characteristics. This unique information allows us to overcome several identification problems. Our key finding is that monetary policy affects loan approval rates of poorer business owners more than those of wealthier business owners. Specifically, contractionary monetary policy reduces the probability of loan approval for the less wealthy, as well as decreases the respective loan amounts and increases loan spreads, and vice versa for expansionary monetary policy. The corresponding effects on the wealthier business owners are, by contrast, minimal. These results are in line with the risk-taking channel of monetary policy where banks that perceive private wealth as pledgeable collateral feel a lower need to rely on collateral when monetary policy is expansionary.

Further, we show that the first-order effects on loan approval and loan terms trigger second-order future income & wealth effects. Using an RDD model based on the credit score's cutoff rule, and hence comparing firms that just got their loan application granted to very similar firms that just got their loan application rejected, we show that loan approval significantly increases business owners' future income and wealth. As we have first shown that loan approval is heterogeneously affected by monetary policy conditional on owners' initial private wealth, it implies that monetary policy may impact future income & wealth differentially for poorer and richer entrepreneurs.

Last, we show that this heterogeneous transmission of monetary policy occurs mainly through banks with low liquidity and low capital, which are less constrained during periods of monetary expansion.

References

Altavilla, C., Brugnolini, L., Gürkaynak, R. S., Motto, R., and Ragusa, G. (2019). Measuring euro area monetary policy. *Journal of Monetary Economics*, 108:162–179.

Amberg, N., Jansson, T., Klein, M., and Picco, A. R. (2021). Five Facts about the Distributional Income Effects of Monetary Policy Shocks. *American Economic Review: Insights*.

Andersen, A., Johannesen, N., Jorgensen, M., and Peydro, J.-L. (2021). Monetary policy and inequality. *UPF working paper*.

Auclert, A. (2019). Monetary policy and the redistribution channel. *American Economic Review*, 109(6):2333–67.

Banerjee, A. and Duflo, E. (2014). Do firms want to borrow more? testing credit constraints using a directed lending program. *Review of Economic Studies*, 81:572–607.

Berg, T. (2018). Got rejected? real effects of not getting a loan. *Review of Financial Studies*, 31(12):4912–4957.

Bernanke, B. and Blinder, A. S. (1992). The federal funds rate and the transmission of monetary policy. *American Economic Review*, 82(4):901–21.

Cattaneo, M., Jansson, M., and Ma, X. (2018). Manipulation testing based on density discontinuity. *Stata Journal*, 18:234–261.

Cattaneo, M., Titiunik, R., and Vazquez-Bare, G. (2016). Inference in regression discontinuity design under local randomization. *Stata Journal*, 16:331–367.

Ciccarelli, M., Maddaloni, A., and Peydró, J.-L. (2015). Trusting the bankers: A new look at the credit channel of monetary policy. *Review of Economic Dynamics*, 18(4):979–1002.

Coibion, O., Gorodnichenko, Y., Kueng, L., and Silvia, J. (2017). Innocent Bystanders? Monetary policy and inequality. *Journal of Monetary Economics*.

Dagher, J. and Kazimov, K. (2015). Banks' liability structure and mortgage lending during the financial crisis. *Journal of Financial Economics*, 116(3):565–582.

Dass, N. and Massa, M. (2011). The impact of a strong bank-firm relationship on the borrowing firm. *Review of Financial Studies*, 24:1204–1260.

De Graeve, F., De Jonghe, O., and Vander Vennet, R. (2007). Competition, transmission and bank pricing policies: Evidence from Belgian loan and deposit markets. *Journal of Banking & Finance*, 31(1):259–278.

Degryse, H., De Jonghe, O., Jakovljević, S., Mulier, K., and Schepens, G. (2019). Identifying credit supply shocks with bank-firm data: Methods and applications. *Journal of Financial Intermediation*, 40:100813.

Delis, M. D., Fringuellotti, F., and Ongena, S. (2023). Credit and income inequality. *FRB of New York Staff Report*, (929).

Delis, M. D., Hasan, I., Iosifidi, M., and Ongena, S. (2022). Gender, credit, and firm outcomes. *Journal of Financial and Quantitative Analysis*, pages 1–31.

Frid, C. J., Wyman, D. M., Gartner, W. B., and Hechavarria, D. H. (2016). Low-wealth entrepreneurs and access to external financing. *International Journal of Entrepreneurial Behavior & Research*.

Heider, F., Saidi, F., and Schepens, G. (2019). Life below Zero: Bank Lending under Negative Policy Rates. *The Review of Financial Studies*, 32(10):3728–3761.

Holm, M. B., Paul, P., and Tischbirek, A. (2021). The transmission of monetary policy under the microscope. *Journal of Political Economy*, 129(10):2861–2904.

Holmstrom, B. and Tirole, J. (1997). Financial intermediation, loanable funds, and the real sector. *Quarterly Journal of Economics*, 112(3):663–691.

Hülsewig, O., Mayer, E., and Wollmershäuser, T. (2006). Bank loan supply and monetary policy transmission in germany: An assessment based on matching impulse responses. *Journal of Banking & Finance*, 30(10):2893–2910.

Ioannidou, V., Ongena, S., and Peydró, J.-L. (2014). Monetary Policy, Risk-Taking, and Pricing: Evidence from a Quasi-Natural Experiment*. *Review of Finance*, 19(1):95–144.

Iyer, R. and Puri, M. (2012). Understanding bank runs: Do depositors monitor banks? *The American Economic Review*, 102(4):1414–1445.

Jarociński, M. and Karadi, P. (2020). Deconstructing monetary policy surprises—the role of information shocks. *American Economic Journal: Macroeconomics*, 12:1–43.

Jiménez, G., Ongena, S., Peydró, J.-L., and Saurina, J. (2014). Hazardous times for monetary policy: What do twenty-three million bank loans say about the effects of monetary policy on credit risk-taking? *Econometrica*, 82(2):463–505.

Kaplan, G., Moll, B., and Violante, G. L. (2018). Monetary Policy According to HANK. *American Economic Review*, 108(3):697–743.

Kashyap, A. K. and Stein, J. C. (2000). What do a million observations on banks say about the transmission of monetary policy? *American Economic Review*, 90(3):407–428.

Kishan, R. P. and Opiela, T. P. (2000). Bank size, bank capital, and the bank lending channel. *Journal of Money, Credit and Banking*, pages 121–141.

Levine, R. (2021). Finance, growth, and inequality. *IMF Working Paper*, WP/21/164.

Loutskina, E. and Strahan, P. E. (2009). Securitization and the declining impact of bank finance on loan supply: Evidence from mortgage originations. *The Journal of Finance*, 64(2):861–889.

Maddaloni, A. and Peydró, J.-L. (2011). Bank Risk-taking, Securitization, Supervision, and Low Interest Rates: Evidence from the Euro-area and the U.S. Lending Standards. *The Review of Financial Studies*, 24(6):2121–2165.

McKay, A. and Wolf, C. (2023). Monetary policy and inequality. *Journal of Economic Perspectives*, 37:121–144.

Mumtaz, H. and Theophilopoulou, A. (2017). The impact of monetary policy on inequality in the UK. An empirical analysis. *European Economic Review*.

Rajan, R. and Ramcharan, R. (2011). Land and credit: A study of the political economy of banking in the united states in the early 20th century. *Journal of Finance*, 66:1895–1930.

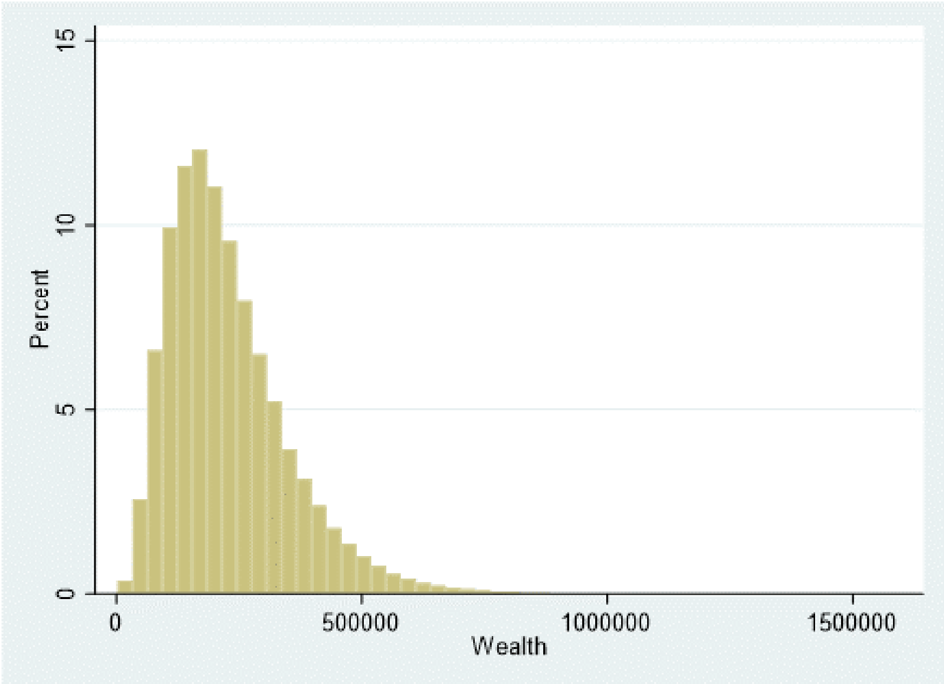
Smith, M., Yagan, D., Zidar, O., and Zwick, E. (2019). Capitalists in the Twenty-First Century*. *The Quarterly Journal of Economics*, 134(4):1675–1745.

Song, J., Price, D., Guvenen, F., Bloom, N., and Wachter, T. v. (2019). Firming up inequality. *Quarterly Journal of Economics*, 134(1):1–50.

Wu, J. C. and Xia, F. D. (2016). Measuring the macroeconomic impact of monetary policy at the zero lower bound. *Journal of Money, Credit and Banking*, 48(2-3):253–291.

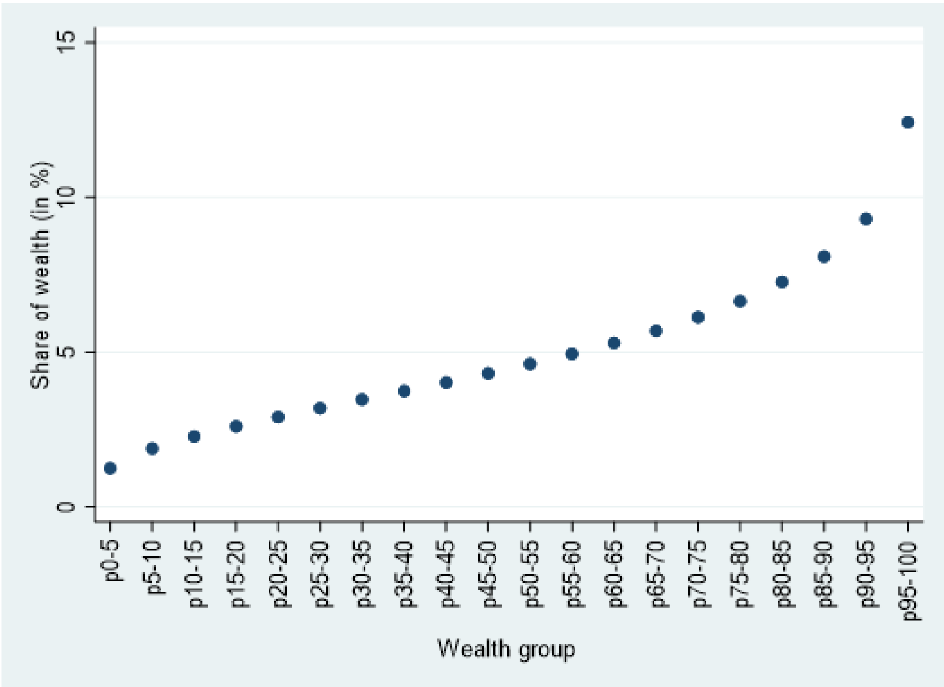
Figures

Figure 1: Histogram of owner's private wealth in our dataset from the large euro area bank



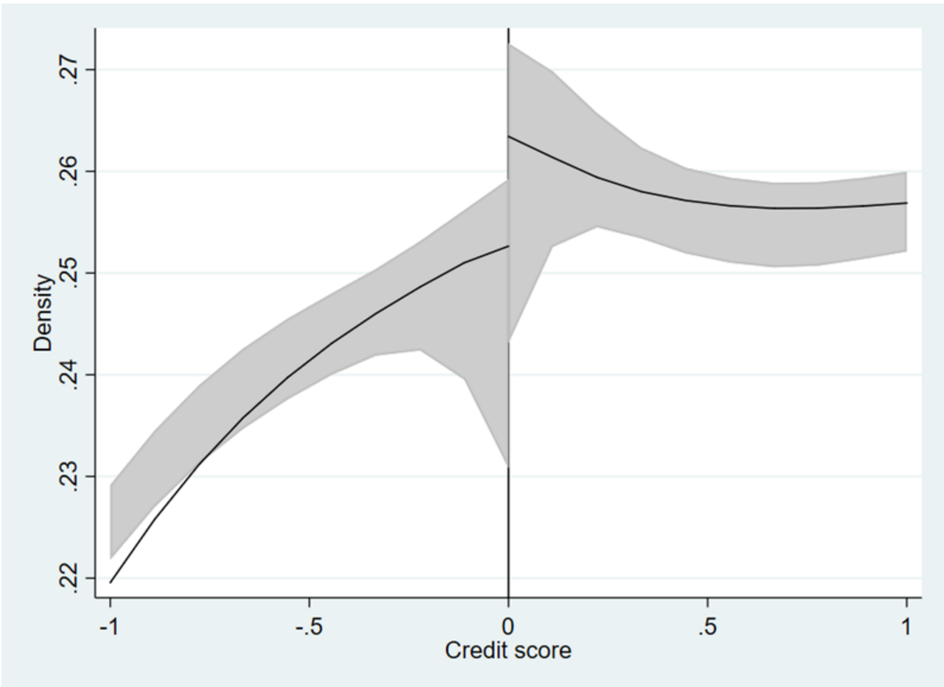
This Figure shows the histogram of owners' private wealth as reported to the large euro area bank to which they apply for a business loan. Wealth is the euro amount of owners' total wealth other than the assets of the firm (this includes all movable assets, e.g., financial assets in bank accounts, stocks, bonds, etc.) and minus any household debt the owner might privately have.

Figure 2: Distribution of wealth among the business owners in our dataset from the large euro area bank



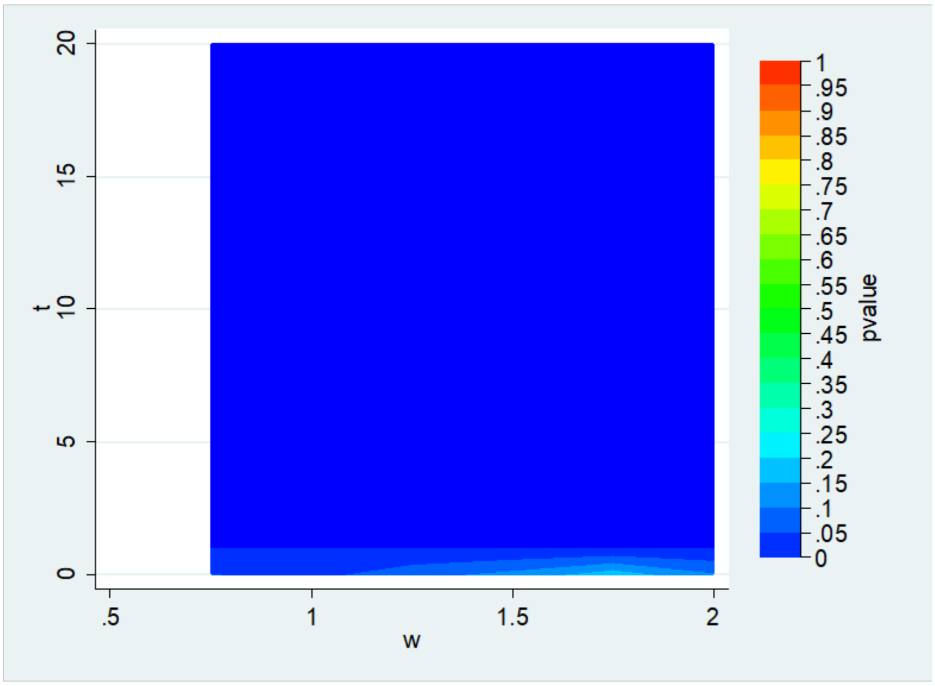
This Figure shows the histogram of owners' private wealth as reported to the large euro area bank to which they apply for a business loan. Wealth is the euro amount of owners' total wealth other than the assets of the firm (this includes all movable assets, e.g., financial assets in bank accounts, stocks, bonds, etc.) and minus any household debt the owner might privately have.

Figure 3: Manipulation test RDD



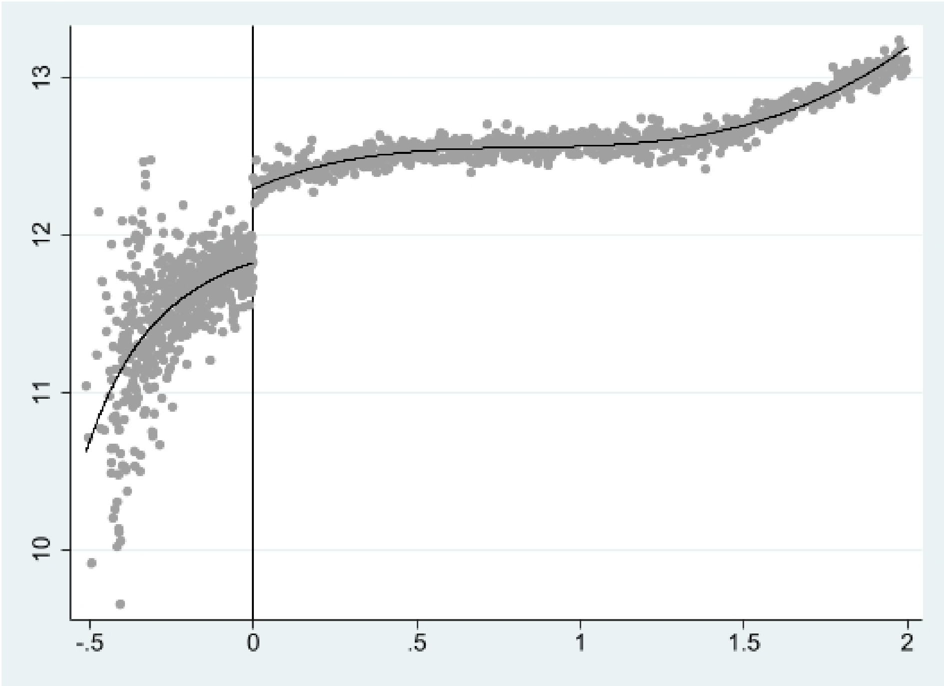
This Figure shows results from the manipulation testing procedure using the local polynomial density estimator proposed by Cattaneo et al. (2018). To perform this test, we rely on the local quadratic estimator with cubic bias-correction and triangular kernel. The test rejects the hypotehsis that the credit score is manipulated (p-value = 0.381)

Figure 4: Sensitivity analysis RDD



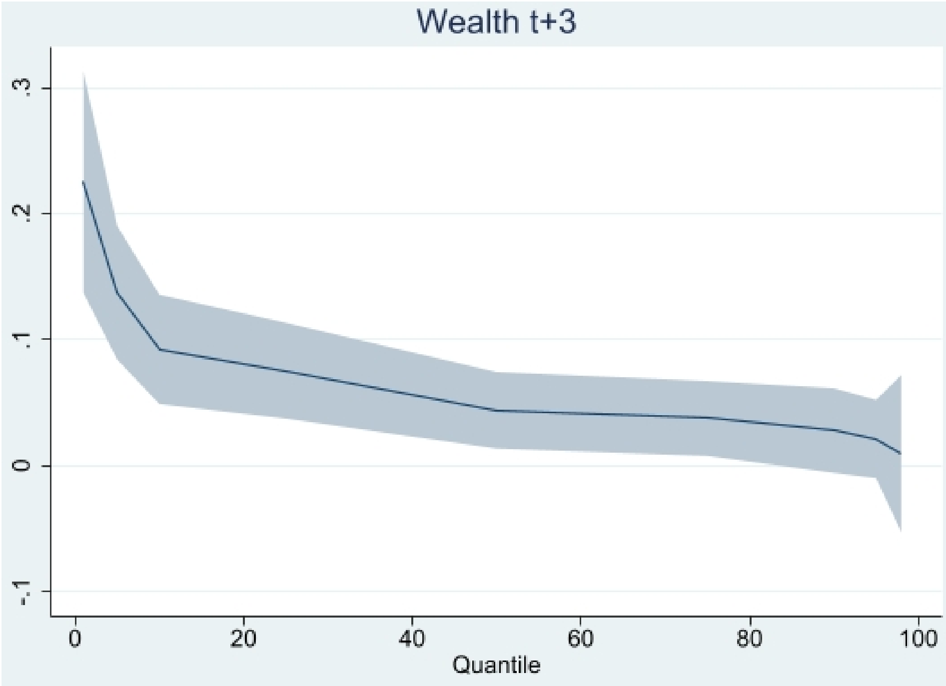
This Figure shows results from a sensitivity analysis under local randomization (see Cattaneo et al. (2016)). We perform a sequence of hypotheses tests for different windows around the cutoff. Specifically, we show the test statistic of the null hypothesis of no treatment effect (x-axis) against the window length (y-axis). The p-values are calculated using randomization inference methods.

Figure 5: Graphical result of the RDD model: Effect on future wealth



This Figure shows the effect of the bank's decision to grant the loan (credit score above the 0 cutoff) on the loan applicant's wealth 3 years onward. The figure displays one single cutoff point and a clear discontinuity on the cutoff.

Figure 6: Loan approval and future wealth: Quantile regressions results



This Figure shows the effect of the bank's decision to grant the loan on the loan applicant's wealth 3 years onward. The figure displays the effect from a quantile regression along the loan applicants' wealth distribution.

Tables

Table 1: Data and variable definitions

Variable	Description
Shadow rate	The monthly shadow rate as defined by Wu and Xia (2020). From 2002 to 2004 we use use the quarterly refinancing rate, which coincides with the shadow rate until the emergence of quantitative easing.
Monetary policy shock	Euro Area monetary policy shocks computed as in Altavilla et al. (2019)
A. Panel data on loan applications from a large North European bank	
Loan applicants	Loan applicants are business owners (owning a majority stake of $\geq$ 50%) who have an exclusive relationship with the bank. These borrowers apply to the bank for one or more business loans during the period 2002-2018 and the loan is either originated (fully or at least 75%of the requested loan amounted) or rejected (bank advises against proceeding with the application, fully rejects, or only originates up to 25% of the requested loan amount). Due to the exclusive relationship, the bank holds information on the applicants even outside the year of loan application.
Year	The sample covers the period 2002-2019. Applications end in 2018 and we use one more year of firm financial ratios (2019) to examine future firm outcomes.
Apply	A dummy variable equal to 1 if the individual applied for a loan in a given year and 0 otherwise.
Granted	A dummy variable equal to 1 if the loan is originated (Credit score >0) and 0 otherwise (Credit score <0).
Credit score	The credit score of the applicant, as calculated by the bank. There is a 0 cutoff: positive values indicate that the loan is granted, and negative values indicate that the loan is denied.
Wealth	Euro amount of individuals' private liquid assets other than the assets of the firm minus total private consumer debt (in log). The bank observes this in the year of the loan application and the two years before the application. For the missing years, we input the predicted value of the regression of the last available observation of wealth on the mean wealth by region, year, and industry.
Income	The euro amount of individuals' total annual income (in log) in the year of the loan application and the two years before the application. For the missing years, we input the predicted value of the regression of the last available observation of income on the mean income by region, year, and industry.
Owner education	An ordinal variable ranging between 0 and 5 if the individual completed the following education. 0: No secondary; 1: Secondary; 2: Postsecondary, nontertiary; 3: Tertiary; 4: MSc; 5: MBA or Ph.D.
Owner age	The applicant's age.
Owner dependents	The number of the applicant's dependents.
Owner gender	A dummy variable equal to 1 if the applicant is a male and 0 otherwise.
Firm size	Total firm's assets (in log).
Firm leverage	The ratio of firm's total debt to total assets.

Table 1: continued

Variable	Description
Firm ROA	The ratio of firm's after tax profits to total assets.
Firm cash holdings	The ratio of cash holdings to total assets.
Forward ROA	The mean *Firm ROA* in the three years after the year of the loan application.
Forward growth	The mean increase in *Firm size* in the three years after the year of the loan application.
Forward leverage	The mean *Firm leverage* in the three years after the year of the loan application.
Number of applications	The number of applications to the bank before the current loan application.
Loan amount	Log of the loan facility amount in thousands of euros.
Loan spread	The difference between the loan rate and the LIBOR (in basis points).
Maturity	Loan maturity in months.
Loan provisions	A dummy variable equal to 1 if the loan has performance-pricing provisions, and 0 otherwise.
Collateral	A dummy variable equal to 1 if the loan has collateral guarantees and 0 otherwise.
B. Panel data on loan applications from the SAFE survey	
Loan applicants	Loan applicants are private family firms for which the majority stake (of $\geq 50\%$) is owned by either a single entrepreneur, multiple entrepreneurs, or a family.
Wave	The time unit of the survey, reflecting a 6-month reference period for which the loan applicants where questioned.
Year	The waves cover the period 2009-2020.
Granted	Dummy equal to 1 if a bank loan application was granted (fully or at least 75% of the requested loan amounted) and 0 if the loan was not granted, or if the firm had to refuse the offer because the costs were too high.
Accumulated dividends	The difference between the sum of the firm's net income over the past 10 years and the firm's increment in retained earnings over the same period. $(\sum_{t=-10}^{t=-1} \text{Net income}_t)$ - (Retained earnings$_{it-1}$ - Retained earnings$_{it-10}$)
Wealth	The ratio of firm's accumulated dividends to total assets
Firm ROE	The ratio of firm's P/L after tax to total equity.
Firm equity ratio	The ratio of firm's total equity to total assets.
Firm cash flow ratio	The ratio of firm's free cash flow to total assets.
Firm size	Total firm's assets (in log).
Bank liquidity ratio	The ratio of liquid assets to total assets of the firm's main bank.
Bank capital ratio	The ratio of tier 1 common equity to total assets of the firm's main bank.

Table 2: Summary statistics

The table reports the number of observations, mean, standard deviation, minimum, and maximum for the variables used in the empirical analysis. The variables are defined in Table 1, except from *Application probability*, which is obtained from the prediction of equation (1). * in thousands of euros, ** decimal values are used in the regression analyses.

	Obs.	Mean	St. dev.	Min.	Max.
A. Panel data on loan applications from a large North European bank: full sample					
Apply	414,730	0.33	0.47	0	1
Granted	137,321	0.84	0.37	0	1
Shadow rate	414,730	0.18	2.94	-6.40	4.28
Monetary policy shock	367,998	1.02	5.77	-16.75	15.95
Wealth	414,730	12.07	0.61	7.21	14.29
Income	414,730	10.94	0.42	9.73	12.78
Education	414,730	2.99	1.01	0	5
Age	414,730	44.94	15.87	20	78
Dependents	414,730	1.89	1.49	0	7
Gender	414,730	0.80	0.39	0	1
Firm size	414,730	12.89	0.44	9.96	14.37
Firm leverage	414,730	0.20	0.12	0.12	0.83
Firm ROA	414,730	0.08	0.10	-0.40	0.58
Firm cash holdings	414,730	0.08	0.03	0.00	0.25
Number of applications	414,730	6.83	1.46	1	9
Credit score	414,730	0.65	0.60	-0.77	3.50
Default	414,730	0.02	0.10	0	1
Loan amount	137,321	3.51	1.99	0.69	11.41
Loan spread	114,641	340.7	246.1	33.45	985.7
Maturity	137,321	47.9	37.29	4	278
Loan provisions	114,641	0.41	0.45	0	1
Collateral	114,641	0.69	0.49	0	1
Application probability	414,730	0.26	0.03	0.14	0.61
B. Panel data on loan applications from the SAFE survey					
Granted	14,346	0.82	0.38	0	1
Shadow rate	16,447	-2.26	2.43	-7.35	0.98
Accumulated dividends*	16,447	1,248	4,594	0	35,167
Wealth (in %)**	16,447	11.48	24.48	0	150.74
Firm ROE	16,072	0.05	0.38	-1.33	1.27
Firm equity ratio	16,447	0.30	0.25	-0.58	0.89
Firm cash flow ratio	15,652	0.06	0.08	-0.19	0.31
Firm size*	16,445	13,721	28,487	54.00	159,000
Bank liquidity ratio	4,962	0.26	0.10	0.01	0.67
Bank capital ratio	3,710	0.06	0.03	0.03	0.15

Table 3: Summary statistics for the sample around the credit score cutoff

The table reports the number of observations, mean, standard deviation, minimum, and maximum for the variables used in the empirical analysis. The variables are defined in Table 1, except from *Application probability*, which is obtained from the prediction of equation (1). * in thousands of euros, ** decimal values are used in the regression analyses.

	Mean	St. dev.	Min.	Max.	Mean diff.	Std. error
Apply	0.26	0.44	0	1	0.007	0.014
Granted	0.66	0.47	0	1	1	0
Shadow rate	-0.19	3.28	-6.40	4.28	0.017	0.016
Monetary policy shock	0.02	2.31	-7.10	4.74	0.004	0.008
Wealth	11.50	0.60	7.21	13.97	0.020	0.026
Income	10.69	0.30	9.73	11.49	0.027	0.026
Education	2.13	0.99	0	5	0.033	0.021
Age	44.80	15.86	20	76	0.238	0.252
Dependents	1.86	1.47	0	6	0.004	0.036
Gender	0.81	0.39	0	1	0.009	0.006
Fim size	12.72	0.40	9.96	14.09	0.011	0.007
Firm leverage	0.20	0.03	0.15	0.74	0.002	0.002
Firm ROA	0.06	0.09	-0.40	0.49	0.005	0.002
Firm cash holdings	0.07	0.03	0.01	0.16	0.000	0.001
Number of applications	7.22	1.48	1	9	0.091	0.070
Credit score	0.06	0.16	-0.30	0.30	0.277	0.073
Default	0.04	0.11	0	1	0.000	0.003
Loan amount	1.98	0.54	0.71	7.01	0.099	0.008
Maturity	44.13	35.94	4	233	0.841	0.570
Loan provisions	0.46	0.50	0	1	0.023	0.036
Collateral	0.69	0.45	0	1	0.011	0.027

Table 4: Monetary policy, wealth, and loan decisions

The Table reports coefficient estimates and standard errors (clustered by firm) in parentheses. The dependent variable is the bank's loan decision (granted or denied loan), and all variables are defined in Table 1. The lower part of the table reports the number of observations, the adjusted R-squared, and the type of fixed effects used in each specification. All specifications are estimated with OLS, except from specifications 7 and 8, which are estimated with Heckman's two-stage model. For specifications 7 and 8, we also report the number of observations used in the first stage and the estimate on Lambda. In specification 1, we use the full sample; in specifications 2 to 8, we use observations in -0.3 to 0.3 around the 0 cutoff of the credit score; and in specification 9, we use observations in -0.1 to 0.1 around the cutoff. The ***, **, and * marks denote statistical significance at the 1%, 5%, and 10% levels.

	(1) Granted	(2) Granted	(3) Granted	(4) Granted	(5) Granted	(6) Granted	(7) Granted	(8) Granted	(9) Granted
Wealth	0.016***	0.013***	0.013***	0.012***	0.005***	0.013***	0.014***	0.014***	0.012***
	(0.002)	(0.003)	(0.004)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
Shadow rate	-0.239***	-0.212***	-0.196***	-0.223***	-0.116*		-0.206***	-0.226***	-0.202***
	(0.063)	(0.074)	(0.113)	(0.066)	(0.061)		(0.056)	(0.049)	(0.066)
Shadow rate × Wealth	0.022***	0.017***	0.014**	0.019***	0.020***	0.018***	0.020***	0.020***	0.018***
	(0.005)	(0.006)	(0.007)	(0.005)	(0.007)	(0.004)	(0.005)	(0.004)	(0.005)
Shadow rate × Credit score					0.044***				
					(0.009)				
Lambda							-0.172	-0.162	
							(0.164)	(0.135)	
Credit score bandwidth	[-∞,+∞]	[-0.3,0.3]	[-0.3,0.3]	[-0.3,0.3]	[-0.3,0.3]	[-0.3,0.3]	[-0.3,0.3]	[-0.3,0.3]	[-0.1,0.1]
Firm type	all	all	limited liability	unlimited liability	all	all	all	all	all
Observations	137,321	32,310	27,140	5,170	32,310	32,310	32,310	32,310	18,028
Observations (first stage)							414,730	675,327	
Adj. R-squared	0.723	0.706	0.709	0.698	0.935	0.720			0.819
Controls and Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year:quarter FE	No	No	No	No	No	Yes	No	No	No

Table 5: Results using Euro Area monetary policy shocks

The table reports results using the sample of the signle bank and Euro Area monetary policy shocks computed as in Altavilla et al. (2019) instead of the shadow rate as the measure of monetary policy. It reports coefficient estimates and standard errors (clustered by firm) in parentheses. The dependent variable is the bank's loan decision (granted or denied loan), and all variables are defined in Table 1. The lower part of the table reports the number of observations, the adjusted R-squared, and the type of fixed effects used in each specification. All specifications are estimated with OLS, except from specifications 7 and 8, which are estimated with Heckman's two-stage model. For specifications 7 and 8, we also report the number of observations used in the first stage and the estimate on Lambda. In specification 1, we use the full sample; in specifications 2 to 8, we use observations in -0.3 to 0.3 around the 0 cutoff of the credit score; and in specification 9, we use observations in -0.1 to 0.1 around the cutoff. The ***, **, and * marks denote statistical significance at the 1%, 5%, and 10% levels.

	(1) Granted	(2) Granted	(3) Granted	(4) Granted	(5) Granted	(6) Granted	(7) Granted	(8) Granted	(9) Granted
Wealth	0.012***	0.011***	0.010***	0.010***	0.012***	0.019***	0.013***	0.015***	0.010***
	(0.003)	(0.002)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.005)	(0.002)
Mon. pol. shock	-0.296***	-0.257***	-0.229***	-0.266***	-0.233**		-0.257***	-0.269***	-0.237***
	(0.112)	(0.091)	(0.094)	(0.086)	(0.087)		(0.067)	(0.074)	(0.083)
Mon. pol. shock × Wealth	0.022**	0.020**	0.016**	0.023***	0.017**	0.022***	0.021***	0.024***	0.017***
	(0.009)	(0.008)	(0.080)	(0.007)	(0.007)	(0.006)	(0.007)	(0.008)	(0.006)
Mon. pol. shock × Credit score					0.064***				
					(0.010)				
Lambda							-0.171	-0.194	
							(0.163)	(0.179)	
Credit score bandwidth	[-∞,+∞]	[-0.3,0.3]	[-0.3,0.3]	[-0.3,0.3]	[-0.3,0.3]	[-0.3,0.3]	[-0.3,0.3]	[-0.3,0.3]	[-0.1,0.1]
Firm type	all	all	limited liability	unlimited liability	all	all	all	all	all
Observations	121,540	28,750	24,150	4,600	28,750	28,750	28,750	28,750	16,101
Observations (first stage)							367,988	599,214	
Adj. R-squared	0.718	0.707	0.708	0.696	0.776	0.720			0.803
Controls and Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year:quarter FE	No	No	No	No	No	Yes	No	No	No

Table 6: Loan amount and loan spread

The table reports coefficient estimates and standard errors (clustered by firm) in parentheses, using the sample of the single bank. The dependent variable is listed on the first row of the table (Loan amount or Loan spread), and all variables are defined in Table 1. The lower part of the table reports the number of observations, the adjusted R-squared, and the type of fixed effects used in each specification. All specifications are estimated with OLS and include the control variables in Tables 4 and 5 plus *Maturity*, *Loan provisions*, and *Collateral*. The *Loan amount* specifications include *Spread* as a control and vice versa. The ***, **, and * marks denote statistical significance at the 1%, 5%, and 10% levels.

	(1) Loan amount	(2) Loan amount	(3) Spread	(4) Spread
Wealth	0.014**	0.012**	-0.055***	-0.048***
	(0.006)	(0.006)	(0.012)	(0.010)
Shadow rate	-0.319***		-0.131**	
	(0.095)		(0.063)	
Shadow rate × Wealth	0.030***		-0.099***	
	(0.009)		(0.017)	
Monetary policy shock		-0.428***		0.120
		(0.162)		(0.102)
Monetary policy shock × Wealth		0.032***		-0.120***
		(0.012)		(0.021)
Observations	26,972	24,004	26,972	24,004
Adj. R-squared	0.840	0.831	0.732	0.726
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year:quarter FE	Yes	Yes	Yes	Yes

Table 7: Loan approval and future income and wealth

The table reports coefficient estimates and standard errors (clustered by firm) in parentheses. The dependent variable is listed on the first row of the table (Wealth or Income three years after loan origination), and all variables are defined in Table 1. In the first two specifications, *Granted* is as defined in Table 1; in the last two specifications, *Granted* equals the partial prediction of *Granted* from *Shadow rate* × *Wealth*, as obtained from specification 1 of Table 4. The lower part of the table reports the number of observations, the adjusted R-squared, and the type of fixed effects used in each specification. All specifications are estimated with OLS on the RDD model described in the text and include the control variables in Tables 4 and 5 plus *Maturity*, *Loan provisions*, and *Collateral*. The ***, **, and * marks denote statistical significance at the 1%, 5%, and 10% levels.

	(1)	(2)	(3)	(4)
	Income	**Wealth**	**Income**	**Wealth**
	3 years after loan origination	3 years after loan origination	3 years after loan origination	3 years after loan origination
Granted	0.072***	0.053***		
	(0.015)	(0.010)		
$\widehat{Granted}$			0.041***	0.038***
			(0.013)	(0.009)
Shadow rate	-0.012**	-0.011**	-0.011**	-0.011*
	(0.006)	(0.005)	(0.006)	(0.005)
Credit score	0.006	0.005	0.007	0.006
	(0.004)	(0.004)	(0.005)	(0.005)
Credit score × Granted	-0.009	-0.006		
	(0.006)	(0.005)		
Credit score × $\widehat{Granted}$			-0.010	-0.007
			(0.007)	(0.005)
Income	0.036***		0.032***	
	(0.007)		(0.006)	
Wealth		0.025***		0.023***
		(0.005)		(0.005)
Observations	77,510	77,510	77,510	77,510
Adj. R-squared	0.703	0.629	0.680	0.617
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes

Table 8: Loan default and private wealth

The table reports coefficient estimates and standard errors (clustered by firm) in parentheses. The dependent variable is listed on the first row of the table (Probability of loan default one year after origination or Probability of loan default three years after origination), and all variables are defined in Table 1. The lower part of the table reports the number of observations, the adjusted R-squared, and the type of fixed effects used in each specification. All specifications are estimated with OLS and include the control variables in Tables 4 and 5 plus *Maturity*, *Loan provisions*, and *Collateral.* The ***, **, and * marks denote statistical significance at the 1%, 5%, and 10% levels.

	(1)	(2)	(3)	(4)	(5)	(6)
	Default 1 year after origination			**Default** 3 years after origination		
Wealth	-0.029***	-0.027***	-0.038***	-0.032***	-0.030***	-0.047***
	(0.008)	(0.007)	(0.009)	(0.009)	(0.007)	(0.010)
Credit score	-0.048**	-0.048**	-0.049**	-0.051***	-0.052***	-0.051***
	(0.022)	(0.022)	(0023)	(0.020)	(0.020)	(0.017)
Firm type	all	limited liability	unlimited liability	all	limited liability	unlimited liability
Observations	119,648	95,602	24,046	77,510	61,935	15,875
Adj. R-squared	0.629	0.631	0.608	0.703	0.716	0.695
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 9: Success of the loan application: Using the survey data for multiple banks

The table shows estimation results from equation (1) using the sample of multiple banks. The dependent variable is Granted_{itcb} and all varaibles are defined in Table 1. Estimation method is OLS with robust standard errors clustered at the wave and firm levels. The ***, **, and * marks denote statistical significance at the 1%, 5%, and 10% levels.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Granted	Granted	Granted	Granted	Granted	Granted	Granted	Granted
Wealth	0.11***	0.07***	0.05**	0.07***	0.12***	0.05**	0.01	0.08
	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.08)	(0.07)
Shadow rate	-2.21***	-1.51***	-1.54***					
	(0.33)	(0.33)	(0.36)					
Shadow rate×Wealth	2.61***	2.21***	2.20***	2.27***	3.10***	2.24***	3.03***	2.90***
	(0.80)	(0.52)	(0.53)	(0.52)	(0.71)	(0.53)	(0.92)	(0.87)
Control variables:								
Firm ROE		0.06***	0.07***	0.06***		0.07***		0.04**
		(0.01)	(0.01)	(0.01)		(0.01)		(0.02)
Firm equity ratio		0.29***	0.32***	0.29***		0.32***		0.37***
		(0.02)	(0.02)	(0.02)		(0.02)		(0.08)
Firm cash flow ratio		0.99***	0.78***	0.99***		0.78***		0.22*
		(0.05)	(0.06)	(0.05)		(0.06)		(0.11)
Firm size		0.03***	0.03***	0.03***		0.03***		0.04
		(0.00)	(0.00)	(0.00)		(0.00)		(0.03)
Observations	16,447	15,627	15,627	15,627	15,627	15,627	9,556	9,556
No. firms	9,714	9,158	9,158	9,158	9,158	9,158	3,087	3,087
R-squared	0.01	0.12	0.15	0.12	0.06	0.16	0.65	0.65
Country FE	No	No	Yes	No	Yes	Yes	Yes	Yes
Wave FE	No	No	No	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	No	No	No	No	Yes	Yes

Table 10: Success of the loan application: The role of bank liquidity

The table shows estimation results from equation (1) using the sample of multiple banks. The dependent variable is Granted_{itcb} and all varaibles are defined in Table 1. Estimation method is OLS with robust standard errors clustered at the wave and firm levels. The ***, **, and * marks denote statistical significance at the 1%, 5%, and 10% levels.

	(1) Granted	(2) Granted	(3) Granted	(4) Granted	(5) Granted	(6) Granted	(7) Granted	(8) Granted	(9) Granted
A: Above average bank liquidity ratio									
Wealth	0.07	0.19***	0.07*	0.05	0.06*	0.13***	0.04	-0.24*	-0.10
	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)	(0.03)	(0.13)	(0.16)
Shadow rate	-1.27**	-1.69***	-0.72	-0.83					
	(0.45)	(0.50)	(0.51)	(0.51)					
Shadow rate×Wealth		3.61**	2.21**	2.16**	1.79*	2.91**	1.74*	0.80	1.13
		(1.39)	(1.01)	(0.98)	(0.90)	(1.23)	(0.89)	(1.69)	(1.70)
Observations	2,443	2,443	2,329	2,329	2,329	2,329	2,329	1,719	1,719
No. firms	1,215	1,215	1,131	1,131	1,131	1,131	1,131	521	521
R-squared	0.01	0.01	0.11	0.12	0.13	0.04	0.13	0.62	0.62
B: Below average bank liquidity ratio									
Wealth	-0.04	0.08	0.15**	0.14**	0.13**	0.16**	0.12**	0.19	0.19
	(0.05)	(0.07)	(0.06)	(0.06)	(0.05)	(0.06)	(0.05)	(0.19)	(0.16)
Shadow rate	-2.80***	-3.28***	-2.46***	-2.57***					
	(0.36)	(0.40)	(0.43)	(0.48)					
Shadow rate×Wealth		4.02**	5.39***	4.43**	5.21***	4.94***	4.10**	6.48***	6.17***
		(1.65)	(1.43)	(1.59)	(1.32)	(1.74)	(1.46)	(2.19)	(2.11)
Observations	2,519	2,519	2,328	2,328	2,328	2,328	2,328	1,565	1,565
No. firms	1,372	1,372	1,263	1,263	1,263	1,263	1,263	500	500
R-squared	0.02	0.02	0.11	0.18	0.12	0.12	0.19	0.65	0.66
Controls	No	No	Yes	Yes	Yes	No	Yes	No	Yes
Country FE	No	No	No	Yes	No	Yes	Yes	Yes	Yes
Wave FE	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	No	No	No	No	No	Yes	Yes

Table 11: Success of the loan application: The role of bank capital

The table shows estimation results from equation (1) using the sample of multiple banks. The dependent variable is Granted_{itcb} and all varaibles are defined in Table 1. Estimation method is OLS with robust standard errors clustered at the wave and firm levels. The ***, **, and * marks denote statistical significance at the 1%, 5%, and 10% levels.

	(1) Granted	(2) Granted	(3) Granted	(4) Granted	(5) Granted	(6) Granted	(7) Granted	(8) Granted	(9) Granted
A: Above average bank capital ratio									
Wealth	-0.17**	-0.11	-0.11	0.06	-0.13	0.10	0.05	0.06	0.18
	(0.07)	(0.10)	(0.09)	(0.10)	(0.09)	(0.08)	(0.09)	(0.29)	(0.29)
Shadow rate	-3.59***	-3.78***	-2.30***	-1.38**					
	(0.64)	(0.65)	(0.60)	(0.61)					
Shadow rate×Wealth		2.11	1.36	2.73	0.30	3.13	1.99	-1.62	-0.11
		(3.19)	(3.27)	(2.89)	(2.97)	(2.71)	(2.58)	(6.67)	(7.07)
Observations	1,536	1,536	1,422	1,422	1,422	1,422	1,422	872	872
No. firms	923	923	858	858	858	858	858	308	308
R-squared	0.04	0.04	0.12	0.20	0.14	0.15	0.22	0.71	0.72
B: Below average bank capital ratio									
Wealth	0.05	0.21**	0.23***	0.19**	0.19**	0.21**	0.16**	-0.03	-0.03
	(0.05)	(0.09)	(0.08)	(0.08)	(0.08)	(0.07)	(0.08)	(0.20)	(0.15)
Shadow rate	-3.44***	-3.99***	-3.05***	-2.77***					
	(0.54)	(0.60)	(0.60)	(0.56)					
Shadow rate×Wealth		4.39**	5.37***	4.91***	4.67***	5.03***	4.38**	4.16**	2.91
		(1.86)	(1.59)	(1.60)	(1.51)	(1.62)	(1.56)	(1.87)	(2.00)
Observations	2,174	2,174	2,042	2,042	2,042	2,042	2,042	1,378	1,378
No. firms	1,205	1,205	1,108	1,108	1,108	1,108	1,108	444	444
R-squared	0.03	0.04	0.13	0.15	0.14	0.08	0.15	0.66	0.67
Controls	No	No	Yes	Yes	Yes	No	Yes	No	Yes
Country FE	No	No	No	Yes	No	Yes	Yes	Yes	Yes
Wave FE	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	No	No	No	No	No	Yes	Yes

Table 12: Success of the loan application: Firm characteristics

The table shows estimation results from equation (1) using the sample of multiple banks. The dependent variable is Granted_{itcb} and all varaibles are defined in Table 1. Estimation method is OLS with robust standard errors clustered at the wave and firm levels. The ***, **, and * marks denote statistical significance at the 1%, 5%, and 10% levels.

	(1) Granted	(2) Granted	(3) Granted	(4) Granted	(5) Granted	(6) Granted	(7) Granted
Wealth	0.05*	0.11***	0.07***	0.05**	0.07***	0.05**	0.09
	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.07)
Shadow rate	-1.92***	-2.21***	-0.52	-1.06			
	(0.32)	(0.33)	(1.12)	(1.13)			
Wealth × Shadow rate		2.61***	2.17***	2.20***	2.19***	2.22***	3.07***
		(0.80)	(0.52)	(0.52)	(0.53)	(0.53)	(0.88)
Interactions:							
Firm ROE			0.28	-0.07	0.37	0.02	0.05
× Shadow rate			(0.45)	(0.41)	(0.45)	(0.42)	(0.78)
Firm equity ratio			0.85	0.80	1.00	0.98	0.06
× Shadow rate			(0.70)	(0.66)	(0.70)	(0.65)	(1.01)
Firm cash flow ratio			-1.39	-0.77	-1.06	-0.38	-2.89
× Shadow rate			(2.45)	(2.26)	(2.53)	(2.36)	(3.56)
Firm size			-0.14	-0.08	-0.12	-0.05	-0.00
× Shadow rate			(0.09)	(0.09)	(0.09)	(0.09)	(0.14)
Control variables:							
Firm ROE			0.07***	0.07***	0.07***	0.07***	0.05
			(0.02)	(0.01)	(0.02)	(0.01)	(0.03)
Firm equity ratio			0.31***	0.34***	0.31***	0.34***	0.36***
			(0.03)	(0.02)	(0.03)	(0.02)	(0.08)
Firm cash flow ratio			0.96***	0.76***	0.96***	0.77***	0.15
			(0.07)	(0.08)	(0.07)	(0.08)	(0.16)
Firm size			0.03***	0.03***	0.03***	0.03***	0.04
			(0.00)	(0.00)	(0.00)	(0.00)	(0.03)
Observations	16,447	16,447	15,627	15,627	15,627	15,627	9,556
No. firms	9,714	9,714	9,158	9,158	9,158	9,158	3,087
R-squared	0.01	0.01	0.12	0.15	0.12	0.16	0.65
Country FE	No	No	No	Yes	No	Yes	Yes
Wave FE	No	No	No	No	Yes	Yes	Yes
Firm FE	No	No	No	No	No	No	Yes

Appendix A

Figures

Figure 7: Overview SAFE waves

Fieldwork and reference periods for each survey round

#	Survey round	Fieldwork period	Publication date	Round	Reference period - last six months
1	2009H1	17 June 2009-23 July 2009	21 September 2009	Common	January-June 2009
2	2009H2	19 November-18 December 2009	16 February 2010	ECB round	July-December 2009
3	2010H1	27 August-22 September 2010	22 October 2010	ECB round	March-September 2010
4	2010H2	21 February-25 March 2011	27 April 2011	ECB round	September 2010-February 2011
5	2011H1	22 August-7 October 2011	01 December 2011	Common	April-September 2011
6	2011H2	29 February-29 March 2012	27 April 2012	ECB round	October 2011-March 2012
7	2012H1	3 September-11 October 2012	02 November 2012	ECB round	April-September 2012
8	2012H2	18 February-21 March 2013	26 April 2013	ECB round	October 2012-March 2013
9	2013H1	28 August-4 October 2013 *	14 November 2013	Common	April-September 2013
10	2013H2	20 February-24 March 2014	30 April 2014	ECB round	October 2013-March 2014
11	2014H1	1 September-10 October 2014	12 November 2014	Common	April-September 2014
12	2014H2	16 March-25 April 2015	02 June 2015	ECB round	October 2014-March 2015
13	2015H1	21 September-26 October 2015	02 December 2015	Common	April-September 2015
14	2015H2	10 March-21 April 2016	01 June 2016	ECB round	October 2015-March 2016
15	2016H1	19 September-27 October 2016	30 November 2016	Common	April-September 2016
16	2016H2	6 March-14 April 2017	24 May 2017	ECB round	October 2016-March 2017
17	2017H1	18 September-27 October 2017	29 November 2017	Common	April-September 2017
18	2017H2	12 March-18 April 2018	4 June 2018	ECB round	October 2017-March 2018
19	2018H1	17 September-26 October 2018	28 November 2018	Common	April-September 2018
20	2018H2	11 March-16 April 2019	29 May 2019	ECB round	October 2018-March 2019
21	2019H1	16 September-25 October 2019	29 November 2019	Common	April-September 2019
22	2019H2	2 March-8 April 2020	8 May 2020	ECB round	October 2019-March 2020
23	2020H1	7 September – 16 October	24 November 2020	Common	April-September 2020

An overview of the questions used from the SAFE questionnaire to assess the success of loan applications:

- Question 7A_a: Have you applied for the following types of financing in the past six months? Bank loan (new or renewal; excluding overdraft and credit lines)
  - 1: Applied
  - 2: Did not apply because of possible rejection
  - 3: Did not apply because of sufficient internal funds
  - 4: Did not apply for other reasons
  - 9: DK/NA

- Question 7B_a: If you applied and tried to negotiate for this type of financing over the past six months, what was the outcome? Bank loan (new or renewal; excluding overdraft and credit lines)
  - 1: Received everything
  - 2: Applied but only got part of it (up to 2010H1)
  - 5: Received 75% and above (from 2010H1 onward)
  - 6: Received below 75% (from 2010H1 onward)
  - 3: Refused because the cost was too high
  - 4: Was rejected
  - 8: Application is still pending
  - 9: DK/NA
- Question 9A_a: For each of the following types of financing, would you say that their availability has improved, remained unchanged or deteriorated for your enterprise over the past six months?: Bank loans (excluding overdraft and credit lines)
  - 1: Improved
  - 2: Remained unchanged
  - 3: Deteriorated
  - 7: Not applicable
  - 9: DK/NA