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GRANULAR CREDIT RISK

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ABSTRACT

What is the impact of granular credit risk on banks and 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 Gabaix and Koijen (2022, 2023)'s granular instrumental variable strategy to show that idiosyncratic borrower risk survives aggregation in banks' portfolios. We 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, affecting sizeably the macroeconomy.

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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 "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 2003-2015 period[3]. This data-rich environment enables us to study the transmission

[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.

[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.

mechanism and heterogeneous treatment effects at many levels of aggregation.

Our empirical strategy consists of five steps. First, we establish that the distribution of loan 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 × 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). An example of such an idiosyncratic shock in our sample is the closure of the main waste management facility of the company Hera Vekst by the authorities because of "smell far in excess of what the local population should tolerate" (nrk.no, 2011).

Third, we establish the pass-through from these idiosyncratic firm shocks to loan-level returns[4]. We investigate how such shocks affect returns on loans within the same bank, industry, county, year, and loan type[5]. Importantly, our specification controls for time-varying confounding bank-side supply factors, potentially specific to a given industry, county, or contractual type[6]. 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 34-36 basis points. We explore numerous dimensions of heterogeneity, including firm characteristics, geographical location, ownership, etc.

Fourth, we look at the impact of idiosyncratic borrower shocks on banks' portfolio-

[4]This step constitutes one of the key ways in which we differ from the contribution by Amiti and Weinstein (2018). Amiti and Weinstein (2018) provide a *decomposition* of investment growth in Japan into idiosyncratic bank x time and firm x time components. They show that the idiosyncratic bank-side factor, driven particularly by *granular banks*, matters a lot for aggregate investment dynamics. In contrast, we estimate the *pass-through* of estimated idiosyncratic performance shocks hitting *granular borrowers* onto loan, bank, and macroeconomic outcomes.

[5]Conceptually, this step can be viewed as a "reverse Khwaja and Mian (2008)" approach. In Khwaja and Mian (2008), authors trace out the impact of bank supply shocks for the same firm borrowing from different banks. 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 not only within the same bank but also within the same industry and county.

[6]Our saturation of specifications with time × bank and other fixed effects is similar to Jimenez et al. (2014) who study monetary policy and loan applications of the same firm to different banks in the same period of time.

level outcomes. This is a critical step in our analysis. Once aggregated to the level of a bank, we potentially lose the appealing properties of loan-level analysis: the loan share-weighted firm shock series could be contaminated by bank $\times$ year confounding factors, such as time-varying differences in the efficacy of "monitoring devices" (Stiglitz and Weiss, 1981), which we no longer have the power to deal with[7]. For this stage, we adopt the "Granular Instrumental Variable" (GIV) approach, newly developed in a series of papers by Gabaix and Koijen (2022, 2023). Intuitively, the GIV extracts variation in the share-weighted aggregated firm shock series that can be attributed to "granular" borrowers. Specifically, the instrument in its simplest form is the difference between size-weighted and unweighted aggregated firm shocks. The GIV thus purges away any bank $\times$ year factor, e.g. monitoring capacity. Conditional on the distribution of credit shares being fat-tailed, idiosyncratic shocks to large borrowers allow us to achieve identification and validity. Our various parametric and non-parametric specifications allow for a flexible number of bank factors and, importantly, for loadings on bank factors to be either homogenous or *heterogeneous* across firms within any bank's portfolio.

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[8]. We investigate heterogeneity at the bank level and find that the pass-through of granular credit shocks is stronger for banks with high portfolio risk weights, low assets, high loan portfolio concentration, and high profitability. We also find that the *number* of loans in credit portfolios does not affect the transmission mechanism, indicating that granular credit risk is not merely a "small-N" problem.

[7]In recent work, Jimenez et al. (2020) extend the Khwaja and Mian (2008) loan-level estimator to firm-level, thus offering a way to achieve identification despite aggregation. We pursue a novel and complementary approach that exploits the fat tail of the loan share distribution.

[8]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.

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?[9] 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 interest flows. 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 threshold (such as the median) in the pooled distribution of all credit shares[10]. We show that a one-standard-deviation bank-level negative granular credit shock reduces loan supply and increases interest flows by as much as 23% and 17%, respectively, of the dependent variables' standard deviations. This identifies a leftward shift of the credit supply curve: quantities fall while prices rise. There are "granular credit risk spillovers": idiosyncratic borrower shocks spill over to other firms that borrow from the same bank[11].

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 significantly elevated bankruptcy rates. A one-standard deviation negative granular credit supply shock increases the likelihood of bankruptcy by roughly 3%-9% over the unconditional probability of bankruptcy of 1.10% per annum, or 3-10 basis points p.a.. Granular credit risk has sizable implications for the aggregate economy, and our back-of-the-envelope calculations suggest that it results in tens of millions of dollar-equivalent bankruptcy-associated losses every year.

An important question is whether banks hedge granular risk with alternative sources of

[9] For example, negative granular credit shocks could be perceived as sudden and detrimental changes to the banks' financial positions, which in turn translate into adverse lending and pricing decisions (Paravisini, 2008).

[10] The tendency to pass along adverse economic shocks to their clients, especially small firms, is not uncommon for banks. In their classic paper, Peek and Rosengren (2000) find that the 1990s Japanese banking crisis had a negative effect on commercial real estate activity in the U.S. through the network of banks exposed to both markets. Klein et al. (2002) further document that unequal access to credit by Japanese firms during the 1990s led to the decline in the number of FDI projects by the same firms into the United States. Lin and Paravisini (2012) trace out the pass-through of the collapse of WorldCom on firms that shared the same lender. 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.

[11] It is possible that our spillover result is in part driven by production network linkages, i.e. granular and non-granular borrowers are linked not only via the balance sheet of their common lender but through some other channel as well. We account for these potential production network effects with the use of the Norwegian input-output table and find that our results do not change.

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 interest markups for risky clients. Unfortunately, despite the precautions we take and the robustness checks we run, properly accounting for ex-ante compensation of granular credit shocks is difficult in our setting due to data limitations and lack of access to contract-level information. Empirical designs that leverage contract- or application-level data, such as the influential work of Jimenez et al. (2014), are better equipped at addressing this concern.

Finally, we end the empirical analysis by quantifying the implications of our findings for aggregate outcomes and explore several counterfactual scenarios. We show that granular credit shocks account for 8% to 20% of the total variation in credit growth to smaller firms that is attributed to generic bank supply factors. This illustrates that granular credit shocks constitute an important part of time-varying credit supply to smaller firms, which are generally more bank-reliant. While not making any normative conclusions, we also show that a reallocation of exposures to granular credit risk could substantially reduce volatility in bank returns and spillovers to other firms. For instance, allocating credit to mimic a representative bank serving the full corporate sector would reduce the impact of granular credit risk on bank returns by 66%, *ceteris paribus*.

How valid are our methodology and results externally? Baena et al. (2022) apply a variant of our approach to the *Anacredit* database and find very similar results in the context of French credit registry data. Our tractable approach is thus easily applicable to a general class of empirical settings that rely on bank-firm linkages. In addition to the above, to what extent is credit portfolio concentration a uniquely Norwegian phenomenon or a ubiquitous feature of financial markets? We discuss at great length how portfolio concentration appears to be indeed very common across various countries and asset classes. We also ourselves document the degree of portfolio concentration for a completely different but important setting: equity holdings of US institutional investors. We find that concentration in the Norwegian corporate credit sector is quantitatively very similar to the universe of U.S. equity investors. Our analysis concludes that both the methodology and results are applicable to many other situations and environments.

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, 2021), international finance (di Giovanni et al., 2018), asset management (Choi et al., 2017), life insurance (Chodorow-Reich et al., 2021), exchange rates (Camanho et al., 2022), banking (Bremus et al., 2018; Kundu and Vats, 2021). In important work, Amiti and Weinstein (2018) develop a methodology that decomposes loan growth into time-varying bank supply and firm demand components and find that idiosyncratic bank supply fluctuations, particularly those of granular lenders, have a large impact on aggregate lending and investment in Japan. In contrast to Amiti and Weinstein (2018), we estimate idiosyncratic firm performance shocks and study how these shocks *transmit* to bank outcomes and the real economy. We contribute to the "granular hypothesis" literature by showing that, when the loan distribution is fat tailed, idiosyncratic performance shocks to granular borrowers do not wash out at the lender's portfolio level. We also study *spillovers* of granular credit shocks on the rest of the economy by tracing out how affected banks pass on granular credit risk to other firms.

Second, we relate to the literature studying the trade-off between credit concentration and diversification. On the one hand, diversification enhances credit monitoring and information provision capacity (Diamond, 1984; Boyd and Prescott, 1986). Recently, Doerr and Schaz (2021) have shown that geographically diversified banks not only lend more during local crises in their borrower countries, but also mitigate the transmission of such shocks to borrowers in other countries. 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. 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 in detail in Section 5.4.

There is an emerging new literature on credit concentration that, like us, takes advantage of detailed microeconomic data. 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. Our paper differs from this literature because 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. Thus our paper provides an empirical basis for the work of Mendicino et al. (2020) 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.

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 summarizes additional results and offers a discussion of relevant conceptual questions. Section 6 concludes. All of our supplementary results and robustness tests are listed and discussed in the Online Appendix.

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.[12][13] Because the data is collected and maintained by the tax authority as a basis for corporate taxation, the variables are essentially measurement error-free.[14] 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

[12]We do not observe the contracted interest rate nor the loss-given-default on individual loans, but use our data to construct an ex-post return on each loan.

[13]Loans to firms constitute around 40% of all bank loans on average.

[14]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.

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.

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.

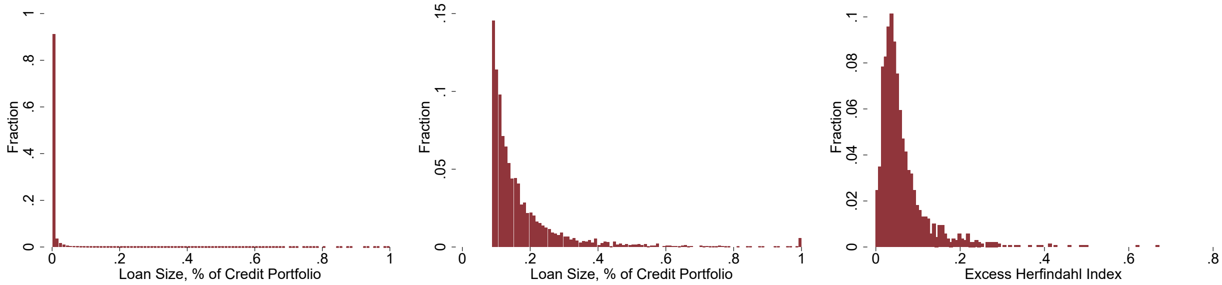
Table 1: Descriptive Statistics

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			
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 (years)	277707	12.94	11.81	0.00	159.00
		Banks			
Return on Loans (%)	1380	6.40	1.46	0.06	14.39
Total Assets (1000NOK)	1377	21130037.71	1.35e+08	92384.00	1.96e+09
Total Equity (1000NOK)	1377	1491611.98	8512785.73	16139.00	1.51e+08
Assets / Equity Ratio	1377	10.90	3.20	1.32	41.48
Cash Balances / Assets	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
		Firm Performance Shocks			
Firm-level	277707	0.02	0.27	-1.42	1.15
Bank-level (loan-share-weighted)	1380	-0.02	0.11	-0.78	0.69
Granular IV	1380	-0.02	0.09	-0.76	0.46

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 = 10.7 NOK as of September 9, 2023. Firm shocks are estimated according to specification 2. 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.

Figure 1: Granularity in the Distribution of Bank Loan Portfolios

(a) All Loan Shares **(b)** Loan Shares 95th Percentile **(c)** Excess Portfolio Herfindahl



Notes: This graph presents the distribution of bank loan shares and of excess portfolio Herfindahls. Panel (a) plots the full distribution of loan shares. Panel (b) zooms in on the 95th percentile. 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 panels plot the pooled shares for all banks and years. The Pareto rate of the 95th percentile is 1.82. Panel (c) plots the distribution of excess loan portfolio Herfindahls (eHHI), as defined in main text.

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.[15] More formally, we fit the Pareto I density to the right tail of the distribution, defined as the 95th percentile and plotted on Panel (b), and estimate a Pareto rate of 1.82.[16] If defined by the 99th percentile, the estimate drops to 1.15. Any estimate below 2 implies that idiosyncratic shocks to large loans potentially survive risk pooling and cause portfolio-level disturbances.

Second, we plot the distribution of excess loan portfolio Herfindahls (eHHI), pooled across all banks and years. The eHHI is defined as:

$$eHHI_{i,t} = \sqrt{\sum_j s^2_{i,j,t} - \frac{1}{N_{i,t}}} \tag{1}$$

with $s_{i,j,t}$ the loan share of firm j in bank i's portfolio in year t, and $N_{i,t}$ the number of loans in the respective portfolio. A greater eHHI implies higher concentration. Given the level and right-skewness of the resulting histogram, as shown on Panel (c) of Figure 1, there is

[15] This is also true if we focus on bank-level distributions of portfolio shares irrespective of bank size.

[16] One concern is that pooling observations across years may bias the estimate. If we constrain the sample to the year 2015 - the final year in our sample - the Pareto rate falls to 1.75, which is still below the threshold of 2.

strong evidence suggesting that bank loan portfolios are very concentrated.

Overall, given the degree of portfolio concentration in our data it is not implausible to suspect that loan-level disturbances do not average out in the aggregate. We will be returning to this point during the discussion of our instrumental variable approach below, particularly when discussing the validity of our instrument. Interestingly, our estimates imply that roughly 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).

A Simple Model of Granular Credit Motivated by the descriptive evidence on loan portfolio concentration, in Appendix G 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.

3.2 Estimates of Idiosyncratic Firm Shocks

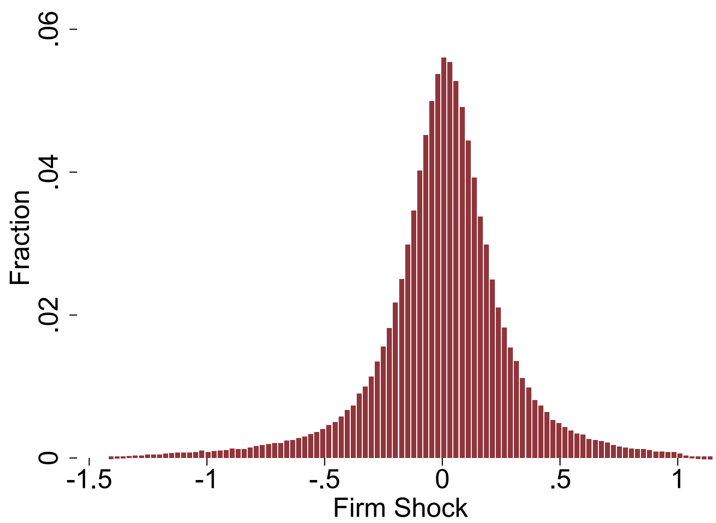
The next step of our empirical approach consists of extracting idiosyncratic firm shocks, measured as unexplained idiosyncratic variation in firm value added. Our approach follows closely a large number of studies in labor and macro economics that extract idiosyncratic sales or performance shocks. (Foster et al., 2008; Hsieh and Klenow, 2009; di Giovanni et al., 2014; Foster et al., 2017; Fagereng et al., 2018).[17] 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 the following regression:

$$\ln VA_{j,t} = \alpha_j + \theta_{g(j),t} + \beta_1 \ln K_{j,t} + \beta_2 \ln W_{j,t} + \lambda' \mathbf{X_{j,t}} + \epsilon_{j,t} \tag{2}$$

[17]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), Gabaix and Koijen (2023)).

Figure 2: Distribution of Idiosyncratic Firm Shocks



Notes: This graph plots the pooled distribution of idiosyncratic firm shocks estimated from equation (2).

where VA stands for firm value added, K represents book capital, W the wage bill, and X are other controls including leverage, liquidity, credit rating, and a quadratic polynomial in age.[18] The term α_j captures the firm fixed effect, while $\theta_{g(j),t}$ captures time varying group-level fixed effects, specified as the interaction of year × firm industry × firm county fixed effects. 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.[19]

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 trying to capture 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, fraud and mismanagement, operational and logistical accidents, human error, etc. In Section C of the Online Appendix we provide a headline and narrative-based explanation for some of the most negative shock realizations in our sample.

Figure 2 plots the distribution of our baseline shock measure $\epsilon_{j,t}$, pooled across all firms and years. It is noticeably left-skewed, i.e. with a larger mass in the left tail.

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

[19] 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).

Factor Analysis Despite controlling for a variety of firm characteristics and fixed effects, there is still concern that our shocks $\epsilon_{j,t}$ may pick up some latent common components. In Section A.1 of the Online Appendix, we generalize the reduced-form specification in (2) and formally extract parameteric and non-parameteric common factors from the residual $\epsilon_{j,t}$. All our results and insights remain unchanged.

3.3 Loan Outcomes

We now identify the impact of idiosyncratic firms shocks on loan-level returns. Different banks hold different portfolios of firms at different times, and are thus exposed to different combinations of shocks. Therefore, we first define an object $\mathbb{P}(i,t)$ which signifies the set of all firms that borrow from bank i in year t. The dependent variable is $R_{i,j,t}$ which is the realized return on a credit relationship (RoL) that bank i earns from firm j in year t. The main independent variable is our measure $\epsilon_{j,t}$, which stands for shocks that originate at firms j in year t. The granularity of our data allows us to control for time-varying bank supply factors, such as monitoring skill or risk aversion, by including interacted bank × year fixed effects.[20] In practice, we do even more and also account for firm industry and county fixed effects. Our most restrictive specification implies that the impact of shocks is identified by comparing loan-level returns across firms in the same county, industry, year, and 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 from credit lines. This allows us to also consider specifications which include a loan type fixed effect.[21] Formally, we we run the following panel specification for bank i and firm j relationships in year t, i.e. for $j \in \mathbb{P}(i,t)$:

$$R_{i,j,t} = \beta \epsilon_{j,t} + \theta_{g(i,j,t),i,t} + \alpha_j + \nu_{i,j,t} \tag{3}$$

where α_i refers to a firm fixed effect and $\theta_{(\cdot)}$ to the interaction of bank × year fixed effects with group fixed effects defined at the level of the relationship. Specifically, in our most conservative specification $\theta_{(\cdot)}$ includes the full interaction of bank × year × firm industry × firm county × loan type fixed effects. Because the main RHS variable is *estimated*, our standard errors are corrected for the additional uncertainty due to an estimated regressor via bootstrapping.[22]

[20] Coimbra and Rey (2023), 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 important issue.

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

[22] Specifically, to compute standard errors for the main coefficients of interest we perform a nonparametric bootstrap estimation with 5,000 replications, with replacement, for every considered regression specification.

3.4 Granular Credit Risk: Bank Outcomes

After investigating how idiosyncratic firm shocks affect loan returns, we then move up to the level of a bank portfolio. First, we build our main regressor by aggregating the firm shock measure in the following manner:

$$\bar{\epsilon}_{i,t} = \sum_{j \in \mathbb{P}(i,t)} s_{i,j,t}\epsilon_{j,t} \tag{4}$$

where $s_{i,j,t}$ is firm j's loan share in the portfolio of bank i as of year t, normalized to follow $\sum_{j \in \mathbb{P}(i,t)} s_{i,j,t} = 1$. The main dependent variable is bank-level return on all corporate loans (RoA) $R^b_{i,t}$, which is computed as the loan-share weighted average of loan-level returns. We proceed by analyzing the following relationship:

$$R^b_{i,t} = \alpha_i + \alpha_t + \beta\bar{\epsilon}_{i,t} + \omega'_{i,t}\gamma + \nu_{i,t} \tag{5}$$

where ω is a vector of observable bank-level controls, α_i and α_t denote bank and time fixed effects, and ν is the residual that is defined to be orthogonal to the control vector.

Identification Our loan-level analysis exploited within-bank-year variation to control for confounding credit supply-side factors. This is no longer possible when we turn our focus to outcomes at the bank level as the set of loans selected by each bank $\mathbb{P}(i,t)$ is likely to depend on bank factors and the performance of these loans may be correlated with or impacted by those bank factors. For example, monitoring capabilities of the bank may have an effect on the performance of firms (Stiglitz and Weiss, 1981). Consider the set of firms j borrowing from bank i in year t. A problem occurs whenever the following holds:

$$\epsilon_{j,t} = \eta'_{i,t}\delta_i + u_{i,j,t} \quad , \quad \forall j \in \mathbb{P}(i,t) \tag{6}$$

where $\eta'_{i,t}$ is a vector of bank i characteristics and $u_{i,j,t}$ is the residual of firm j's shock, defined to be orthogonal to bank i characteristics $\eta'_{i,t}$.[23] Whenever η and ν are correlated, we have that $Corr(\bar{\epsilon}_{i,t}, \nu_{i,t}) \neq 0$. In words, firm shocks could be contaminated via a non-zero loading δ on some vector of uncaptured time-varying bank characteristics η'. In order to address this concern, we adopt a newly proposed "granular instrumental variable" (GIV) (Gabaix and Koijen, 2022, 2023) approach that constructs an instrument for the "endogenous"

[23] Notice that the firm shock can be expressed as $\epsilon_{j,t} = \sum_k \mathbb{I}^k_{j,t}\eta'_{k,t}\delta_k + e_{j,t}$, with $\mathbb{I}^k_{j,t}$ a dummy variable equal to 1 if firm j borrows from bank k in year t. The residual in (6) is then given as $u_{i,j,t} = \sum_{k \neq i} \mathbb{I}^k_{j,t}\eta'_{k,t}\delta_k + e_{j,t}$ for firms borrowing from bank i ($\mathbb{I}^i_{j,t} = 1$).

covariate $\bar{\epsilon}_{i,t}$ by exploiting excess concentration of loan shares. Specifically, the granular instrument $Z^{GIV}_{i,t}$ is built by subtracting the unweighted average of firms shocks from the loan-share weighted average of firm shocks, all belonging to the corporate loan portfolio of bank i in year t:

$$Z^{GIV}_{i,t} = \sum_{j \in \mathbb{P}(i,t)} \left(s_{i,j,t} - \frac{1}{N_{i,t}} \right) \epsilon_{j,t} \tag{7}$$

where $N_{i,t}$ is the number of firm relationships in bank i's portfolio in year t. It is useful to re-write the instrument formula in the following manner

$$Z^{GIV}_{i,t} = \sum_{j \in \mathbb{P}(i,t)} s_{i,j,t} \epsilon^{*}_{i,j,t} \tag{8}$$

with

$$\epsilon^{*}_{i,j,t} = \epsilon_{j,t} - \frac{1}{N_{i,t}} \sum_{j \in \mathbb{P}(i,t)} \epsilon_{j,t} \quad , \quad \forall j \in \mathbb{P}(i,t) \tag{9}$$

that is, $\epsilon^{*}_{i,j,t}$ is the shock of firm j after the subtraction of the average firm shock in bank i's portfolio.[24] Given the relation in (6), the GIV purges out the confounding supply side factors and $\epsilon^{*}_{i,j,t} = u_{i,j,t} - \frac{1}{N_{i,t}} \sum_{j \in \mathbb{P}(i,t)} u_{i,j,t}$ becomes an observable proxy for the unobserved exogenous firm component u.

The *exclusion restriction* for our instrument can be stated precisely as:

$$\mathbb{E}\left[\left(\sum_{j \in \mathbb{P}(i,t)} \underbrace{s_{i,j,t}}_{\text{Weights}} \overbrace{\epsilon^{*}_{i,j,t}}^{\text{Firm Shocks}} \right) \nu_{i,t} \right] = 0 \tag{10}$$

Now, with our exclusion restriction in mind, identification is achieved if at least one of the following two conditions is satisfied:

1. Firm shocks $\epsilon^{*}_{i,j,t}$ are as-good-as randomly assigned.

2. Weights $s_{i,j,t}$ are as-good-as randomly assigned.

Our main argument that the exclusion restriction is satisfied rests on the first condition. We take countless precautions and conduct a number of robustness checks to argue that firm shocks $\epsilon^{*}_{i,j,t}$ are as-good-as randomly assigned. First, we perform two robustness checks addressing potential threats to the exclusion restriction. In Section A.2 of the

[24]Notice that in the case firm j borrows from more than one bank in year t, $\epsilon^{*}_{i,j,t}$ will differ across banks because they hold different firms in their portfolios.

Online Appendix we relax the homogeneous loading assumption, implicit in (6) since δ_i does not vary with j, and show robustness to allowing for bank factors to have firm-specific loadings. In Section A.3 we address the concern that unobserved bank factors may correlate and break the exclusion restriction whenever firms have multiple bank connections. Second, we run our bank-level analysis by horizon and document the absence of any "pre-trends" in Section 3.4. Third, as explained in more detail below and in Online Appendix F, we show that our results are robust to restricting the identifying firm shock variation to the 1 percent largest clients of the bank. Fourth, already in the initial firm shock extraction specification in (2), we include firm fixed effects and time-varying firm controls which should absorb any persistent and measurable time-varying dependence on $\nu_{i,t}$ through time. Fifth, in Online Appendix C we provide narrative-based explanation supporting the notion that the value added fluctuations extracted in (2) are non-systematic and occur at the level of the firm, while in Appendix E we document that these fluctuations are uncorrelated in the cross section or across time. Overall, we provide a multi-dimensional account in favor of as-good-as-exogeneity of our firm shock measure.

We now discuss the second potential identifying condition: random assignment of weights. First, as was mentioned previously, 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 and makes it more likely that shares are "pre-determined" with respect to shocks in time t. Second, loan shares and firm shocks are reassuringly contemporaneously uncorrelated in our sample.[25] But banks clearly allocate funds across firms in a systematic fashion due to, for instance, specialization in an industry or region, and although we observe that credit relationships are typically persistent across time, credit shares are unlikely to be assigned randomly. However, even if the distribution of weights is "endogenous", i.e. the second exclusion condition is violated, we can still achieve identification if the first condition holds. In fact, this very point is analysed in detail also by Borusyak et al. (2022) in the context of Bartik instruments or shift-share designs, which we discuss later in this section and in Section B of the Appendix.

Instrument Relevancy Now, while identification is achieved through the assumption of as-good-as-random assignment of our firm shock measure, instrument *relevance* and power arise from the excess concentration of loan shares. The overarching motivation for instrument power stems from the granular hypothesis (Gabaix, 2011): independently from whether shocks are truly idiosyncratic or not, the GIV is a relevant instrument for

[25]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. We also compute and discuss absolute average correlations in the Online Appendix.

the analysis of whether the impact of shocks vanishes out in the aggregate if weights are concentrated. In other words, shocks that hit individual firms are more likely to affect bank-level outcomes if the firm constitutes a large share in that bank's portfolio.

The importance of excess concentration is evident from the theoretical, model-independent correlation between the instrument and the endogenous covariate. In Section B.2 of the Online Appendix we show that this correlation can be expressed as:[26]

$$Corr(Z^{GIV}, \bar{\epsilon}) = \sqrt{\frac{eHHI}{\frac{\sigma_\eta^2}{\sigma_u^2} + HHI}} \tag{11}$$

where HHI refers to the loan share Herfindahl index and $eHHI = HHI - 1/N$ to the excess Herfindahl index. For the instrument to be relevant we thus need large idiosyncratic shocks (high σ_u^2) hitting large borrowers (high $eHHI$).

Several arguments support the relevancy of our instrument. First, our motivating Figure 1 documents that credit shares in the Norwegian banking sector feature a fat tail, i.e. are very concentrated. Second, the *aggregate* excess loan share Herfindahl for the whole banking sector is persistently positive, never vanishes to zero, and varies mildly over time. This can be seen from Panel (A) of Figure 8, which we discuss in more detail later in the context of the external validity of our study. This observation is also captured by the $eHHI$ term in equation (11). In the language of Borusyak et al. (2022), the "weight concentration index" requirement appears to be satisfied in our case, both in the cross section and in the aggregate across time. Third, the Pearson correlation between the instrument $Z_{i,t}^{GIV}$ and the endogenous covariate $\bar{\epsilon}_{i,t}$ is very high: 0.863, suggesting that most of the variation in loan share-weighted firm shocks comes from shocks that hit granular borrowers. There is therefore much evidence to suggest that the granular IV is a powerful instrument in our context. Moreover, as Section 5.1 will emphasize, portfolio concentration appears to be an ubiquitous observation and the GIV could be useful in many other settings.

Our main bank-level specification is then a simple two-stage least squares regression with $Z_{i,t}^{GIV}$ as instrument for $\bar{\epsilon}_{i,t}$.[27][28]

[26]To arrive at the theoretical expression in (11) we consider a single bank and simplify the analysis by assuming that loan shares $s_{i,j,t}$ and the number of clients $N_{i,t}$ are constant across time.

[27]We estimate the first and the second stages in one step by IV as encouraged by Angrist and Pischke (2009).

[28]Since the main regressor is estimated, standard errors are again computed by nonparametric bootstrap with 5,000 replications. When conditioning on $\bar{\epsilon}_{i,t}$ to be positive or negative - as discussed in Section 3.4 - a bootstrap is performed for each specification separately.

Relation to Shift-Share Instruments Our empirical approach and reliance on the granular IV is related to a complementary econometric framework - the Bartik (1991) instrument, also known as shift-share designs. A rich literature has developed over the past few years that studies this framework both theoretically and in applied settings (Adao et al., 2019; Goldsmith-Pinkham et al., 2020; Borusyak and Hull, 2021; Borusyak et al., 2022). In Appendix B.1 we discuss in more detail how our empirical setup would look like if we instead adopted the shift-share approach. The main takeaway of that discussion is that while shift-share instruments are more appropriate for many other settings, the GIV is more suitable in our context.

Large Loan Dynamics There is a rich tradition in macroeconomics to approximate aggregate economic dynamics with the granular residual, i.e. idiosyncratic disturbances stemming from the largest agents alone (Gabaix, 2011). For example, in a Hopenhayn (1992)-style model of business cycles with a finite number of heterogeneous firms, Carvalho and Grassi (2019) show that dynamics of the *single largest* firm explains a non-trivial fraction of aggregate fluctuations. As a supplement to our baseline granular instrument, we entertain a similar idea in our context. In this alternative implementation we focus exclusively on the transmission of idiosyncratic shocks hitting borrowers that are in the top 1 % of loan shares in their respective banks' portfolios while *controlling* for the average firm shock to the bottom 99 %. In other words, we construct a granular credit residual[29]. In Appendix F, we document that all main results in this paper remain unchanged using this alternative approach.

3.5 Granular Credit Risk Spillovers: Loan and Firm Outcomes

In order to study the economic consequences of granular credit risk, we investigate the relationship between bank-level aggregated firm shocks and credit market outcomes. We follow a large literature in banking relying on the methodology in Khwaja and Mian (2008). We focus on a sub-sample of firms that borrow from multiple banks and compare - for the same firm - loan supply and interest flow outcomes from banks that experienced good or bad granular credit shocks. In particular, 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, defined as a certain percentile of the loan share distribution, e.g. the median. We will be considering a discrete measure of non-granularity where we iteratively restrict

[29] We thank an anonymous referee for this suggestion.

the estimation sample to firms with a loan share below the $20, 21, \ldots, 99$ percentiles.

The dependent variable in our loan-level analysis is $\Delta y_{j,i,t}$, which is the yearly change in either loan supply or interest flow for firm j that borrows from bank i in year t. The independent variable is $\Delta \hat{u}_{i,t}$, which is the fitted value from the regression of the change in the endogenous bank-level shock $\Delta \bar{\epsilon}_{i,t}$ on the change in the granular instrument $\Delta Z^{GIV}_{i,t}$. We run the following 2SLS specification:

$$\Delta y_{j,i,t} = \beta \Delta \hat{u}_{i,t} + \alpha_i + \theta_{g(j),j,t} + \nu_{j,i,t} \tag{12}$$

where $\theta_{g(j),j,t}$ is a time varying firm fixed effect interacted with group level fixed effects at the firm industry $\times$ county level, and α_i is a bank fixed effect.[30]

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 onto firm balance sheet aggregates such as fixed capital spending. We also look at the impact of granular credit risk on firm bankruptcies. We run the following firm-level regressions:

$$\Delta y_{j,t} = \beta \Delta \hat{u}_{j,t} + \alpha_j + \theta_{g(j),t} + \nu_{j,t} \tag{13}$$

where $\theta_{g(j),t}$ are firm industry x county x year interacted fixed effects and $y_{j,t}$ are now firm-level outcomes such as (yearly changes in) fixed capital spending and an indicator variable which takes the value of unity if the firm is bankrupt and zero otherwise. In these spillover regressions the series of shocks $\Delta \hat{u}_{j,t}$ is treated as a shock to the intermediaries' balance sheet, which is then passed on to the rest of the economy as a bank-side disturbance. The difference between our paper and the rest of the literature is that the origin of this bank-side risk is (uninsured) idiosyncratic risk from large, granular borrowers.[31]

4 Main Empirical Results

We investigate how firm value added shocks affect loan returns in section 4.1. In section 4.2, we aggregate 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 test whether there are spillovers from granular credit risk onto other firms and trace out their real economic consequences. Finally in section 4.5 we assess the contribution of granular credit risk for overall bank credit supply variation and explore the benefits of limiting portfolio concentration, keeping everything

[30]Just as before, we run both stages of the 2SLS regression in a single step.
[31]We test and discuss the insurability of granular credit risk in Section 4.3.

Table 2: Loan Outcomes

	(1)	(2)	(3)	(4)
	Depend. Variable: Return on Loan (RoL)			
Firm Shock (std.)	0.334	0.335	0.361	0.336
	(0.015)	(0.017)	(0.019)	(0.017)
Bank x Industry x Year FE	-	✓	-	-
Bank x Industry x Year x Loan-type x County FE	-	-	✓	✓
Firm FE	-	-	-	✓
Observations	333289	317186	292825	282002
R^2	0.001	0.114	0.167	0.528
$\mathbb{E}$(RoL)	9.012%	9.029%	9.098%	9.076%
SD(RoL)	8.921%	8.928%	8.923%	8.687%

Notes: This table reports results from the regression of loan-level returns on idiosyncratic firm shocks. The exact specification is described by equation (3). Firm shocks are normalized by their standard deviation. 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 and year levels and computed by bootstrapping with 5,000 replications. The last two rows report the unconditional sample mean and standard deviation of the dependent variable.

else constant.

4.1 Loan Outcomes

Table 2 presents the impact of firm shocks on loan returns, obtained by estimating equation (3). Overall, firm shocks have a large and significant (at the 1% level) effect on loan-level returns. Our preferred specification is column (4) which features the most restrictive constellation of fixed effects. The result is the following: a 1-standard-deviation increase in the firm shock measure affects loan returns by 33.6 basis points, which quantitatively amounts to about 4% of the dependent variable's standard deviation. 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 std. unexpected reduction in firm performance reduces loan returns by roughly a third of a percentage point.[32]

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 little margin of adjustment for the bank to insure against realized bad loan-level outcomes. The natural next question

[32]Note that the coefficient stays virtually unchanged from moving from a specification with no controls (column 1) to the specification with a full set of controls (column 4), while the R^2 increases substantially, providing further support to the exogeneity of our firm shock measure (Altonji et al., 2005; Oster, 2019).

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
Weighted Firm Shock (std.)	0.129	0.136	0.116	0.016	0.194	0.117	0.056	0.176
	(0.029)	(0.027)	(0.031)	(0.094)	(0.074)	(0.030)	(0.087)	(0.072)
First stage F-stat			1429.683	138.772	396.907	1137.722	150.136	263.982
Bank FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Bank Controls	-	✓	-	-	-	✓	✓	✓
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 aggregated firm shocks $\bar{\epsilon}_{i,t}$. Columns (1)-(2) show OLS results for specification (5), while columns (3)-(8) instrument the independent variable with the granular IV. Positive (negative) shock specifications include only observations in which the shock measure $\bar{\epsilon}_{i,t}$ 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. Standard errors (in parentheses) are clustered at the bank level and computed by bootstrapping with 5,000 replications.

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 with our bank-level analysis. Results are reported in Table 3, where we have normalized the bank shock by its standard deviation.

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 2SLS regression.[33] Our results show that a one standard deviation GIV-instrumented firm shock, on average, affects bank loan portfolio returns by 11-12bps, which amounts to roughly 8% of the dependent variable's standard deviation.[34] We have specifications

[33] In Figure D3 of the Online Appendix 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. Formal statistical diagnostic tests also show validity of the GIV as a good instrument. The first-stage F-statistic in Table 3 is above the Stock and Yogo (2005) criterion for 5% maximal relative bias.

[34] In our sample, the average bank's RoA is 6.350% and the average annual interest flow (return) is NOK41.2 million. Thus, a one-std. negative granular credit shock lowers RoA to 6.174% and interest collected to NOK40.05 million - a reduction of NOK1.15 million per bank per year. The number of unique banks in the estimation sample is 111. Thus, total realized loss that could be attributed to granular credit risk equals NOK127.65 million (or 12.97$ million) per year, on average. For reference, this accounts for

with and without additional bank controls which include lagged values of book leverage, liquidity, total assets, number of loans, deposit-to-asset ratio, and financial assets to total asset ratio.[35] Results are qualitatively and quantitatively robust to the exclusion of these controls.[36]

A second key 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 loan share-weighted firm shock $\bar{\epsilon}_{i,t}$ 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.[37] 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.[38]

Figure 3 provides a visual representation of this 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, respectively. We construct the binned scatter plots by first regressing both bank RoA and the GIV-instrumented firm shocks on bank and time fixed effects, then computing the residuals, and adding back the mean of each variable. We then construct 50 equally-sized

11.5% of the standard deviation of the *aggregate* variation in total sector-wide bank returns from corporate loans across time. By all accounts, this is an economically significant fraction of the aggregate fluctuation in bank profitability.

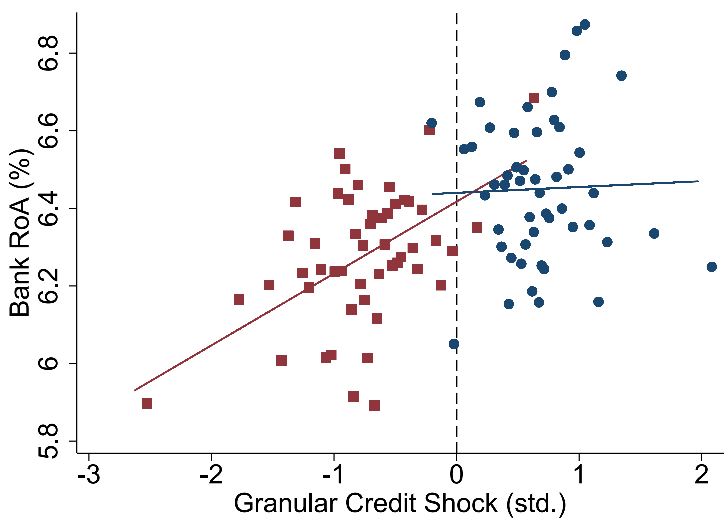
[35]Theoretically, if the exclusion restriction holds, the GIV approach would not require any further bank-time controls. The reason is that GIV, by construction, would be purged from any bank-time factors. For robustness, we still include observable bank controls. Results do not change in any substantial matter, which adds validity to the method. In addition, in Section A.2 we also control for latent bank-time factors, extracted using PCA. Results do not change either.

[36]Bank-level return on corporate loans (RoA) is the main dependent variable in this section. We have also experimented with loan writedowns and portfolio-level Sharpe ratios. Table D7 of the Online Appendix reports the results. We find some evidence that granular credit risk, when instrumented by the GIV, is weakly positively (negatively) associated with the Sharpe Ratio (writedowns).

[37]For robustness, we also estimate a non-linear IV on the full sample, where we allow the impact of weighted firm shocks to differ based on the sign of $\bar{\epsilon}_{i,t}$. The non-linear IV delivers similar asymmetry as in Table 3. In the case of no bank controls, the point estimate (std. error) for negative shocks is 0.163 (0.045) and for positive shocks 0.043 (0.075). A non-linear IV with bank controls produces estimates of 0.159 (0.041) and 0.055 (0.056).

[38]We explore the extensive margin in detail in Section D.1 of the Appendix.

Figure 3: Granular Credit Risk and Bank Outcomes

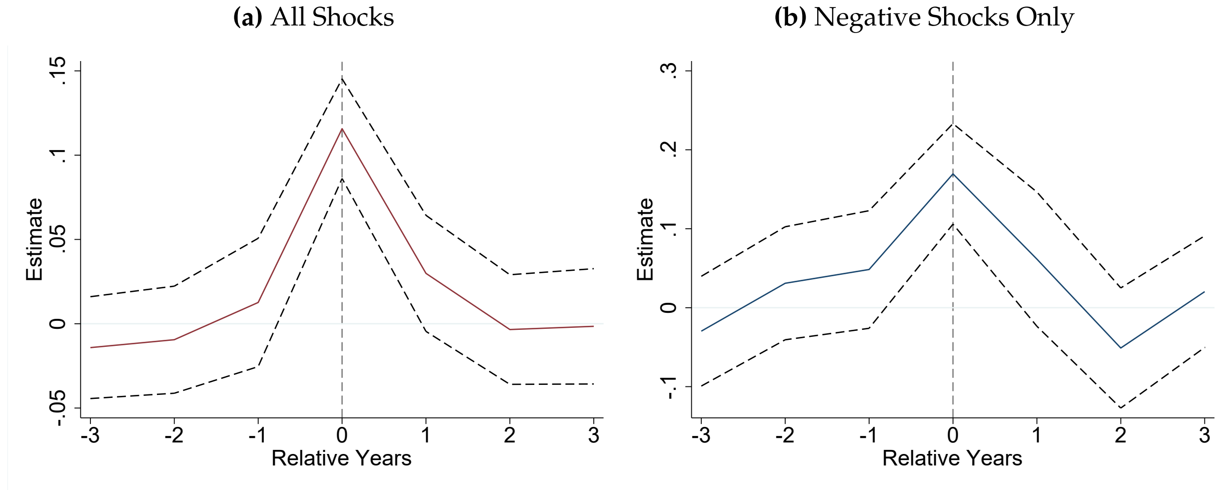


Notes: This figure visualises the relationship between residualized bank-level return on loans and residualized instrumented bank-level aggregated firm shocks. The red squares (blue circles) are binned scatterplots conditional on negative (positive) values of the weighted firm shock $\bar{\epsilon}_{i,t}$. 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. 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 bank-level loan return on instrumented shocks, conditional on $\bar{\epsilon}_{i,t} < 0 (> 0)$.

bins of the residual shock variable. Figure 3 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 further validation that our measure of firm shocks is indeed economically informative.

In Figure 4 we report bank 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 statistically significant implying the absence of any pre-trends, especially for the case of all shocks in Panel (a). This is important for the validation of the exclusion restriction, as previously mentioned in Section 3.4.

Figure 4: Bank Outcomes by Horizon



Notes: This figure plots the results from regressing leads and lags of bank-level returns on the bank-level aggregated firm shock measure $\bar{\epsilon}_{i,t}$ that is instrumented by the granular IV. 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.

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. To attempt answering this question, we collect bank-level data on income from fees, derivatives, equity and bond holdings, and dividends. All of these variables have been scaled by total corporate loans. 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 4 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. Few of the measures of non-interest income are significantly associated with our shock measure, and the magnitudes are quantitatively very small. A one standard deviation change in the granular shock results in these income measures moving less than 1 percent relative to total firm loans. Importantly, most forms of income are if anything very weakly *positively* correlated with idiosyncratic credit shocks, which questions their usefulness as a hedging instrument.

Table 4: Hedging Granular Credit Risk

	(1)	(2)	(3)	(4)	(5)
Dependent Variable: Income from	Fees	Derivatives	Equity	Bonds	Dividends
			Pooled		
GIV-Instrumented Firm Shock (std.)	-0.000	0.001	0.016	0.003	0.002
	(0.002)	(0.001)	(0.016)	(0.002)	(0.002)
Bank FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Observations	1211	1210	1103	1198	1181
R^2	0.025	0.012	0.011	0.008	0.017
			Negative Shocks Only		
GIV-Instrumented Firm Shock (std.)	0.003	0.004	-0.000	0.006	0.003
	(0.003)	(0.002)	(0.000)	(0.004)	(0.003)
Bank FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Observations	697	679	632	692	684
R^2	0.049	0.043	0.273	0.044	0.032

Notes: This table reports results from regressing bank-level non-interest income components, in percent of total firm loans, 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 (7). Standard errors (in parentheses) are clustered at the bank level. Data on all bank non-interest income is from the financial supervisory database ORBOF.

A drawback of this analysis is that the various hedging instruments analyzed in Table 4 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 fully analyse 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.[39]

4.4 Granular Credit Risk Spillovers: Loan and Firm Outcomes

Loan Outcomes 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

[39]Banks could also dilute single-name concentration risk by engaging in syndicated lending. In the case of Norway, however, syndicated loans constitute a very small fraction of external financing for firms.

Table 5: Spillovers from Granular Credit Shocks: Loan-Level Supply

	(1)	(2)	(3)	(4)	(5)
	Dependent Variable: Δ Loans (std.)				
Δ Bank Shock (std.)	0.007	0.056	0.051	0.246	0.231
	(0.013)	(0.037)	(0.038)	(0.115)	(0.112)
Non-Granular Firms (50%)	-	✓	✓	-	-
Non-Granular Firms (20%)	-	-	-	✓	✓
Year x Industry x County x Firm FE	✓	✓	✓	✓	✓
Bank FE	-	-	✓	-	✓
Instrumented by GIV	✓	✓	✓	✓	✓
Observations	15279	3479	3443	232	212

Notes: This table reports results from regressing year-on-year changes in (log) bank debt on the year-on-year change in bank-level aggregated firm shocks which are instrumented by the granular IV. Specifications are based on equation ((12)). Both dependent and independent variables have been standardized. Column (1) includes all firms. Columns (2)-(5) include only non-granular firms. Non-granular firms are defined as firms whose bank loan shares are less than the 50th (columns (2)-(3)) or the 20th (columns (4)-(5)) percentiles of the loan share distribution, which is pooled over all banks and years. The full distribution of loan shares was plotted on Figure 1. Standard errors (in parentheses) are double clustered at the bank and firm level.

the rest of their corporate portfolio. We are interested in seeing whether banks react by reducing loan supply or raising interest flow, in particular on non-granular firms. The specification behind the results below is equation (12).

Table 5 reports our results on the supply of credit. In all specifications we impose a stringent configuration of interacted firm × year × industry × 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. Both dependent and independent variables have been standardized. In column (1), we start with the sample of all firms and find no significant relationship. In columns (2)-(5) 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} (columns (2)-(3)) or 20^{th} (columns (4)-(5)) percentiles of the loan share distribution. We do find a statistically significant relationship in this case, particularly when the threshold is the 20th percentile. In columns (3) and (5) we add a bank fixed effect to the baseline configuration of fixed effects and results do not change substantially. Overall, a one-standard deviation negative granular credit shock reduces loan supply growth to non-granular borrowers by up to 5% (24%) of the dependent variable's standard deviation in the case of 50th (20th) percentile thresholds. These magnitudes are comparable to for instance the effects of bank-level liquidity shocks on loan growth as in Khwaja and Mian (2008). Specifically, their estimates (Table 3 - column 1) imply that a 1 s.d liquidity shock at the bank-level leads to a 15 % decline in the growth of loan volumes. Finally, later in this subsection we consider other thresholds for the non-granular firm definition.

Table 6: Spillovers from Granular Credit Shocks: Loan-Level Interest Flow

	(1)	(2)	(3)	(4)	(5)
	Dependent Variable: Δ Interest Flow (std.)				
Δ Bank Shock (std.)	-0.004	-0.087	-0.101	-0.079	-0.166
	(0.014)	(0.043)	(0.042)	(0.113)	(0.116)
Non-Granular Firms (50%)	-	✓	✓	-	-
Non-Granular Firms (20%)	-	-	-	✓	✓
Year x Industry x County x Firm FE	✓	✓	✓	✓	✓
Bank FE	-	-	✓	-	✓
Instrumented by GIV	✓	✓	✓	✓	✓
Observations	15279	3479	3443	232	212

Notes: This table reports results from regressing year-on-year changes in (log) interest flows on the year-on-year change in bank-level aggregated firm shocks which are instrumented by the granular IV. Specifications are based on equation ((12)). Both dependent and independent variables have been standardized. Column (1) includes all firms. Columns (2)-(5) include only non-granular firms. Non-granular firms are defined as firms whose bank loan shares are less than the 50th (columns (2)-(3)) or the 20th (columns (4)-(5)) percentiles of the loan share distribution, which is pooled over all banks and years. The full distribution of loan shares was plotted on Figure 1. Standard errors (in parentheses) are double clustered at the bank and firm level.

In Table 6 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 loan pricing. A one-standard deviation decline in the granular credit shock increases interest flow growth on loans to non-granular clients by up to 10.1% (16.6%) of the dependent variable's standard deviation in the case of 50th (20th) percentile thresholds. 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 induces a leftward shift in the supply schedule, leading to a reduction in quantities and an elevation in 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. We return to the issue of network effects more formally in Section 5.2.

Firm Capital Expenditure Next, we ask whether spillovers on non-granular firms ultimately lead to significant economic consequences. We aggregate our data to the firm level and consider fixed capital stock growth as the dependent variable. The empirical specification of interest is now equation (13). We allow for the interacted year × industry × county fixed effects as well as the firm fixed effect. In addition, we focus on the same samples of non-granular firms where non-granularity is defined based on bank loan

Table 7: Firm Outcomes from Granular Credit Shocks

	(1)	(2)	(3)	(4)	(5)
	Dependent Variable: Δ Capital (std.)				
Δ Bank Shock (std.)	0.005	0.025	0.037	0.044	0.025
	(0.003)	(0.009)	(0.011)	(0.025)	(0.059)
Non-Granular Firms (50%)	-	✓	✓	-	-
Non-Granular Firms (20%)	-	-	-	✓	✓
Industry x County x Year FE	✓	✓	✓	✓	✓
Firm FE	-	-	✓	-	✓
Instrumented by GIV	✓	✓	✓	✓	✓
Observations	157642	66648	55770	19608	13719

Notes: This table reports results from firm-level regressions where the outcome variable is year-on-year change in the (log) fixed capital stock. The key independent 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 ((13)). Non-granular firms are defined as firms whose bank loan shares are less than the 50th or 20th percentile of the loan share distribution. For firms with multiple banking relationships, we define a firm as non-granular if the mode credit relationship is non-granular. Standard errors (in parentheses) are clustered at the firm level.

shares being below the 50$^{\text{th}}$ or 20$^{\text{th}}$ 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 5 and 6.

Results are reported in Table 7. We find that granular credit risk is positively associated with fixed capital growth, particularly in the sample of non-granular borrowers. A one-standard deviation negative shock causes a decline in firms' fixed capital investment growth by roughly 2.5%-4.4% of the dependent variable's standard deviation. These numbers are comparable, but somewhat smaller than the effects of a more general bank shock on capital investment as in Amiti and Weinstein (2018). The impact on non-granular firms defined by the median loan share cut-off, in particular, is strongly statistically significant (columns (2)-(3)). This finding shows that frictions in financial intermediation - specifically credit concentration risk - can affect the real, physical side of the economy.

Firm Bankruptcy Finally, we investigate whether granular credit risk not only affects firm balance sheet variables but also triggers a higher frequency of corporate bankruptcies. The dependent variable is now an indicator variable which takes the value of unity if a firm is bankrupt and zero otherwise. The independent variable is the lagged $\Delta\hat{u}_{j,t}$. Our specifications include year, industry, and county fixed effects which collectively account for various aggregate or correlated shocks that could confound our main channel. We also include additional firm controls: lagged total assets, wage bill, leverage, liquidity, and credit rating.

Table 8 reports the results from probit regressions. Across all specifications, neg-

Table 8: Firm Bankruptcy from Granular Credit Shocks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent Variable: Prob. of Bankruptcy$_t$						Pr.(Ever Bankrupt)	
Δ BankShock$_{t-1}$	-0.010	-0.010	-0.032	-0.033	-0.076	-0.090	-0.050	-0.095
	(0.010)	(0.009)	(0.010)	(0.008)	(0.046)	(0.049)	(0.009)	(0.017)
Non-Granular Firms (50%)	-	-	✓	✓	-	-	✓	-
Non-Granular Firms (20%)	-	-	-	-	✓	✓	-	✓
Firm Controls	-	✓	-	✓	-	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓	✓	✓
County FE	✓	✓	✓	✓	✓	✓	✓	✓
Pseudo R^2	0.039	0.096	0.039	0.100	0.037	0.089	0.039	0.034
Observations	165000	165000	78511	78511	27828	27828	79965	28754

Notes: This table reports results from firm probit regressions of an indicator variable for firm bankruptcy on the bank-level granular credit shock. In columns (1)-(6), the outcome variable is probability of contemporaneous firm bankruptcy. In columns (7)-(8), the outcome variable is the probability that a firm ever goes bankrupt. Firm controls include lagged total assets, wage bill, leverage, liquidity, and credit rating. 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 mode credit relationship is non-granular. Standard errors (in parentheses) are clustered at the year level. Firm bankruptcy information is from the credit rating agency Bisnode.

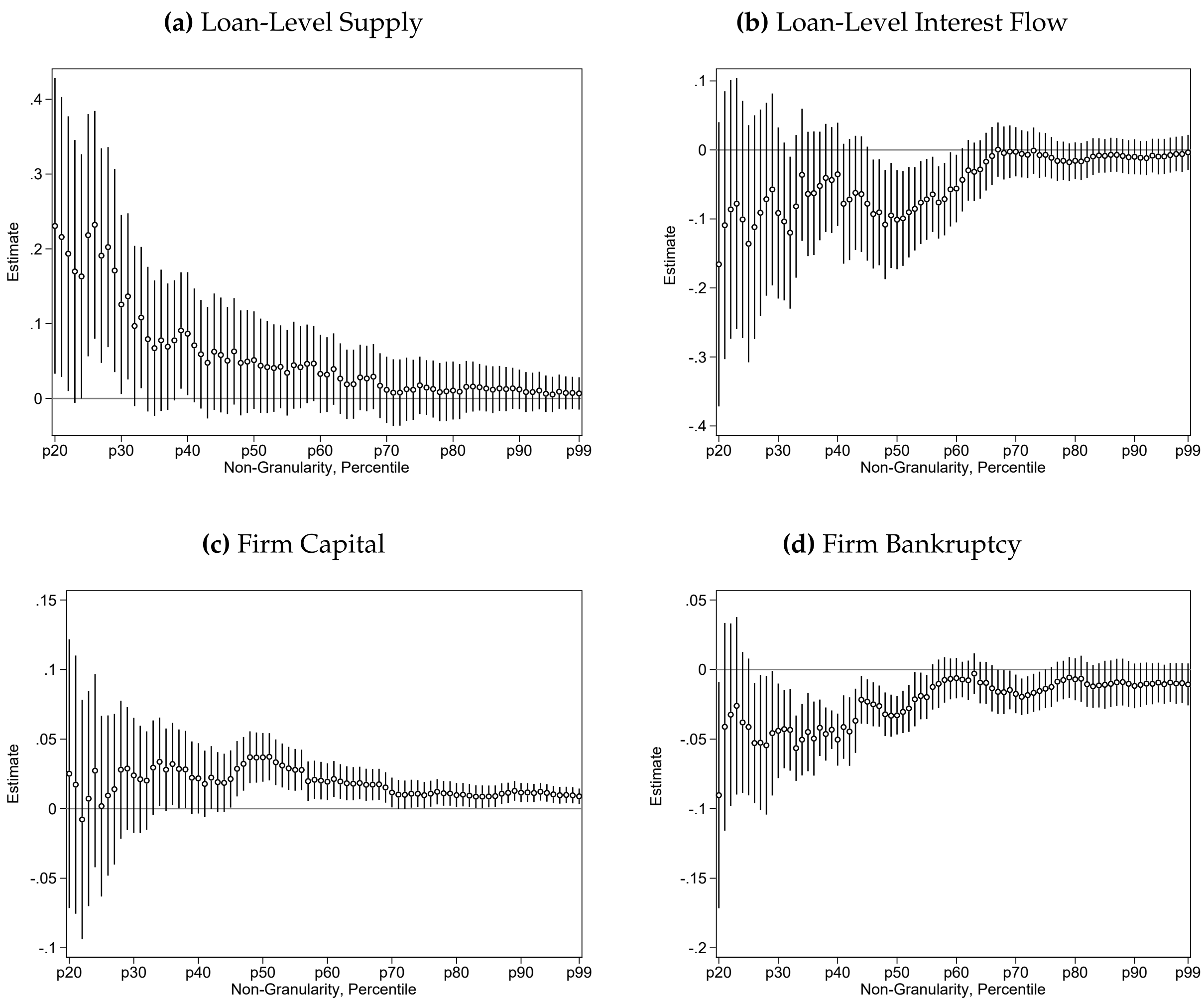
ative granular credit shocks are positively associated with the likelihood of corporate bankruptcy. In the case of non-granular firms, defined by the usual 50% or 20% loan share thresholds, the relationships are also statistically significant (columns (3)-(6)). A one standard-deviation negative granular credit shock raises the probability of bankruptcy for non-granular firms by around 3%-9%. Note that the unconditional probability for the same sub-sample of firms is 1.10% per annum. Therefore, the impact is around 3-10 basis points p.a. In columns (7)-(8) we regress the probability of a firm filing for bankruptcy at any point over its existence in our dataset on the lagged granular credit shock and find quantitatively similar results.

Discrete Measure of Non-Granularity In our analysis of spillover effects we have so far been focusing only on two non-granularity cut-offs: 50th and 20th percentiles of the loan share distribution. It is possible that our results are accidentally driven by the peculiar choice of these cut-offs. In an important test of robustness and generality of our spillover results, we now regard non-granular firms as those with bank loan shares less than the *Pth* percentile of the pooled credit share distribution. Unlike previously, we now re-estimate our four spillover exercises for every P in the discrete interval $[20, 99]$. All specifications, including the presence of fixed effects or controls, are otherwise the same as before.

Figure 5 reports the results. Panels (a) and (b) report loan-level spillover results for loan supply and interest flow (both in yearly changes) as dependent variables. Panels (c) and (d) portray firm-level spillover results for fixed capital (in yearly changes) and the firm bankruptcy indicator as dependent variables. In all four panels, the x-axis shows the discrete non-granularity interval $[20, 99]$. The y-axis shows point estimates and 90% confidence bands for each corresponding case. The overarching conclusion is that our spillover results are not driven by a particular choice of the non-granularity cut-off but are instead fairly universal.

Two general observations are noteworthy. First, the impact of granular credit risk is inversely related to the non-granularity of affected firms. This can be vividly seen in panels (a), (b), and (d): spillover estimates on loan supply and interest flow as well as bankruptcy probability tend to become economically greater the more non-granular firms are. Second, for very low values of P we often obtain noisy estimates. This occurs because the sample sizes shrink; qualitatively, however, point estimates generally remain in the same ballpark. Overall, all of the above is highly indicative of a "pecking order" of credit relationships: banks adjust lending conditions with their non-granular borrowers in order to compensate for portfolio losses stemming from their granular corporate clients.

Figure 5: Spillovers from Granular Credit Shocks: Discrete Measure of Non-Granularity



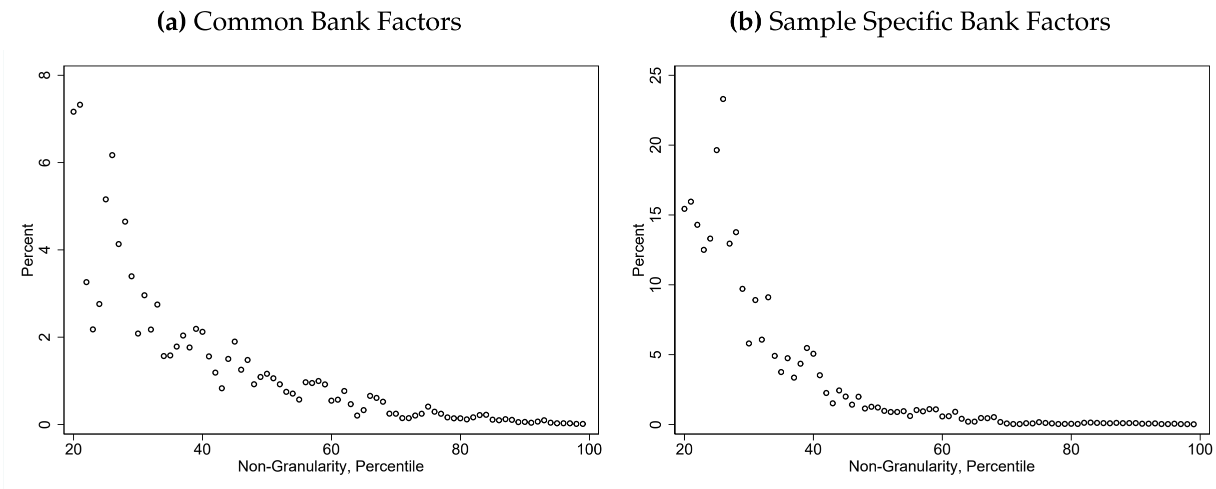
Notes: This figure reports results from the four baseline spillover exercises but for varying non-granularity cut-offs. Panels (a) and (b) show loan-level spillover results for loan supply and interest flow as dependent variables, respectively. Panels (c) and (d) show firm-level spillover results for fixed capital and bankruptcy indicator as dependent variables, respectively. In each panel, non-granular firms are defined as firms whose bank loan shares are less than the Pth percentile of the loan share distribution, which is pooled over all banks and years. Percentiles $P = 20, 21, \ldots, 99$ are shown on the x-axes and the y-axes show point estimates and 90% confidence bands for each respective case.

4.5 Quantification and Counterfactuals

In this section we provide back-of-the-envelope quantitative calculations of further implications of granular credit risk.

Contribution to bank loan supply In Section 4.4 we saw that granular credit risk propagates to bank credit supply and leads to a significant contraction of credit to smaller firms,

Figure 6: Granular Credit Risk and Bank Supply Factors

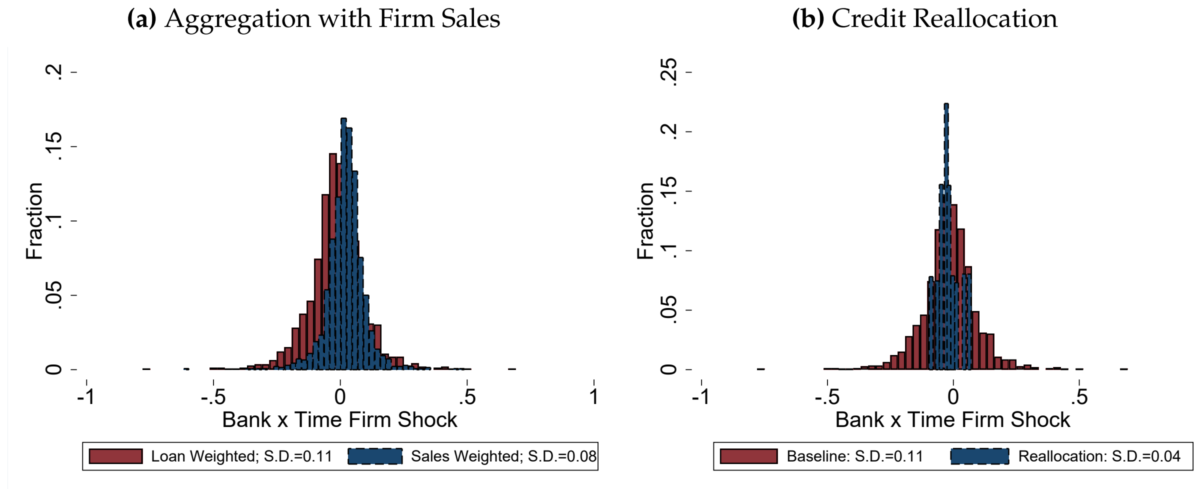


Notes: This Figure plots the marginal R^2 of granular credit shocks relative to the marginal R^2 of bank-time fixed effects on the y-axes. The marginal R^2 is measured as the increase in R^2 when controlling for either the granular credit shock or bank-time FE, relative to a baseline estimation of equation (13) with neither of these controls. The x-axes represents different sub-sample regressions, where the estimation of equation (13) is restricted to firms below a non-granularity percentile threshold p20,...p99. Non-granular firms are defined as firms whose bank loans shares are less than the pth percentile of the loans share distribution pooled over all banks and years. In panel (a) the bank-supply factor is first extracted as bank-time FE from estimating equation (13) on the full firm sample (p100 threshold). These supply factors are subsequently used as control variables in the different sub-sample regressions. In panel (b) the bank-supply factor is re-estimated as bank-time FE on each sub-sample regression.

explaining up to one-quarter of a standard deviation in firm level credit growth. We now assess the contribution of granular credit shock for overall bank credit supply variation, by comparing the R^2 contribution of generic bank-time factors to the contribution of our granular shock in the estimation of equation (13). The R^2 contribution is measured by how much R^2 increases when controlling for either the granular credit shock or bank-time fixed effects, relative to a baseline estimation of (13) with neither of these controls. We perform this exercises for various non-granular firms' cut-offs.

The results are displayed in Figure 6, where we plot the relative R^2 contribution. In panel (a) we first estimate the bank supply factors on the entire firm sample and subsequently use those fixed effects as bank supply controls in the sub-sample regressions. In panel (b) we re-estimate the bank-time fixed effect for each sample cut-off. In both cases we see that granular credit shocks account for 8% to 20% of the total variation in credit growth to smaller firms that is attributed to generic bank supply factors. We interpret this as granular credit shocks representing a non-trivial part of time-varying bank credit supply to smaller firms. Not surprisingly, as the non-granularity threshold is increased and the credit growth impact of granular shocks diminishes (panel (a), Figure 5), these shocks begin to gradually represent a smaller part of bank supply variation for that

Figure 7: Counterfactual Scenarios



Notes: This Figure plots pulled densities of $\bar{\epsilon}_{i,t}$ under alternative aggregation scenarios. Panel (a) plots shocks that are aggregated to the bank-year level either with loan shares or firm sales as weights; in each case, shares sum up to unity in each bank-year observation. Panel (b) plots the distribution of shocks that are aggregated with weights that equal loan shares of firms in the whole economy. The histogram is over-layed on the histogram of baseline shocks that are aggregated with the usual loan shares.

particular non-granularity cut-off.

Counterfactuals Our flexible empirical setup allows for a variety of counterfactual tests. In particular, we can feed alternative distributions of either weights or shocks into our main granular credit risk measure and re-evaluate pass-through estimates. First, we are interested in the extent to which our results are driven by excess credit risk concentration which is not simply caused by a fat-tailed firm size distribution. To this end, we construct bank-time shock measures $\bar{\epsilon}_{i,t}$ by using either actual loan shares or firm sales as weights. In both cases, weights are normalized to sum to unity in each bank-time portfolio. We use firm sales as a usual proxy for size following Gabaix (2011). Results are shown via histograms in Panel (a) of Figure 7. The density of shocks that are weighted with loan shares is more dispersed (standard deviation of 0.11 relative to 0.08) and more left-skewed, reflecting the shape of the underlying distribution of firm shocks, while the firm sales-weighted distribution is less dispersed and almost symmetrical around 0. This points to the existence and importance of bank loan portfolio concentration over and above the firm size distribution.

Our second counterfactual entertains a different aggregation scheme and answers the following question: could the impact of granular credit risk be reduced if that risk was distributed across portfolios of financial intermediaries differently? Suppose that the empirically observed distribution of weights $s_{i,j,t}$ is sub-optimal and could be improved

Table 9: Main Results under Counterfactual Scenarios

	(1)	(2)	(3)
	Scenario		
Point Estimate	Baseline	Alternative Aggregation	Credit Reallocation
Bank Returns	0.129	0.086	0.043
Spillovers - Loan Supply	0.051	0.034	0.017
Spillovers - Interest Flow	-0.101	-0.067	-0.034
Spillovers - Firm Δ Capital	0.037	0.025	0.012
Spillovers - Firm Bankruptcy	-0.033	-0.022	-0.011

Notes: This Table reports point estimates of the main empirical tests under alternative dispersions of the key regressor. Column (1) reports baseline results: impact of a one-standard-deviation increase in the regressor on the corresponding dependent variable. Columns (2)-(3) scale the point estimates by the standard deviations that are computed under counterfactual scenarios while not re-estimating the specifications.

upon. We can perform a simple but nevertheless informative exercise. Specifically, in each year banks are exposed to the same distribution of firm shocks as before but the weights are now those of a hypothetical universal banker lending to all firms in the sample: $\bar{\epsilon}_{i,t} = \sum_{j\in\mathbb{P}(t)} s_{j,t}\epsilon_{j,t}$. One could think of this experiment as the reallocation of existing firm credit across banks that would occur if all banks had ownership shares in the universal bank, with shares reflecting the banks' relative size as measured by total credit volume. Figure 7, Panel (b), plots the resulting density of this counterfactual credit shock together with the baseline. The standard deviation of the distribution of granular credit shocks under this extreme reallocation is 0.04, i.e. it falls roughly by a factor of three. Thus, there could be significant gains from macroeconomic stabilization of granular credit risk just from a more efficient redistribution of credit shares and thus risk exposures (keeping everything else constant, which may be an unrealistic assumption in this context).

The two counterfactual exercises grant us new values for the *standard deviations* of the bank-time distributions of firm shock measures. Equipped with those, we now compute counterfactual elasticities under scenarios where firm shocks are aggregated differently. Importantly, we do *not* re-estimate our regressions. We use the same estimated coefficients as before, compare standard deviations of our main regressor across the baseline and two counterfactual scenarios and re-evaluate the pass-through estimate. Table 9 reports the results for our five major empirical tests: the impact of granular credit risk on bank returns and the four forms of spillover effects. First, elimination of credit concentration that is in excess of firm size concentration could reduce the pass-through of granular credit shocks on the macroeconomy by roughly 40%. Second, reallocating credit into a portfolio of a universal bank further reduces pass-through by an additional half.

An important limitation of the above exercises is their partial equilibrium nature. Costs of transition to new steady-state equilibria could be equally substantial. The trade-offs between portfolio concentration risk, effiency, stability, and mis-allocation could therefore only be studied in a more structural framework.

Taking Stock We conclude this section by reiterating our main findings. First, idiosyncratic firm shocks have large and significant effects 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 Discussion and Supplementary Results

In this section, we expand on several issues that are relevant for our analysis. First, we argue for the external validity of our empirical approach and findings. Second, we discuss the production networks literature and show that our spillover results are not driven by firm-side inter-connectedness. Third, we explore heterogeneous effects in our bank-level analysis. Fourth, we discuss the potential origins of credit concentration and large loan exposure. Finally, we list further additional results and robustness checks that are delegated to the Online Appendix.

5.1 External Validity

A relevant question to consider is how concentration of Norwegian banks' loan portfolios compares to other countries. Our empirical analysis has underlined that granularity in the distribution of exposure shares is important for the transmission of idiosyncratic shocks to granular exposures to portfolio-level outcomes of the lender. But is this setup unique to the banking sector in Norway? The Norwegian economy is admittedly bank-dependent when it comes to sources of external financing. Thus, our approach could potentially not be applicable to other countries.

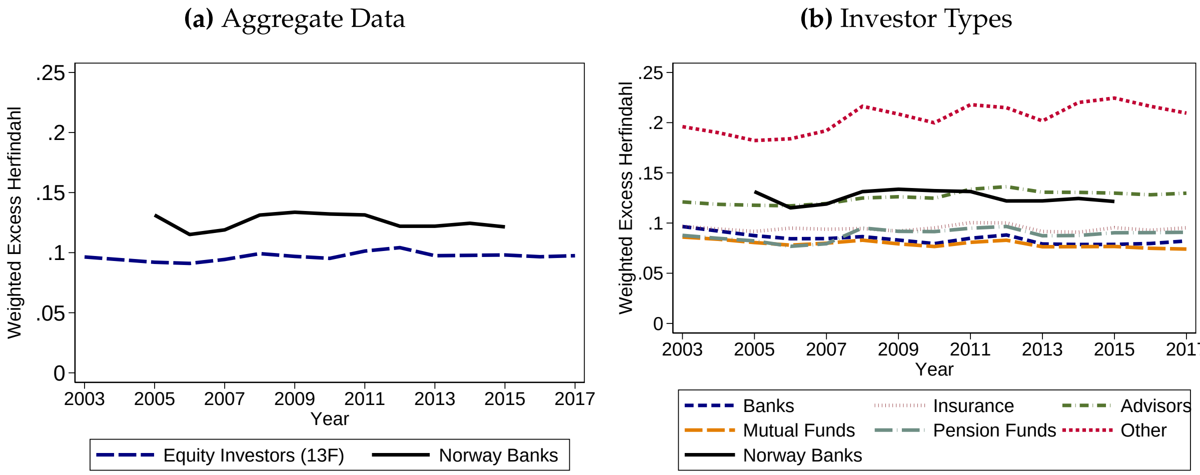
A recent paper by Baena et al. (2022) applies our methodology to the European credit register *Anacredit* and finds results that are consistent and in line with ours. First, they document a substantial degree of concentration and right-skewness of the loan share distribution in the context of bank credit in France. Second, Baena et al. (2022) also quantify the pass-through of estimated idiosyncratic firm performance shocks to bank portfolio outcomes and find equally economically and statistically significant effects. Thus, our findings on the non-trivial effects of *single-name* concentration risk on bank outcomes appear to be not unique to the Norwegian setting. Moreover, our approach is very tractable and general enough that it could be applied to any other empirical setting with registers that link borrowers to lenders.

It is well known that bank-dependency has diminished over the past decades in some countries, e.g. the U.S.. Thus, single-name borrower concentration risk may become less important in aggregate terms if firms switch increasingly more towards bonds-based financing. In other words, how unique is portfolio concentration risk to banking? From numerous applied studies, we observe that portfolio concentration risk is indeed ubiquitous and important for our general understanding of aggregate financial and economic fluctuations. Studying U.S. banks, Kundu and Vats (2021) find that state-level idiosyncratic shocks transmit through bank networks across states and have macroeconomic implications. Chodorow-Reich et al. (2021) document granularity and concentration in portfolios of life insurers and demonstrate how it matters for the equity market. Camanho et al. (2022) use the granular IV methodology in the context of foreign exchange market fluctuations and fund-level rebalancing decisions and also find significant aggregate effects. An attractive feature that underpins all of these empirical studies is a solid theoretical basis foundation, i.e. the granular hypothesis (Gabaix, 2011).

To further complement our own empirical findings for Norwegian banks and the studies just mentioned, we perform an additional simple test of external validity.[40] Namely, we compute the time-varying degree of concentration in equity holdings of U.S. institutional investors. Specifically, for each institutional investor in the SEC 13F holdings data from Thomson/Refinitiv we compute the excess Herfindal index as: $eHHI_{i,t} = \sqrt{\sum_j s_{i,j,t}^2 - \frac{1}{N_{i,t}}}$ where $s_{i,j,t}$ is the share of exposure j in investor i's portfolio in quarter t and $N_{i,t}$ is the number of exposures. We aggregate by taking value-weighted averages for all investors and also for each individual investor type; we obtain the corrected types from Koijen and Yogo (2018).

[40] We thank Ralph Koijen, our discussant, for suggesting this idea.

Figure 8: Granularity in Equity Portfolios of U.S. Institutional Investors



Notes: This figure plots weighted excess Herfindahl indices for equity portfolios of U.S. institutional investors and corporate loan portfolios of Norwegian banks. Institutional investor data comes from SEC Form 13F filings and was obtained from Thomson/Refinitiv. Investor types are from Koijen and Yogo (2018) and have thus been corrected for measurement and labelling errors.

Results are plotted in Figure 8. We observe that in terms of portfolio concentration the Norwegian corporate loan sector is not very dissimilar to the universe of U.S. equity investors - the weighted excess Herfindahl is in the 0.1-0.13 ballpark for both situations. Panel (b) of Figure 8 plots heterogeneity by investor type. We see that loan concentration in Norwegian banks is closest (in fact, quantitatively almost identical) to that of Investment Advisors, the category which constitutes more than 70% of the entire sample. All in all, we therefore conclude that the Norwegian context is not exceptional and our analysis and conclusions can potentially extend to other circumstances, countries, and asset classes.

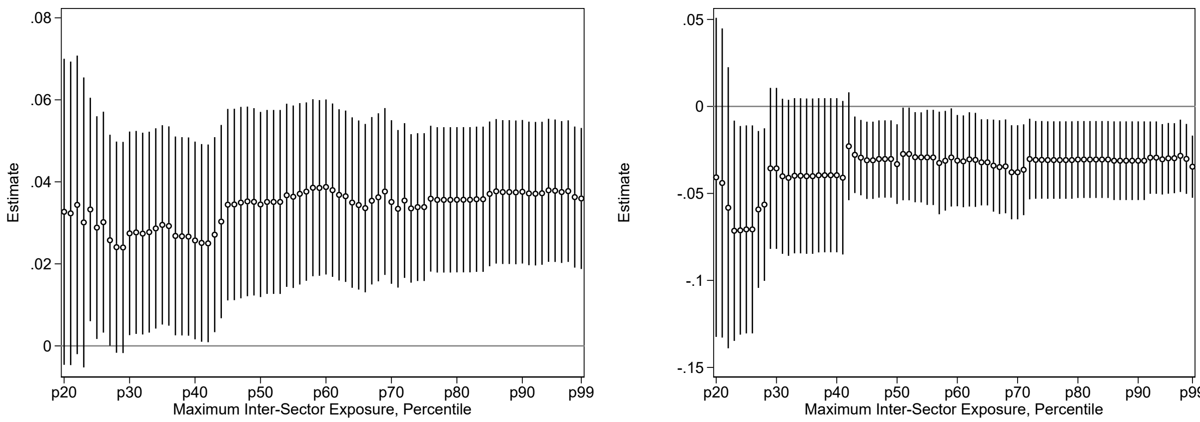
5.2 Network Effects

A vibrant new literature emphasizes the role of networks in the amplification and propagation of idiosyncratic financial shocks (Huremovic et al., 2020; Dewachter et al., 2020; Elliott et al., 2020). In important work, Huremovic et al. (2020) show that bank credit supply shocks propagate along firm production networks, causing sizable real economic effects. This presents a potential threat to identification of our firm spillover regressions. For instance, granular borrowers could be linked to non-granular borrowers not only via their common lender but also by being an important customer of the non-granular borrower directly, or vice-versa. If that is the case, production network spillovers could be an alternative explanation for the positive association between granular credit shocks

Figure 9: Firm Spillovers: Accounting for Production Networks

(a) Firm Capital

(b) Firm Probability of Bankruptcy



Notes: This figure reports results from either firm-level regressions of year-on-year changes in (log)capital (left panel) or probit regressions of likelihood of firm bankruptcy (right panel) on changes in the bank-level granular credit shock, instrumented by the GIV. The sample is restricted only to firms operating in sectors in the Pth percentile of the distribution of maximum inter-sector exposures. The samples, indicated by their percentile cut-offs $P = 5, 6, \ldots, 50$, are shown on the x-axes and the y-axes show point estimates and 90% confidence bands obtained on each respective sample. In the left panel we report estimation results obtained by running the same regression specification as in Table 7 Column (3). In the right panel estimation results are obtained from running the same specification as in Table 8 Column (4).

and real outcomes of non-granular borrowers.

To alleviate these concerns, we perform a robustness exercise where we use aggregate two-digit NACE-level input-output tables for the Norwegian economy in order to restrict attention to non-granular borrowers that are sufficiently downstream, i.e. firms that have low dependence on the demand from other firms. Specifically, for each pair of sectors i and j we compute the fraction of sales of i that is accounted for by j - including i's own sector - and refer to that as the inter-sector exposure between i and j. We then compute the maximum inter-sector exposure across all j's for each i, and restrict attention to firms from bottom percentiles of that inter-sector exposure measure. Intuitively, such firms would have low exposure to all other sectors and are thus far downstream, i.e. they sell primarily to households. For such firms the conjecture is that demand from granular borrowers would be of limited importance. Thus, if our firm spillover results are indeed driven solely by production network effects, we should then find no effects for low-inter-sector exposure firms. A limitation of our approach is that firm-to-firm linkages are not available.

Figure 9 reports the results. We iteratively restrict the estimation sample to firms operating in sectors in the Pth percentile of the distribution of the maximum inter-sector exposure measure. Firms in the lower percentiles are more downstream. We re-run our firm capital and bankruptcy regressions for each P in [20,99] (which are plotted on the x-axis) while always focusing on non-granular firms as defined by the 50th percentile of the loan share distribution. Specifically, in Panel (a) we present point estimates and 90% confidence bands for the same regression specification as in Column (3) of Table 7 but for different Ps. Similarly, in Panel (b) we present point estimates and 90% confidence bands for the same regression specification as in Column (4) of Table 8 but for different Ps. From both panels we see that our results remain robustly and quantitatively unaffected by the degree of inter-sector connectedness. If anything, we notice that the impact on the probability of bankruptcy (Panel (b)) is somewhat *greater* for more downstream (low-P) firms. These findings suggest that granular credit risk spillovers are distinct from and complementary to production network spillovers that studies such as Huremovic et al. (2020) emphasize.

5.3 Bank Heterogeneity

A growing literature emphasizes the role of heterogeneity in the financial intermediation sector for business and financial cycle fluctuations (Corbae and D'Erasmo, 2021; Begenau and Landvoigt, 2021; Coimbra and Rey, 2023; Jamilov and Monacelli, 2023). In this section we ask whether granular credit shocks have differential effects on bank portfolios. We consider several dimensions of bank heterogeneity: portfolio risk weights, (log of) risk-weighted assets (RWA), regulatory capital ratio, loan portfolio Herfindahl (HHI), (log of) number of loans, the liquidity ratio, and the profitability ratio.[41] We compute portfolio risk weights by dividing RWA by book assets. The regulatory capital ratio is defined as regulatory capital over RWA. Liquidity is defined as the ratio of cash holdings to book assets. Profitability is defined as the ratio of profits before taxes to book assets. All characteristics are lagged. For each characteristic we define a dummy variable based on the median of the respective lagged distribution. Table 10 presents the results. The dependent variable is the return on corporate loans at the bank level, as before. Each column reports coefficients for interactions of GIV-instrumented bank-level firm shocks and dummies for respective lagged bank characteristics. All specifications include the time and bank fixed effects as well as the usual set of bank controls.

From the table we observe several notable results. First, the number of loans does not materially affect the transmission of granular credit shocks, in the sense that the pass-

[41] We use RWA as a proxy for bank size, broadly defined. We have also experimented with book assets, book equity, and regulatory capital as alternative size measures. Results do not change. In addition, we also condition on whether banks are domestically or foreign owned. Baseline results are quantitatively very close to the sub-sample of privately-owned banks; estimates based on foreign banks are consistently imprecise.

Table 10: Bank Outcomes - Heterogeneity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent Variable: Bank Return on Loans (RoA)						
Lagged Bank Characteristic:	Risk Weights	RWA	Capital Ratio	HHI	Loans Number	Liquidity	Profit
Shock x Low Characteristic	0.104	0.173	0.090	0.068	0.135	0.095	0.109
	(0.042)	(0.037)	(0.040)	(0.040)	(0.046)	(0.045)	(0.045)
Shock x High Characteristic	0.137	0.029	0.134	0.138	0.090	0.135	0.126
	(0.040)	(0.036)	(0.039)	(0.039)	(0.030)	(0.038)	(0.037)
Bank FE	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓
Instrumented with GIV	✓	✓	✓	✓	✓	✓	✓
Observations	1208	1208	1208	1211	1211	1211	1211
R^2	0.101	0.106	0.101	0.103	0.102	0.102	0.101

Notes: This table reports results from regressions of bank-level returns on corporate loans on GIV-instrumented idiosyncratic shocks interacted with lagged bank characteristics. In all columns, characteristics are cut based on the 50th percentile. Risk weights are obtained by dividing risk-weighted assets (RWA) by book assets. The regulatory capital ratio is defined as regulatory capital over RWA. HHI refers to the within-bank Herfindahl index of loan concentration. Liquidity is defined as cash holdings over book assets. Profitability is defined as profit before taxes over book assets. All specifications include the following bank controls: lagged total assets, leverage, liquidity, number of loans, deposit to assets ratio, and financial assets to total assets ratio. Standard errors (in parentheses) are clustered at the bank level.

through is also significant for banks with a high number of loans (column (5)). Hence granular credit risk is not merely a "small N" problem. Second, the pass-through is stronger for banks with low RWA (column (2)) and high capital ratios (column (3)). The two effects are interconnected, since in the cross section larger banks are more levered and thus have lower capital ratios.[42] Third, the pass-through is twice as large for banks with high loan portfolio concentration (column (4)). This is reassuring, since given the same volatility of idiosyncratic firm shocks, higher concentration should make banks more exposed to shocks stemming from the right tail of the loan share distribution.

Last but not least, in column (1) we see that banks with higher risk weights tend to be more affected by granular credit shocks.[43] This is potentially an important finding because credit concentration risk and the risk-taking channel may form complementarities that could impact an array of macroeconomic outcomes, ranging from the financial boom-and-bust cycle to the transmission of monetary policy (Bruno and Shin, 2015).[44] In order to

[42]The observation that smaller banks are more exposed to granular credit shocks is in line with the existing theories that emphasize the role of bank size heterogeneity in the transmission of aggregate and idiosyncratic disturbances (Stavrakeva, 2019; Davila and Walther, 2020). In particular, smaller banks generally tend to have a greater balance sheet sensitivity with respect to exogenous shocks.

[43]Risk weights are not correlated with any of the proxies of bank size: RWA, capital, book assets, or book equity. They are also uncorrelated with the bank-level share of corporate credit to total assets.

[44]It is possible that banks with high risk weights are exposed to firms that are inherently riskier, similarly to the "evergreening" behavior analyzed by Peek and Rosengren (2005) or assortative matching in the credit market as in Chang et al. (2021).

Table 11: Bank Outcomes - Inspecting the Risk-Taking Channel

	(1)		(2)		(3)	
Second Interaction:	Low RWA	High RWA	Low CapRatio	High CapRatio	Low HHI	High HHI
Shock x Low RW	0.156	-0.005	0.070	0.119	0.056	0.117
	(0.050)	(0.058)	(0.054)	(0.051)	(0.067)	(0.048)
Shock x High RW	0.212	0.061	0.108	0.168	0.075	0.187
	(0.070)	(0.039)	(0.058)	(0.062)	(0.051)	(0.063)
Bank FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Observations	1208	1208	1208	1208	1208	1208
R^2	0.105	0.105	0.101	0.101	0.103	0.103

	(4)		(5)		(6)	
Second Interaction:	Low Loans Number	High Loans Number	Low Liquid	High Liquid	Low Profit	High Profit
Shock x Low RW	0.120	0.079	0.060	0.131	0.114	0.086
	(0.063)	(0.043)	(0.076)	(0.048)	(0.057)	(0.057)
Shock x High RW	0.162	0.105	0.127	0.149	0.095	0.163
	(0.065)	(0.045)	(0.047)	(0.074)	(0.049)	(0.059)
Bank FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Observations	1208	1208	1208	1208	1208	1208
R^2	0.102	0.102	0.101	0.101	0.101	0.101

Notes: This table reports results from regressions of bank-level returns on corporate loans on GIV-instrumented idiosyncratic shocks, double interacted with bank risk weights (RW) and additional characteristics. In all specifications, characteristics are cut based on the lagged 50th percentile. For example, column (1) presents estimates for banks with low risk weights and low risk-weighted assets (RWA), low risk weights and high RWA, high risk weights and low RWA, and high risk weights and high RWA. Similarly for all other columns. Risk weights are obtained by dividing risk-weighted assets (RWA) by book assets. The regulatory capital ratio (CapRatio) is defined as regulatory capital over RWA. HHI refers to the within-bank Herfindahl index of loan concentration. NumLoans refers to the (log) number of loans in the portfolio. Liquid refers to the liquidity ratio, defined as cash holdings over book assets. Profit refers to the profitability ratio, defined as profit before taxes over book assets. All specifications include the following bank controls: lagged total assets, leverage, liquidity, number of loans, deposit to assets ratio, and financial assets to total assets ratio. Standard errors (in parentheses) are clustered at the bank level.

inspect and better understand this mechanism, we run an additional exercise below.

The risk-taking channel We now examine the impact of granular credit risk on bank returns, while interacting the granular credit risk shock with both portfolio risk weights and other bank characteristics. Table 11 reports the results. Each column reports estimates from a second interaction of the respective characteristic with the GIV-instrumented shock interacted with risk weights. For example, column (1) shows results for a double interaction of the shock measure with risk weights and risk-weighted assets. As before, high and low dummies are based on the median of the each respective variable's lagged distribution. Overall, we observe that (with the exception of the left column in specification (6)) estimates for banks with high risk weights are *always* higher than for banks with low risk weights. In other words, estimates corresponding to the "Shock x High RW" row are always greater than estimates from the "Shock x Low RW" row, regardless of what the second interaction is. This suggests that the credit concentration risk and risk-taking channels are positively associated.

The most notable are results in columns (1), (3), and (6). These suggest that the pass-through of granular credit shocks, conditional on the sample of banks with high risk weights, is stronger if banks are small, have concentrated loan portfolios, and record high profits. The result on profits (column (6)) is particularly interesting since it is consistent with the risk-taking channel: in good states of the world, i.e. when individual firm performance is high, banks with low risk aversion build riskier, concentrated portfolios and record higher profits. However, as our paper argues, this comes at the (seemingly unhedged) cost of greater exposure to granular credit risk and eventual portfolio losses during the bad state, i.e. when firm performance is low. Overall, our results add an interesting new angle of portfolio concentration to the literature on endogenous financial cycles driven by risk taking of heterogeneous financial intermediaries (Coimbra and Rey, 2023).

5.4 Origins of Large Exposures

The ubiquitous nature of concentration in the portfolios of banks as well as other financial actors is seemingly at odds with standard models in finance (Merton, 1987). Diversification as an equilibrium outcome is a benchmark takeaway of classical portfolio theory (Markowitz, 1952). Deviations from this "null hypothesis" merit a special discussion and understanding potential *causes* of concentration is useful for the rationalization of our empirical findings. In what follows, we discuss several potential causes of credit concentration. Our benchmark explanation is the borrower size distribution for which we provide a simple theoretical model in Section G of the Appendix. We also briefly discuss asymmetric information, home bias, and behavioral biases as alternative frictions and channels.

Firm size distribution 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 (2021) 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, on average, large borrowers - a condition which is true in our data - the Pareto rate of the credit share distribution could be driven by the Pareto rate of the firm size density.

In order to explore this notion, we write down a simple extension of the Gabaix (2011) granular economy in Section G of the Online Appendix. The core idea is that the variance of bank loans depends on the distribution of firm-level demand for loans, which is a power function of firm size. We provide conditions under which, conditional on firm sizes being drawn from a power law distribution, the distribution of bank loans would also have fat tails. If such conditions are satisfied, loan variance decays at a slower rate than $\frac{1}{\sqrt{N}}$ where N is the number of firms in the economy. In other words, idiosyncratic shocks to firms - through the loan demand function - pass through directly to bank portfolios and have aggregate implications. Importantly, we are able to prove that the sufficient condition for "granularity" of the loan share distribution is the following inequality: $1 < \alpha\tau < 2$ where $\alpha \geq 1$ is the power law exponent of the firm size distribution and τ is the inverse of the elasticity of firm loan demand with respect to firm size. In words, $\alpha\tau$ is a measurable sufficient statistic that determines the speed of decay of loan variance. When taken directly to our Norwegian loan and firm data, we find that the $\alpha\tau$ object is firmly within the [1,2] bounds. Thus, our empirically-validated theoretical model confirms that credit risk is granular.

While this is a very natural explanation for the observed credit concentration, we note that in our data we 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, 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 - are important as well. We discuss them briefly below.

Asymmetric information In practice, costly information could prevent banks from holding fully diversified loan portfolios (Grossman and Stiglitz, 1980). When information is a tool for conditional return variance reduction, equilibrium under-diversification is possible (Van Nieuwerburgh and Veldkamp, 2010; Kacperczyk et al., 2016). Concentrated lending could also 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). In the credit market equilibrium, the price of the loan contract depends on the degree of information asymmetry and the magnitude of idiosyncratic fluctuations. Ivashina (2009) argues that there is a trade-off between diversification and asymmetric information which, in equilibrium, determine the return on the loan.

Home bias Home bias is a perennial stylized fact in international finance, banking, and macroeconomics (Coeurdacier and Rey, 2013). Different underlying theories - be it information frictions of behavioral - could materialize as observable home bias. For example, 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 and generating home bias and concentration in portfolio holdings. Juelsrud and Wold (2020) document a substantial degree of within-county bias in the Norwegian banking system (see Figure D4 in the Online Appendix). 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%.

Behavioral biases Huberman (2015), among others, shows that some investors tend to ignore portfolio diversification theory and invest in familiar assets. Fuster et al. (2010) reviews the extensive literature on the departures from rational expectations in finance and macroeconomics. The exclusion restriction of our instrument in Section 3.4 would be valid under this "familiarity effect" at the bank level. In that case, over-exposure of bank i to firm j at time t is largely *independent* of the firm's present characteristics and is instead a function of i's persistent subjective beliefs. Thus, behavioural biases of this kind would also be compatible with our empirical approach.

For the purpose of the empirical analysis, we note that the aforementioned classes of models that we put forward to explain the origin of credit concentration (firm size distribution, asymmetric information and home bias, and behavioral biases) are all compatible with our findings. Those theories would have, however, different normative implications.

5.5 Additional Results

In the Online Appendix we provide numerous supplementary results and perform a battery of robustness tests. In Appendix A we run several sets of factor analyses at the firm and bank levels, thus relaxing many of our identifying assumptions and generalizing the baseline empirical approach. Appendix B provides further details on the granular

IV, particularly its relationship to the Bartik instrument and an analytical exposition of instrument relevancy and power. Appendix C provides a narrative-based discussion of our estimated firm shock measure, highlighting its idiosyncratic and unexpected nature. Appendix D presents many additional empirical results, including on firm heterogeneity, loan-level asymmetric effects, and the pricing and compensation of granular credit risk. Appendix E presents all the robustness checks that we have run. Those include, among others, pairwise correlation tests and placebo regressions. Appendix F shows that all our main results are reproduced if we instead define the granular credit shock as the shock to the top 1 % of borrowers in terms of loan shares. Finally, Appendix G lays out our theoretical model, which provides an analytical motivation for our discussion of the origins of credit concentration in Section 5.4.

6 Conclusion

This paper has developed the first bottom-up causal quantification of *single-name credit concentration risk* on bank-level outcomes and on the economy. While the previous literature focused on the effects of sectoral or geographic exposure risk, we drill down to the very granular level of individual loans. Empirically, we show that 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-round 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 and formalization of firm demand-side shocks at the level of bank portfolios by employing the "granular instrument variable" approach developed in the influential recent work by Gabaix and Koijen (2022, 2023). This method takes advantage of the fact that the distribution of loan shares features a fat tail and allows us to rigorously analyze pass-through of granular risk. We also present a simple theory of the "granularity of credit" building on the well-known fact that the size of firms follows a power law distribution. Using our high-quality comprehensive dataset we can estimate the parameters of the Pareto distribution governing the distribution of loans and confirm its granularity.

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. bank capital that is at risk if a granular borrower suffers a bad negative shock. Our estimate of the loan share Pareto power in Section G 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 "red flag" for prudential authorities. 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* credit concentration risk.

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Online Appendix for “Granular Credit Risk”

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Contents

A Factor Analysis

A.1 Factor Extraction at the Firm Level

Our baseline firm shock measure is the residual $\epsilon_{j,t}$ obtained from estimating equation (2) in main text, repeated here:

$$\ln VA_{j,t} = \alpha_j + \theta_{g(j),t} + \beta_1 \ln K_{j,t} + \beta_2 \ln W_{j,t} + \lambda' \mathbf{X_{j,t}} + \epsilon_{j,t}. \tag{A1}$$

The residual $\epsilon_{j,t}$, although orthogonal to a range of time-varying firm characteristics and fixed effects, may still contain components which are common across firms. To address this concern we now consider a robustness exercise in which we extract both parametric and non-parametric factors explicitly. Formally, we assume that the residual can be expressed as:

$$\epsilon_{j,t} = \delta^{x'}_{j,t} \eta^x_t + \delta'_j \eta_t + u_{j,t} \tag{A2}$$

for a vector of parametric η^x_t and non-parametric η_t factors. For the parametric factors, the firm-specific time-varying loading vector $\delta^x_{j,t}$ is assumed to be a function of observable firm characteristics. For the non-parametric factors we assume a constant firm-specific loading vector δ_j. The goal is to estimate both common components ($\delta^{x'}_{j,t}\eta^x_t$ and $\delta'_j \eta_t$) and to replace our firm shock measure $\epsilon_{j,t}$ with a more robust alternative $u_{j,t}$.

We proceed in two steps. First, we extract parametric common components by estimating a richer version of equation (A1), in which we interact all time-varying firm-specific regressors ($\ln K_{j,t}, \ln W_{j,t}, \mathbf{X_{j,t}}$) with year dummies. Hence, $\delta^x_{j,t}$ is given by the vector of explanatory variables in equation (A1). Formally, we re-estimate equation (A1) assuming time-varying coefficients:[1]

$$\ln VA_{j,t} = \alpha_j + \theta_{g(j),t} + \beta_{1,t} \ln K_{j,t} + \beta_{2,t} \ln W_{j,t} + \lambda'_t \mathbf{X_{j,t}} + \check{\epsilon}_{j,t}. \tag{A3}$$

In the second step, we perform Principal Component Analysis (PCA) on the residual $\check{\epsilon}_{j,t}$ by estimating:

$$\check{\epsilon}_{j,t} = \delta'_j \eta_t + u_{j,t} \tag{A4}$$

Since our firm panel is unbalanced, we employ an iterative Expectation Maximization (EM) algorithm as in Gabaix and Koijen (2023), and estimate principal components recursively. Starting with the first factor, the algorithm repeatedly regresses $\check{\epsilon}_{j,t}$ on η^1_t and then $\check{\epsilon}_{j,t}$ on δ^1_j until convergence. For factors $f = 2, \ldots, f^{max}$, least squares iterations are per-

[1] We make one adjustment relative to the specification in equation (A1), by replacing the quadratic age specification with one-year age fixed effects.

Table A1: Loan Outcomes with Firm Factors Extraction

	(1)	(2)	(3)
	Dep. Var.: Return on Loan		
(1) Firm Shock: $\check{\epsilon}_{j,t}$	0.307	0.307	0.333
	(0.016)	(0.017)	(0.018)
(2) Firm Shock: $u^1_{j,t}$	0.279	0.279	0.299
	(0.016)	(0.017)	(0.018)
(3) Firm Shock: $u^2_{j,t}$	0.239	0.237	0.255
	(0.016)	(0.017)	(0.018)
Bank x Industry x Year FE	-	✓	-
Bank x Industry x Year x Loan-type x County FE	-	-	✓

Notes: This table reports results from the regression of loan-level returns on loans on three alternative measures of idiosyncratic firm shocks. Row (1) refers to the shock measure after extracting parametric common components. Row (2) refers to the shock measure after extracting parametric common components and one latent common component. Row (3) refers to the shock measure after extracting parametric common components and two latent common components. All shocks have been normalized by their standard deviations. Standard errors (in parentheses) are double clustered at the firm-year level.

formed on the remaining residual from equation (A4) after extracting $f-1$ components, denoted $u^{f-1}_{j,t}$.[2] In our analysis below we consider $f^{max} = 2$ components and denote by $u^1_{j,t}$ and $u^2_{j,t}$ the residuals obtained after extracting one and two factors, respectively.[3]

We then run our loan-level regressions based on equation (3) in main text with the three new estimated firm shock measures: $\check{\epsilon}_{j,t}$, $u^1_{j,t}$ and $u^2_{j,t}$. In other words, we substitute the baseline shock variable $\epsilon_{j,t}$ with potentially more refined and idiosyncratic versions. In order to obtain bank-level estimates, we proceed as in the main text. First, we aggregate by computing loan size-weighted averages of the three new shock measures $\bar{\check{\epsilon}}_{i,t}$, $\bar{u}^1_{i,t}$, and $\bar{u}^2_{i,t}$, where

$$\bar{x}_{i,t} = \sum_{j \in \mathbb{P}(i,t)} s_{i,j,t} x_{j,t} \tag{A5}$$

for $x \in (\check{\epsilon}, u^1, u^2)$. Second, we construct three new Granular IVs $GIV^{\check{\epsilon}}_{i,t}$, $GIV^{u^1}_{i,t}$, and $GIV^{u^2}_{i,t}$, as in equation (7) in the main text, where now

$$GIV^x_{i,t} = \sum_{j \in \mathbb{P}(i,t)} \left(s_{i,j,t} - \frac{1}{N_{i,t}} \right) x_{j,t} \tag{A6}$$

for $x \in (\check{\epsilon}, u^1, u^2)$. Third, we run our IV regressions for $\bar{\check{\epsilon}}_{i,t}$, $\bar{u}^1_{i,t}$, and $\bar{u}^2_{i,t}$, instrumenting each

[2]Following the suggestion in Stock and Watson (2016), iterations are initiated with factors that are extracted from the balanced sub-sample of firms.

[3]The f^{max} threshold is chosen by performing a standard PCA on a balanced sub-sample of firms, and applying the IC_{p2} criterion in Bai and Ng (2002) to determine the number of factors.

Table A2: Bank Outcomes with Firm Factors Extraction - New Shocks, New Instruments

	(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
(1) Granular Credit Shock: $\bar{\check{\epsilon}}_{i,t}$	0.118	0.125	0.106	0.015	0.212	0.105	0.027	0.186
	(0.027)	(0.026)	(0.035)	(0.081)	(0.075)	(0.030)	(0.071)	(0.073)
(2) Granular Credit Shock: $\bar{u}^1_{i,t}$	0.092	0.092	0.079	-0.117	0.160	0.072	-0.087	0.136
	(0.025)	(0.024)	(0.031)	(0.078)	(0.073)	(0.029)	(0.075)	(0.068)
(3) Granular Credit Shock: $\bar{u}^2_{i,t}$	0.106	0.100	0.090	-0.082	0.136	0.083	-0.067	0.119
	(0.027)	(0.025)	(0.032)	(0.072)	(0.058)	(0.029)	(0.072)	(0.053)
Bank FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Bank Controls	-	✓	-	-	-	✓	✓	✓

Notes: This table reports results from regressing bank-level return on loans on bank-level aggregated firm shocks. Columns (1)-(2) are standard OLS, while columns (3)-(8) instrument the weighted shock with a granular IV. Row (1) is based on the shock $\check{\epsilon}_{j,t}$ and instrument $GIV^{\check{\epsilon}}_{i,t}$, which refer to the residual after extracting parametric common components. Row (2) is based on the shock $u^1_{j,t}$ and instrument $GIV^{u^1}_{i,t}$, which refer to the residual after extracting parametric common components and one latent common component. Row (3) is based on the shock $u^2_{j,t}$ and instrument $GIV^{u^2}_{i,t}$, which refer to the residual after extracting parametric common components and two latent common components. Standard errors (in parentheses) are clustered at the bank level.

with their respective $GIV^{\check{\epsilon}}_{i,t}$, $GIV^{u^1}_{i,t}$, and $GIV^{u^2}_{i,t}$.

Table A1 reports loan outcomes after factor extraction. Columns (1)-(3) are based on the same set of controls and fixed effects as in columns (1)-(3) of Table 2. Rows (1)-(3) show results for the three new shock measures. Recall that baseline estimates from Table 2 are in the 0.334-0.361 range. We see that after the extraction of parametric and two non-parametric factors, estimates are still large, statistically significant, and quantitatively very close to our baseline results.

Table A2 reports results at the bank level. Columns (1)-(8) are based on the same specifications and sets of controls and fixed effects as columns (1)-(8) in Table 3 from main text. Recall that baseline estimates from Table 3 are roughly 0.117 and 0.180 for the specifications with pooled and only negative shocks, respectively. We find that our strictest model, which extracts parametric and two non-parameteric factors, leads to estimates of 0.083 and 0.119 for pooled and only negative shocks specifications, respectively. All coefficients are very similar to our baseline results and are statistically significant at least at the 5% level.

We now consider an alternative approach where instead of replacing the baseline shock measure $\epsilon_{j,t}$ itself, we keep $\epsilon_{j,t}$ as the shock variable but build the Granular IV based on the

Table A3: Bank Outcomes with Firm Factors Extraction - Old Shocks, New Instruments

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable: Bank Return on Loans (RoA)					
	Pooled	Positive	Negative	Pooled	Positive	Negative
(1) $GIV^{\check{e}}_{i,t}$	0.110	0.003	0.182	0.111	0.035	0.165
	(0.035)	(0.078)	(0.071)	(0.030)	(0.070)	(0.068)
(2) $GIV^{u^1}_{i,t}$	0.114	-0.021	0.216	0.112	0.035	0.189
	(0.032)	(0.092)	(0.074)	(0.028)	(0.095)	(0.065)
(3) $GIV^{u^2}_{i,t}$	0.144	0.039	0.266	0.133	0.061	0.234
	(0.038)	(0.140)	(0.084)	(0.032)	(0.135)	(0.071)
Bank FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Bank Controls	-	-	-	✓	✓	✓
Instrumented with GIV	✓	✓	✓	✓	✓	✓

Notes: This table reports results from regressing bank-level return on loans on bank-level aggregated firm shocks $\bar{\epsilon}_{i,t}$ instrumented by three alternative Granular IVs. In row (1) the GIV is based on $\bar{\check{e}}_{i,t}$, which refers to the shock measure after extracting parametric common components. In row (2) the GIV is based on $\bar{u}^1_{i,t}$, which refers to the shock measure after extracting parametric common components and one latent common component. In row (3) the GIV is based on $\bar{u}^1_{i,t}$, which refers to the shock measure after extracting parametric common components and two latent common components. Positive (negative) shock specifications include only observations in which the bank level shock $\bar{\epsilon}_{i,t}$ is above (below) zero. Standard errors (in parentheses) are clustered at the bank level.

three new shocks $GIV^{\check{e}}_{i,t}$, $GIV^{u^1}_{i,t}$, and $GIV^{u^2}_{i,t}$. In other words, we keep the same endogenous regressor as in the main text, but instrument it with new, more robust instruments. Results are reported in Table A3. All estimates are quantitatively in line with our baseline results. Coefficients from specifications with pooled or negative only shocks are all statistically significant at least at the 5% level.

A.2 Factor Extraction at the Bank Level

By subtracting the unweighted mean from bank-level weighted firm shocks, our Granular IV in equation (7) in the main text removes a common bank factor with loadings δ_i assumed to be identical across the bank's firm borrowers. If the loadings are truly heterogeneous, this procedure might not be sufficient to ensure exogeneity of the instrument. Rather than constructing an instrument based on the assumption that a bank's factor influences all its clients identically, we now consider a generalized procedure taking into account heterogeneous loadings of the bank factor.

We build on the procedure in Section A.1, where we in the first step remove parametric factors (to obtain $\check{e}_{j,t}$) and in the second step remove non-parametric factors (to obtain $u_{j,t}$). But now, rather than doing the non-parametric factor extraction jointly for all firms, the

Table A4: Bank Factors Extraction - Controlling for Factors Directly

	(1)	(2)	(3)	(4)
	Dep. Var.: Bank Return on Loans (RoA)			
	OLS	Instrumented with GIV		
	Pooled	Pooled	Positive	Negative
Granular Credit Shock	0.127	0.109	0.033	0.182
	(0.025)	(0.028)	(0.070)	(0.067)
Bank FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Bank Controls	✓	✓	✓	✓
$\eta_{i,t}$ controls	✓	✓	✓	✓

Notes: This table reports the results from regressing bank-level return on loans on bank-level aggregated firm shocks $\bar{\epsilon}_{i,t}$. The Granular IV is constructed as the difference between the size-weighted and unweighted means of the firm shock $\epsilon_{j,t}$. Positive (negative) shock specifications include only observations in which the bank shock $\bar{\epsilon}_{i,t}$ is above (below) zero. In addition to the standard set of bank controls, all regressions include the first two latent bank-level factors obtained from running PCA separately on each banks' sample of borrowers using equation (A7) to the set of bank controls. Standard errors (in parentheses) are clustered at the bank level.

second step is performed separately at the bank level. This implies running the EMPCA algorithm separately on each bank's sample of borrowers, i.e. for all firms j borrowing from bank i at time t:

$$\check{\epsilon}^*_{i,j,t} = \eta'_{i,t}\delta_{i,j} + u_{i,j,t} \quad , \quad \forall j \in \mathbb{P}(i,t) \tag{A7}$$

where $\check{\epsilon}^*_{i,j,t}$ denotes the demeaned firm shock $\check{\epsilon}_{j,t}$, and $\check{\epsilon}_{j,t}$ is the firm shock residual net of parametric factors from equation (A3) in Section A.1 . The demeaning is performed cross-sectionally at the bank level, such that:

$$\check{\epsilon}^*_{i,j,t} = \check{\epsilon}_{j,t} - \frac{1}{N_{i,t}} \sum_{j \in \mathbb{P}(i,t)} \check{\epsilon}_{j,t} \quad , \quad \forall j \in \mathbb{P}(i,t)$$

where $N_{i,t}$, as before, denotes bank $i's$ number of corporate borrowers j in year t.[4] For each bank, we extract up to $f = 2$ factors, following the algorithm outlined in A.1, and denote the associated residuals $u^f_{i,j,t}$, with $f \in \{1, 2\}$.[5]

Our main exercise is to use the extracted bank factors $\eta^1_{i,t}$ and $\eta^2_{i,t}$ as explicit controls in our bank-level regressions. This approach is similar to the application proposed in

[4]Notice that since this demeaning is performed at the level of the bank, the demeaned firm shock will vary at the bank-firm level i, j.

[5]Because very few banks in our sample have fully balanced sub-samples (portfolios) with many borrowers, we now initiate the algorithm with random guesses of realizations for each factor f ($\eta^f_1, \eta^f_2, ..., \eta^f_T$) with 100 different seeds and pick the specification that produces the lowest average sum of squared residuals $u^{f^{max}}_{j,t}$ after extracting $f^{max} = 2$ components.

Gabaix and Koijen (2023). Specifically, we run the same specification as in equation (5) in the main text, but adding the extracted factors as control variables:

$$R^b_{i,t} = \alpha_i + \alpha_t + \beta_1 \bar{\epsilon}_{i,t} + \beta_2 \eta^1_{i,t} + \beta_3 \eta^2_{i,t} + \omega'_{i,t}\gamma + \nu_{it} \tag{A8}$$

Results are reported in Table A4. In every column we have added the two extracted factors $(\eta^1_{i,t}, \eta^2_{i,t})$ to the list of our usual bank-level controls. Results are essentially unchanged relative to our baseline estimation. This indicates that endogeneity issues due to unobserved time-varying bank factors are minor.

A.3 Correlated Bank Factors

Now we consider a related, but different deviation from the baseline GIV. Even with homogeneous loadings, the subtraction of the unweighted mean in equation (7) in the main text might not be enough to ensure orthogonality between the GIV and the bank-level error term if the bank's customer base also borrows from other banks. To see this, consider the following general representation of the firm-level shock equation (6) in the main text:

$$\epsilon_{j,t} = \sum_k \mathbb{I}^k_{j,t} \eta'_{k,t} \delta_k + e_{j,t} \tag{A9}$$

where the indicator function $\mathbb{I}^k_{j,t}$ equals 1 if firm j borrows from bank k in year t, $\eta'_{k,t}$ and δ_k are vectors of bank k factors and loadings, and $e_{j,t}$ a residual defined to be orthogonal to all bank factors. In this case, the residual in equation (6) which the GIV attempts to proxy, depends on other banks' factors $u_{i,j,t} = \sum_{k \neq i} \mathbb{I}^k_{j,t} \eta'_{k,t} \delta_k + e_{j,t}$. If other banks' factors $\eta_{k \neq i}$ correlate with bank i's structural error term $\nu_{i,t}$ in equation (5) this may invalidate instrument exogeneity.

To address this issue we generalize the granular instrument in equation (7) in the main text by removing not only the bank i's own factor, but also bank factors associated with all the banks that firms in the set $\mathbb{P}(i,t)$ (which we use to denote the set of firms that bank i lends to in year t) borrow from at time t. To do so, we run the following dummy variable regression:

$$\epsilon_{j,t} = \sum_k D_{k,j,t} + \hat{\epsilon}_{j,t} \tag{A10}$$

where $D_{k,j,t}$ is a dummy variable equal to 1 if firm j borrows from bank k in year t. We then construct the instrument as the difference between the size-weighed and unweighted means of the residuals $\hat{\epsilon}_{j,t}$. Results from using this generalization of the GIV are presented in Table A5 which shows that the bank-level impact of granular shocks remain

Table A5: Correlated Bank Factors

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable: Bank Return on Loans (RoA)					
	Instrumented with GIV					
	Pooled	Positive	Negative	Pooled	Positive	Negative
Granular Credit Shock	0.118	0.006	0.210	0.118	0.048	0.189
	(0.033)	(0.076)	(0.064)	(0.028)	(0.067)	(0.062)
Bank FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Bank Controls	-	-	-	✓	✓	✓

Notes: This table reports results from regressing bank-level return on loans on bank-level aggregated firm shocks $\bar{\epsilon}_{i,t}$, instrumented by an alternative Granular IV. The Granular IV is constructed as the difference between size-weighed and unweighted means of $\hat{\epsilon}_{j,t}$, obtained from equation (A10). Positive (negative) shock 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. Standard errors (in parentheses) are clustered at the bank level.

quantitatively unchanged compared to the results reported in Table 3 in the main text.

B Details on the Granular IV

B.1 Relation to Shift-Share Instruments

In this appendix we discuss how our granular IV strategy relates to the very widely-used shift-share approach. For completeness, we re-state the definition of the granular IV:

$$Z_{i,t}^{GIV} = \sum_{j \in \mathbb{P}(i,t)} s_{i,j,t}\epsilon_{j,t} - \frac{1}{N_{i,t}} \sum_{j \in \mathbb{P}(i,t)} \epsilon_{j,t}$$

Following the exposition in Borusyak et al. (2022), the shift-share instrument that is applied to our setting can be defined as:

$$Z_{i,t}^{SS} = \sum_{j \in \mathbb{P}(i,t)} s_{i,j,t}\epsilon_{j,t} \tag{B1}$$

In words, $Z_{i,t}^{SS}$ is our loan share-weighted weighted firm shock $\epsilon_{j,t}$, which in turn equals to the sum of bank factor loadings and the loan share-weighted sum of $u_{i,j,t}$. Now, exclusion restrictions for the $Z_{i,t}^{GIV}$ and $Z_{i,t}^{SS}$ can be summarized, respectively, as follows:

$$\mathbb{E}\left[\left(\sum_{j \in \mathbb{P}(i,t)} \left(s_{i,j,t} - \frac{1}{N_{i,t}}\right) u_{i,j,t}\right) \nu_{i,t}\right] = 0 \tag{B2a}$$

$$\mathbb{E}\left[\left(\eta'_{i,t}\delta + \sum_{j \in \mathbb{P}(i,t)} s_{i,j,t}u_{i,j,t}\right) \nu_{i,t}\right] = 0 \tag{B2b}$$

In the limiting case of large loan portfolios (large N), the two restrictions are identical except for the presence of bank factor loadings in B2b. In the case of small N, the appropriate definition of the weights in B2a becomes the *excess* loan share distribution; apart from this nuance the two conditions are once more the same. Importantly, the term $\eta'_{i,t}\delta$ never vanishes out in B2b. In addition to requiring either loan shares or firm shocks to be randomly assigned, the Bartik instrument's exclusion restriction also demands $\eta'_{i,t}\delta$ to be uncorrelated with the structural error. In other words, the shift-share instrument requires strictly more assumptions than the GIV. Even though our bank-level specifications include an array of controls, this could be problematic since accounting and controlling for every measurable time-varying bank characteristic is unfeasible. Therefore, the GIV is more promising for achieving identification in our particular setting because bank factors get purged out mechanically.

This does not hold generally since, as discussed in Gabaix and Koijen (2023), the GIV is not necessarily appropriate for cross-sectional settings such as Autor et al. (2013) where idiosyncratic shocks are hard to construct. In our context, however, such shocks could be computed and, as we have argued extensively in main text, could also be as-good-as-randomly assigned.

B.2 Instrument Relevancy

Suppose we have one bank and a fixed number of firms N with constant loan shares s_j. Let the firm shock be decomposed into two mean-zero orthogonal components: a common bank factor and a truly i.i.d. idiosyncratic component:

$$\epsilon_j = \eta + u_j \tag{B1}$$

with variances σ_η^2 and σ_u^2, where we have dropped the time subscript. The granular instrument can be written as:

$$Z^{GIV} = \sum_j^N \left(s_j - \frac{1}{N}\right)\epsilon_j = \sum_j^N \tilde{s}_j \epsilon_j = \sum_j^N \tilde{s}_j u_j \tag{B2}$$

where the last equality follows from $\sum_j^N s_j = 1$, and $\tilde{s}_j = s_j - 1/N$ is the loan share in excess of the homogeneous share 1/N. The endogenous covariate is given by:

$$\bar{\epsilon} = \sum_j^N s_j \epsilon_j = \eta + \sum_j^N s_j u_j \tag{B3}$$

The variance of the instrument and endogenous covariate can be written as:

$$\sigma_{GIV}^2 = \sigma_u^2 \sum_j^N \tilde{s}_j^2 \tag{B4}$$

$$\sigma_{\bar{\epsilon}}^2 = \sigma_\eta^2 + \sigma_u^2 \sum_j^N s_j^2 \tag{B5}$$

where in the last equation we exploit the orthogonality between η and u. The covariance is:

$$\begin{aligned}
Cov(Z^{GIV}, \bar{\epsilon}) &= Cov(\sum_j^N \tilde{s}_j u_j, \eta + \sum_j^N s_j u_j \epsilon_j) && \text{(B6)}\\
&= Cov(\sum_j^N \tilde{s}_j u_j, + \sum_j^N s_j u_j \epsilon_j) && \text{(B7)}\\
&= \sum_j^N \sum_i^N \tilde{s}_j s_i Cov(u_j, u_i) && \text{(B8)}
\end{aligned}$$

where the last equality follows from the bilinearity of covariances. When the shocks u_j are truly iid, we have that $Cov(u_j, u_i) = 0 \; \forall i \neq j$, and the expression simplifies to:

$$Cov(Z^{GIV}, \bar{\epsilon}) = \sigma_u^2 \sum_j^N \tilde{s}_j s_j \tag{B9}$$

The sum of the product of excess and actual loan share is simply the excess Herfindahl

$$eHHI := \sum_j^N \tilde{s}_j s_j = \sum_j^N \tilde{s}_j^2 - 1/N \tag{B10}$$

It follows that the correlation between the instrument and the endogenous covariate can be expressed as

$$\begin{aligned}
Cor(Z^{GIV}, \bar{\epsilon}) &= \frac{Cov(Z^{GIV}, \bar{\epsilon})}{\sqrt{Var(Z^{GIV}) Var(\bar{\epsilon})}} && \text{(B11)}\\
&= \frac{\sigma_u^2 eHHI}{\sqrt{\sigma_u^2 (\sum \tilde{s}_j^2)(\sigma_\eta^2 + \sigma_u^2 \sum s_j^2)}} && \text{(B12)}
\end{aligned}$$

Dividing through by σ_u^2 and noting that $\sum \tilde{s}_j^2 = eHHI$ and $\sum s_j^2 = HHI$ we get that:

$$Cor(GIV, \bar{\epsilon}) = \sqrt{\frac{eHHI}{\frac{\sigma_\eta^2}{\sigma_u^2} + HHI}}, \tag{B13}$$

which is the equation shown in Section 3.4 of main text.

C Shock Narratives

In this section we validate our baseline idiosyncratic firm shock $\epsilon_{j,t}$ with a narrative-based approach. It is important to confirm that $\epsilon_{j,t}$ truly reflect economically meaningful information about firm performance. We focus on the bottom 1st percentile of realizations of $\epsilon_{j,t}$ in the final shock distribution used in our analysis and search through the Norwegian news media for corresponding narratives.[6] In a lot of cases, some of which are outlined below, we find that our idiosyncratic shock matches actual, sizable economic events.

One of the most adverse shocks in our sample was experienced by Hera Vekst - a waste management company - in 2008. For that year, we estimate an unexpected idiosyncratic shock $\epsilon_{j,t}$ of -1.39, corresponding to approximately an unexpected drop in value added of -139%. This drop was seemingly generated by the sudden closure of the company's main facility, enforced by local authorities. Local authorities enforced the closure due to the company's repeated violation of air pollution standards. According to local news reports, the smell from the waste management facility was "far in excess of what the local population should tolerate" (nrk.no, 2011).

The company Nergard Sild, a mid-sized herring farmer, experienced an idiosyncratic shock $\epsilon_{j,t}$ of -1.2 in 2010 according to our estimates. National news reports attributed this loss to over-investment in a processing facility for herring (nrk.no, 2012). The investment had been planned in 2009 "when the quota was 1 million tons." Once the realized quota turned out to be much smaller than expected (370,000 tons), Nergard Sild closed down the processing facility, leading to substantial losses.

Staying in the domain of fish farming, another major shock in our sample is for the company Wilsgard Fiskeoppdrett. Wilsgard Fiskeoppdrett - a fish farming company specializing in salmon - experienced an idiosyncratic shock of -1.23 in 2015. According to national media, the reason for this drop was a massive outbreak of salmon lice (iLaks.no, 2015). The outbreak was so severe that the Norwegian Food Safety Authority threatened the company with a daily fine until the situation got under control, worrying that the outbreak would spread along the coast.

Subaru Norge AS - the lead importer of Subaru in Norway - had an idiosyncratic shock of -1.21 in 2007 according to our estimates. The drop was generated by a tax hike on gasoline-fueled cars, which changed the relative price on gasoline-fueled vs. diesel-fueled cars. While the tax was levied on all gasoline-fueled cars, Subaru was the only major brand without a viable diesel alternative (DN, 2007). As a consequence, the number of new cars sold for Subaru dropped from 3800 to 344 cars by August the following year.

[6] The 1st percentile of the idiosyncratic shock distribution is -.905, while the 5th percentile is -.459.

The horticulture company F.Dalene Gartneri AS had an idiosyncratic shock of -1.17 in 2008. According to local news media, the manager of the company was engaged in substantial fraud, which culminated in arson on the main facility to recoup an insurance premium of approximately 5 million USD (pd.no, 2011).

Fraud is the reason for another one of the most negative shocks in our sample. FIBO - an aluminum producer - experienced an idiosyncratic shock of -1.25 in 2007 according to our estimates, which ultimately lead to their subsequent bankruptcy in 2009. The bankruptcy trustee had substantial criticism towards the board of the company, going far in pointing to outright fraud and stating that the case was so severe that its ”report would and should be sent to the Financial Supervisory Authority for further study” (jarlsbergavis.no, 2011).

Next, consider the case study of the furniture producer Ekornes, which in 2015 had an estimated idiosyncratic shock of -1.24. The company blamed adverse conditions in the German consumer market, one of their largest client bases. Looking for the causes, the CEO of Ekornes pinpointed the uncertain economic environment and the conflict between Russia and Western Europe. ”Germans are careful. They save in bad times. The conflict between Western Europe and Russia has affected Germans more than in Norway” (e24.no, 2014).

Other notable shocks in our sample include the shipping company Volstad Shipping, which in 2008 experienced an idiosyncratic shock of -1.28 due to misplaced foreign currency positions (smp.no, 2012), and the company Bergen Group Intech which in 2010 experienced an idiosyncratic shock of -1.33 due to under-performance of their investments in Iceland. Those assets were subsequently sold due to ”not being within the core areas of the company” (Finansavisen, 2011).

Our estimated shocks also pick up less dramatic events. For instance, consider the firm GC Rieber Oils, a firm specializing in producing Omega 3-based products. In 2013, they recorded an $\epsilon_{j,t}$ of -0.24. The incident which caused this, according to local newspapers, was an accidental spill of between 500 and 800 litres of raw material from the company's factories into the local harbor (Naeringsliv, 2013). The spill was eventually managed and dealt with thanks to the local municipality and fire services. The spill lead to ”substantial economic losses” for the company, according to the CEO (Naeringsliv, 2013).

Table D1: Loan Outcomes - Firm Balance Sheet Heterogeneity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent Variable: Return on Loan						
Lagged Firm Characteristic:	Leverage	Assets	Equity	Debt Duration	Bank Depend.	Credit Rating	Age
Shock x Low Characteristic	0.345	0.345	0.352	0.289	0.314	0.250	0.313
	(0.020)	(0.018)	(0.020)	(0.020)	(0.022)	(0.025)	(0.020)
Shock x High Characteristic	0.450	0.976	0.410	0.753	0.497	0.483	0.576
	(0.047)	(0.170)	(0.044)	(0.046)	(0.031)	(0.026)	(0.041)
All Fixed Effects	✓	✓	✓	✓	✓	✓	✓
Additional controls	✓	✓	✓	✓	✓	✓	✓
Observations	292825	292825	292825	292825	292825	292825	292825
R^2	0.167	0.167	0.167	0.167	0.167	0.167	0.167

Notes: This table reports 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 (defined as equity over assets), share of bank credit to total credit, and share of short-term debt to total debt; firms in the lowest deciles of total assets and total equity; firms with an below-A credit rating; and firms younger than 3 years. All specifications include interacted bank x firm industry x year x loan-type x firm county fixed effects. Standard errors (in parentheses) are double clustered at the firm-year level.

D Additional Empirical Results

D.1 Firm Balance Sheet Heterogeneity

We start by exploring heterogeneous effects of idiosyncratic firm shocks originating from firms with different characteristics. Specifically, we augment specification (3) by interacting our extracted shocks 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 and 0 otherwise.

Table D1 presents the results. Overall, there is rich firm heterogeneity behind our loan-level outcomes. Relative to the baseline, the pass-through of idiosyncratic firm shocks is stronger for firms with high leverage, short debt duration, high reliance on bank debt, lower-than-"A" credit ratings, and firms younger than 3 years. All of 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 micro-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

Table D2: 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
	(0.019)	(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)
All Fixed Effects	✓	✓	✓	✓	✓
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 interacted bank x firm idustry x year x loan-type x firm county interacted fixed effects. Standard errors (in parentheses) are double clustered at the firm-year level.

non-levered corporates.

D.2 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 D2 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 by both the

Table D3: Loan Outcomes - Firm Ownership Heterogeneity

	(1)	(2)	(3)	(4)	(5)
	Dependent Variable: Return on Loan				
	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	✓	✓	✓	✓	✓
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 D4: 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	✓	✓	✓	✓	✓	✓
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.

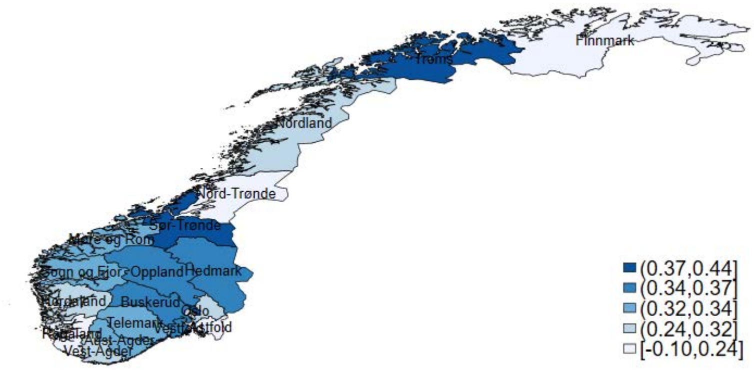
intensive and the extensive margin.

D.3 Firm Ownership and Industry Heterogeneity

Next, we investigate whether our results are driven by firms with a particular ownership structure or industry classification. For example, is the shock transmission stronger among special financial vehicles or construction firms? In Table D3 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 D4 explores heterogeneous effects by firm sector. Our baseline estimates are

Figure D1: Geographical Distribution 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 3. Shapefiles are from the Norwegian Mapping Authority (*Kartverket*).

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 significantly smaller.

D.4 Geographical Heterogeneity

Are our loan-level results driven by idiosyncratic shocks to firms located in particular geographical regions of Norway? Figure D1 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[7]. 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.

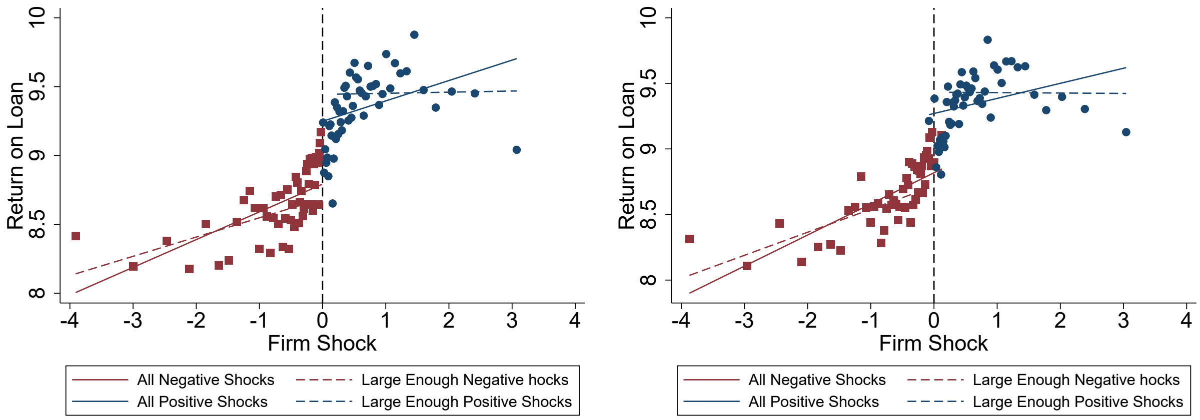
D.5 Loan-level Asymmetric Effects

In Section 3.4 we documented and discussed asymmetric effects of granular credit risk at the bank level. We now ask whether similar asymmetric patterns are observed at the loan

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

Figure D2: Loan-Level Asymmetry

(a) Without Fixed Effects **(b)** With Fixed Effects



Notes: This figure plots the binned scatter plots of the relationship between loan-level return on loans and idiosyncratic firm shocks. Negative (positive) shocks are conditioned on being less (greater) than zero. Large enough negative (positive) shocks are conditioned on being less than the last quartile (greater than the first quartile) of the distribution of negative (positive) shocks. Panel (b) includes interacted bank x time fixed effects. The independent variable is standardized.

level, i.e. within our loan-level specification 3. To this end, we condition firm shocks $\epsilon_{j\in\mathbb{P}(i,t)}$ to be strictly negative or positive. Since the distribution of firm shocks is heavily centered around zero and the average shock is small in magnitude, we also consider specifications where $\epsilon_{j\in\mathbb{P}(i,t)}$ are *sufficiently* large in absolute terms, thus avoiding the bunching of shocks around zero. Sufficiently large positive $\epsilon_{j\in\mathbb{P}(i,t)}$ are defined as those that are greater than the first quartile of the distribution of positive shocks; sufficiently negative $\epsilon_{j\in\mathbb{P}(i,t)}$ are those that are smaller than the last quartile of the distribution of negative shocks.

Figure D2 reports binned scatter plots for the relationship between loan-level returns on loans and $\epsilon_{j\in\mathbb{P}(i,t)}$. The plots are constructed in a similar fashion as described in detail in Section 4.2. Panel (a) shows the raw specifications without any fixed effects while panel (b) shows specifications with the inclusion of interacted bank x year fixed effects that control for time-varying credit supply-side factors. Eye balling the plots is enough to notice a non-linear relationship. When we condition on firm shocks being large enough (dashed blue lines), the asymmetric and concave patterns are revealed in both panels. In other words, we find the same concave relationship between firm disturbances and loan-level outcomes as we did at the bank level. Important to this result is avoidance of firm shocks that are too small and close to zero, i.e. those that are not severe enough to trigger any material intensive- or extensive-margin response.

Table D5: Pricing and Compensation of Granular Credit Risk

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable: Return on Loan					
	Pricing of GCR		Compensation for GCR			
Log (Loan Size)	-3.361	-4.916	-4.309	-6.374	-4.821	-9.357
	(0.031)	(0.072)	(0.053)	(0.119)	(0.103)	(0.246)
Loan Share, % of bank portfolio	0.170	0.310				
	(0.012)	(0.033)				
Bank-level HHI			-0.404	-0.631	-2.234	-0.686
			(0.099)	(0.218)	(0.241)	(0.569)
Non-Granular firms (50%)	n.a.	n.a.	✓	✓	-	-
Non-Granular firms (20%)	n.a.	n.a.	-	-	✓	✓
Controls	-	✓	-	✓	-	✓
All Fixed Effects	-	✓	-	✓	-	✓
R^2	0.139	0.498	0.138	0.544	0.103	0.600
Observations	333289	283217	166642	139286	66652	52370

Notes: This table reports the results from regressing loan-level return on loans onto (log) size of the loan, the loan share (in %) of the loan and the bank-level credit portfolio Herfindahl (HHI). All fixed effects include bank, industry, year, and firm levels. Controls include firm-level log(sales), capital, the wage bill, leverage, liquidity, credit rating, and a quadratic polynomial in age. Standard errors, in parantheses, are double-clustered at the firm and year levels. Independent variables have been standardized.

D.6 Pricing and Compensation of Granular Credit Risk

Two questions that are key for understanding both positive and normative implications of granular credit risk are (1) whether banks charge premia on loans that contribute to portfolio concentration and (2) whether loans to non-granular borrowers are compensated through lower rates for the fact that banks with concentrated portfolios potentially cut lending once granular borrowers experience a negative performance shock. In this section, we explore both these dimensions empirically. An important limitation of this analysis is that in our Norwegian register we do not observe actual contract-based loan prices as in, for example, the influential work of Jimenez et al. (2014). Given the nature of our data, it is thus impossible to completely capture *ex-ante* or "equilibrium" compensation for granular credit risk. What follows is an account of *ex-post* compensation through realized returns. Ex-ante and ex-post returns, while potentially correlated, do not necessarily equalize.

Pricing We start by investigating whether granular credit risk is priced. This is potentially challenging, empirically, as there is a large literature emphasizing the returns to scale in bank lending (see e.g. Ivashina (2009)). To proceed, we assume that returns to scale in lending are a function of the *loan amount* and not the loan share. In that case, we can exploit the fact that, conditional on loan amounts, there's sizable variation in loan shares.

In columns (1) and (2) of Table D5 we report results from regressing loan-level returns on loans (RoL) on the (log) size of the loan and the share of the loan in the bank's overall portfolio. First, note that the dependent variable is significantly negatively associated with the size of the loan itself, an observation that is consistent with scale efficiencies in intermediation. To the extent that contributions to granular credit risk are priced, we would expect banks to earn a *higher* return on the loans that constitute a larger fraction of the overall portfolio (conditional on the size of the loan). In general, we find precisely that, even in a restricted specification (column (2)) that includes additional controls and fixed effects.

Compensation We have shown in main text that non-granular borrowers experience a contraction in loan supply and an elevation in interest flows following a negative granular credit shock to their bank. Here, we explore whether these non-granular borrowers are compensated for this risk. We operationalize the idea by regressing loan returns on the bank-level corporate credit portfolio Herfindahl index (HHI). As before, we define non-granular borrowers as firms with a loan share below the 50% and 20% percentiles: our baseline thresholds. If the compensation channel is active, then we expect a negative and significant relationship: firms that borrow from banks with more concentrated credit portfolios, on average and everything else equal, should pay less. We report the results from these regressions in columns (3) - (6) of Table D5. In general, we find a negative association which is also statistically significant (at the 1% level) in three out of four cases.

We have thus documented two results. First, granular credit risk appears to be priced in ex-post terms: banks collect higher returns per loan from loans that constitute a higher share in their portfolio. Second, non-granular borrowers pay less to banks with more concentrated corporate loan portfolios. These findings are interesting for two reasons. First, they are consistent with what we previously documented with respect to bank heterogeneity analysis and risk-taking in Section 5.3. Specifically, the seemingly positive complementarity between exposure to granular credit risk, risk taking, and profitability. Second, the normative implications or our results are not obvious (on top of the many reasons outlined before due to optimal loan selection when there are frictions). On one hand, there is significant pass-through from granular firm shocks to bank portfolios and then to non-granular borrowers. On the other hand, we find some evidence that this source of risk is compensated for ex post. The *net* "welfare" effect of granular credit risk is therefore ambiguous. Again, because we can not speak of ex-ante compensation due to the nature of our data, the findings in this section should be corroborated in future

Table D6: Impact of Aggregate Shocks

	(1)	(2)	(3)
Granular Credit Shock	0.117		
	(0.030)		
Log (GDP)		0.348	
		(0.075)	
Log (Oil Price)			0.522
			(0.029)
Bank FE	✓	✓	✓
Year FE	✓	-	-
Bank Controls	✓	✓	✓
R^2	0.627	0.152	0.242
Observations	1211	1211	1211

Notes: this table presents results from bank-level regressions of bank-level returns on corporate loans on idiosyncratic and aggregate shocks. In column (1) the main regressor is the baseline GIV-instrumented idiosyncratic firm shock measure. In columns (2)-(3) the main regressors are the standardized logs of Norwegian real GDP and Brent oil prices, respectively. All specifications include the usual set of bank controls. Standard errors (in parentheses) are clustered at the bank level.

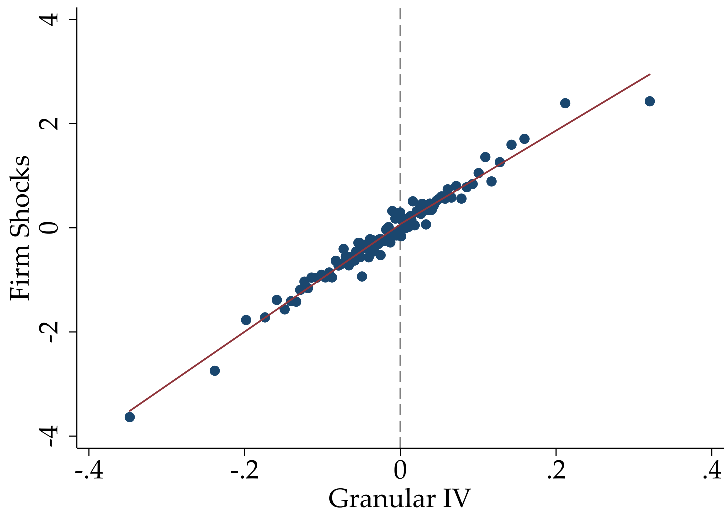
research.

D.7 Impact of Aggregate Shocks

In this paper our primary focus is on the effect of idiosyncratic firm shocks on banks and the broader economy. But how do idiosyncratic shocks compare to aggregate risk? Section 4.3 demonstrates that idiosyncratic borrower-level risk is not insured in practice, but the margin of adjustment when it comes to hedging aggregate risk is surely even harder. We re-estimate our baseline bank-level regression with two proxies of aggregate risk on the right-hand side: Norway's real GDP and the price of Brent oil. We look at oil prices because exports of crude oil and natural gas accounted for 17% of the country's GDP in 2015.

Results are reported in Table D6. Column (1) restates the baseline estimates from Table 3, Column (6). In columns (2)-(3) the main regressors are now (standardized) real GDP and oil prices, respectively. Point estimates for GDP and oil prices are greater by factors of 3 and 5, respectively, and are statistically significant but nevertheless remain within the same order of magnitude as the estimate in Column (1). Of course, neither of the two aggregate variables are truly "shocks" and these regression estimates are likely biased upwards. Therefore, the relative effect of idiosyncratic borrower risk compared to aggregate risk is most likely larger than what we can capture with this simple exercise.

Figure D3: First Stage - Firm Shocks and the Granular IV

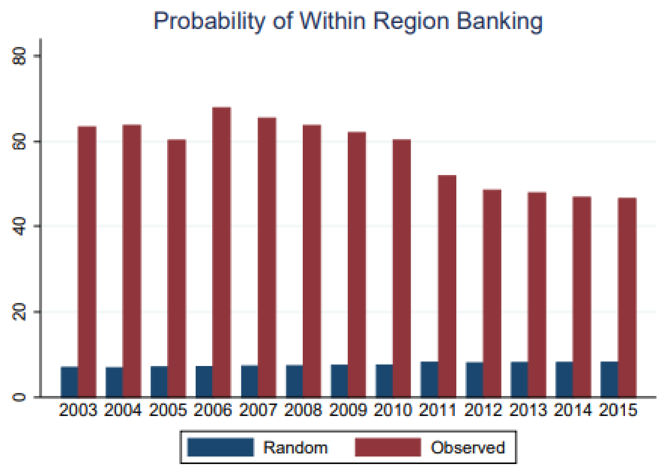


Notes: This figure plots the relationship between the endogenous covariate $\bar{\epsilon}_{i,t}$ and the instrument, $GIV_{i,t}$. On the vertical axis we have the idiosyncratic firm shock which is loan size-weighted and aggregated to the level of a bank. Idiosyncratic firm shocks are extracted from specification 2. The granular instrument (horizontal axis) is constructed based on equation (7). Correlation between the two variables is 0.863.

D.8 Supplementary Figures and Tables

In this section we present supplementary figures and tables that complement our main results and text. Figure D3 plots the relationship between the granular instrument $GIV_{i,t}$ and the weighted firm shock $\bar{\epsilon}_{i,t}$: the test of the first stage. Figure D4 demonstrates the probability of within-region banking over time in Norway. The figure, sourced from Juelsrud and Wold (2020), represents a measure of regional home bias in lending. Finally, Table D7 reports results from bank-level regressions of loan writedowns and the Sharpe ratio on size-weighted firms shocks - either instrumented by the granular IV or not.

Figure D4: 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 D7: Bank Loan Portfolio Writedowns and Sharpe Ratio

	(1)	(2)	(3)	(4)
	Writedowns		Sharpe Ratio	
Granular Credit Shock	-0.016	-0.015	0.057	0.052
	(0.009)	(0.011)	(0.069)	(0.037)
Bank FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Bank Controls	✓	✓	✓	✓
Instrumented by GIV	-	✓	-	✓
Observations	1184	1184	1206	1206
R^2	0.937	0.071	0.654	0.025

Notes: This table reports results from regressing bank-level (log) loan writedowns and the Sharpe ratio on portfolio-level aggregated firm shocks $\bar{\epsilon}_{i,t}$. Columns (1) and (3) are standard OLS, while in columns (2) and (4) firm shocks are instrumented with the granular IV. 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.

Table E8: Robustness to the 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
	(0.019)	(0.032)	(0.022)	(0.030)	(0.051)	(0.037)
All Fixed Effects	✓	✓	✓	✓	✓	✓
Bank Controls				✓	✓	✓
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.

E Robustness Tests

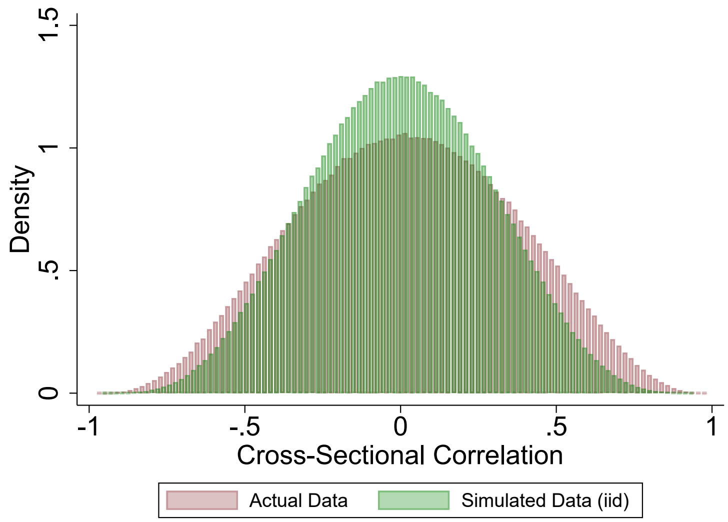
In this section, we provide several additional robustness checks. First, we test robustness with respect to the Great Financial Crisis (GFC). Second, we check that idiosyncratic firm shocks have a pairwise correlation of approximately zero. Third, we conduct several placebo tests at various levels of aggregation to lend further support to our baseline results. Finally, in order to check if our idiosyncratic shock measure is serially correlated, we estimate a linear panel fixed effects model with AR(1) disturbances at all levels of aggregation.

E.1 Robustness to the Great Financial Crisis

In order to investigate whether the relationship between granular credit risk and loan or bank outcomes is robust to the Great Financial Crisis, we re-do our estimation focusing on years either before or after the GFC. Table E8 reports the results. We highlight three main observations. First, our results do not vanish for either of the two sub-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.

Figure E5: Pairwise Cross-Sectional Correlation of Firm Shocks (Balanced Panel)

Panel A: Histogram



Panel B: Summary Statistics

	Number of Pairs	Mean	Abs. Mean	Skewness	Std. Dev.	Min	Max
Firm Shock	1,861,485	0.019	0.282	-0.002	0.342	-0.977	0.985
Simul. Firm Shock	1,861,485	0.000	0.235	-0.001	0.289	-0.961	0.943

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. *Abs. Mean* refers to the average of the absolute value of the correlation coefficients. Firm shocks are extracted based on specification 2. For the simulated data the estimated firm shocks are replaced by draws from a standard normal distribution.

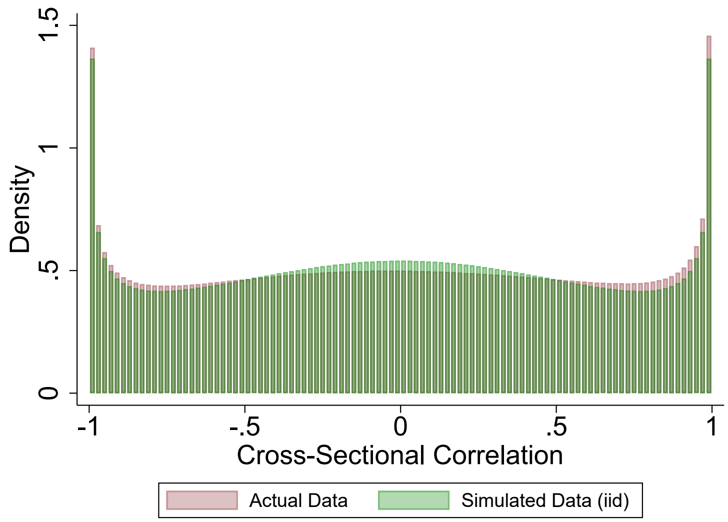
E.2 Pairwise Correlations Tests

An important question that must be addressed is potential pair-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. Figures E5 and E6 present histograms and summary statistics of all pairwise correlations of firm shocks. We report results for a balanced panel sub-sample of firms over the time period 2003-2015 (Figure E5), as well as all firms pairs in our sample with at least 3 overlapping observations (Figure E6).

The average pairwise correlation in the balanced sub-sample is 0.019, with the standard deviation of 0.34, while in the full sample the average is 0.005 with the standard deviation

Figure E6: Pairwise Cross-Sectional Correlation of Firm Shocks (Full Sample)

Panel A: Histogram



Panel B: Summary Statistics

	Number of Pairs	Mean	Abs. Mean	Skewness	Std. Dev.	Min	Max
Firm Shock	477,819,876	0.005	0.519	-0.005	0.601	-1.000	1.000
Simul. Firm Shock	477,819,876	0.000	0.502	0.000	0.588	-1.000	1.000

Notes: These figures report all pairwise cross-sectional correlation coefficients for idiosyncratic firm shocks. The sample includes firm pairs with at least three overlapping years over 2003-2015. Panel A presents the histogram, and Panel B reports summary statistics. *Abs. Mean* refers to the average of the absolute value of the correlation coefficients. Firm shocks are extracted based on specification 2. For the simulated data the estimated firm shocks are replaced by draws from a standard normal distribution.

of 0.60. In both samples, the skewness coefficient is essentially zero (-0.0016 in the balanced panel, -0.005 in the full sample). Hence, the distribution of the pairwise correlation coefficients is centered at zero and highly symmetric. In contrast, if there were important common factors driving our idiosyncratic shocks, the distribution would display non-zero skewness and a non-zero mean. The relatively large standard deviation is likely stemming from the short time dimension in our data.[8] In the balanced sub-sample, each pairwise correlation coefficient is based on 13 data points, which effectively induces spurious co-movements. To illustrate this, we also report correlations when we replace our estimated firm shocks with firm shocks drawn from a standard normal distribution. Even when shocks are iid by construction, the standard deviation is high at 0.29 in the balanced sub-sample of firms and 0.58 in the full sample.

The pairwise correlations are centered at zero, highly symmetric, and display remark-

[8]With only two overlapping observations, the correlation coefficient is by definition either 1 or -1.

Table E9: 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	838	0.838
Permuted Firm Shock, Negative Only	1000	0.194	0	0.000

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.

ably similar patters to shocks drawn from a standard normal distribution. While this finding is not a proof, it does provide very 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.[9]

E.3 Placebo Regressions

To ensure that we do not falsely reject the null hypothesis due to potentially serially correlated error terms, we run two sets of placebo tests. First, 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 Table E9. 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 0.84, while the negative-only shock estimate has a p-value of 0.000.

In addition to the above, in order 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 2. The results from using these drawn shocks for the loan-

[9] Additional reassurance comes from our analysis of networks in 5.2 and our robustness checks in Section A.1 and A.2 of the Online Appendix where we show that our results are robust to a procedural cleaning our shock measure from potential common factors.

Table E10: Placebo Regressions - Random Shocks

	Number of Draws	Mean	Std. Dev.	Min	Max
		Loan Outcomes			
Placebo Firm Shock	1000	0.001	0.007	-0.018	0.021
		Bank Outcomes			
Placebo Firm Shook, Pooled	1000	0.000	0.005	-0.016	0.018
Placebo Firm Shock, Positive Only	1000	0.001	0.018	-0.053	0.049
Placebo Firm Shock, Negative Only	1000	-0.000	0.014	-0.041	0.046

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.

and bank-level analyses are reported in Table E10. Across all specifications and levels of aggregation we find no association between these randomly generated shocks and loan or bank outcomes.

Second, as highlighted in Adao et al. (2019), similar exposures to the same idiosyncratic shocks can yield under-estimated standard errors at the aggregate level and hence an over-rejection of the null hypothesis. We therefore run a re-sampling exercise that is suggested in Adao et al. (2019). Specifically, we construct 1,000 samples where we - in each sample - simulate i.i.d firm shocks from a normal distribution with the same mean and standard deviation as the empirical shock distribution. We then re-do the exercise by aggregating these generated firm shocks to the bank level, constructing the GIV, and running our baseline bank-level regressions. For each sample, we keep the coefficient estimate and the estimated standard error. We compare the dispersion of the distribution of the coefficient estimates with the median estimated standard error and compute the rejection rate across all samples. If the standard errors in our setting are correct, we would expect to reject the null hypothesis in 5% of the cases. Results are shown in Table E11. As is clear from the table, this placebo exercise yields, on average, estimates that are close to zero. Importantly, we reject the null hypothesis in close to 5% of the cases at a significance level of 5%, suggesting that it is unlikely that we under-estimate standard errors in the baseline analysis.

Table E11: Standard Errors and Rejection Rates of $H_0 : \beta = 0$ at the 5% Significance Level

Estimate		Median std. error	Rejection rate
Mean	*Std.dev*		
(1)	(2)	(3)	(4)
-0.002	0.032	0.031	6.8%

Notes: This table indicates the mean and standard deviation of the estimation of our baseline bank-level regression across 1000 placebo samples (columns 1 and 2), the median standard error (column 3) and the percentage of placebo samples for which we reject the null hypothesis $H_0 : \beta = 0$ at 5% significance level. Results are based on 1,000 placebo samples.

E.4 Fitting a Fixed Effects Model with AR(1) Disturbance

We now run our firm shocks through an autoregressive linear model of order 1 in order to establish whether they are autocorrelated 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 Table E12. Parameters of the process - the 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 i.i.d. process is likely to approximate granular credit risk rather well.

Table E12: 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	0.267	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 2 and then aggregated to different levels with loan shares as weights.

F Large Loan Dynamics

In this Appendix, we construct a granular loan residual for the portfolio of every bank in every year. This approach supplements our baseline implementation of the granular instrument in the main text. Specifically, we use the weighted shock to the top 1% of clients (according to the loan share) of every portfolio as the key independent variable, while controlling for the average (unweighted) shock to the bottom 99%. All of our main results - including the direct effects on bank outcomes and the indirect, second-round spillover effects on the economy - remain unchanged. The fact that main results are robust to this alternative approach illustrates the importance of the very largest clients for the outcomes considered: another way of illustrating the relevance of the granular hypothesis in our setting. Moreover, it reinforces the conclusion that results in the main text are not driven by unobserved, common bank factors. In fact, we find qualitatively and quantitatively similar results as in the main text for bank returns (Table F13), credit spillovers (Tables F14 and F15), capital growth (Table F16) and firm defaults (Table F17). Importantly, we control for the average shock of all other firms in every bank's portfolio.

Table F13: Bank Returns

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable: Bank Return on Loans (RoA)					
	Pooled	Positive	Negative	Pooled	Positive	Negative
Alternative bank shock (std.)	0.059	-0.027	0.110	0.060	-0.037	0.125
	(0.026)	(0.051)	(0.062)	(0.026)	(0.054)	(0.061)
Bank FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Controls				✓	✓	✓
Observations	1206	552	647	1206	552	647
R^2	0.747	0.815	0.728	0.764	0.831	0.749

Notes: This table reports results from regressing the bank-level return on loans on the weighted average of the firm performance shock to the top 1% loan clients according to loan share. We include the unweighted shock to the bottom 99% as a control variable in all specifications. Columns (3) - (6) show the results when we additionally include bank controls. Columns (1) and (4) consider all shocks, (2) and (5) consider the sub-sample where the alternative bank shock is positive and columns (3) and (6) considers the sub-sample where the alternative shock is negative. Positive (negative) shock specifications include only observations in which the shock measure $\bar{\epsilon}_{i,t}$ 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.

Table F14: Spillovers: Credit Growth

	(1)	(2)	(3)	(4)	(5)
			Δ loans (std.)		
Δ Alternative bank shock (std.)	-0.00327	0.0454	0.0254	0.305	0.330
	(0.0126)	(0.0472)	(0.0465)	(0.176)	(0.214)
Non-Granular Firms (50%)	-	✓	✓	-	-
Non-Granular Firms (20%)	-	-	-	✓	✓
Year x Industry x County x Firm FE	✓	✓	✓	✓	✓
Bank FE	-	-	✓	-	✓
Instrumented by GIV	✓	✓	✓	✓	✓
Observations	15279	3479	3443	232	212

Notes: This table reports results from regressing year-on-year changes in (log) loan volumes on the year-on-year change in the weighted average of the firm performance shock to the top 1% loan clients according to loan share. We include the unweighted shock to the bottom 99% as a control variable in all specifications. Specifications are based on equation (12). Both dependent and independent variables have been standardized. Column (1) includes all firms. Columns (2)-(5) include only non-granular firms. Non-granular firms are defined as firms whose bank loan shares are less than the 50th (columns (2)-(3)) or the 20th (columns (4)-(5)) percentiles of the loan share distribution, which is pooled over all banks and years. The full distribution of loan shares was plotted on Figure 1. Standard errors (in parentheses) are double clustered at the bank and firm level.

Table F15: Interest Flows

	(1)	(2)	(3)	(4)	(5)
	Δ interest flows (std.)				
Δ Alternative bank shock (std.)	-0.0158	-0.109	-0.134	-0.153	-0.139
	(0.0137)	(0.0457)	(0.0522)	(0.190)	(0.185)
Non-Granular Firms (50%)	-	✓	✓	-	-
Non-Granular Firms (20%)	-	-	-	✓	✓
Year x Industry x County x Firm FE	✓	✓	✓	✓	✓
Bank FE	-	-	✓	-	✓
Instrumented by GIV	✓	✓	✓	✓	✓
Observations	15279	3479	3443	232	212

Notes: This table reports results from regressing year-on-year changes in (log) interest flows on the year-on-year change in the weighted average of the firm performance shock to the top 1% loan clients according to loan share. We include the unweighted shock to the bottom 99% as a control variable in all specifications. Specifications are based on equation (12). Both dependent and independent variables have been standardized. Column (1) includes all firms. Columns (2)-(5) include only non-granular firms. Non-granular firms are defined as firms whose bank loan shares are less than the 50th (columns (2)-(3)) or the 20th (columns (4)-(5)) percentiles of the loan share distribution, which is pooled over all banks and years. The full distribution of loan shares was plotted on Figure 1. Standard errors (in parentheses) are double clustered at the bank and firm level.

Table F17: Firm Bankruptcy

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent Variable: Prob. of Bankruptcy$_t$						Pr.(Ever Bankrupt)	
Δ Alternative bank shock$_{t-1}$	-0.001	-0.002	-0.043	-0.051	-0.078	-0.097	-0.039	-0.092
	(0.011)	(0.012)	(0.028)	(0.027)	(0.050)	(0.053)	(0.015)	(0.028)
Non-Granular Firms (50%)	-	-	✓	✓	-	-	✓	-
Non-Granular Firms (20%)	-	-	-	-	✓	✓	-	✓
Firm Controls	-	✓	-	✓	-	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓	✓	✓
County FE	✓	✓	✓	✓	✓	✓	✓	✓
Pseudo R^2	0.039	0.096	0.039	0.100	0.037	0.089	0.039	0.034
Observations	164710	164710	78468	78468	27827	27827	79922	28753

Notes: This table reports results from firm-level regressions where the outcome variable is a dummy variable for firm default. The key independent variable is the year-on-year change in the weighted average of the firm performance shock to the top 1% loan clients according to loan share. We include the unweighted shock to the bottom 99% as a control variable in all specifications. Specifications are based on Equation (13). Non-granular firms are defined as firms whose bank loan shares are less than the 50th or 20th percentile of the loan share distribution. For firms with multiple banking relationships, we define a firm as non-granular if the mode credit relationship is non-granular. Standard errors (in parentheses) are clustered at the firm level.

Table F16: Capital growth

	(1)	(2)	(3)	(4)	(5)
	Δ Capital (std.)				
Δ Alternative bank shock (std.)	0.001	0.020	0.024	0.059	-0.025
	(0.003)	(0.013)	(0.016)	(0.034)	(0.060)
Non-Granular Firms (50%)	-	✓	✓	-	-
Non-Granular Firms (20%)	-	-	-	✓	✓
Industry x County x Year FE	✓	✓	✓	✓	✓
Firm FE	-	-	✓	-	✓
Instrumented by GIV	✓	✓	✓	✓	✓
Observations	157642	66648	55770	19608	13719

Notes: This table reports results from firm-level regressions where the outcome variable is year-on-year change in the (log) fixed capital stock. The key independent variable is the year-on-year change the weighted average of the firm performance shock to the top 1% loan clients according to loan share. We include the unweighted shock to the bottom 99% as a control variable in all specifications. Specifications are based on Equation (13). Non-granular firms are defined as firms whose bank loan shares are less than the 50th or 20th percentile of the loan share distribution. For firms with multiple banking relationships, we define a firm as non-granular if the mode credit relationship is non-granular. Standard errors (in parentheses) are clustered at the firm level.

G 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.[10] 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.

G.1 Model

Suppose there are N firms in the economy[11]. 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:

$$\frac{\Delta L_{i,t+1}}{L_{it}} = \sigma_i \epsilon_{i,t+1} \tag{G1}$$

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:

$$D_t = \sum_{i}^{N} L_{it} \tag{G2}$$

[10] As noted in section 5.4, other frictions would have to be added to fully account for the data.

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

and growth of financial debt in the economy is

$$\frac{\Delta D_{t+1}}{D_t} = \sum_i^N \sigma_i \frac{L_{it}}{D_t} \epsilon_{i,t+1} \tag{G3}$$

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 $\sigma_i = \sigma \; \forall \, i$, we have:

$$\sigma_D = \Big[\sum_i^N \sigma \Big(\frac{L_{it}}{D_t} \Big)^2 \Big]^{\frac{1}{2}} \tag{G4}$$

It is clear from equation G4 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:

$$\mathbb{P}(y > x) = (1 + x)^{-\alpha} \tag{G5}$$

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}:

$$L_{it} = y_{it}^{\lambda_i} \tag{G6}$$

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:

$$\mathbb{P}(L > x) \sim (1 + x^{\tau})^{-\alpha} \tag{G7}$$

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 ¡ ατ ¡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: Section G.3 of the Online Appendix.

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.

G.2 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 (G6) and then take the median of the resulting distribution. We conduct this step for all three definitions of size as well.

Table G1: 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 G. 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.

As a result, we have three estimates for $\alpha\tau$ - the sufficient statistic that determines the speed of decay of σ_D.

Table G1 in the Online Appendix 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.

G.3 Proof of Proposition 1

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:

$$\lim_{x\to\infty} B(tx)/B(x) = \frac{\lim B(tx)}{\lim B(x)} = 1 \tag{G8}$$

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:

$$\lim_{N\longrightarrow\infty}\left(N^{\frac{1}{\alpha\tau}}\right)^{-1}\sum_i^N L_i \xrightarrow{d} \eta \sim L\acute{e}vy(\alpha\tau) \tag{G9}$$

In the remainder of the proof, we apply equation (G9) 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:

$$N^{1-\frac{1}{\alpha\tau}}\frac{\left(N^{\frac{-2}{\alpha\tau}}\sum_i^N L_i^2\right)^{1/2}}{N^{-1}\sum_i^N L_i} \xrightarrow{d} \frac{L\acute{e}vy^{1/2}}{\mathbb{E}(L)} \tag{G10}$$

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 $N^{1-\frac{1}{\alpha\tau}}$:

$$\sigma_D \sim \frac{1}{N^{1-1/(\alpha\tau)}} L\acute{e}vy^{1/2}\sigma \tag{G11}$$

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 $\alpha\tau$. ■

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