Granular Credit Risk*

Sigurd Galaasen Rustam Jamilov Ragnar Juelsrud Hélène Rey

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Abstract

What is the impact of granular credit risk on banks and on the economy? We provide the first causal identification of single-name counterparty exposure risk in bank portfolios by applying a new empirical approach on an administrative matched bank-firm dataset from Norway. Exploiting the fat tail properties of the loan share distribution we use a Gabaix and Koijen (2020a,b) granular instrumental variable strategy to show that idiosyncratic borrower risk survives aggregation in banks portfolios. We also find that this granular credit risk spills over from affected banks to firms, decreases investment, and increases the probability of default of non-granular borrowers, thereby sizably affecting the macroeconomy.

Keywords: Granular credit risk, credit concentration, granular borrowers, large exposures regulation, granular instrumental variable, granular hypothesis

*Galaasen: Norges Bank, sigurd-molster.galaasen@norges-bank.no. Jamilov: London Business School, rjamilov@london.edu. Juelsrud: Norges Bank, ragnar.juelsrud@norges-bank.no. Rey: London Business School, CEPR, and NBER, hrey@london.edu. This working paper should not be reported as representing the views of Norges Bank. The views expressed are those of the authors and do not necessarily reflect those of Norges Bank. We thank our discussant José-Luis Peydró as well as Christoph Basten, Svetlana Bryzgalova, Andreas Fagereng, Julian di Giovanni, Francisco Gomes, Refet Gürkaynak, Victoria Ivashina, Joseba Martinez, Atif Mian, Steven Ongena, Elias Papaioannou, Anna Pavlova, Kasper Roszbach, Stephen Schaefer, Vania Stavrakeva, Kjetil Storesletten, Paolo Surico, Gianluca Violante and seminar participants at the CEPR/ERC/LBS Conference on Granularity and Applications, EEA 2020, SNDE 2020, WEAI 2020, LBS, Norges Bank, Oslo Macro Group, Statistics Norway and the University of Zurich for valuable comments and suggestions. Rey is very grateful to the ERC (Advanced Grant 695722). All errors are our own.

1 Introduction

What is the impact of idiosyncratic borrower risk on banks and the economy? It has been understood for years that if individual loans are small enough relative to the overall size of the portfolio then credit risk pooling should achieve perfect insurability against idiosyncratic shocks (Diamond, 1984). But what if some loans are large? What if the distribution of loan sizes is fat-tailed: can the performance of a single large loan directly affect portfolio-level outcomes and lending? A rapidly growing literature, originating from the seminal contribution by Gabaix (2011), has emphasized the micro - or "granular" - origins of macroeconomic outcomes in a variety of theoretical and applied contexts. According to the granular hypothesis, shocks to large, non-atomistic agents generate non-diversifiable "grains" of economic and financial activity, which can directly affect aggregate fluctuations and, via general equilibrium effects, all other agents.

Curiously, there are few empirical applications of the granular hypothesis to banking. This is puzzling because in practice the hypothesis maps directly into the "large exposure regulation" of the Basel Committee on Banking Supervision (BCBS). The BCBS has been regulating bank credit concentration risk for decades, formally at least since the Basel I Accords. The *Core Principles for Effective Banking Supervision* emphasize that local country laws should "set prudent limits on large exposures to a single borrower" (BIS, 2013). In practice however, the Principles admit that "material differences in scope of application, the value of large exposure limits, methods for calculating exposure values, and more lenient treatments for certain types of exposures exist". As a result, the document concludes, "although a concentration risk adjustment could be made to mitigate these risks, these adjustments are neither harmonised across jurisdictions, nor designed to control traumatic losses from a single counter-party default".

This paper is the first to provide causal empirical evidence on the importance and implications of "single-name" credit concentration risk[1]. We develop a new empirical approach and apply it to a novel administrative firm-bank matched dataset from Norway[2]. We merge our loan-level administrative database with firm and bank balance sheet data. We cover every single bank loan made to limited liability companies (LLC) in Norway over the 2003-

[1]We follow the BCBS vocabulary where "single-name"refers to the level of an individual borrower or counterparty. This is in contrast, for example, to how BCBS defines and treats sectoral or geographical exposures where the unit of analysis is either a whole industry or region.

[2]Throughout the paper we focus on corporate clients and loans. Our empirical approach however, is general and flexible enough to be applied to other borrower types such as households, state institutions, or other intermediaries.

2015 period[3]. This data-rich environment enables us to study the transmission mechanism and heterogeneous treatment effects at many levels of aggregation.

Our empirical strategy consists of five steps. First, we establish that the distribution of loans shares in our dataset is fat-tailed. Our estimate of the Pareto power implies that 80% of all credit is concentrated in 20% of the loans. Interestingly, we provide therefore another example of the famous "80-20" Pareto principle that occurs in a variety of settings in economics as well as more generally in social and physical sciences (Gabaix, 2009).

Second, we construct a measure of idiosyncratic borrower risk. We use data on firm balance sheets and income statements to estimate idiosyncratic value-added shocks for the universe of all LLC firm $\times$ years in Norway over 2003-2015. We extract non-systematic variation in firm value-added by controlling for a variety of balance sheet items like firm size and costs as well as firm, industry, year, and geographical fixed effects. Our approach follows very closely a large literature in labor economics and macroeconomics (Guiso et al., 2005; Hsieh and Klenow, 2009; Fagereng et al., 2018)[4].

Third, we establish the pass-through from these idiosyncratic firm shocks to loan-level returns. We investigate how such shocks affect returns on loans within the same bank, industry, county, year, and loan type. Importantly, our specification controls for any confounding bank-side supply factors, potentially specific to a given industry, county, or contractual type[5]. We find that idiosyncratic firm shocks have a strong effect on loan returns. In our preferred specification with a full set of controls and fixed effects, a one standard deviation negative firm shock causes annual loan-level returns to fall by 36 basis points. We explore numerous dimensions of heterogeneity, including firm characteristics, geographical location, ownership, and sector.

Fourth, we look at the impact of idiosyncratic borrower shocks on banks portfolio-level outcomes. This is a critical step in our analysis. Once aggregated to the level of a bank, we potentially lose the positive properties of loan-level analysis: the loan share-weighted firm shock series could be potentially contaminated by bank $\times$ year confounding factors which we no longer have the power to deal with. For this stage, we adopt the "Granular Instrumen-

[3]LLC is by far the most commonly used organizational structure in Norway. For most years, our firm data accounts for more than 90% of total employment in the private sector.

[4]We perform a variety of validation and robustness checks to discipline our measure. In particular, we establish that shocks are not cross-sectionally correlated or persistent across time. We also run a variety of placebo permutation tests. Finally, we show that these shocks only have contemporaneous and lead effects on loan and bank outcomes, i.e. that there are no "pre-trends".

[5]Conceptually, this step can be viewed as a "reverse Khwaja and Mian (2008)". In Khwaja and Mian (2008), authors trace out the impact of bank supply shocks onto firms that borrow from the same bank. This way, they are able to control for any confounding firm-side factors. Our strategy is to compare loan outcomes within the same bank in order to control for supply-side factors. Our approach is very "granular", since we zoom in on firms within the same bank, *and* industry and county.

tal Variable" (GIV) approach, newly developed in a series of papers by Gabaix and Koijen (2020a,b). Intuitively, the GIV extracts the variation in the share-weighted aggregated firm shock series that can be attributed to "granular" borrowers. Specifically, the instrument is simply the difference between size-weighted and unweighted aggregated firm shocks. The GIV thus eliminates any bank $\times$ year factors. Conditional on the distribution of credit shares being fat-tailed, idiosyncratic shocks to large borrowers allows us to achieve identification.

One important result of our paper is that idiosyncratic firm shocks, instrumented by the GIV, have a large and significant effect on portfolio-level return on loans (RoA). A one-standard-deviation granular credit shock causes portfolio RoA to move by 11.6 basis points on average. Given that in the estimation sample the standard deviation of RoA is 1.35, our estimate can explain 8.6% of the total dispersion of bank returns. We also find that the relationship is strongly concave, driven mainly by negative shocks. In particular, if we condition on positive share-weighted shocks, the estimated coefficient becomes a noisy zero. In contrast, when conditioning on negative share-weighted shocks, the estimate jumps to as high as 19.4 basis points, which is 15% of the sample standard deviation of RoA - an increase of 74% over the average estimate[6]. We investigate heterogeneity at the bank level and find that the pass-through is the strongest for banks that are small and have few credit relationships. However, we also find that the effect is still large and significant for banks with many credit relationships, indicating that granular credit risk is not merely a small-N problem.

Fifth, having established that shocks to granular borrowers have a direct effect on portfolio-level returns, we ask whether banks pass on these shocks to the real economy. In other words, are there macroeconomic spillovers from granular credit risk? We start by examining credit supply effects, by comparing bank loan quantity and rate changes in response to granular credit shocks. We restrict the sample to firms with multiple bank relationships, and ask if banks that experience bad granular credit outcomes reduce credit supply or increase prices. The within-firm analysis allows us to control for demand side effects using time-varying firm fixed effects, thus isolating the supply side. We find strong evidence, both in terms of quantity and price effects, that banks pass on granular credit shocks to their *non-granular* clients, i.e. firms with a loan share that is less than a certain thresh-

[6]The concave relationship is reassuring to us for the simple reason that it reflects the basic payoff structure of the debt contract. While there is no upside for the lender from borrowers experiencing positive value-added shocks, the downside is capped only by the principal of the loan, not counting default-related costs, be they pecuniary or not. Apart from the intuitive economic interpretation, we also view our finding of strong asymmetric effects as an important sign of validation that our measure of idiosyncratic shocks is indeed economically informative.

old (such as the median) in the pooled distribution of all credit shares[7]. We show that a one-standard-deviation bank-level granular credit shock reduces loan supply and increases interest rates by as much as 71.7 and 63.4 basis points, respectively. This identifies a leftward shift of the credit supply curve: quantities fall while prices rise. There are "granular credit risk spillovers": firms are affected by granular shocks of others via their bank.

We then ask whether affected non-granular firms experience negative real economic outcomes. We find that affected non-granular firms cut investment. Moreover, these firms experience elevated bankruptcy rates for up to 3 years after the initial shock. A one-standard deviation negative granular credit supply shock increases the likelihood of bankruptcy by roughly 32-60 basis points for all firms, and 68-98 basis points for non-granular borrowers. Granular credit risk has therefore sizable implications for the aggregate economy.

An important question is whether banks hedge granular risk with alternative sources of income. For example, in states of the world where credit income is low derivative income could be high. We collect detailed bank-level data on non-interest income and find that none of the measures we have correlate with GIV-instrumented firm shocks. We see no correlation between our shock measures and fees income, equity and bond appreciations, dividend income, or derivatives income. Another issue is that banks could potentially pre-insure against granular borrower shocks by charging higher markups for risky clients. But when extracting value-added shocks we control for firm size, liquidity, credit ratings, leverage and time-invariant factors. From the bank's perspective, unless markups are stochastic for some very unique reason, any firm shock comes therefore as a surprise relative to the firm's average performance and its creditworthiness, both of which would in turn be very highly correlated with the loan contract's price.

Finally, we supplement our empirical analysis by providing a theoretical motivation. We introduce parsimoniously bank credit into the canonical framework of Gabaix (2011). We model firm borrowing needs as a power function of firm size, which in turn is drawn from a power law density. Under this assumption, the distribution of bank loans (or, equivalently, firm borrowing) follows the Singh-Maddala (SM) family of densities (Singh and Maddala, 1976). The SM distribution has been used extensively to model wealth and income inequality. Our main contribution is the derivation of sufficient statistics-based parameter restrictions under which the bank loan distribution also has a fat tail. If that is the case, then shocks to large borrowers may survive aggregation and impact bank-level portfolio outcomes. Using our dataset, we provide maximum likelihood estimates of the sufficient statistics and

[7]The tendency to pass along adverse portfolio shocks to smaller clients is not uncommon for banks. In a recent paper, Greenwald et al. (2020) show that banks that experience larger credit line drawdowns restrict lending to firms that borrow through term loans - a negative spillover effect on smaller borrowers.

confirm that all the restrictions are satisfied on average.

Literature Review Our paper relates to several literatures. First, it builds on the rapidly growing literature on the "granular hypothesis" and its applications. Some of the more salient contributions across fields range from papers on business cycles (Carvalho and Gabaix, 2013), to trade (Gaubert and Itskhoki, 2018), international finance (di Giovanni et al., 2018), asset management (Choi et al., 2017), and banking (Amiti and Weinstein, 2018; Bremus et al., 2018). The latter strand focuses on how idiosyncratic bank *supply* shocks can have aggregate real implications whereas we focus on the transmission of shocks to (large) borrowers onto banks and the real economy. This paper's contribution is to show the existence of important granular credit risk spillovers on the economy.

Second, we relate to the literature studying the trade-off between credit concentration and diversification. On one hand, diversification enhances credit monitoring and information provision capacity (Diamond, 1984; Boyd and Prescott, 1986). On the other hand, some empirical studies found a positive correlation between portfolio concentration, returns, and monitoring efficiency (Acharya et al., 2006). Beck et al. (2017) have shown that bank specialization and concentration potentially have positive implications for systemic financial stability. Our paper contributes to this debate in at least two ways. We argue that as long as the distribution of credit shares features a fat tail, banks remain exposed to idiosyncratic shocks to their (granular) borrowers. Everything else equal, this is detrimental for financial stability. Because we find that banks pass on granular credit shocks to the real economy, credit concentration induces negative economic outcomes on average, *ceteris paribus*. But a normative interpretation of our results depends on the precise theories generating loan concentrations in the first place, an issue we discuss further in Section 6.

There is an emerging new literature on credit concentration that, like us, takes advantage of detailed microeconomic data. In a recent study, Agarwal et al. (2020) find that Mexican banks that specialized in energy lending around the 2014 collapse of energy prices amplified the sectoral shock to the rest of the real economy. Paravisini et al. (2020) find that persistent bank market-specific specialization can explain a significantly larger fraction of within-firm variation in credit than actual bank supply shocks. Goetz et al. (2016) show that geographic diversification by banks has no impact on average loan quality and is associated with a reduction of exposure to local idiosyncratic risks. Finally, Huremovic et al. (2020) and Dewachter et al. (2020) study the role of production networks in Spain and Belgium, respectively, for the propagation of bank shocks[8]. Our paper differs from this literature be-

[8]We do not have information on production linkages in our data so we cannot explore this potentially complementary channel of propagation.

cause we work explicitly with *single-name* concentration risk, while most of the literature deals with either sectoral or geographical specialization. In addition, we emphasize both empirically and theoretically the importance of granularity of the loan share distribution for the pass-through of idiosyncratic shocks to the aggregate bank portfolio[9].

The remainder of the paper is structured as follows. Section 2 provides a description of our data. Section 3 describes the different stages of our empirical approach. Section 4 reports the main empirical results. Section 5 explores heterogeneity at different levels of aggregation and reports results from various robustness checks. Section 6 discusses the assumptions we make in our empirical approach and the implications of our findings. Section 7 lays out our theoretical motivation. Finally, section 8 concludes.

2 Data

Our empirical investigation is based on a unique dataset assembled from three major sources: administrative data from the Norwegian Tax Authority, credit rating agency data from Bisnode and supervisory data from ORBOF. They were merged using the unique identifiers for banks and firms. The Norwegian Tax Authority data is a high-quality matched firm-bank administrative register. The unit of observation in this database is an individual loan and the frequency is annual. For every loan, we observe the firm-bank identifiers as well as the flow of interest paid during the year and the end-of-year stock of debt. Because the data is collected and maintained by the tax authority as a basis for corporate taxation, the variables are essentially measurement error-free.[10] The data set covers all limited liability companies for the time period of 2003-2015, which accounts for roughly 90% of private sector employment for most years. We aggregate all loans into a single annual firm-bank "relationship" unit. The terms loan and relationship are used interchangeably, and refer to the sum of loans and interests paid across all individual loans between a bank and a firm.

A key measure in our analysis is the return on a loan, or a credit relationship (RoL). This is not directly observed, and hence we impute it. Specifically, we observe interest collected throughout year t (R_t) and the end-of-year stock of outstanding debt (D_t). We then define the RoL in year t as $R_t/(0.5D_{t-1} + 0.5D_t)$, which is equivalent to interest received relative to the average of debt outstanding at the beginning and end of the calendar year.

[9] Thus our paper provides an empirical basis for the work of Mendicino et al. (2019) who show in a quantitative model that if banks are not perfectly diversified, the interaction between borrowers' and banks' solvency has important effects on the probability and severity of crises.

[10] Provision of false tax information carries substantial legal, financial and reputational penalties. Additionally, the information about outstanding debt and interest paid is reported to the tax authority by the banks, and not the firms themselves.

We merge the loan-level data with detailed information on Norwegian firms and banks. Our firm data comes from the credit rating agency Bisnode. In addition to information about the firms' credit rating scores and firm characteristics such as age, location and industry, the data set includes annual balance sheet and income statement items on all Norwegian firms for 1999-2019. The bank data is from a supervisory registry (ORBOF) and includes annual balance sheet and income statement information covering all Norwegian banks over 1987-2019. The data set also provides us with confidential information on non-interest income, including income from derivatives, equity and bond investment, dividends, and loan fees.

We perform several cleaning and truncation steps on the raw data. First, we drop observations that are clearly erroneous, such as cases of liquidity ratios being greater than 1. Second, following Foster et al. (2008) we truncate the distribution of cost-to-total-cost ratios for each cost type at the 10% and 90% in each industry and year. Cost types include wage bill, energy, material and other costs. This is important as firms could dump all their operational costs to a particular fiscal year in order to receive tax advantages, and what we would thus pick up are in fact endogenous outcomes rather than unanticipated performance shocks. Third, we truncate the extracted firm shock distribution at the 1% and 99% levels. All our main results at the loan and bank levels are quantitatively robust to alternative cleaning rules. Table 1 provides summary statistics for some of the key variables used in our analysis.

Table 1: **Descriptive Statistics**

Variable	Observations	Mean	Std. Dev	Min	Max
		Loans			
Interest Received	333289	196645.31	1620919.78	1.00	2.67e+08
Loan Amount Outstanding	333289	4035259.25	43884811.59	1.00	7.00e+09
Return on Loan	333289	9.01	8.92	0.00	100.00
		Firms			
Idiosyncratic Firm Shock	277707	0.02	0.27	-1.42	1.15
Sales (1000 NOK)	277707	26532.69	217768.69	0.00	33761000.00
Total Assets (1000 NOK)	277707	42361.08	1052017.18	2.00	1.20e+08
Wage Costs (1000 NOK)	277707	6827.88	65057.01	1.00	7098000.00
Material Costs (1000 NOK)	277707	11643.95	103640.10	0.00	15313000.00
Equity / Assets Ratio	277707	0.27	0.18	0.00	1.00
Liquidity Ratio	277707	0.16	0.17	0.00	1.00
Employees	277707	15.81	156.66	0.00	20781.00
Firm Age	277707	12.94	11.81	0.00	159.00
		Banks			
Return on Loans	1380	6.40	1.46	0.06	14.39
Size-weighted Firm Shock	1380	-0.02	0.11	-0.78	0.69
Granular IV	1380	-0.02	0.09	-0.76	0.46
Total Assets	1377	21130037.71	1.35e+08	92384.00	1.96e+09
Total Equity	1377	1491611.98	8512785.73	16139.00	1.51e+08
Assets / Equity Ratio	1377	10.90	3.20	1.32	41.48
Liquidity Ratio	1377	0.03	0.03	0.00	0.33
Number of Loans	1380	220.88	854.18	1.00	8940.00
Loan Herfindahl Index	1380	0.10	0.12	0.00	1.00
Share of 10% Largest Loans	1380	0.54	0.13	0.20	1.00
Share of 5 Largest Loans	1380	0.51	0.20	0.07	1.00
Deposits to Assets Ratio	1377	0.66	0.12	0.01	0.91
Financial Assets Ratio	1321	0.08	0.06	0.00	0.48

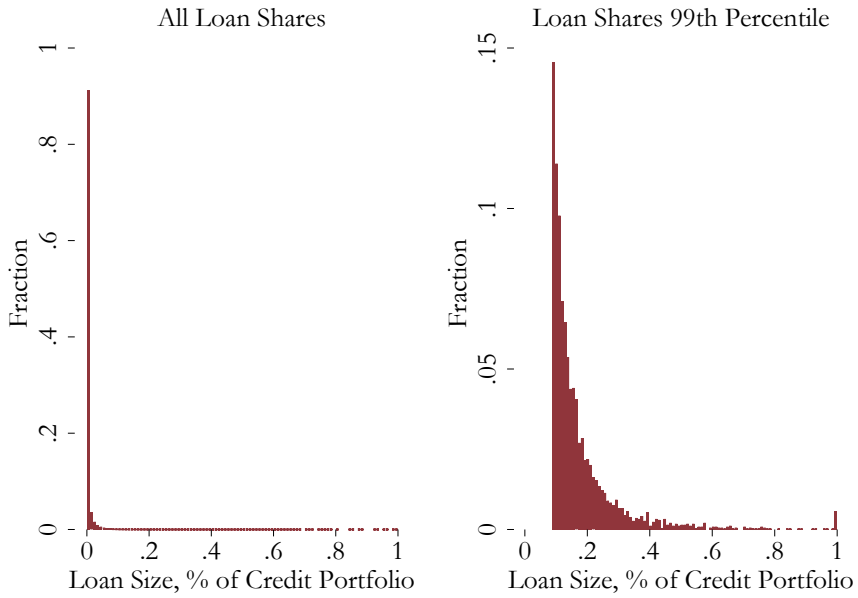
Notes: This table shows summary statistics of key loan, firm, and bank characteristics. All stock and earnings values are in thousands of Norwegian Kronas (NOK). 1 US Dollar = 9.45 NOK as of October 1, 2020. Firm shocks in panel 2 are estimated according to specification 1. Granular instrumental variable in panel 3 is constructed according to formula 6. Loan data is from the Norwegian Tax Authority. Firm data is from the credit rating agency Bisnode. Bank data is from the financial supervisory database ORBOF. Sample includes all bank loans to limited liability companies in Norway over 2003-2015.

3 Empirical strategy

3.1 Granularity of the Distribution of Loan Shares

We begin by establishing that the distribution of loans shares in our dataset is fat-tailed. In Figure 1 we plot the histogram of all loan shares, pooled across all banks and years over 2003-2015. Eyeballing the distribution is enough to notice its extreme skewness. More formally, we fit the Pareto I density to the data and estimate a Pareto rate of 1.15. Any estimate below 2 implies that idiosyncratic shocks to large loans potentially survive risk pooling and cause portfolio-level disturbances. This follows directly from the proofs in Gabaix (2011). Interestingly, our estimate of the Pareto power implies that 80% of all credit is concentrated in 20% of the loans. Thus the loan share distribution provides yet another example of the famous "80-20" Pareto principle that occurs in a variety of settings in economics as well as in many social and physical sciences applications (Gabaix, 2009). In section 7, we introduce a parsimonious model of bank credit into the canonical framework of Gabaix (2011). In our model, the fat tail of the firm size distribution feeds directly into the fat tail of the loan share distribution under certain parameter restrictions. We estimate the main parameters of the model using our data and confirm that those restrictions are on average satisfied.

Figure 1: **Distribution of Bank Loan Shares**



Notes: This graph presents the distribution of bank loan shares. The left picture plots the full distribution. The right picture zooms in on the 99th percentile of the shares. The share of each loan is computed as the ratio of a singular loan's amount to total corporate loans of a given bank in a given year. The figures plot the pooled shares for all banks and years. The Pareto rate of the 99th percentile is 1.16.

3.2 Estimates of Idiosyncratic Firm Shocks

The next step of our empirical approach consists of extracting idiosyncratic firm shocks, measured as unexplained idiosyncratic variation in firm value-added. Our approach follows closely a large number of studies in labor and macro economics that extract idiosyncratic sales or performance shocks. (Foster et al., 2008; Hsieh and Klenow, 2009; di Giovanni et al., 2014; Foster et al., 2017; Fagereng et al., 2018)[11]. To extract unexplained variation in firm value-added, we regress the log of firm value-added on a set of time-varying firm-level controls that includes measures of input usage and firm riskiness. Importantly, since our focus is on idiosyncratic variation, we remove common (across firms) components by controlling for the interaction of time, industry and county fixed effects. Finally, across-firm variation attributed to time-invariant firm characteristics is absorbed by firm fixed effects.

Formally, for a firm j, operating in an industry s from a county z in year t, we estimate

[11]Using idiosyncratic shocks as "instruments" for estimating microeconomic or macroeconomic elasticities is increasingly common in applied microeconomics and finance (see Leary and Roberts (2014), Amiti et al. (2019) and Gabaix and Koijen (2020a)).

the following regression:

$$\ln \mathrm{VA}_{j,t} = \alpha_{j,t,s(j),z(j)} + \beta_1 \ln \mathrm{K}_{j,t} + \beta_2 \ln \mathrm{W}_{j,t} + \lambda' \mathbf{X_{j,t}} + \epsilon_{j,t} \tag{1}$$

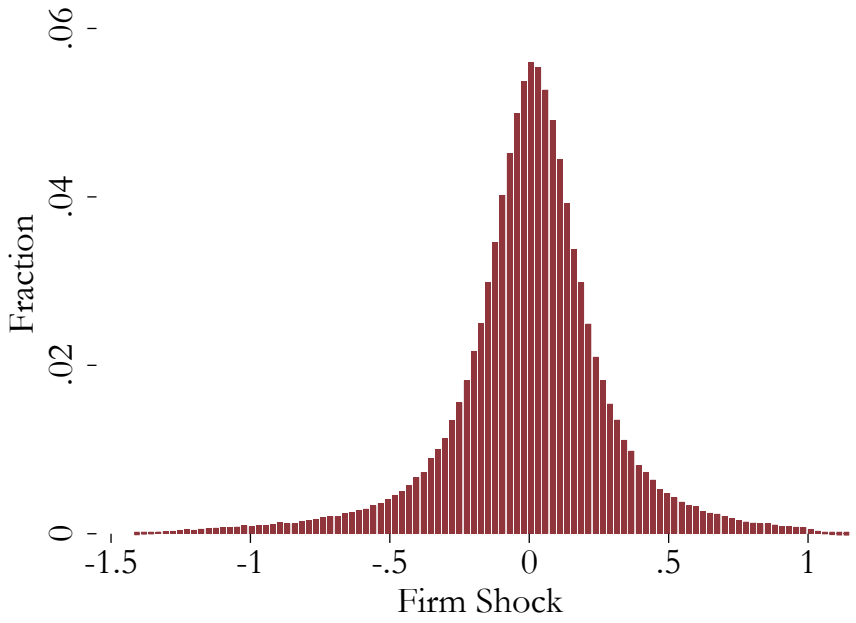
where VA stands for firm value-added[12], K represents book capital, W the wage bill, and X are other controls including leverage, liquidity, credit rating, and a quadratic polynomial in age. The term $\alpha_{(.)}$ captures a combination of fixed effects at the firm and industry $\times$ year $\times$ county levels. Here, K and W are proxies for capital and labor inputs, while X are various measures of firm riskiness. These factors should capture the banks' information set well. In addition to the specification in (1) we also consider a less conservative specification, which only includes fixed effects but not any of the other controls, in the spirit of di Giovanni et al. (2014).

The object of interest is the residual from this regression, $\epsilon_{j,t}$, which is the main right-hand side variable for the rest of the paper. Essentially, what we are capturing are unforeseen changes in firm performance that banks, despite observing multiple layers of data, could not have anticipated. Examples of such events include a factory collapse, labor union strike, operational risk issues, mismanagement, human errors, etc.[13] We trim the year-specific shock distributions at the 1% and 99% levels in order to mitigate the influence of outliers. Figure 2 plots the distribution pooled across all years. It is noticeably left-skewed, with a larger mass in the left tail.

[12] Value added is measured as sales minus material, energy, and other costs.

[13] A potentially important factor that is missing from this specification is market prices. The share of publicly traded firms in our data is, however, very small. Moreover, credit rating arguably captures the same information that would be embedded in the stock price (albeit updated far less regularly).

Figure 2: **Distribution of Idiosyncratic Firm Shocks**



Notes: This graph plots the pooled distribution of idiosyncratic firm shocks estimated from equation (1).

In order to check that our extracted shock indeed captures non-predictable idiosyncratic movements in firm performance, we conduct a series of robustness tests. First, we confirm that the shock series is not correlated across firms. Second, for each main regression specification at either the loan- or bank-level we also run a series of placebo regressions. We return to these robustness checks in Section 5.

3.3 Loan Outcomes

To identify the impact of idiosyncratic firms shocks on loan-level returns, we exploit the granular nature of our dataset. Individual bank-firm relationships enable us to control for time-varying bank supply factors, such as risk aversion or monitoring skills, by including bank $\times$ year fixed effects. Bank supply factors could confound our demand-side shocks[14]. We also control for interacted county $\times$ year $\times$ industry fixed effects. This specification implies that the impact of shocks is identified by comparing loan-level returns across firms in the same county, industry, year, who are borrowing from the *same* bank. For some firm-bank relationships in our dataset we also observe the fraction of total loan volume that comes

[14]Coimbra and Rey (2019), among others, show that heterogeneity in risk appetite among financial intermediaries is a determining factor for financial and business cycles. Our fixed effects specification takes care of this issue.

from credit lines. This allows us to also consider specifications which include a loan type fixed effect[15]. Formally, we estimate the following specification:

$$R_{i,j,t} = \alpha_{i,t,s(j),z(j),l(i,j)} + \beta\epsilon_{j,t} + \nu_{i,j,t} \tag{2}$$

where i is a bank that lends to firm j from county z, industry s, year t via loan type l. R_{ijt} is the loan-level return and ϵ_{jt} is the estimated firm-level shock from our first step. Because the main RHS variable is *estimated*, our standard errors are corrected for the estimated regressor bias via bootstrapping. Importantly, our specification features a wide range of fixed effects captured by the term $\alpha_{(.)}$. Specifically, in our most conservative specification we include the full interaction of bank $\times$ year $\times$ firm industry $\times$ firm county $\times$ loan type fixed effects.

3.4 Granular Credit Risk: Bank outcomes

After investigating how idiosyncratic firm shocks affect loan returns, we then move up to the level of the bank portfolio. We aggregate the realized idiosyncratic firm shocks to the bank level by weighing the shocks with loan shares and refer to the resulting measure as "granular credit risk". Intuitively, granular credit risk captures shocks to banks' clients that eventually do not average out and instead impact portfolio-level outcomes.

To evaluate the bank-level impact, we proceed by analyzing the following relationship between bank-level returns on all corporate loans $R^b_{i,t}$ and firm shocks for bank i at year t:

$$R^b_{i,t} = \alpha_i + \alpha_t + \beta\bar{\epsilon}_{i,t} + \nu_{i,t} \tag{3}$$

where α_i and α_t denote bank and time fixed effects, $\bar{\epsilon}_{i,t} = \sum_{j\in J_i} s_{i,j,t}\epsilon_{j,t}$ are bank-level firm shocks that are weighted by loan shares $s_{i,j,t}$, and $\nu_{i,t}$ the error term. The portfolio loan return $R^b_{i,t}$ is computed as the loan-share weighted average of loan level returns.

There is one key identification challenge associated with the naive specification above. Our loan-level analysis exploited within-bank-year variation to control for confounding credit supply shocks. This is no longer possible when we turn our focus to outcomes at the bank level. Consider a generic time t relationship of bank outcome $y_{i,t}$, bank-time supply factor $\eta_{i,t}$, and demand-side idiosyncratic firm disturbance $\epsilon_{i,j,t}$:

$$y_{i,t} = \beta \sum_j s_{i,j,t}\epsilon_{i,j,t} + \alpha_i\eta_{i,t} \tag{4}$$

[15] A firm-bank relationship is classified as a credit line loan in year t if more than 50 percent of total credit comes from credit lines.

where $s_{i,j,t}$ measures the normalized exposure of bank i to firm j ($\sum_j s_{i,j,t} = 1$). Regressing bank outcomes on the demand-side disturbance potentially results in a biased estimate of β if the unobserved bank-time factor is correlated with the demand-side disturbance.

In order to alleviate this concern, we adopt a newly proposed "granular instrumental variable" (Gabaix and Koijen, 2020a) approach. Specifically, we assume that the demand-side disturbance $\epsilon_{i,j,t}$ can be written as

$$\epsilon_{i,j,t} = \lambda_i \eta_{i,t} + u_{i,j,t} \tag{5}$$

where λ_i is the loading on the bank supply factor.

The granular instrumental variable ("GIV") is the time-varying difference between the size(exposure)-weighted firm shocks and the equally-weighted firm shocks aggregated to the level of each bank. This way, the bank-time supply-side factor $\eta_{i,t}$, which is potentially correlated with firm disturbances is purged out. The GIV is formally constructed in the following way:

$$GIV_{i,t} = \sum_j s_{i,j,t}\epsilon_{i,j,t} - \sum_j \frac{1}{N_i}\epsilon_{i,j,t} = \sum_j s_{i,j,t}u_{i,j,t} - \sum_j \frac{1}{N_i}u_{i,j,t} \tag{6}$$

where N_i denotes the number of firm exposures of a given bank i. We now replace our naive specification in Equation 3 with the following regression:

$$R^b_{i,t} = \alpha_i + \alpha_t + \beta \hat{u}_{i,t} + \nu_{it} \tag{7}$$

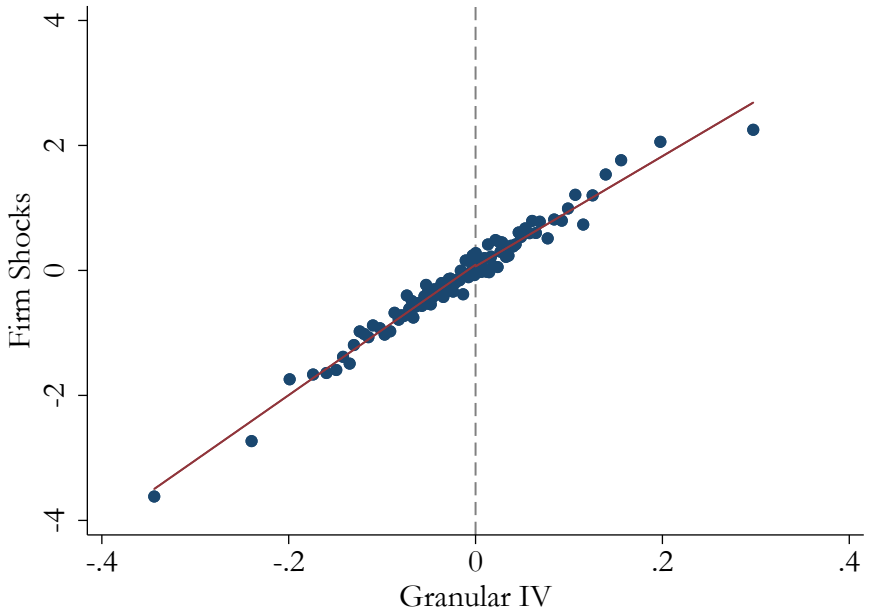
where $\hat{u}_{i,t}$ is the fitted value from the "first-stage" regression of the endogenous covariate $\bar{\epsilon}_{i,t}$ on the granular instrument $GIV_{i,t}$. This way, all variation in $\bar{\epsilon}_{i,t}$ is driven by fluctuations originating from the "granular borrowers", i.e. those with a large credit share. Naturally, if there are no granular borrowers, this approach does not work as there is no variation in the instrument. But as we have seen from Figure 1, the distribution of loan shares is very skewed. The main identifying assumption of this empirical approach is the following condition:

$$\sum_j^N \mathbb{E}\left[s_{i,j,t}u_{i,j,t}\nu_{i,t}\right] = 0 \tag{8}$$

for all i and t.

In words, identification is achieved if the shocks $s_{i,j,t}u_{i,j,t}$ are orthogonal to the error-term in the bank-level regressions. This is the "exclusion" assumption. The main concern is that loan shares could be endogenous, i.e. correlated with firm shocks. This is not a problem

Figure 3: **First Stage - Firm Shocks and the Granular IV**



Notes: This figure plots the relationship between the endogenous covariate $\bar{\epsilon}_{i,t}$ and the instrument, $GIV_{i,t}$. On the vertical axis we have the idiosyncratic firm shock which is loan size-weighted and aggregated to the level of a bank. Idiosyncratic firm shocks are extracted from specification 1. The granular instrument (horizontal axis) is constructed based on Equation 6. Correlation between the two variables is 0.863.

for us for several reasons. First, credit demand in absolute terms correlates with firm size. Given how we extract idiosyncratic value-added shocks (i.e. controlling for size), our shock series is mechanically orthogonal to firm size. Similar logic applies to other firm factors such as leverage, liquidity, credit rating or age. Second, as a proxy for contemporaneous loan shares, our loan share measure is computed using average debt between periods t and t-1. This mitigates any contemporaneity concerns. Finally, loan shares and firm shocks are reassuringly uncorrelated in our sample[16].

To confirm the validity of the instrument, in Figure 3 we plot the relationship between the GIV and the raw endogenous covariate $\bar{\epsilon}_{i,t}$. There is a strong, positive relationship between the two variables with a Pearson correlation of 0.863.

3.5 Granular Credit Risk Spillovers: Credit Supply and Firms

In order to study the economic consequences of granular credit risk, we investigate the relationship between bank-level aggregated firm shocks and the credit supply. We follow a

[16]The raw correlation between loan shares and firm shocks in our sample is –0.02. The correlation is computed for each bank, and we report the average across banks.

large literature in banking relying on the methodology in Khwaja and Mian (2008). Specifically, we focus on a sub-sample of firms borrowing from multiple banks and compare - for the same firm - quantity and rate outcomes from banks that experienced good or bad granular credit shocks. We test whether banks pass on shocks originating from their granular borrowers to the rest of their credit portfolio (non-granular borrowers). We define non-granular borrowers as firms whose loan share is below a certain threshold (such as the 50%th or the 25%th percentile) of the loan share distribution. In response to negative shocks due to granular clients, the bank may have to scale back their relationship with non-granular borrowers, alter the pricing of the loans or both.

We run the following regressions on yearly changes:

$$\Delta y_{i,j,t} = \alpha_i + \alpha_{j,t,s(j),z(j)} + \beta \Delta \hat{u}_{i,t} + \nu_{i,j,t} \tag{9}$$

where $\Delta \hat{u}_{i,t}$ is the fitted value from the "first-stage" regression of the endogenous bank level shock $\Delta \bar{\epsilon}_{i,t}$ on the granular instrument $\Delta GIV_{i,t}$, $\alpha_{j,t,s(j),z(j)}$ is a firm x year x industry x county fixed effect and α_i is a bank fixed effect. $\Delta y_{i,j,t}$ is either loan volumes or interest flows. The regression is run either on firms with a loan share below the 50^{th} or 25^{th} percentile of the loan share distribution.

After investigating loan-level responses, we aggregate our data to the firm level and test whether there are any spillover effects from granular credit shocks to firm balance sheet aggregates such as investment or cash balances. We also look at the impact of granular credit risk on firm bankruptcies, contemporaneously or with a lag. We run the following firm-level regressions:

$$\Delta y_{j,t} = \alpha_{s,z,t} + \beta \Delta \hat{u}_{j,t} + \nu_{j,t} \tag{10}$$

with similar notations as above. $\Delta y_{j,t}$ are now firm level outcomes such as (changes in) capital, sales, wage bill, cash as well as probability of bankruptcy (in levels). Essentially, in these spillover regressions the bank $\times$ year series of GIV-instrumented firm shocks is treated as a typical liquidity shock to the intermediaries' balance sheet, which is then passed on to the rest of the economy as a supply-side disturbance. The difference between our paper and the rest of the literature is that the origin of this bank-side liquidity risk is (uninsurable) idiosyncratic risk from large, granular borrowers[17].

[17] We test the insurability of granular credit risk in Section 4.3.

Table 2: **Loan Outcomes**

	(1)	(2)	(3)	(4)	(5)
	Dependent Variable: Return on Loan (RoL)				
Firm Shock	0.134	0.146	0.334	0.335	0.361
	(0.012)	(0.012)	(0.016)	(0.017)	(0.018)
Bank x Industry x Year FE	No	No	No	Yes	No
Bank x Industry x Year x Loan-type x County FE	No	Yes	No	No	Yes
Additional controls	No	No	Yes	Yes	Yes
Number of Observations	479754	434662	333289	317186	292825
R^2	0.000	0.195	0.001	0.114	0.167
$\mathbb{E}$(RoL)	7.988%	7.975%	9.012%	9.029%	9.098%
SD(RoL)	7.993%	7.928%	8.921%	8.928%	8.923%

Notes: This table reports results from the regression of loan-level returns on loans on idiosyncratic firm shocks. The exact specification is described by Equation 2. Columns (1)-(2) are based on firm shocks from specifications where (log) value-added is regressed only on a set of firm and county×industry×year×loan type fixed effects. Columns (3)-(5) are based on firm shock specifications that include additional controls: total assets, wages, leverage, liquidity, credit rating, age, and age squared. The firm shock variable is normalized by its standard deviation. For example, 0.334 should be interpreted as an increase in the return on loans of 33.4 basis points in response to a 1 standard deviation idiosyncratic firm shock. Loan types include regular and credit-line loans. Counties are 19 administrative areas (*fylke*) in Norway. Industries are 99 2-digit sectors. Standard errors (in parentheses) are double clustered at the firm-year level and corrected for the estimated regressor bias with bootstrapping. The last two rows report the unconditional sample mean and standard deviation of the dependent variable.

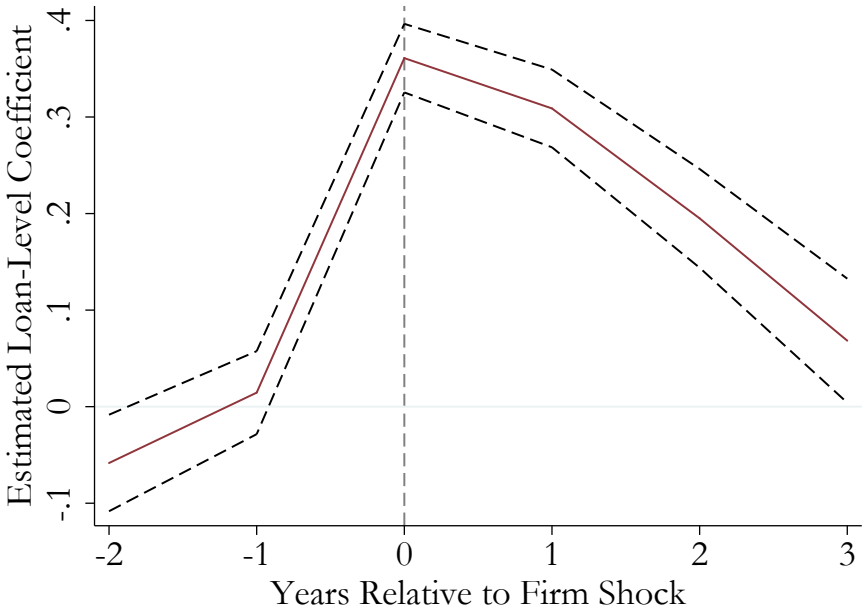
4 Main Empirical Results

We investigate how idiosyncratic firm value-added shocks affect loan returns in section 4.1. In section 4.2, we aggregate idiosyncratic firm shocks to the bank level, and see whether the effect is still significant despite portfolio-level risk pooling. In section 4.3 we ask whether granular credit risk goes unhedged at the bank level. In section 4.4, we investigate potential spillover effects from granular credit risk onto other firms and their real economic consequences.

4.1 Loan Outcomes

Table 2 presents the effect of idiosyncratic firm shocks on loan returns obtained from estimating Equation 2. Idiosyncratic firm shocks have a large and significant (at the 1% level) effect on loan-level returns. In columns (1)-(2) we proxy the firm shock by the residual of firm value-added variation after controlling for fixed effects only (as in di Giovanni et al.

Figure 4: **Loan Outcomes by Horizon**



Notes: This graph plots results in the form of an event study where we regress loan-level returns on leads and lags of the idiosyncratic firm shock. Coefficients are plotted by horizon (in years) of the dependent variable. Specifications are based on Equation 2. Firm shocks are estimated based on specification 1. Dashed lines are 95% confidence bands.

(2014)).[18] In columns (3)-(5) the shock is measured by the residual obtained from estimating (1) and controlling for different combinations of fixed effects to purge out potential confounding factors. Our preferred specification is reported in column (5). Here, the firm shock captures fluctuations in firm value-added which are purged from fixed effects and orthogonal to a set of time-varying firm factors including leverage, liquidity, size, age, and credit rating. Firm shocks are standardized so the interpretation of the regression coefficients in the table is the following: a 1-standard-deviation firm shock affects returns by 36.1 basis points as in column (5). In words, when comparing a bank's loan return across firms within the same year, industry, county, and through the same loan facility, a 1 standard deviation reduction in firm performance reduces loan returns by roughly a third of a percentage point.

Figure 4 reports loan outcome estimates at different horizons: we regress loan returns on leads and lags (in years) around the firm shock ("event" at date 0) and plot the dynamic of the interval estimates over time. First, we observe that there is no effect for years prior to the shock, which points at the absence of any pre-trends. Second, the impact of idiosyn-

[18] This specification has no additional controls and extract firm-level value-added variation that is orthogonal to industry × county × time × loan type and firm fixed effects.

cratic firm shocks on loan outcomes is felt for a long time: at least for 3 years on average. We interpret this result through the lens of relationship-based lending. Termination of a credit relationship is costly, for either side, because of the presence of asymmetric information in credit markets. Even if a bad idiosyncratic outcome reveals new information about the borrower's "type", ex-post monitoring of the repeated borrower may still be a more cost-effective alternative than forming a new relationship (Williamson, 1987). Lenders may understand and internalize the adverse selection problem in the market for switching borrowers (Sharpe, 1990). Finally, the cost of asymmetric information may be bigger for smaller firms, which are also potentially more likely to experience a negative idiosyncratic shock and have more to gain from sticking to the original lender (Chodorow-Reich, 2014). In equilibrium, the lender agrees that the borrower postpones a fraction of the loan repayment to the future period. Our extensive margin analysis will later reveal that it is indeed the intensive margin, i.e. temporary non-performance and payment delay, which drives our loan-level results, and not necessarily firm exit.

4.2 Granular Credit Risk: Bank Outcomes

The finding that firm-level idiosyncratic shocks impact loan returns merely reflects the fact that individual loans are inherently risky investments. There is no margin of adjustment for the bank to insure against loan-level bad outcomes. The natural next question is whether these idiosyncratic shocks average out at the level of bank *portfolios*. In other words, can/do banks take advantage of risk pooling and diversify idiosyncratic firm risk away? To answer this question we proceed by estimating the relationship in (7). Results are reported in Table 3, where we have normalized the bank shock by its standard deviation.

Table 3: **Bank Outcomes**

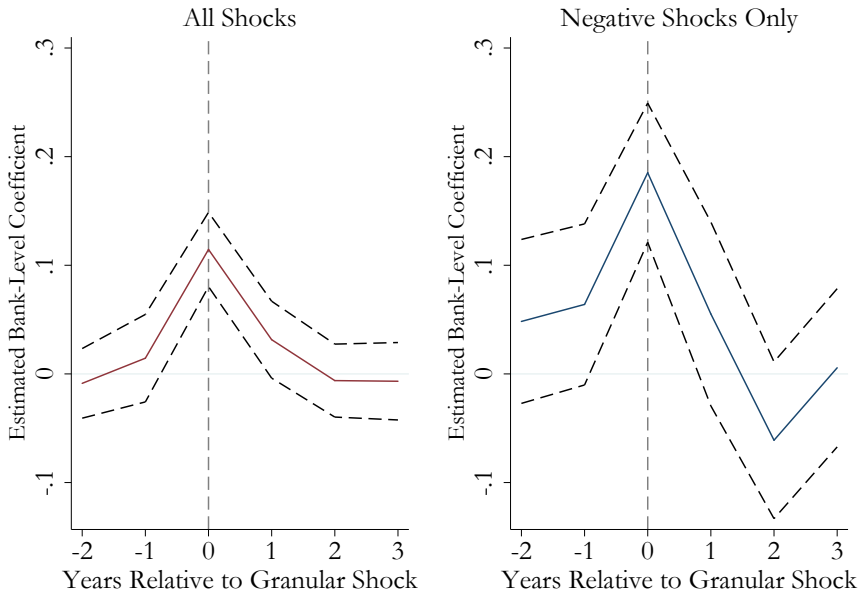
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent Variable: Bank Return on Loans (RoA)							
	OLS		Instrumented with GIV					
	Pooled	Pooled	Pooled	Positive	Negative	Pooled	Positive	Negative
Granular Credit Shock	0.129	0.136	0.116	0.016	0.194	0.117	0.056	0.176
	(0.027)	(0.025)	(0.034)	(0.075)	(0.068)	(0.029)	(0.067)	(0.065)
First stage F-stat			1429.683	138.772	396.907	1137.722	150.136	263.982
J-statistic			0	0	0	0	0	0
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Controls	No	Yes	No	No	No	Yes	Yes	Yes
Observations	1211	1211	1211	508	694	1211	508	694
R^2	0.752	0.770	0.599	0.646	0.569	0.627	0.683	0.592
$\mathbb{E}$(RoA)	6.350%	6.350%	6.350%	6.460%	6.289%	6.350%	6.460%	6.289%
Sd(RoA)	1.354	1.354	1.354	1.403	1.295	1.354	1.403	1.295

Notes: This table reports results from regressing bank-level return on loans on bank-level aggregated firm shocks $\bar{\epsilon}_{i,t}$. Columns (1)-(2) are standard OLS on Equation 3, while columns (3)-(8) instrument the aggregated shock by the granular IV as in Equation 7. The GIV is constructed following Equation 6. Positive (negative) shocks specifications include only observations in which the bank shock $\bar{\epsilon}_{i,t}$ is above (below) zero. Bank controls include lagged total assets, leverage, liquidity, number of loans, deposit to assets ratio and financial assets to assets ratio. The last two rows report the unconditional sample mean and standard deviation of the dependent variable. The F-stat is the Kleibergen-Paap rk Wald F statistic for the test of weak identification. J-stat is the Hansen's J-statistic for the instrument overidentification test. Standard errors (in parentheses) are clustered at the bank level and corrected for the estimated regressor bias with bootstrapping.

We report two sets of specifications: with and without the granular instrumental variable (GIV). In the first two columns (OLS estimates) we find that even at the level of banks' portfolios, idiosyncratic credit risk is associated with large and significant effects on bank returns. To address potential endogeneity concerns, columns (3)-(8) report results from the IV regression[19]. Our results show that a one standard deviation GIV-instrumented firm shock, on average, affects bank loan portfolio returns by 11-12bps. We have specifications with and without additional bank controls which include lagged values of bank leverage, liquidity, total assets, number of loans, deposit-to-asset ratio, and financial assets to total

[19]Formal statistical diagnostic tests show validity for the GIV as a good instrument. The first-stage F-statistic is above the Stock and Yogo (2005) criterion for 5% maximal relative bias. The Hansen J-statistic cannot reject the null hypothesis of the instrument being exogenous.

Figure 5: **Bank Outcomes by Horizon**



Notes: This figure plots results in the form of an event study where we regress bank-level returns on leads and lags of the bank-level aggregated firm shock $\bar{\epsilon}_{i,t}$ instrumented by the granular IV. Specifications are based on Equation 7. The GIV is constructed following Equation 6. The left panel includes all shocks, and the right panel includes negative shocks only ($\bar{\epsilon}_{i,t} < 0$). Coefficients are plotted by horizon (in years) of the dependent variable. Dashed lines are 95% confidence bands.

asset ratio[20]. The results are qualitatively and quantitatively robust to the exclusion of these controls[21]. In Figure 5 we report bank loan outcomes by horizon. We find that the impact of GIV-instrumented firm shocks on bank RoA lasts for up to 1 year, i.e. a shock at t has a significant effect on returns even at t+1. In addition, the effects of lags are not significant implying the absence of any pre-trends.

[20]The GIV approach theoretically does not require to include any further bank-time controls. The reason is that GIV is by construction purged from any common bank-time factors. For robustness, we still include bank controls. Interestingly, results do not change in any substantial matter, which further adds validity to the method.

[21]Bank-level return on corporate loans is the main dependent variable in this section. We have also experimented with loan writedowns and portfolio-level Sharpe ratios. Table 4 reports the results. We find some evidence that granular credit risk is weakly associated with both with the expected sign when we use the GIV instrument.

Table 4: **Bank Loan Portfolio Writedowns and Sharpe Ratio**

	(1)	(2)	(3)	(4)
	Writedowns		Sharpe Ratio	
Granular Credit Shock	-0.014	-0.013	-0.007	0.015
	(0.009)	(0.011)	(0.028)	(0.019)
Bank FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes
Instrumented by GIV	No	Yes	No	Yes
Observations	1184	1184	1206	1206
R^2	0.937	0.073	0.383	0.008

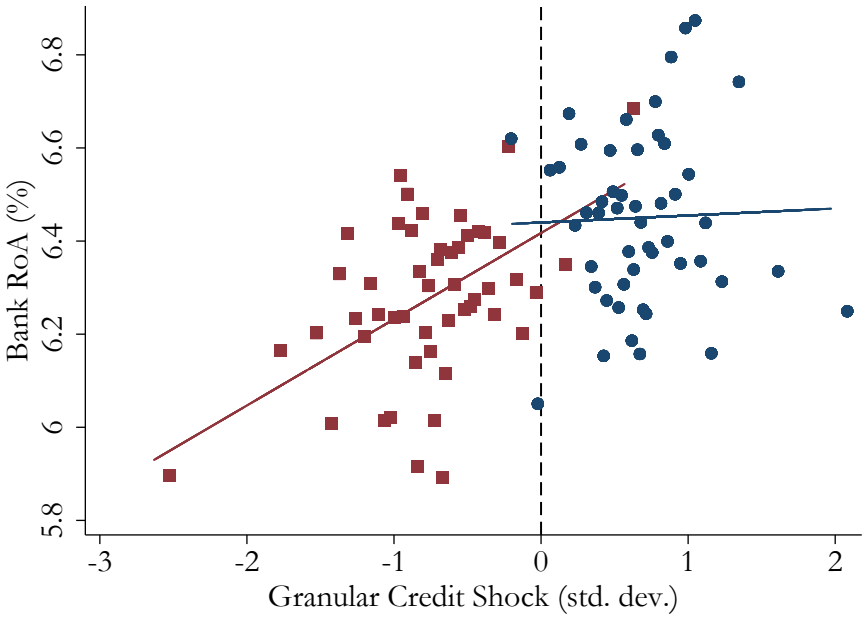
Notes: This table reports results from regressing bank-level (log) loan writedowns and the Sharpe ratio on bank-level aggregated firm shocks $\bar{\epsilon}_{i,t}$. Columns (1) and (3) are OLS on Equation 3, while in columns (2) and (4) the aggregated shocks are instrumented by the granular IV as in Equation 7. The GIV is constructed following Equation 6. Bank controls include lagged bank total assets, leverage, liquidity, number of loans, deposit to assets ratio and financial assets to assets ratio. Standard errors (in parentheses) are clustered at the bank level.

A second set of results is related to the asymmetric effects of granular firm risk. In columns (4)-(5) and (7)-(8) of Table 3 we explore positive- and negative-only firm shocks with and without bank controls. Specifically, we condition on the endogenous covariate $\bar{\epsilon}_{i,t}$ in Equation 3 being positive or negative only, and instrument it by the GIV. Only negative shocks have a significant impact on bank returns. The impact of positive shocks is not statistically significantly different from zero. A one standard deviation negative granular firm shock lowers bank returns by up to 19.4bps, which is much larger than the average effect and amounts to roughly 15% percent of the standard deviation of banks' portfolio returns. Due to the payoff structure of the debt contract this very concave relationship is not surprising. Because of debt contracts, banks find it difficult to extract higher dividends from firms that are performing well, while at the same time remaining exposed to potential downside risk from firms that perform poorly. In case of a negative shock, the firm's loan may become nonperforming, the firm may default on the obligation, or exit the industry altogether[22].

Figure 6 provides a visual representation of the concave relationship. The figure depicts the (binned) scatter plot of the impact of GIV-instrumented firm shocks on banks' returns on loans (RoA). Blue circles (red squares) represent positive and negative shocks, respec-

[22]We explore the extensive margin in detail in Section 5.1.

Figure 6: **Granular Credit Risk and Bank Outcomes**



Notes: This figure visualises the relationship between residualized bank-level return on loans and residualized instrumented bank-level aggregated firm shocks. The red squares (blue circles) are binned scatterplots conditional on negative (positive) values of the weighted firm shock $\bar{\epsilon}_{i,t}$. The shock variable is normalized by its standard deviation. We construct the conditional binned scatterplot in three steps, and each step is performed separately on positive and negative values of $\bar{\epsilon}_{i,t}$. First, we residualize bank-level returns on loans and instrumented firm shocks. The instrumented shocks represent fitted values from regressing $\bar{\epsilon}_{i,t}$ on the GIV. The residualized return and shock values are obtained from regressing each variable on bank and time fixed effects, computing the residual, and adding back the mean of each variable. Second, we construct 50 equally-sized bins based on the residualized shock. Third, we plot the mean residual bank return within each bin versus the bin's mean residual shock. The red (blue) line represents the linear fit from regressing the bank-level loan return on the instrumented shock, conditional on $\bar{\epsilon}_{i,t} < 0 (> 0)$.

tively. We construct the binned scatter plots by first regressing both bank RoA and the GIV-instrumented firm shocks on bank and time FE, computing the residuals, and adding back the mean of each variable. We then construct 50 equally-sized bins of the residual shock variable. Figure 6 plots the mean residual bank RoA within each bin versus the bin's mean residual shock. Finally, we overlay the linear fits for the respective specifications. The asymmetry of the result is rather striking: the line of best fit for positive shocks is flat, while the slope for negative shocks is downward-sloping and highly significant. The bins are all equally-sized, so each dot represents 10+ underlying bank $\times$ time observations. Our results are thus not driven by any individual outliers. We interpret the concave relationship as a validation that our measure of firm shocks is indeed economically informative.

Table 5: **Hedging Granular Credit Risk**

	(1)	(2)	(3)	(4)	(5)
Dependent Variable: Δ Income from	Fees	Derivatives	Equity	Bonds	Dividends
			Pooled		
Granular Credit Shock	0.219	-0.658	-1.323	0.163	0.173
	(0.131)	(1.214)	(1.477)	(0.140)	(0.631)
Bank FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	1211	344	1058	1197	1174
R^2	0.010	0.049	0.011	0.013	0.046
			Negative Shocks Only		
Granular Credit Shock	0.330	-0.133	-3.420	0.461	-0.209
	(0.236)	(2.944)	(5.466)	(0.470)	(0.170)
Bank FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	697	197	606	690	680
R^2	0.021	0.037	0.023	0.021	0.164

Notes: This table reports results from regressing bank-level year-on-year growth rate in non-interest income components on bank-level aggregated firm shocks, instrumented by the granular IV. The top panel presents results for all shocks, positive or negative. The bottom panel presents results for negative shocks only ($\bar{\epsilon}_{i,t} < 0$). The granular IV is constructed based on Equation 6. Standard errors (in parentheses) are clustered at the bank level. Data on all bank non-interest income is from the financial supervisory database ORBOF.

4.3 Hedging

We have so far established that idiosyncratic shocks to individual corporate clients affect bank portfolio returns. However, it is possible that financial intermediaries hedge granular credit risk with derivatives and other instruments. As a first pass attempt in answering this question, we collect bank-level data on income from fees, derivatives, equity and bond holdings, and dividends. We then correlate changes in returns from these sources with our GIV-instrumented shocks. The conjecture is that in the same state of the world in which banks are hit with bad idiosyncratic shocks to their loan books, returns are compensated through alternative departments within the same bank. For example, banks could command higher fees for late interest payments, hedge negative states with credit derivatives, short stocks of firms they are also lending to, etc. Table 5 reports the results.

As can be seen from the table, the data cannot consistently reject the null hypothesis of little to no insurance against granular credit risk. None of the measures of non-interest

income are significantly associated with our shock measure. If anything, some forms of income are in fact *positively* correlated with idiosyncratic credit shocks, which questions their usefulness as a hedging instrument.

A drawback of this analysis is that the various hedging instruments analyzed in Table 5 are only observable at the bank level. A more detailed analysis would construct matched derivatives holdings at the level of individual credit relationships. This would increase the odds for banks to hedge *firm-specific* risk, something that we can not plausibly establish by looking at portfolio-level data. This would be possible only for a very small subset of large firms that are (a) listed and (b) have a liquid market for credit derivatives such as credit default swaps (CDS). The mass of such firms is small and the CDS market is not very liquid in Norway. Regardless, insurability of granular credit risk is an important question, to which we can give only a partial answer given the data constraints.

4.4 Granular Credit Risk Spillovers: Credit Supply and Firm Outcomes

The previous sections have documented that granular credit risk has quantitatively important effects on bank portfolio outcomes, and that this risk is unhedged. In this section, we ask whether banks hedge these shocks "ex-post", i.e. by passing it on to the rest of their corporate portfolio. We are interested to see whether banks react by reducing loan supply or raising interest rates, in particular for non-granular firms.

Table 6 reports our results on the supply of credit. Our approach follows closely Khwaja and Mian (2008). In all specifications we impose a stringent configuration of interacted firm $\times$ year $\times$ industry $\times$ county fixed effects. Our specifications regress year-on-year changes in the granular credit shock on year-on-year changes in loan-level credit supply. In columns (1)-(2), we look at the impact of bank-level granular credit shocks - either instrumented or not - on all firms and find no significant relationship. In columns (3)-(4) we restrict the sample to non-granular firms only. Non-granular firms are defined as those whose bank loan shares are below the 50^{th} (column (3)) or 25^{th} (column (4)) percentiles of the loan share distribution. For example, the median loan share is 0.000211 percent across all loans. We do find a statistically significant relationship in this case, particularly when the threshold for non-granular firms is the 25th percentile. In columns (5)-(6) we add a bank fixed effect to the baseline specification and results do not change substantially. Overall, a one-standard deviation decline in the granular credit shock reduces loan supply growth to non-granular borrowers by up to 71 basis points. This effect is strongly significant. These results are suggestive of a "pecking order" of credit relationships where banks keep credit relationships with their main clients unchanged but adjust lending conditions with their non-granular

Table 6: **Spillovers from Granular Credit Shocks: Credit Supply**

	(1)	(2)	(3)	(4)	(5)	(6)
Δ Bank Shock	0.023	0.022	0.165	0.625	0.168	0.717
	(0.043)	(0.043)	(0.129)	(0.288)	(0.136)	(0.311)
Year x Industry x County x Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	No	No	No	Yes	Yes
Non-Granular Firms (50%)	No	No	Yes	No	Yes	No
Non-Granular Firms (25%)	No	No	No	Yes	No	Yes
Instrumented by GIV	No	Yes	Yes	Yes	Yes	Yes
Observations	15279	15279	3449	348	3413	322
R^2	0.484					

Notes: This table reports results from regressing year-on-year changes in (log) bank debt at the bank-firm level on the year-on-year change in bank-level aggregated firm shocks which are either instrumented by the granular IV as in columns (2)-(6) or not, as in column (1). Specifications are based on Equation 9. The GIV is constructed based on Equation 6. Columns (1)-(2) include all firms. Columns (3)-(6) include only non-granular firms. Non-granular firms are defined as firms whose bank loan shares are less than the 50th (columns (3)-(4)) or the 25th (columns (5)-(6)) percentiles of the loan share distribution, which is pooled over all banks and years. The full distribution of loan shares is plotted on Figure 1. Standard errors (in parentheses) are double clustered at the bank and firm level.

borrowers in order to compensate for portfolio losses.

In Table 7 we repeat the same exercise but with interest flow as the left-hand-side variable. We find a strong negative relationship between year-on-year changes in granular credit risk and yearly growth in loan-level interest flows. We interpret these changes in flows as an effect on the loan interest rate. A one-standard deviation decline in the granular credit shock increases interest rate growth on loans to non-granular clients by up to 63.4 basis points. Taken together with the positive association with credit quantities, we have identified granular credit risk as a textbook supply-side disturbance: a negative granular credit shock results in a leftward shift in the supply schedule, leading to a reduction in quantities and elevation in credit market prices. In addition, the pass-through mechanism can also be interpreted as operating through a kind of bank credit supply network: two firms that may otherwise not be connected can impact each other's performance through their association with a common lender[23].

[23]We control for firm county and industry fixed effects as well as the bank fixed effects. We cannot fully rule out, however, that these firms are not also associated through a production network as we do not have the data on firm linkages to test that hypothesis.

Table 7: **Spillovers from Granular Credit Shocks: Interest Rates**

	(1)	(2)	(3)	(4)	(5)	(6)
Δ Bank Shock	-0.004	-0.017	-0.361	-0.341	-0.421	-0.634
	(0.064)	(0.066)	(0.189)	(0.417)	(0.190)	(0.448)
Year x Industry x County x Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	No	No	No	Yes	Yes
Non-Granular Firms (50%)	No	No	Yes	No	Yes	No
Non-Granular Firms (25%)	No	No	No	Yes	No	Yes
Instrumented by GIV	No	Yes	Yes	Yes	Yes	Yes
Observations	15279	15279	3449	348	3413	322
R^2	0.533					

Notes: This table reports results from regressing year-on-year changes in (log) interest flows at the bank-firm level on the year-on-year change in bank-level aggregated firm shocks, which are either instrumented by the granular IV (columns (2)-(6)) or not (column (1)). Specifications are based on Equation 9. The granular instrument is constructed based on Equation 6. Columns (1)-(2) includes all firms. Columns (3)-(6) include only non-granular firms. Non-granular firms are defined as firms whose bank loan shares are less than the 50th (columns (3)-(4)) or the 25th (columns (5)-(6)) percentiles of the loan share distribution, which is pooled over all banks and years. The full distribution of loan shares is plotted on Figure 1. Standard errors (in parentheses) are double clustered at the bank and firm level.

Next, we ask whether the impact on non-granular firms ultimately leads to significant economic consequences. We aggregate our data to the firm level and consider several firm outcomes as dependent variables. Those include growth in sales, the wage bill, capital and the cash position. In all of the specifications, we include year $\times$ industry $\times$ credit rating, as well as firm and bank fixed effects. In addition, we focus on the sample of non-granular firms where non-granular firms are defined as those whose bank loan shares are below the 50^{th} or 25^{th} percentile of the global distribution of loan shares. In other words, we trace out the economic consequences of a credit supply shock on the same non-granular firms that we show were impacted in Tables 6 and 7. Results are reported in Table 8.

Table 8: **Firm Outcomes from Granular Credit Shocks**

	(1) Capital	(2) Capital	(3) Capital	(4) Sales	(5) Wages	(6) Cash
ΔBank shock	0.040	0.241	0.129	0.001	0.007	0.142
	(0.030)	(0.095)	(0.251)	(0.031)	(0.040)	(0.146)
E(dependent variable)	-0.081	-0.095	-0.105	0.026	0.034	0.067
SD(dependent variable)	0.603	0.640	0.683	0.290	0.344	1.037
Year-industry-county FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Non-Granular Firms (50%)	No	Yes	No	Yes	Yes	Yes
Non-Granular Firms (25%)	No	No	Yes	No	No	No
Instrumented by GIV	Yes	Yes	Yes	Yes	Yes	Yes
Observations	90800	39861	15444	44547	45452	43994

Notes: This table reports results from firm-level regressions where the outcome variable is either firm-level year-on-year change in log(capital), log(sales), log(wage bill), or log(cash). The control variable is the year-on-year change in bank-level aggregated firm shocks which are instrumented by the granular IV. Specifications are based on Equation 10. The granular instrument is constructed based on Equation 6. Non-granular firms are defined as firms whose bank loan shares are less than the 50th or 25th percentile of the loan share distribution. For firms with multiple banking relationships, we define a firm as non-granular if the largest loan share of that firm across all credit relationships is less than the 50th or the 25th percentile of the loan share distribution. For these firms, the bank shock is computed as the average across all lending relationships. The full distribution of loan shares is plotted on Figure 1. All specifications include interacted year x industry x county fixed effects and firm fixed effects. Standard errors (in parentheses) are clustered at the firm level.

The most notable results are columns (2)-(3), where we document that a change in the granular credit shock at the bank level is positively associated with capital growth at the firm level for non-granular borrowers. This suggests that a one-standard deviation negative credit supply shock causes a decline in firms fixed capital investment growth by roughly 13-24 basis points. The impact on non-granular firms defined by the median loan share cut-off is strongly statistically significant. This result has immediate implications for the real macroeconomy. We also considered outcomes such as sales, the wage bill and the firms cash position. For these variables our coefficient estimates are imprecise, and in all of these cases we are unable to reject the null hypothesis.

Even if non-granular firms have relatively low loan shares, they constitute an important fraction of the economy. Specifically, non-granular firms that are defined by the median loan share cutoff account for at least 15% of total aggregate capital in the sample in any given year. Granular credit shocks therefore affect a sizable fraction of aggregate capital

Table 9: **Firm Bankruptcy from Granular Credit Shocks**

Probit Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Probability of bankruptcy$_t$							Ever bankrupt
ΔBankShock$_t$	-0.609	-0.680	-0.920					
	(0.110)	(0.196)	(0.316)					
ΔBankShock$_{t-1}$				-0.322	-0.965	-0.980		
				(0.123)	(0.203)	(0.345)		
ΔBankShock$_{t-3}$							-0.703	
							(0.239)	
ΔBankShock$_t$								-1.273
								(0.281)
Non-Granular Firms (50%)	No	Yes	No	No	Yes	No	Yes	Yes
Non-Granular Firms (25%)	No	No	Yes	No	No	Yes	No	No
Instrumented by GIV	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	61819	35965	18990	50897	29451	15220	16648	35965

Notes: This table reports results from firm probit regressions of likelihood of firm bankruptcy on the bank-level granular credit shock. In columns (1)-(7), the outcome variable is probability of contemporaneous firm bankruptcy. In column (8), the outcome variable is the probability that a firm ever goes bankrupt. In columns (1)-(3), the control variable is the contemporaneous mean (change in the) bank-level credit shock which is instrumented by the granular IV. In columns (4)-(7), the RHS variable is the GIV-instrumented bank-level credit shock lagged by either one or three years. Columns (1) and (4) are for all firms in sample. Remaining columns restrict the sample to non-granular firms only. Non-granular firms are defined as firms whose bank loan shares are less than the 50th or the 25th percentiles of the loan share distribution, which is pooled over all banks and years. For firms with multiple banking relationships, we define a firm as non-granular if the largest loan share of that firm across all credit relationships is less than the 50th or the 25th percentile of the loan share distribution. For these firms, the bank shock is computed as the average across all lending relationships. The full distribution of loan shares is plotted on Figure 1. Standard errors in parentheses. Firm bankruptcy information is from the credit rating agency Bisnode.

via credit spillovers. It is also important to emphasize that our estimates constitute a *lower bound* - we can not rule out further second- and third-order spillover effects to granular clients as well. Granular credit risk can therefore potentially affect an even larger fraction of aggregate investment through the broader credit supply network as well as through general equilibrium effects.

Finally, we investigate whether the reduction in credit not only affects firm balance sheet outcomes but ultimately firm default. We ask whether a change in the granular credit shock at the bank level is associated with a higher frequency of bankruptcies at the firm level. Table 9 reports the results from our baseline probit regressions. In column (1), we include all firms in the estimation sample. In column (2), we restrict the sample to non-granular firms only, with the threshold being the 50th percentile of the loan share distribution. For both specifications we find a strong negative association. For columns (4)-(6) and (7) we trace out the

impact of granular credit shocks in t-1 and t-3, respectively, on the probability of bankruptcy at t. In columns (3) and (6) we run the same regressions but restricting the sample to firms with a loan share below the 25^{th} percentile of the distribution. Finally, in column (8) we regress the probability of a firm filing for bankruptcy at any point over its existence in our dataset on its average granular credit shock. That is, we ask if firms that ever default also experience, on average, worse granular credit supply shocks from their lenders. Overall, across all 8 specifications, we find a very strong negative association between granular credit risk and firm bankruptcy probability. The impact is quantitatively very large - a one-standard deviation negative granular credit supply shock increases the likelihood of bankruptcy by roughly 32-60 basis points for all firms, and 68-127 basis points for non-granular borrowers. Additionally, we do find that firms that went bankrupt at some point in the sample are also those that experienced abnormally bad granular credit supply shocks. Our results have direct implications for the aggregate economy and consumer welfare, considering that firm bankruptcy proceedings are very costly in practice.

We conclude this section by reiterating our main findings. First, idiosyncratic firm shocks have a large, long-lasting and significant effect on loan-level returns. Second, these shocks survive portfolio aggregation and impact bank-level outcomes. Importantly, these shocks originate from granular, i.e. large, borrowers which is precisely the reason why they do not wash out. Third, banks do not hedge granular credit risk with income from non-loan businesses such as derivatives or equity investments. Fourth, there are considerable loan-level spillovers of granular credit shocks on non-granular borrowers: affected banks reduce loan supply and increase interest rates on their less important, non-granular clients. Fifth, those affected clients in turn reduce their investment in physical capital and are much more likely to file for bankruptcy. Overall, our results show that idiosyncratic shocks to granular borrowers have important implications for the broader financial and real economy. In the language of financial regulators, single-name credit concentration risk is quantitatively important.

5 Heterogeneity and Robustness

In this section, we first provide further evidence on the underlying mechanisms behind our findings. In 5.1 we focus on whether certain firms are more likely to transmit idiosyncratic firm performance shock to their banks, and in 5.2 whether certain banks are more exposed to granular credit risk. In 5.3 we conduct several important robustness checks.

5.1 Firm Heterogeneity

Loan Outcomes - Balance Sheet Heterogeneity We start by exploring heterogeneous effects of idiosyncratic firm shocks originating from firms with different characteristics. Specifically, we interact extracted shocks obtained from specification (2) with lagged firm characteristics. We are interested in how the transmission mechanism differs for firms with high leverage, low asset size, low equity, short average debt duration, high bank credit reliance, low credit rating, and young age. Each characteristic is thus a dummy which equals 1 for firms in that particular category of interest.

Figure A.1 in the Appendix illustrates the results. There is overall rich firm heterogeneity behind our loan-level outcomes. The pass-through of idiosyncratic firm shocks is particularly strong for firms with high leverage, low assets, short debt duration, high reliance on bank debt, lower-than-"A" credit ratings, and firms younger than 3 years. All these firms, relative to the average firm, are more likely to be more "risky" from the bank's perspective. Interestingly, we find that interactions with firm size and debt duration are statistically different from other characteristics. For macro-prudential purposes, these results offer a new dimension for regulation of concentration risk: banks which are heavily exposed to, for example, small, risky, young firms are at much greater risk of suffering from detrimental idiosyncratic credit shocks than intermediaries that lend to liquid and non-levered corporates.

Loan Outcomes - Extensive Margin Are our loan-level results driven by the intensive or the extensive margin? We are interested in seeing whether the transmission of idiosyncratic firm shocks is different among firms that enter/exit the industry or go bankrupt. Our strategy is to construct a dummy variable for each of the three groups of firms. For entrants, the dummy takes the value of unity in the year following the entry, while for leavers and bankrupt firms the variable equals unity in the year prior to the event. We also consider an "ever-bankrupt" dummy which takes the value of unity for firms that filed for bankruptcy at any point during the 2003-2015 period. The latter variable captures potentially some unobserved intangible characteristics such as poor management skills, which are common for unsuccessful firms but cannot credibly be inferred from balance sheet information.

Table A.1 in the Appendix reports the results. We see that the shock transmission mechanism is stronger (weaker) among firms which have just entered (about to exit) the industry. We do not find that the channel is stronger among firms which go bankrupt. Overall, the extensive margin is active but does not dominate our results. In other words, even conditional on firms being non-entrants, non-leavers, and not in bankruptcy, negative idiosyncratic shocks can cause lower bank returns. That implies that our results are driven mostly

by the intensive margin.

Loan Outcomes - Ownership and Industry Heterogeneity Next, we investigate whether our results are driven by firms with a particular ownership structure or industry affiliation. For example, is the shock transmission stronger among special financial vehicles or construction firms? In Appendix Table A.2 we report firm ownership heterogeneity results, along with our baseline estimates. We see clearly that our results reflect conventional privately owned firms and not state, community, or special financial vehicles. Privately owned firms dominate our sample by a wide margin.

Table A.3 explores heterogeneous effects by firm sector. Our baseline estimates are almost identical to results from manufacturing firms. Overall, there doesn't appear to be any abnormality across different industries; the real estate sector is the only one where pass-through appears to be smaller.

Loan Outcomes - Geographical Heterogeneity Are our loan-level results driven by idiosyncratic shocks to firms located in particular geographical regions of Norway? Figure A.2 in the Appendix plots a coloured map of Norway, where each of the 19 counties is colored with a different shade of blue. Darker regions represent a higher local pass-through coefficient of idiosyncratic firm shocks onto loan-level returns. Recall that our baseline average pass-through estimate at the loan level is 0.361. Based on the map we document two main results. First, there is interesting cross-regional heterogeneity in the estimates that is potentially worth exploring in future research. Second, this heterogeneity is not too drastic: county-wide averages are in the [0.19,0.44] range[24]. Finally, we see that our result is not driven solely by Oslo and neighboring counties but is in fact present throughout the country. We therefore conclude that our results are likely not driven by some unusual regional clustering of correlated idiosyncratic shocks.

5.2 Bank Heterogeneity

In this section, we explore whether different banks - conditional on the realization of the granular credit shock - are affected differentially. Our main focus is understanding whether portfolio concentration as a factor is important for the transmission of idiosyncratic firm shocks, or whether this factor can be absorbed by bank size (total assets) or the number of credit relationships that the bank has. Intuitively, idiosyncratic borrower shocks may impact only banks that are small in size or have a small number of loans: in both cases the

[24]The exception is the northernmost county, Finnmark, where we find a point estimate of -0.10. However, this county is also the least populated area of Norway.

bank's margin of adjustment in response to borrower shocks is relatively weaker[25]. Hence we explore whether the relationship between granular credit shocks and bank outcomes varies by bank size, the number of loans, or the loan portfolio Herfindahl index (HHI) - a commonly used measure of concentration.

In Appendix Tables A.4 and A.5 we focus sequentially on the role of the number of loans and bank size (total assets) in the transmission of granular credit shocks. In Table A.4, we find that idiosyncratic firm shocks affect portfolios regardless of the number of loans. In line with theory, point estimates for portfolios with few loans or with high concentration levels are relatively larger. Interestingly, in column (1) we find that the pass-through for banks with a large number of loans is still statistically significant. This result suggests that granular credit risk is not merely a "small N" problem. In column (2) we find that portfolios that are more concentrated, as measured by the loan HHI, are more susceptible to granular credit shocks. This observation is consistent with the granular hypothesis. In Table A.5, column (1), we find that the pass-through is strong for small banks with a limited impact on large institutions.

To conclude, we have shown that idiosyncratic borrower shocks have a stronger impact when bank portfolios are more concentrated. Consistent with existing theories, we do find stronger effects for banks that are small or have few loans. Granular credit risk does not appear to be absorbed by the number of credit relationships: the pass-trough is strong for banks with few *or* many loans. The impact is, however, muted for institutions with high total assets.

5.3 Robustness Checks

In this section, we provide several additional robustness checks. We show that our results are robust to excluding the Great Financial Crisis (GFC). We check that idiosyncratic firm shocks have a pairwise correlation of approximately zero. Finally, we conduct two placebo tests at various levels of aggregation to lend further support to our baseline results.

Robustness to GFC In order to investigate whether the relationship between granular credit risk and loan/bank outcomes is robust to the Great Financial Crisis, we redo our estimation focusing on years before or after the GFC. Appendix Table A.6 reports results. We highlight three main observations. First, our results do not vanish for either of the two sub-

[25]Theoretically we expect that as the number of loans in the portfolio falls, loan-specific shocks begin to matter more at the bank level. Furthermore, the literature has distinguished between small and large banks in terms of their capacity to transmit and withstand exogenous shocks (Davila and Walther, 2020; Stavrakeva, 2019)

periods. Second, this is true for both loan-level and bank-level estimations. Third, estimates are slightly noisier for the pre-GFC period, although still statistically significant.

Pairwise Correlations Test An important question that must be addressed is potential piece-wise correlation of our idiosyncratic firm shocks. Systematic residual correlation across firms may indicate that our shocks are still driven by common factors, which would invalidate our conjecture that fluctuations are truly idiosyncratic. For example, we could be capturing some unobserved network effects such as the ones induced by firm trade credit relationships. To test this, we compute pairwise correlation coefficients across any two pairs of firms in our sample. Appendix Figure A.3 presents the result. In total we have 1,794,321 pairs across a balanced panel of firms over 2003-2015. The average piecewise correlation is 0.019 and the standard deviation is 0.342. This implies that the average correlation coefficient can not be statistically distinguished from zero. This provides reassuring evidence in support of our idiosyncratic firm shocks being truly idiosyncratic and not being driven by unobserved factors that induce cross-sectional correlation, such as production networks.

Placebo Regressions To ensure that we do not falsely reject the null hypothesis due to potentially serially correlated error-terms, we follow Chetty et al. (2009) and implement a nonparametric permutation test for whether the true effect of idiosyncratic firm shocks on loan returns is zero. In order to do so, we randomly reassign the estimated firm-level shocks and redo the analysis at the loan and bank levels. Placebo Monte-Carlo permutations results are reported in Appendix Table A.7. We find that we can reject the null hypothesis of no association (at the 1% level) under this non-parametric distribution. In words, it's highly unlikely that our results are due to random chance. Furthermore, at the level of the bank, we confirm that our finding of strong asymmetric effects is not coincidental since the permuted positive-only shock estimate has a p-value of 68% while the negative-only shock estimate has a p-value of 0.008.

Further, to illustrate how our idiosyncratic shocks pick up economically meaningful information, we run a series of placebo regressions where firm shocks are randomly drawn from a uniform distribution instead of being extracted from the economic specification 1. The results from using these drawn shocks at the loan- and bank-level are reported in Appendix Table A.8. Across all specifications and levels of aggregation we find no association between the random shocks and loan returns.

Fitting an Fixed Effects Model with AR(1) Disturbance We run our firm shocks through an autoregressive linear model of order 1 in order to establish whether shocks are persis-

tent or not. We also want to facilitate future structural analysis of models with a financial sector that is subject to "idiosyncratic granular borrower risk". Specifically, we fit the full cross-section of firm shocks into a linear fixed effects model with an AR(1) disturbance term. Results are reported in Appendix Table A.9. Parameters of the process - autoregressive coefficient and the standard deviation of the error term - are reported for all levels of aggregation. Overall, we find that the idiosyncratic firm shock is volatile (standard deviation of roughly 0.2) and not persistent at all (auregressive coefficient of roughly 0.12-0.32). A volatile iid process is likely to approximate granular credit risk rather well.

6 Discussion

In this section, we discuss several issues relevant for our empirical analysis. First, we discuss the literature on firm and bank credit networks and its implications for our results and methodology. Second, we discuss the *origins* of large exposures.

6.1 Network Effects

A vibrant new literature emphasizes the role of bank and firm credit networks in the amplification and propagation of non-systematic shocks. One stream of the literature shows that bank credit supply shocks propagate along firm production networks, causing sizable real economic effects (Huremovic et al., 2020; Dewachter et al., 2020). We relate to this literature in two ways. First, in our analysis of economic spillovers, we essentially identify a *credit supply network*: there exists a pass-through mechanism for idiosyncratic borrower risk between two potentially unrelated firms that are "connected" via the balance sheet of their common lender. Second, a negative granular credit shock, passed onto non-granular borrowers via higher rates or lower quantities of credit, is a leftward shift of the credit supply curve and maps into the bank credit supply shocks in Huremovic et al. (2020) and Dewachter et al. (2020). We establish the first-degree direct effect of these shocks on firm performance and bankruptcy rates. However, because we do not observe the Norwegian input-output or firm trade-credit network, we can not speak of higher-degree effects from these networks. Thus, our analysis of economic spillovers of granular credit shocks in Section 4.4 establishes a *lower bound* on the total pass-through to the real economy.

Another stream of the literature such as Elliott et al. (2020) has recently shown that when banks are individually exposed to the same set of firm industries, idiosyncratic industry-specific risk gets amplified as opposed to getting mitigated by wholesale interbank trading markets. More broadly, mismeasured idiosyncratic *firm* disturbances could actually mas-

querade some unobserved/unmeasured borrower-side *network*-level risk. In the first stage of our analysis, it is possible that our measure of firm value-added shocks is in fact some kind of common local production network risk. This problem is mitigated considerably by the following three factors. First, when extracting firm value-added shocks, we impose a stringent combination of industry, location, and time fixed effects. Any unobserved network factor would have therefore to operate within the same year, industry, and county. Observations are sufficiently dispersed across geographical regions, with four out of 19 counties having more than 100,000 loan $\times$ year observations and the average being just over 50,000. In addition, our industry identifiers are very granular with only 3 out of the 99 two-digit industries having more than 100,000 loan $\times$ year observations. Second, we plotted in Figure A.3 the pairwise cross-sectional correlation of firm shocks and found no indication of common shocks. Third, the presence of local production network effects would not invalidate our GIV approach. As long as the sequence of idisoyncratic shocks is unrelated to bank-side factors, our exogeneity assumption in equation (8) holds regardless of whether the firm-level shocks truly are firm-level or composite outcomes of very local network structures. The question of networks is therefore a matter of composition, not of identification.

6.2 Origins of Large Exposures

Credit concentration is an equilibrium object that is an outcome of more fundamental factors such as monitoring technology, risk preferences, information structure and expectations. Although writing down a micro-founded model of banking concentration is beyond the scope of this paper, discussing theoretical causes of concentration is useful for at least two reasons. First, the orthogonality of loan shares to idiosyncratic firm shocks is a key component of our empirical strategy, as highlighted in equation (8). Second, our paper is related to a large literature on the trade-off between risk concentration and economic performance and any normative implication would have to take into account the underlying causes of concentration.

One reason for the large degree of credit concentration observed in our data is home bias. Juelsrud and Wold (2020) document a substantial degree of within-county bias in the Norwegian banking system (see Figure A.4). Using loan-level data, Juelsrud and Wold (2020) show that over 2003-2015 the average proportion of bank credit to firms that are headquartered in the same region as the lender was 55%. This compares to a random-assignment counterfactual of less than 10%, implying a home bias of 45%. Home bias is, of course, a perennial stylized fact in international finance, banking, and macroeconomics (Coeurdacier and Rey, 2013).

In what follows, we highlight three potential causes of portfolio concentration: asymmetric information, behavioral biases and the distribution of firm sizes. Asymmetric information and behavioral biases are also potential factors behind home bias in portfolios.

Asymmetric Information. Concentrated lending could be a by-product of persistent credit relationships. When information acquisition on new clients is costly, lenders may find it optimal to do business with a recurring set of borrowers, for instance by increasing the number of new commitments per relationship such as offering additional fixed-term loans or extending new credit lines (Sufi, 2007). Along the intensive margin, an increase in the exposure of an informed lender signals a higher quality of the underlying borrower, thereby reducing the cost of asymmetric information (Leland and Pyle, 1977). Van Nieuwerburgh and Veldkamp (2009) show in a rational inattention framework that investors may choose to learn only about assets for which they had an information advantage to start with (such as home assets), thus amplifying initial information asymmetries.

Ivashina (2009) proposes and tests a theory where the price of a loan is determined by a trade-off between diversification and asymmetric information. If a bank raises its exposure to a single borrower, two effects take place. First, the lender demands a higher premium for being more exposed to borrower-specific idiosyncratic risk. Second, assuming that expenditures on monitoring scale with exposure, concentration also reduces information asymmetry between the lender and the borrower, thus reducing the premium. In equilibrium, the price of the contract depends on the degree of information asymmetry and the magnitude of idiosyncratic fluctuations.

In our data, we observe a substantial degree of credit concentration. This is true at all levels of aggregation: single name, geographical, sectoral. In light of Ivashina (2009), this may suggest that Norwegian lenders attach large benefits to information acquisition. This is intuitive, given that the majority of firms in our data are not publically listed and are instead locally-focused small enterprises. Information collection and monitoring is therefore costly, and potentially increases with distance. This could explain both the regional home bias and the single name credit concentration facts. Banks' portfolio-level (over-)exposure to single borrowers solves the structural asymmetric information problem, but at the cost of an elevated vulnerability towards idiosyncratic shocks. Sensitivity to a given distribution of idiosyncratic borrower shocks (the loan share distribution $s_{i,j,t}$) can be explained by the banks' decision to invest in localized information acquisition, which is in turn driven by predetermined factors such as the returns to information acquisition. This class of explanations validates our empirical approach.

Behavioral Biases. A second theory that could rationalize credit concentration rests on behavioral biases and overconfidence[26]. Huberman (2015) shows that some investors tend to ignore portfolio theory and invest in familar assets. In recent work, Bordalo et al. (2018) develop a theory of "diagnostic expectations" and apply it to canonical macroeconomic models of credit cycles. In their theory, agents persistently overweight future outcomes that have become more likely given recent data. Investors in this framework would make predictable forecast errors and could be "over-" or "underconfident" relative to the rational expectations benchmark.

The diagnostics expectations theory could potentially explain why lenders engage in excessive, unhedged credit concentration. Having established a credit relationship with a client that a bank trusts, the bank "specializes" in that client conditional on having exuberantly positive expectations about for instance the bank's own ability to pick superior portfolios and generate above-average returns based on own skill. Conditional on this expectations formation mechanism, the bank therefore "rationally" ignores the considerable downside risk of the strategy, i.e. the concentration risk. Our exogeneity assumption (8) is valid under diagnostics expectations at the bank-level. In that case, overexposure of bank i in firm j at time t is largely *independent* of the firm's present characteristics but is instead a function of i's subjective beliefs. Thus, behavioural biases of this kind would also be compatible with our empirical approach.

Distribution of firm sizes. Finally, credit concentration could be a by-product of the underlying firm size distribution also being fat tailed, which is definitely the case for Norway. Studies by Carvalho and Gabaix (2013) and Carvalho and Grassi (2019), among others, have shown that the presence of a small number of large firms can explain a substantive percentage of aggregate macroeconomic fluctuations. Similarly, Gaubert and Itskhoki (2018) show that up to 20% of international export intensity can be attributed to granular firms. In the case of bank lending, if large firms are also large borrowers - a condition which is true in our data - the Pareto rate of the credit share distribution is driven by the Pareto rate of the firm size density. While this is a very natural explanation for the observed credit concentration and the one we pursue below in Section 7, it is worth nothing that in our data we also observe substantial heterogeneity in portfolio Herfindahl indices *across* banks, even among lenders of the *same* region. Banks do not all hold the same portfolio. Thus, (local) firm size concentration is not enough to completely explain either the home bias in bank lending or portfolio concentration. Financial frictions - be it informational, technological, or behavioral

[26] Fuster et al. (2010) review the extensive literature on the departures from rational expectations in finance and macroeconomics.

- are important as well.

For the purpose of the empirical analysis, we note that the three classes of models that we put forward to explain the origin of credit concentration (asymmetric information, behavioural biases, distribution of firm sizes) are all compatible with our empirical approach and identification strategy.[27]

7 Theoretical Motivation

Throughout the paper, we have exploited the stylized fact that the distribution of bank credit exhibits a fat tail. In this section, we provide one simple possible theoretical rationalization for this observation.[28] In the data, the right tail of the loan distribution is populated by a small number of very large loan contracts (as a share of the bank portfolio). These large loan contracts are almost always underwritten to big firms, a fact which we verify from our dataset. It is well known that the size distribution of firms is fat-tailed. If firm credit is a function of firm size, then we can precisely derive how the granularity of the firm distribution translates into the granularity of credit and affects portfolio-level outcomes.

A theoretical challenge encountered when formalizing this intuition is the fact that both firm loan and firm size distributions could potentially have infinite variances. In this particular case, standard central limit theorems break down. Following Gabaix (2011), we therefore resort to Lévy's generalized central limit theorems that can accommodate distributions with fat tails. In this section, we provide sufficient conditions for distributional parameter values to ensure that - assuming the firm size distribution has a fat tail - the firm credit distribution also has a fat tail.

A Simple Model of Firm Debt Suppose there are N firms in the economy[29]. Before production can begin, firms must obtain funding. By assumption, each firm i is cash-strapped and has to start the period by borrowing L_{it} from a bank. The growth rate of firm debt demand evolves according to:

$$\frac{\Delta L_{i,t+1}}{L_{it}} = \sigma_i \epsilon_{i,t+1} \tag{11}$$

[27] Those theories would have, however, different normative implications.

[28] As noted in section 6.2, other frictions would have to be added to fully account for the data.

[29] Alternatively, suppose there are N borrowers in a given bank's portfolio and we treat the bank as the "economy".

where σ_i is the volatility of firm-level debt growth and $\epsilon_{i,t+1}$ are i.i.d. random variables. Economy-wide total stock of firm debt is:

$$D_t = \sum_i^N L_{it} \tag{12}$$

and growth of financial debt in the economy is

$$\frac{\Delta D_{t+1}}{D_t} = \sum_i^N \sigma_i \frac{L_{it}}{D_t} \epsilon_{i,t+1} \tag{13}$$

The variance of growth of total debt is the weighted sum of the variance of the volatility of idiosyncratic shocks to debt demand, with the shares equaling the squared share of firm *i*'s borrowing in the total economy. Assuming $\sigma_i = \sigma$, we have:

$$\sigma_D = \Big[\sum_i^N \sigma_i \Big(\frac{L_{it}}{D_t} \Big)^2 \Big]^{\frac{1}{2}} \tag{14}$$

It is clear from equation 14 that the variance of total debt depends on the distribution of firm-level debt demand L_{it}. In our data, we see that firm-level borrowing is strongly positively correlated with firm size. Let firm size, proxied by either total assets or sales, be y_{it}. Assume idiosyncratic volatility of firm growth σ_y is constant and common to all firms. Following Gabaix (2011), we assume that $y_1, \ldots, y_N$ are drawn from a power law distribution:

$$\mathbb{P}(y > x) = (1 + x)^{-\alpha} \tag{15}$$

with the exponent $\alpha \geq 1$. Note that we set the location and scale parameters to zero and unity, for simplicity. In the literature, this precise specification of a power law corresponds to a Pareto distribution of Type II.

Now, we assume a specific functional form for the amount of borrowing L_{it} as a function of size y_{it}:

$$L_{it} = y_{it}^{\lambda_i} \tag{16}$$

where $\lambda_i > 0 \, \forall i$. We proceed with the assumption that $\lambda_i = \lambda$ is homogenous across all firms.

Drawing from the literature on statistics, economics, and actuarial sciences, we know that once y_i follows a power law, then y_i^λ follows a Champernowne (1952) distribution, also known as the Burr Type XII, with parameters $\{\tau, \alpha\}$ where $\tau = 1/\lambda$ (Rodriguez, 1976). In

economics, this distribution is commonly referred to as the Singh-Maddala (SM) density (Singh and Maddala, 1976). It has been used widely to model household income and wealth inequality. Formally:

$$\mathbb{P}(L > x) \sim (1 + x^{\tau})^{-\alpha} \tag{17}$$

with $\tau > 0$. For the special case of $\tau = 1$, firm debt becomes linear in size, the distribution collapses to a Pareto Type II, and we are back to Gabaix (2011). In general, the rate of decay of σ_D, as the sample size grows, will depend on the value of structural parameters. For the special case of $1 < \tau\alpha < 2$, the SM random variable has an infinite variance and standard limit theorems break down. There is therefore a direct link between the fat tail of the firm distribution and of the credit distribution. This result is summarized in our main proposition below:

Proposition 1. *Let firm sizes $y_i \dots y_N$ be drawn from a power law distribution with exponent $\alpha \geq 1$. Suppose each firm has non-rationed access to the credit market, through which on demand it borrows a fraction $y^{\lambda-1}$ of its size, with λ>0. Firm-level borrowing is thus $L = y^{\lambda}$, which grows with a constant idiosyncratic volatility σ. L follows the Singh-Maddala distribution with power and shape parameters $\{\alpha, \tau\}$:*

$$\mathbb{P}(L > x) \sim (1 + x^{\tau})^{-\alpha}$$

with $\tau = 1/\lambda$. Then, as $N \to \infty$:

- *For 1 < $\alpha\tau$ <2, by the Lévy's central limit theorem, the volatility of aggregate debt D is given by $\sigma_D \sim \sigma \frac{1}{N^{1-1/(\alpha\tau)}} \sqrt{\eta}$, where η is a Lévy random variable with exponent $\frac{\alpha\tau}{2}$*
- *For $\alpha\tau \geq 2$, by the Lindeberg-Lévy classical central limit theorem, the volatility of aggregate debt D is given by $\sigma_D \sim \sigma \frac{1}{N^{1/2}} \sqrt{\eta}$, where η is a constant*

Proof. The strategy of the proof follows closely Appendix 1 and Proposition 2 in Gabaix (2011). First, we show that L, which follows the Singh-Maddala distribution, satisfies Assumptions 1-2 below:

Assumption 1: $\lim_{l\to\infty} \mathbb{P}(L_1 > x)/\mathbb{P}(|L_1| > x) = \kappa \in [0, 1]$

Assumption 2: $\mathbb{P}(|L_1| > x) = x^{-\alpha}B(x)$ with B(x) a slow-moving function.

Assumption 1 is verified trivially because SM is defined on the non-negative real line. Assumption 2 holds once we re-write: $\mathbb{P}(|L_1| > x) = x^{-\alpha}(\frac{x}{1+x^{\tau}})^{\alpha}$. So, $B(x) = (\frac{x}{1+x^{\tau}})^{\alpha}$. For

$\tau = 1$, the function is clearly slow-moving. Generally, for $\tau > 0$ we must show that:

$$\lim_{x\to\infty} B(tx)/B(x) = \frac{\lim B(tx)}{\lim B(x)} = 1 \tag{18}$$

for any t>0 and for as long as the denominator is $\neq 0$. $\lim_{x\to\infty} B(x) = \lim_{x\to\infty} \left[\frac{x}{1+x^{\tau}}\right]^{\alpha} = \lim_{x\to\infty} \left[\frac{1}{1/x+x^{\tau-1}}\right]^{\alpha} = 1$. Similarly for B(tx).

Next, we construct three sequences (a_n, b_n, s_n) that constitute the infinite sum across firms. $a_n = \inf(x : \mathbb{P}(|L_1| > x) \leq 1/N) \sim \left(N^{1/\alpha} - 1\right)^{1/\tau} \approx N^{\frac{1}{\alpha\tau}}$. $b_n = n\mathbb{E}\left(L_1 1_{|L|\leq a_n}\right) = 0$. And $s_n = \sum_i^N L_i$. Thus:

$$\lim_{N\to\infty} \left(N^{\frac{1}{\alpha\tau}}\right)^{-1} \sum_i^N L_i \xrightarrow{d} \eta \sim \text{Lévy}(\alpha\tau) \tag{19}$$

In the remainder of the proof, we apply Equation 19 to the case of constant σ, i.e. when firm-liability volatility is constant over time and not correlated cross-sectionally. When $\alpha\tau > 2$, standard Lindeberg-Lévy applies. When $1 < \alpha\tau < 2$, the loan portfolio Herfindahl decays according to:

$$N^{1-\frac{1}{\alpha\tau}} \frac{\left(N^{\frac{-2}{\alpha\tau}} \sum_i^N L_i^2\right)^{1/2}}{N^{-1} \sum_i^N L_i} \xrightarrow{d} \frac{\text{Lévy}^{1/2}}{\mathbb{E}(L)} \tag{20}$$

When $1 < \alpha\tau < 2$, the denominator (mean of Singh-Maddala) is finite. Since firm-level volatilities are constant, and Lévy is a stable random variable, the volatility of loan growth will be therefore decaying at the rate proportional to $N^{1-\frac{1}{\alpha\tau}}$:

$$\sigma_D \sim N^{1-\frac{1}{\alpha\tau}} \text{Lévy}^{1/2} \sigma \tag{21}$$

For $\tau = 1$ we are in the special case of Singh-Maddala collapsing to the Pareto II distribution and standard results in Gabaix (2011) are obtained up to the slow-moving function B(.). For $\tau \neq 1$ but $\tau > 0$, the sufficient statistic for the comparison of rates of convergence across finite and infinite variance cases is $\alpha\tau$.

□

Our notation means that $\sigma_D \sim \sigma \frac{1}{N^{1-1/(\alpha\tau)}} \sqrt{\eta}$ implies convergence in distribution of $\sigma_D N^{1-1/(\alpha\tau)}$ to $\sigma\sqrt{\eta}$, where η is a stable Lévy random variable. What we have shown is that the distribution of firm debt could have either thin or fat tails. If $\alpha\tau \geq 2$, σ_D decays

according to $\frac{1}{\sqrt{N}}$. However, if $1 < \alpha\tau < 2$, then σ_D decays at the rate of $\frac{1}{N^{1-\frac{1}{\alpha\tau}}}$, i.e. more slowly. In this case, idiosyncratic shocks to borrowers could drive the total debt portfolio and, as in our main empirical experiments, affect aggregate outcomes.

7.1 Model Parameter Estimation

In this section, we test whether the parameter restriction $1 < \alpha\tau < 2$ can be supported by our data. First, we fit the Generalized Pareto density into the size distribution of firms. Most studies in the literature treat sales as the size proxy. We, apart from sales, also consider total equity and total assets as alternative size proxies that could be relevant for deciding on how much bank credit to request. This step grants us three estimates of α. Second, we back out firm-specific λ_i directly from Equation 16 and then take the median of the resulting distribution. We conduct this step for all three definitions of size as well. As a result, we have three estimates for $\alpha\tau$ - the sufficient statistic that determines the speed of decay of σ_D.

Table A.10 reports the results from maximum likelihood estimation of α and other parameters. Our estimates confirm that the $1 < \alpha\tau < 2$ restriction is supported in the data. We find that α is in the [1.26, 1.49] range and $\alpha\tau$ is between 1.38 and 1.64, i.e. firmly within the (1,2) bounds. Our estimation results suggest that both the firm size and the firm loan distributions can be reasonably approximated with fat-tailed densities. The aggregate credit distribution can be affected by firm-level disturbances: credit risk is granular.

8 Conclusion

This paper has developed the first, bottom-up causal quantification of single-name credit concentration risk. To the best of our knowledge, we are the first to provide evidence on *single-name* (individual firm-level) as opposed to sectoral or geographic exposure risk. Empirically, we show there is a causal link between idiosyncratic firm shocks and returns on bank credit. Unexpected shocks to firm value-added affect loan-level and bank-level performance. We capture strong asymmetries associated with the debt contract structure by showing that negative firm shocks lead to a reduction in bank returns, while positive shocks have zero impact. We explored numerous dimensions of heterogeneity at all levels of aggregation.

We find strong evidence of a second-level pass-through effect of granular borrower risk onto other firms. Banks, in response to negative shocks to their granular borrowers, cut credit supply and increase interest rates on loans to their non-granular borrowers. Affected non-granular firms, in turn, reduce investment in physical capital. Affected firms

are also more likely to file for bankruptcy following a negative granular shock to their credit provider. These results suggest that single-name credit concentration risk carries significant implications for the macroeconomy.

The first key message of the paper is therefore that idiosyncratic firm shocks do not wash out and still matter at the level of the bank portfolio. Conventional wisdom that banks are subject only to aggregate risk due to pooling and the law of large number is not borne out in the data. Concentration risk matters quantitatively. Our evidence from non-interest income data further suggests that banks do not compensate for loan book losses through earnings from alternative sources such as derivatives or equity holdings. The second key message of the paper is that there are important *granular credit risk spillovers* affecting the real economy.

Methodologically, we make progress on identification of firm demand-side shocks at the level of bank portfolios by employing the "granular instrument variable" approach developed in recent work by Gabaix and Koijen (2020a,b). This method takes advantage of the fact that the distribution of loan shares features a fat tail and allows for a tightly-identified pass-through of granular risk.

Our results have implications for the regulation of large credit exposures. Our pass-through estimates in Table 3 could be used to compute the *granular value-at-risk*, i.e. the bank capital that is at risk if a granular borrower suffers a bad negative shock. Our estimate of the loan share Pareto power of section 7 could be used as a tool for understanding when banks are becoming prone to granular credit risk. A drop in the Pareto power estimate to 2 or below could constitute a regulatory "red flag". In practice, the parameter could be computed for each financial institution in the cross-section. The system wide weighted average Pareto estimate could become a novel time-series indicator of aggregate concentration whose changes could track fluctuations in *system wide concentration risk*.

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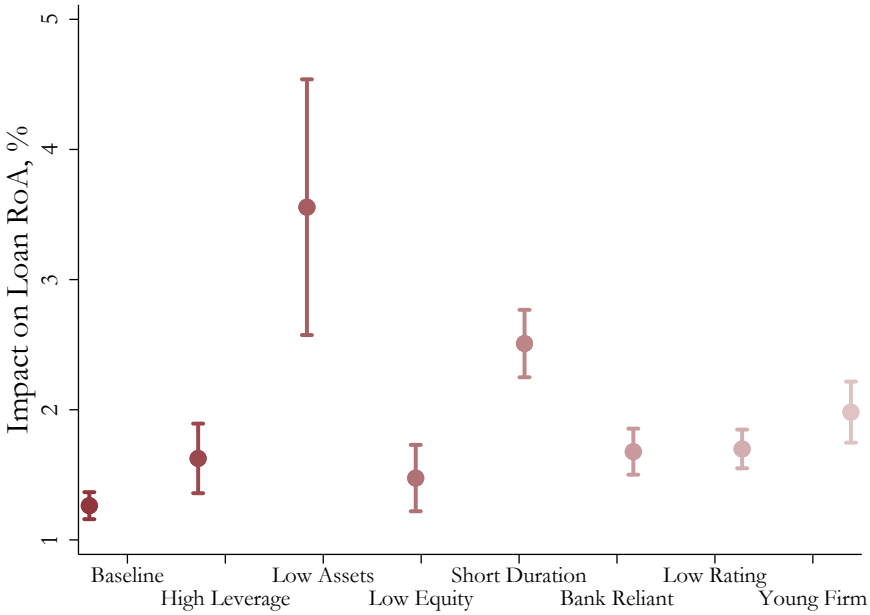
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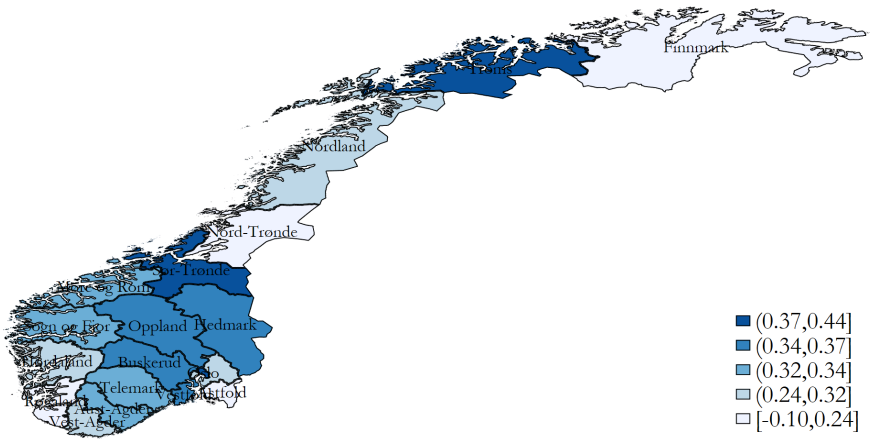
A Additional Figures and Tables

Figure A.1: **Loan Outcomes - Firm Balance Sheet Heterogeneity**



Notes: This figure plots results from loan-level regressions of loan returns on idiosyncratic firm shocks interacted with various lagged firm characteristics. Each characteristic is a dummy which takes the value of 1 for firms which are in the highest decile of leverage, share of bank credit to total credit and share of short-term debt to total debt; firms in the lowest decile of total assets and total equity; firms with an below-A credit rating; and firms younger than 3 years. Bars are 95% confidence bands. Baseline is the pooled estimate from Table 2.

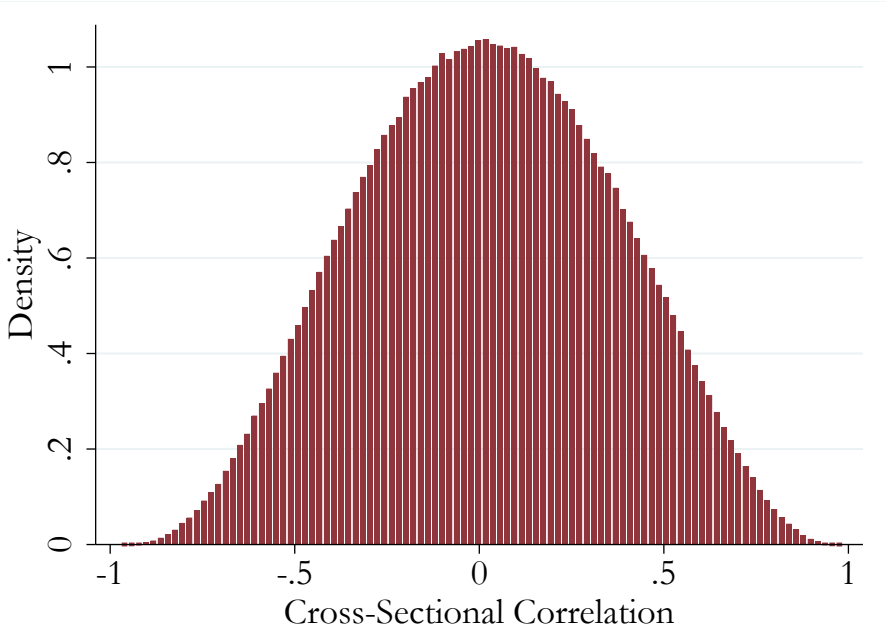
Figure A.2: **Geographical Origins of Granular Credit Risk**



Notes: This picture is a colored map of 19 administrative counties (*fylke*) of Norway. Each shade of blue represents the county-specific strength of the pass-through from idiosyncratic firm shocks to return on loans. These correspond to county-specific slope shifters (slope dummies) introduced into the main loan regression 2. Shapefiles are from the Norwegian Mapping Authority (*Kartverket*).

Figure A.3: **Pairwise Cross-Sectional Correlation of Firm Shocks**

Panel A: Histogram

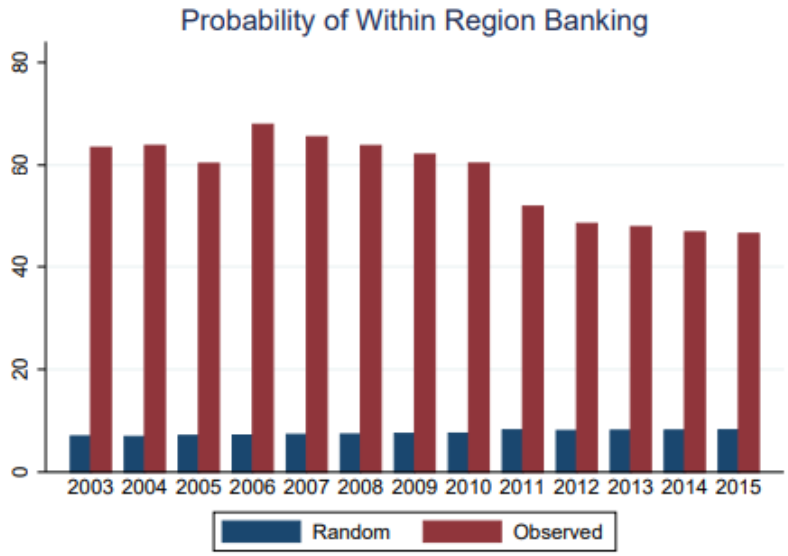


Panel B: Summary Statistics

	Number of Pairs	Mean	Std. Dev.	Min	Max
Firm Shock	1,794,324	0.019	0.342	-0.971	0.985

Notes: These figures report all pairwise cross-sectional correlation coefficients for idiosyncratic firm shocks. The sample includes a balanced panel of firms over 2003-2015. Panel A presents the histogram, and Panel B reports summary statistics. Firm shocks are extracted based on specification 1.

Figure A.4: **Home Bias in Within-Region Banking**



Notes: This figure shows the extent to which there is home-bias in the Norwegian corporate credit market. Source: Juelsrud and Wold (2020). Specifically, red bars show the *observed* fraction of loans within a given year in our sample where the firm and the bank are located in the same county (within-region loans). The blue bars show the counterfactual share of within-region loans, where we assume random matching between firms and banks. Given random matching, the probability that a firm i borrows from a bank j operating in that region is the sum of the aggregate/national market share of bank j.

Table A.1: **Loan Outcomes - Extensive Margin**

	(1)	(2)	(3)	(4)	(5)
	Dependent Variable: Return on Loan				
	Baseline	Firm Exit	Firm Entry	Firm Bankruptcy	Ever Bankrupt
Firm Shock	0.361	0.387	0.322	0.365	0.360
	(0.018)	(0.019)	(0.019)	(0.018)	(0.019)
Exit / Entry / Bankruptcy		0.613	-1.707	0.699	0.572
		(0.075)	(0.073)	(0.161)	(0.079)
Interaction		-0.259	0.260	-0.133	0.014
		(0.067)	(0.059)	(0.133)	(0.068)
Full Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	292825	292825	292825	292825	292825
R^2	0.167	0.167	0.169	0.167	0.167

Notes: This table reports estimates from loan-level regressions of loan returns on firm shocks interacted with firm entry, exit, and bankruptcy dummies. Firm entry (exit) dummies equal 1 for firms which entered (exited) the year before (following) the firm shock. Firm bankruptcy is a dummy that equals 1 for firms which declare bankruptcy the year following the firm shock. Ever bankrupt is a dummy that equals 1 for firms which have *ever* declared bankruptcy during the 2003-2015 period, and not necessarily directly following the firm shock. All specifications include Bank x Firm Industry x Year x Loan-type x Firm County interacted fixed effects. Standard errors (in parentheses) are double clustered at the firm-year level.

Table A.2: **Loan Outcomes - Firm Ownership Heterogeneity**

	(1)	(2)	(3)	(4)	(5)
	Dependent Variable: Loan RoA				
	All Firms	Private Firms	State Firms	Community Firms	Financial Vehicles
Firm Shock	0.335	0.336	0.478	0.089	1.145
	(0.016)	(0.019)	(0.654)	(0.120)	(0.966)
Bank x Year x County FE	Yes	Yes	Yes	Yes	Yes
Observations	330490	234074	162	2526	389
R^2	0.051	0.053	0.243	0.282	0.214

Notes: This table reports estimates from loan-level regressions of loan returns on firm shocks originating from firms with different ownership structure. Each column presents results from a specification in which only that particular ownership type is included. Numbers of observations do not add up because many firms are not assigned ownership classifications. Standard errors (in parentheses) are double clustered at the firm-year level.

Table A.3: **Loan Outcomes - Firm Industry Heterogeneity**

	(1)	(2)	(3)	(3)	(4)	(5)
	Dependent Variable: Return on Loan					
	All Firms	Manufacturing	Mining	Construction	Real Estate	Agriculture
Firm Shock	0.335	0.356	0.401	0.414	0.064	0.215
	(0.016)	(0.050)	(0.251)	(0.040)	(0.034)	(0.055)
Bank x Year x County FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	330490	34232	1097	60169	8531	7773
R^2	0.051	0.091	0.364	0.082	0.197	0.201

Notes: This table reports estimates from loan-level regressions of loan returns on firm shocks coming from firms from different sectors. Each column presents results from a specification in which firms from only that particular sector are included. Mining includes petroleum industries. Numbers of observations do not add up because many firms are not assigned industry classifications. Standard errors (in parentheses) are double clustered at the firm-year level.

Table A.4: **Bank Outcomes Heterogeneity - Concentration and Number of Loans**

	(1)	(2)
Shock x Few Loans$_{t-1}$	0.110	
	(0.045)	
Shock x Many Loans$_{t-1}$	0.098	
	(0.034)	
Shock x Low Loan HHI$_{t-1}$		0.065
		(0.040)
Shock x High Loan HHI$_{t-1}$		0.138
		(0.040)
Bank FE	Yes	Yes
Year FE	Yes	Yes
Bank Controls	Yes	Yes
Observations	1108	1211
R^2	0.082	0.103

Notes: This table reports results from bank-level regressions of return on loans on firm shocks, instrumented by the granular IV. The granular IV is constructed following Equation 6. The RHS is interacted with dummies for percentiles of the loan portfolio Herfindahl index (HHI) and number of loans. Each dummy cuts the distribution of each characteristic into two halves based on the median, denoted as: few and many loans and low and high HHI. Columns (1)-(2) interact the RHS shock variable with the indicator variable for number of loans and HHI, respectively. All specifications include bank controls, which are lagged values of: total assets, leverage, liquidity, number of loans, deposit to assets ratio and financial assets to assets ratio. Standard errors (in parentheses) are clustered at the bank level.

Table A.5: **Bank Outcomes Heterogeneity - Concentration and Bank Size**

	(1)	(2)
Shock x Low Assets$_{t-1}$	0.164	
	(0.038)	
Shock x High Assets$_{t-1}$	0.046	
	(0.038)	
Shock x Low Loan HHI$_{t-1}$		0.065
		(0.040)
Shock x High Loan HHI$_{t-1}$		0.138
		(0.038)
Bank FE	Yes	Yes
Year FE	Yes	Yes
Bank Controls	Yes	Yes
Observations	1211	1211
R^2	0.104	0.103

Notes: This table reports results from bank-level regressions of return on loans on firm shocks, instrumented by the granular IV. The granular IV is constructed following Equation 6. The RHS is interacted with dummies for percentiles of the loan portfolio Herfindahl index (HHI) and bank size, defined as total assets. Each dummy cuts the distribution of each characteristic into two halves based on the median, denoted as: low and high assets and low and high HHI. Columns (1)-(2) interact the RHS shock variable with the indicator variable for bank size and HHI, respectively. All specifications include bank controls, which are lagged values of: total assets, leverage, liquidity, number of loans, deposit to assets ratio and financial assets to assets ratio. Standard errors (in parentheses) are clustered at the bank level.

Table A.6: **Robustness to Great Financial Crisis**

	(1)	(2)	(3)	(4)	(5)	(6)
	Loan-Level			Bank-Level		
Firm Shock	0.361	0.432	0.322	0.117	0.091	0.108
	(0.018)	(0.032)	(0.022)	(0.029)	(0.051)	(0.037)
All Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Bank Controls				Yes	Yes	Yes
Observations	292825	102879	189946	1211	472	737
R^2	0.167	0.158	0.172	0.101	0.066	0.127

Notes: This table reports timing robustness for baseline loan- and bank-level regressions from Tables 2 and 3, respectively. Columns (1)-(3) report results of loan and columns (4)-(6) of bank outcomes, respectively. Columns (1) and (4) are baseline estimates. Columns (2) and (5) include only the pre-2009 period. Columns (3) and (6) include only the post-2009 period.

Table A.7: **Placebo Regressions - Permutation Tests**

	Simulations	True Coefficient	Event Frequency	Event P-value
		Loan Outcomes		
Permuted Firm Shock	1000	0.361	0	0.000
		Bank Outcomes		
Permuted Firm Shook, Pooled	1000	0.116	0	0.000
Permuted Firm Shock, Positive Only	1000	0.016	680	0.680
Permuted Firm Shock, Negative Only	1000	0.194	8	0.008

Notes: This table reports results from Monte Carlo permutation regressions where loan or bank return on loans are regressed on firm shocks that are randomly permuted. The last two rows report results when permuted shocks are positive or negative only, respectively. Columns report the number of simulations, the true coefficients based on Table 2 column (3) and Table 3 columns (3)-(5), the number of events where permutations produced estimates that are as large as the true estimate (in absolute value) by chance, and the associated p-values.

Table A.8: **Placebo Regressions - Random Shocks**

	Number of Draws	Mean	Std. Dev.	Min	Max
		Loan Outcomes			
Placebo Firm Shock	1000	0.001	0.006	-0.015	0.015
		Bank Outcomes			
Placebo Firm Shook, Pooled	1000	-0.001	0.005	-0.011	0.012
Placebo Firm Shock, Positive Only	1000	-0.001	0.008	-0.023	0.016
Placebo Firm Shock, Negative Only	1000	0.000	0.008	-0.023	0.019

Notes: This table reports results from a placebo exercise where loan or bank outcomes are regressed on sequences of randomly generated numbers. In each row, placebo shocks are randomly drawn from the interval of the true shock. The last two rows report results when shocks are positive or negative only, respectively. Columns report the number of random draws and summary statistics of the regression coefficients: mean, standard deviation, minimum, and maximum.

Table A.9: **Estimating Fixed Effect Linear Models with AR(1) Disturbances**

	Borrower Level	Bank Level	Firm Industry Level	County Level
Autoregressive Coef.	0.318	0.122	0.241	0.223
Standard Deviation	0.264	0.107	0.254	0.251

Notes: This table reports parameter estimates of a linear unbalanced panel fixed effects model with a disturbance that follows an autoregressive process of order 1. Estimates for the autoregressive coefficient and the standard deviation of the error term are reported. Columns report results for various levels of aggregation. Idiosyncratic firm shocks are extracted based on specification 1 and then aggregated to different levels with loan shares as weights.

Table A.10: **Theoretical Model Parameter Estimates**

Firm Size	Parameters			Loan Distribution Variance
	α	λ	$\alpha\tau$	
Sales	1.26	1.005	1.388	Infinite
	(0.002)	(0.548)	(0.413)	
Assets	1.321	0.923	1.587	Infinite
	(0.001)	(0.361)	(0.887)	
Equity	1.495	1.086	1.641	Infinite
	(0.002)	(0.467)	(1.144)	

Notes: This table reports estimates of key parameters of the model described in Section 7. α, λ and $\alpha\tau$ represent the Pareto power parameter of the firm size distribution, the firm's debt demand elasticity, and the sufficient statistic of the Singh-Maddala distribution, respectively. Standard errors (standard deviations for λ and $\alpha\tau$) are in parentheses.