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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 quantify single-name exposure risk in bank portfolios by applying a novel empirical strategy to an administrative loan-level dataset from Norway. Exploiting the fat-tailed properties of the loan-share distribution, we use the granular instrumental variable approach to show that idiosyncratic borrower risk survives aggregation within banks' portfolios. These granular credit shocks spill over from affected banks to firms, reducing investment and raising default risk among non-granular borrowers, with sizeable consequences for the real economy.

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1 Introduction

What is the impact of idiosyncratic borrower risk on banks and the broader economy? It has long been understood that if individual loans are small relative to the overall size of a portfolio, then credit risk pooling should provide perfect insurance against idiosyncratic shocks (Diamond, 1984). But what if some loans are large? When the loan-size distribution is fat-tailed, can the performance of a single large loan directly shape portfolio-level outcomes and lending? A rapidly growing literature, originating from the seminal contribution of Gabaix (2011), has emphasized the micro—or "granular"—origins of macroeconomic outcomes across a range 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, through general equilibrium effects, all other agents.

Curiously, there are relatively 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".

Our paper attempts to fill this literature gap by providing 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. We merge our loan-level 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.[2] This data-rich environment enables us to study the transmission mechanism and heterogeneous treatment effects at many levels of aggregation.

Our empirical strategy and presentation of results consist of six steps. First, we

[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]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.

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. Using firm-level data on balance sheets and income statements, we extract non-systematic variation in firm value-added by controlling for a variety of firm-level characteristics like 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). To validate our shock measure, we first run a human audit of a sample of realizations. Then, we validate the universe of shocks with state-of-the-art machine learning and Large Language Modelling (LLM) tools.

Third, we establish the pass-through from these idiosyncratic firm shocks to loan-level returns. We investigate how such shocks affect returns on loans within the same bank, industry, county, year, and loan type. Importantly, our specification controls for time-varying confounding bank-side supply factors, potentially specific to a given industry, county, or contractual type. 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 also explore heterogeneity across firm characteristics, geographical location, ownership, and other dimensions.

Fourth, we look at the impact of idiosyncratic borrower shocks on banks' portfolio-level outcomes. This is a critical step in our analysis. Once aggregated to the level of a bank, we 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. For this stage, we adopt the granular instrumental variable (GIV) approach, which was developed in a series of papers by Gabaix and Koijen (2021, 2024). 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 parameteric and non-parameteric specifications and extensions 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.

A key result of our paper is that idiosyncratic firm shocks, instrumented by the GIV, have a large and significant effect on corporate 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. This relationship is strongly concave, driven mainly by negative shocks. In particular, if conditioned 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.[3] The economic mechanism behind our bank-level result is the increase in the write-downs of non-performing loans. Banks do not appear to hedge granular credit shocks with alternative sources of income such as fees, equity and bond appreciations, dividends, or derivatives. 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. 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.

Fifth, having established that shocks to granular borrowers survive aggregation and have a direct effect on banks' portfolio-level returns, we ask whether banks pass on these shocks to the real economy. We start by examining credit supply effects, by comparing bank loan quantity and rate changes in response to granular credit shocks. Our approach now follows the canonical Khwaja and Mian (2008) method. 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. 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%,

[3]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.

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. Using detailed data from the Norwegian input-output tables, we show that these results are robust to the presence of production network effects.

Sixth and finally, we conclude our main empirical analysis by asking whether the affected non-granular firms subsequently experience negative real economic outcomes. We find that affected non-granular firms cut investment. Moreover, these firms experience significantly higher 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 real economy, and our back-of-the-envelope calculations suggest that it results in tens of millions of dollar-equivalent bankruptcy-associated losses every year.

How externally valid are our methodology and results? We supplement our main analysis with granular data from the AnaCredit project. AnaCredit brings together 20 European credit registers across both euro-area and non-euro-area countries, providing a harmonized loan-level database with some 300 million observations (Altavilla et al., 2020, 2024). We document that concentration in bank loan portfolios is ubiquitous: the average loan-level Herfindahl index across the 20 AnaCredit countries is 0.12, compared to 0.10 in our Norway sample. This suggests that granular credit risk likely extends to other European economies. Moreover, we show that high portfolio concentration is also a robust feature of U.S. institutional equity investor data, indicating that granular exposure risk may be relevant for other asset classes and financial instruments as well.

Literature review. Our paper relates to several strands of the literature. First, we are building on the burgeoning literature on the granular hypothesis (Gabaix, 2011) and the granular instrumental variable (Gabaix and Koijen, 2024). Recent contributions include, among many others, works on business cycles (Carvalho and Gabaix, 2013), 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), and sentiment (Jamilov et al., 2025). There are relatively fewer papers in empirical banking that focus specifically on granularity and the propagation of idiosyncratic shocks, but with some important exceptions. Amiti and Weinstein (2018) develop a methodology that decomposes loan growth into time-varying bank supply and firm demand components. They find that idiosyncratic bank supply shocks, particularly those of granular lenders, have a large impact on aggregate lending and investment in Japan. Bremus et al. (2018) study the relationship between granular banking sectors and aggregate fluctuations. Kundu and Vats (2025) trace out the impact of idiosyncratic regional demand shocks on the reallocation of banks' funds.

Second, we are contributing to the extensive literature on the credit and real outcomes of the bank lending channel (Khwaja and Mian, 2008; Jiménez et al., 2012, 2014, 2020). Our results on spillovers of granular credit shocks onto the rest of the economy are related to several papers that document similar findings (Peek and Rosengren, 2000; Klein et al., 2002; Lin and Paravisini, 2012; Greenwald et al., 2025). A growing literature studies the role of networks in the propagation of shocks within and beyond the banking sector (Costello, 2020; Dewachter et al., 2020). In a related paper, Huremovic et al. (2025) employ administrative data from Spain and show that bank credit supply shocks impact firms and propagate both upstream and downstream along the production network. They also document that upstream propagation is stronger. In a recent paper, Chodorow-Reich et al. (2025) develop a "network GIV" approach to causal identification of shocks in general networks such as industries or firms. Using detailed Norwegian input-output data, we show that our results are robust to production network effects.

Finally, we also relate to the broader literature that studies a general trade-off between credit concentration and diversification. Diversification enhances credit monitoring and information provision capacity (Diamond, 1984; Boyd and Prescott, 1986). 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, concentration can be positively correlated with returns and monitoring efficiency and contribute to the mitigation of the detrimental effects of negative information shocks on borrowing costs (Acharya et al., 2006; Acharya and Yorulmazer, 2008). Giannetti and Saidi (2018) show that specialized banks are better equipped at providing liquidity during times of borrower distress. In addition, Beck et al. (2022) and Goldstein et al. (2022) argue that diversification increases the probability of systemic crises while specialization can have positive implications for financial stability. Our paper contributes to this debate by arguing that as long as the distribution of loan shares features a fat tail, banks can remain exposed to idiosyncratic shocks to their (granular) borrowers. However, 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 Appendix G.

Papers that are most closely related to ours study concentration and over-exposure in the banking sector using micro-data. Paravisini (2008) shows that geographic concentration makes local banks sensitive to exogenous fluctuations in the availability of external financing, leading to under-investment. Goetz et al. (2016) find that geographic diversification by banks has no impact on average loan quality and is associated with a reduction of exposure to local idiosyncratic risks. 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. Saidi and Streitz (2021) and Ross (2010) show that dominant lenders offer lower rates to their borrowers. Paravisini et al. (2023) show that persistent bank market-specific specialization can explain a significantly larger fraction of within-firm variation in credit than actual bank supply shocks. Blickle et al. (2025) leverage supervisory loan-level information on large U.S. banks and document high levels of sectoral concentration. They also show that this specialization is priced and is reflected in measures of default risk.

Our contribution relative to the existing studies is to quantify the impact of *single-name*, i.e. loan-level, concentration risk in banks' credit portfolios on bank-level and real economic outcomes by leveraging a unique administrative dataset from Norway and a new approach. We also show that granular credit risk likely extends to many other countries by documenting new statistics on loan portfolio concentration for the universe of available European credit registers. Our paper also provides an empirical basis for structural models such as Mendicino et al. (2025), who show that if banks are not perfectly diversified, then the interaction between borrowers' and banks' solvency has effects on financial stability.

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

2.1 Data sources and sample construction

Our empirical analysis 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. Because the data is collected and maintained by the tax authority as a basis for corporate taxation, the variables are essentially free from measurement error.[4]

The unit of observation in our dataset is an individual corporate 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.[5][6] The dataset covers all limited liability companies for the time period of 2003-2015, which accounts for roughly 90% of private sector employment for most years. We aggregate all loans into a single annual firm-bank "relationship" unit. The terms loan and relationship are used interchangeably, and refer to the sum of loans and interests paid across all individual loans between a bank and a firm.

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 the information on firms' credit rating scores and firm characteristics such as age, location and industry, the dataset 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 dataset also provides us with confidential information on non-interest income, including income from derivatives, equity and bond investment, dividends, and loan fees. We drop observations that are clearly erroneous, such as cases of liquidity ratios being greater than unity.

Table A1 provides summary statistics for the RoL and other key variables used in our analysis.

2.2 Measurement of key variables

2.2.1 Return on loans

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

[4]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.

[5]We do not observe the contracted interest rate or the loss-given-default on individual loans, but use our data to construct an ex-post return on each loan.

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

to the average of debt outstanding at the beginning and end of the calendar year.

Importantly, our RoL measure should be read as the ex-post collected interest rate, rather than a net-of-losses return. Because the numerator is the sum of interest actually received during year t, it mechanically excludes any scheduled interest that went unpaid in the event of delinquency or default; likewise, it abstracts from principal charge-offs or write-downs that banks may record when a borrower is restructured or liquidated. It does, however, capture cases where the borrower enters negotiations with the bank to postpone some interest payments (and extend the maturity of the loan) to alleviate cash-flow concerns. We will also complement our bank-level analysis with the estimation of the effect of idiosyncratic firm performance shocks on loan write-downs.

2.2.2 Estimates of Idiosyncratic Firm Shocks

A central variable in our analysis is the idiosyncratic firm shock, which we define as residual variation in firm value-added unexplained by observable inputs, firm risk characteristics, and common shocks. Value-added is calculated as total sales minus intermediate inputs (materials, energy, and other operating costs). This approach builds on a large literature in empirical labor economics and macroeconomics that extracts firm-level performance shocks from residuals of value-added or sales regressions (Foster et al., 2008; Hsieh and Klenow, 2009; di Giovanni et al., 2014; Blackwood et al., 2021; Fagereng et al., 2018). Idiosyncratic shocks are increasingly used as quasi-instruments to identify firm responsiveness in applied studies (see, e.g. Leary and Roberts, 2014, Amiti et al., 2019, Gabaix and Koijen, 2024).

To mitigate the influence of reporting distortions, we follow Foster et al. (2008) and reduce the share of each cost component (wage, material, energy, other costs) of total cost to the 10th and 90th percentiles by industry and year. This is important because firms may shift operational costs across fiscal years for tax purposes, mechanically altering value-added without reflecting true performance changes. Moreover, this might be more relevant for large firms, inducing a measurement error of firm performance which is correlated with size. Truncating the cost distribution alleviates some of these concerns. In order to further mitigate concerns with measurement error, we have also estimated firm shocks by using sales instead of value-added. Results do not change.[7]

To estimate firm-specific shocks, we regress (log) value-added on observable

[7] See Section E.6 in the Online Appendix.

production inputs, measures that capture firm risk, and a variety of fixed effects:

$$\ln \mathrm{VA}_{j,t} = \alpha_j + \theta_{g(j),t} + \beta_1 \ln \mathrm{K}_{j,t} + \beta_2 \ln \mathrm{W}_{j,t} + \mathrm{X}'_{j,t}\lambda + \epsilon_{j,t}, \tag{1}$$

where $\mathrm{K}_{j,t}$ denotes book capital, $\mathrm{W}_{j,t}$ the wage bill, and $\mathrm{X}_{j,t}$ includes firm leverage, liquidity, credit rating, and a quadratic in firm age. The firm fixed effect α_j absorbs time-invariant firm characteristics and $\theta_{g(j),t}$ captures year-by-industry-by-county common characteristics. This specification aims to isolate unanticipated firm-level variation in $\epsilon_{j,t}$.

We truncate the distribution of $\epsilon_{j,t}$ at the 1st and 99th percentiles to guard against outliers. Figure 1 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.

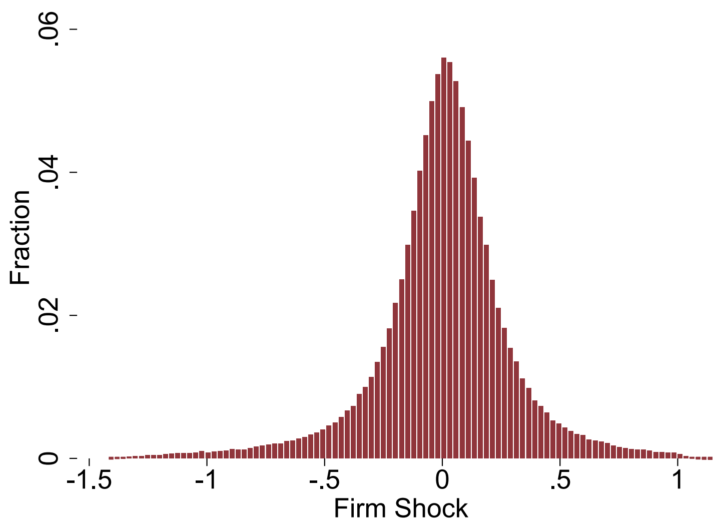
Interpretation. We interpret $\epsilon_{j,t}$ as a realized performance shock that was unlikely to be forecastable by banks. Natural examples include mismanagement, legal issues, or operational accidents. However, as emphasized by Gabaix and Koijen (2024), these shocks can also capture idiosyncratic and *unanticipated* changes in the firm-level loading on common components. For instance, demand for a firm's output declines more than expected following an economic downturn or a policy intervention, or input costs rise by more than expected following a supply shock. We provide case studies of extreme negative shock realizations in Section C of the Online Appendix.[8]

Validation with machine learning and text analysis. In Appendix C, we report results from two complementary machine learning approaches that draw on data from all Norwegian newspapers in the National Library to provide textual context for *all* shocks in our sample. The purpose of this validation exercise is to confirm that our estimated firm shocks are truly idiosyncratic. Using both a dictionary-based method and a Large Language Model (LLM) classification of shocks, we re-estimate our loan-level analysis on the subset of shocks for which we have strong narrative evidence of idiosyncrasy. The results from this systematic exercise are qualitatively and quantitatively consistent with those reported in the main text.

Further ensuring that shocks are firm-specific. Despite controlling for a variety of firm characteristics and fixed effects, there is still a concern that our shock measure $\epsilon_{j,t}$ may pick

[8]The notion of an idiosyncratic shock—used both in our analysis and in the related literature on the granular hypothesis (Gabaix, 2011)—is not necessarily invariant to the firm size distribution. A shock that appears firm-specific for a large firm may, in a counterfactual world where that firm is broken into many smaller units, resemble a common shock across those entities. Nevertheless, given the actual firm size distribution, concentrating a portfolio in large firms exposes banks to idiosyncratic firm-specific risk.

Figure 1: Distribution of Idiosyncratic Firm Shocks



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

up idiosyncratic, but anticipated responses to latent common components. For example, firms within the same industry may operate different technologies, leading to systematic differences in their loading on input prices or technology shocks. This poses a potential identification problem to the extent that banks anticipate firms' loadings and adjust their loan portfolios accordingly, thereby inducing a correlation between loan shares and $\epsilon_{j,t}$. In Section A.1 of the Online Appendix, we generalize the reduced-form specification in (1) and formally extract parametric and nonparametric common factors from the residual $\epsilon_{j,t}$. All our results and insights remain unchanged.

3 Empirical strategy

3.1 Granularity of the Distribution of Loan Shares

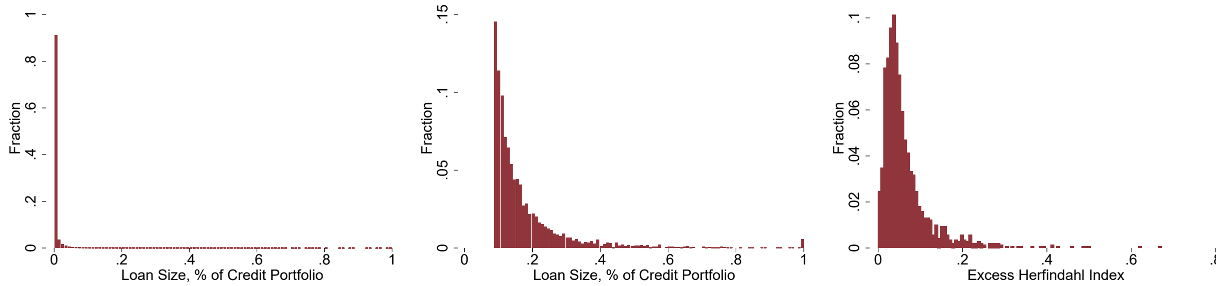
We begin by establishing that the distribution of loans shares in our dataset is fat-tailed. Figure 2 presents the histogram of all loan shares, pooled across all banks and years over 2003-2015. Eyeballing the distribution is enough to notice its extreme skewness.[9] More formally, we fit the Pareto 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.[10] If defined

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

[10]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

Figure 2: 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.

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.

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

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

where $\mathrm{s_{i,j,t}}$ is the loan share of firm j in bank i's portfolio in year t, and $\mathrm{N_{i,t}}$ 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 2, there is 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 H we introduce a parsimonious model of bank credit

of 2.

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 Loan Outcomes

We now estimate 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 $\mathbb{P}(\mathrm{i},\mathrm{t})$ which signifies the set of all firms that borrow from bank *i* in year *t*. The dependent variable is $\mathrm{R}_{\mathrm{i},\mathrm{j},\mathrm{t}}$ 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 $\epsilon_{\mathrm{j},\mathrm{t}}$, 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.[11]

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 between firms in the same county, industry, year and who borrow 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.[12] Formally, we estimate the following panel specification for bank i and firm j relationships in year t, i.e. for $\mathrm{j} \in \mathbb{P}(\mathrm{i},\mathrm{t})$:

$$\mathrm{R}_{\mathrm{i},\mathrm{j},\mathrm{t}} = \beta\epsilon_{\mathrm{j},\mathrm{t}} + \theta_{\mathrm{g}(\mathrm{i},\mathrm{j},\mathrm{t}),\mathrm{i},\mathrm{t}} + \alpha_{\mathrm{j}} + \nu_{\mathrm{i},\mathrm{j},\mathrm{t}}, \tag{3}$$

where α_{j} 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 independent variable is *estimated*, our standard errors are corrected for the additional uncertainty due to an estimated regressor via bootstrapping.[13] Our saturation of specifications with time ×

[11] 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.

[12] 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.

[13] 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.

bank and other fixed effects is similar to Jiménez et al. (2014) who study monetary policy and loan applications of the same firm to different banks in the same period of time.

3.3 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 the 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 $\omega_{i,t}$ 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 characteristics and $u_{i,j,t}$ is the residual of firm j's shock, defined to be orthogonal to bank i's characteristics $\eta'_{i,t}$.[14] Whenever η and ν are correlated, we

[14] 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 ($\mathbb{I}^i_{j,t} = 1$).

have that $\mathrm{Corr}(\bar{\epsilon}_{i,t}, \nu_{i,t}) \neq 0$. 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 employ the granular instrumental variable (GIV) approach of Gabaix and Koijen (2021) and Gabaix and Koijen (2024). We construct an instrument for the "endogenous" covariate $\bar{\epsilon}_{i,t}$ by exploiting excess concentration of loan shares. Specifically, the granular instrument $Z_{i,t}^{GIV}$ 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*:

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

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

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

where

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

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.[15] 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.

[15]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.

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 numerous precautions and conduct a series of robustness checks to support the claim that firm shocks $\epsilon^{*}_{i,j,t}$ are as-good-as randomly assigned. First, we perform two checks addressing potential threats to the exclusion restriction. In Section A.2 of the Online Appendix, we relax the homogeneous loading assumption implicit in (6), since δ_i does not vary with j, and show robustness to allowing 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 when firms borrow from multiple banks. Second, we run our bank-level analysis by horizon and document the absence of any pre-trends in Section 3.3. Third, as detailed below and in Appendix F, we restrict the identifying variation to the top 1 percent of a bank's largest clients and confirm that our results remain robust. Fourth, already in the initial firm shock extraction specification in (1), we include firm fixed effects and time-varying firm controls, which absorb any persistent and measurable dependence on $\nu_{i,t}$ over time. Fifth, in Appendix C, we provide narrative-based evidence supporting the view that the value-added fluctuations extracted in (1) are non-systematic and occur at the firm level. In Appendix E, we further document that these fluctuations are uncorrelated across firms and across time.

Overall, we provide multi-dimensional evidence supporting the as-good-as-exogeneity of our firm shock measure.

We now briefly 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.[16] 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.

[16]The raw correlation between loan shares and firm shocks in our sample is -0.02. The correlation is computed for each bank, and we report the average across banks. We also compute and discuss absolute average correlations in the Online Appendix.

Instrument relevancy. 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 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:[17]

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

where HHI refers to the loan share Herfindahl index and $\mathrm{eHHI} = \mathrm{HHI} - 1/\mathrm{N}$ 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 2 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 $\mathrm{Z}_{\mathrm{i,t}}^{\mathrm{GIV}}$ and the endogenous covariate $\bar{\epsilon}_{\mathrm{i,t}}$ 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

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

with $Z^{GIV}_{i,t}$ as instrument for $\bar{\epsilon}_{i,t}$.[18][19]

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. In Appendix F, we document that all main results in this paper remain unchanged using this alternative approach.

3.4 Granular Credit Risk Spillovers: Loan and Firm Outcomes

In order to study the economic consequences of granular credit risk, we now estimate the effects of bank-level aggregated firm shocks on credit market outcomes. We now follow the canonical loan-level estimator of 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

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

[19] 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 3.3—a bootstrap is performed for each specification separately.

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 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 fixed effects at the firm industry × county level, and α_i is a bank fixed effect.[20]

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.[21]

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

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

Table 1: 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.

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 to overall bank credit supply variation and explore the benefits of limiting portfolio concentration, keeping everything else constant.

4.1 Loan Outcomes

Table 1 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 one 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 other words, when comparing a bank's loan return across firms within the same year, industry, county, and through the same loan facility, a one std. unexpected reduction in firm performance reduces loan returns by roughly a third of a percentage point.[22]

[22]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 plausible exogeneity of our firm shock measure (Altonji et al., 2005; Oster, 2019).

Table 2: 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	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)
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 (standardized) 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 of the first stage. Standard errors (in parentheses) are clustered at the bank level and computed by bootstrapping with 5,000 replications.

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 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 2, 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.[23] Our results show that a one standard deviation GIV-

[23] 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 2 is above the Stock and Yogo (2005) criterion for 5% maximal relative bias.

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.

We have specifications 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.[24] Results are quantitatively robust to the exclusion of these controls. Bank-level return on corporate loans (RoA) is the main dependent variable in this section. We have also experimented with loan write-downs and portfolio-level Sharpe ratios. Table D7 of the Online Appendix reports the results. We provide evidence that granular credit risk, when instrumented by the GIV, tends to increase write-downs, and especially over time. This is the economic mechanism behind our bank-level results. In addition, it tends to lower loan Sharpe ratios.

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 2 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.[25] 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.[26] 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.[27] Our results on loan write-downs strongly corroborate this mechanism.

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'

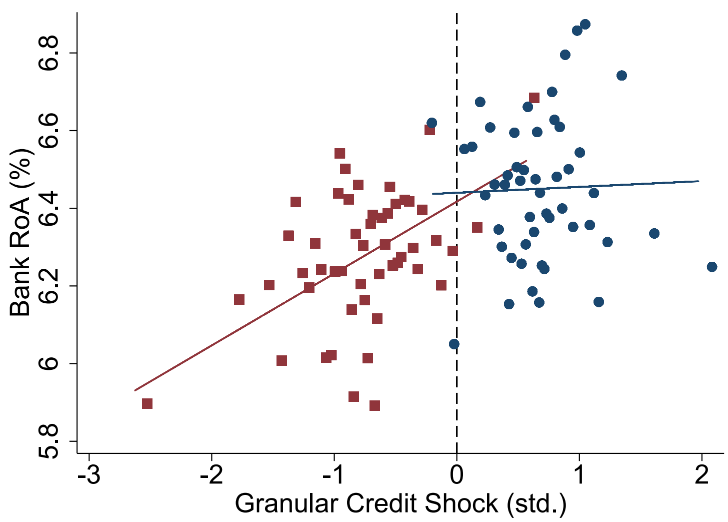
[24]Theoretically, if the exclusion restriction holds, the GIV approach would not require any further bank-time controls. The reason is that GIV, by construction, would be purged from any bank-time factors. For robustness, we still include observable bank controls. Results do not change in any substantial 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.

[25]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 2. 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).

[26]In Appendix D.5, Figure D2, we show that the asymmetry also is present at the loan-level.

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

Figure 3: Granular Credit Risk and Bank Outcomes



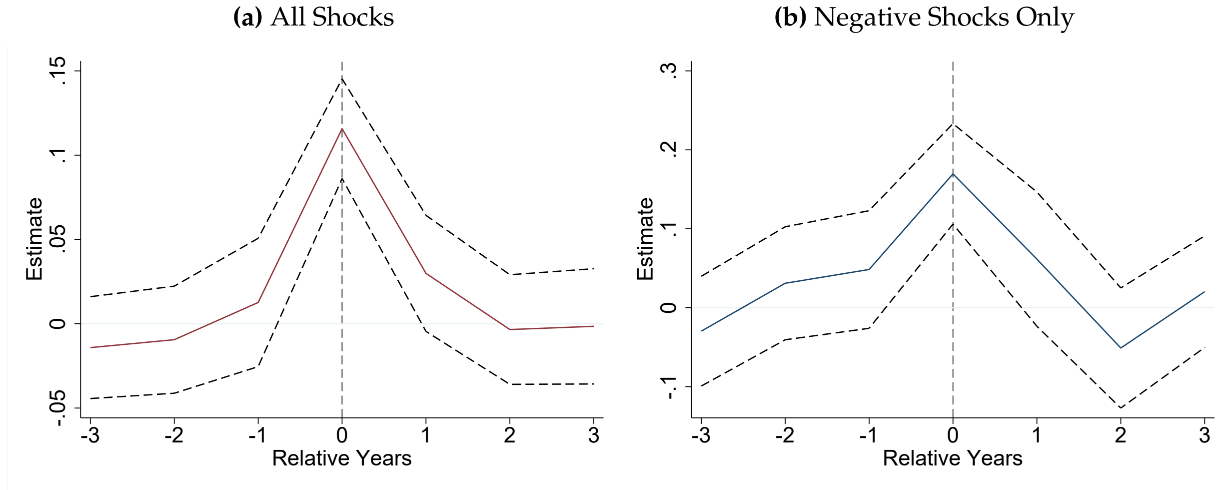
Notes: This figure visualises the relationship between residualized bank-level return on loans and residualized instrumented bank-level aggregated firm shocks. The red squares (blue circles) are binned scatterplots conditional on negative (positive) values of the weighted firm shock $\bar{\epsilon}_{i,t}$.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

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 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 × 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.[28]

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

[28] To the extent that we identify the structural impact of idiosyncratic shocks on loan-level returns, an alternative to the approach in this section is to use the loan-level coefficients together with the GIV-weighted idiosyncratic firm performance shocks to aggregate to the bank-level. In an unreported exercise, we do this and find that results do not change.

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.

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 3.3.

We conclude this section by emphasizing that our measure of bank return on assets (RoA) reflects a gross return—it does not incorporate funding costs, operational expenses, or credit risk. Due to data limitations, we are unable to estimate net returns directly. Nevertheless, evidence from Norges Bank (see Erard (2014) for a measure of net interest margin after accounting for funding costs and Andersen (2020) for an estimate of operational costs) indicates that the average net return on corporate loans over this period, after adjusting for funding and operational costs, is approximately 1.1 percentage points. Consequently, the impact of 11–19 basis points reported in Table 2 corresponds to roughly 10–17 % of the average net interest margin on corporate loans. This indicates that idiosyncratic firm shocks exert a substantial influence on bank profitability.

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

Table 3: 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.

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 3 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.

A drawback of this analysis is that the various hedging instruments analyzed in Table 3 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.[29]

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 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). In general, we expect these spillovers to be heterogeneous: smaller firms that are non-granular have less bargaining power and more limited access to alternative financing. Hence, when banks experience granular credit shocks, the resulting contraction in bank credit and spillover to real outcomes is potentially disproportionately borne by smaller, less granular firms. Our empirical strategy explicitly tests for these differential effects as a function of borrower size and bank loan book granularity.

Table 4 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$^{\text{th}}$ (columns (2)-(3)) or 20$^{\text{th}}$ (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. In terms of the effect on credit growth, the standard deviation of

[29] 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 4: 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 2. Standard errors (in parentheses) are double clustered at the bank and firm level.

loan growth is 34% which implies that a one standard deviation granular credit shock reduces loan growth by about 8%. 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 one std. 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.

In Table 5 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.

Table 5: 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 2. Standard errors (in parentheses) are double clustered at the bank and firm level.

Firm capital expenditure. Next, we ask whether spillovers on non-granular firms ultimately lead to real 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 shares being below the 50^{th} or 20^{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 4 and 5.

Results are reported in Table 6. 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.

Table 6: 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.

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 7 reports the results from probit regressions. Across all specifications, negative 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*

Table 7: 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.

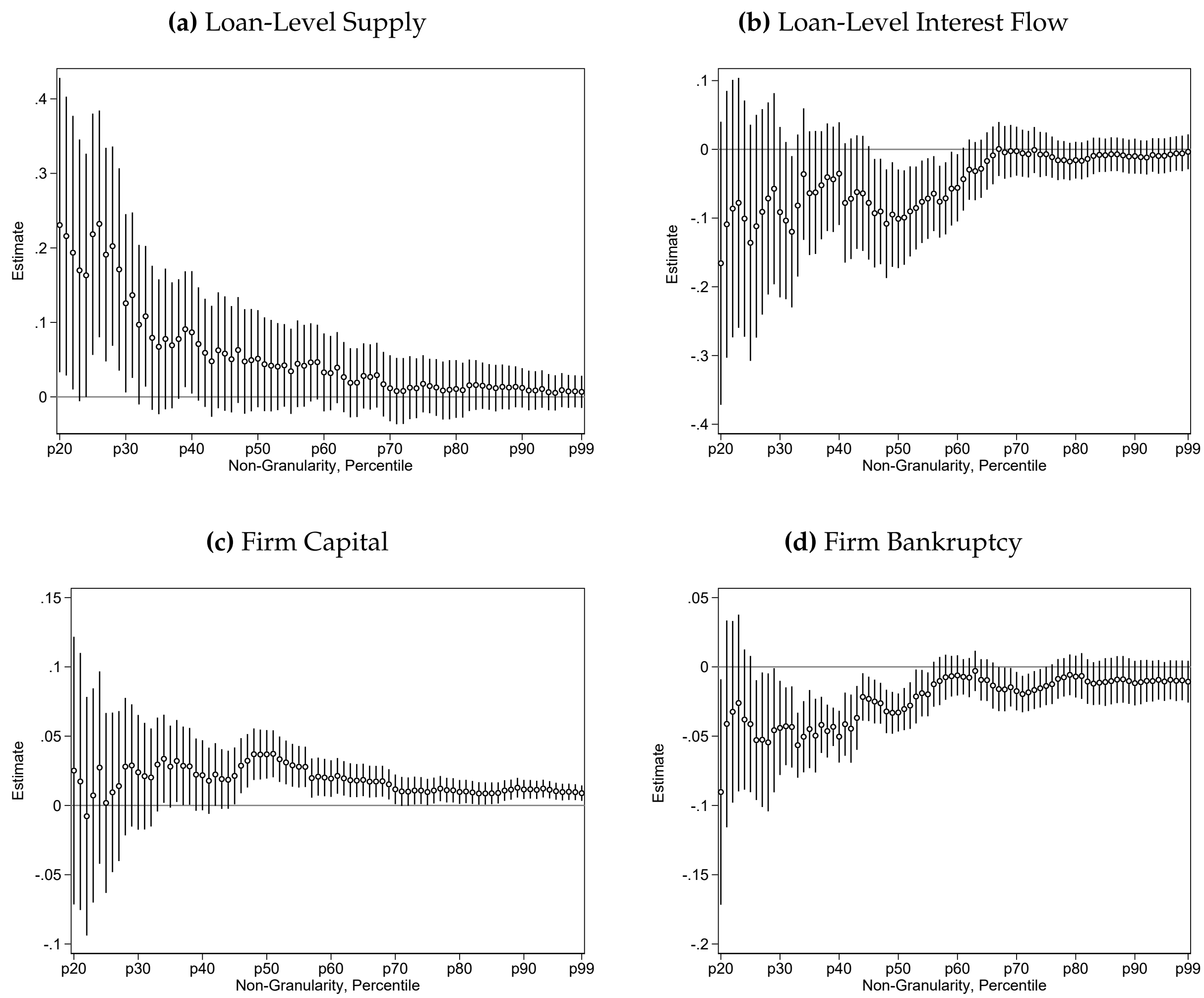
percentile of the pooled credit share distribution. Unlike previously, we now re-estimate our four spillover exercises for every P in the discrete interval $[20, 99]$. All specifications, including the presence of fixed effects or controls, are otherwise the same as before.

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. Moreover, in Appendix E.5, we show that the effects on loan volumes and interest flows are not limited to multiple-bank firms, but extend to the full sample of firms. We also demonstrate that the price response remains clearly negative among non-granular firms when using imputed loan rates instead of interest flows.

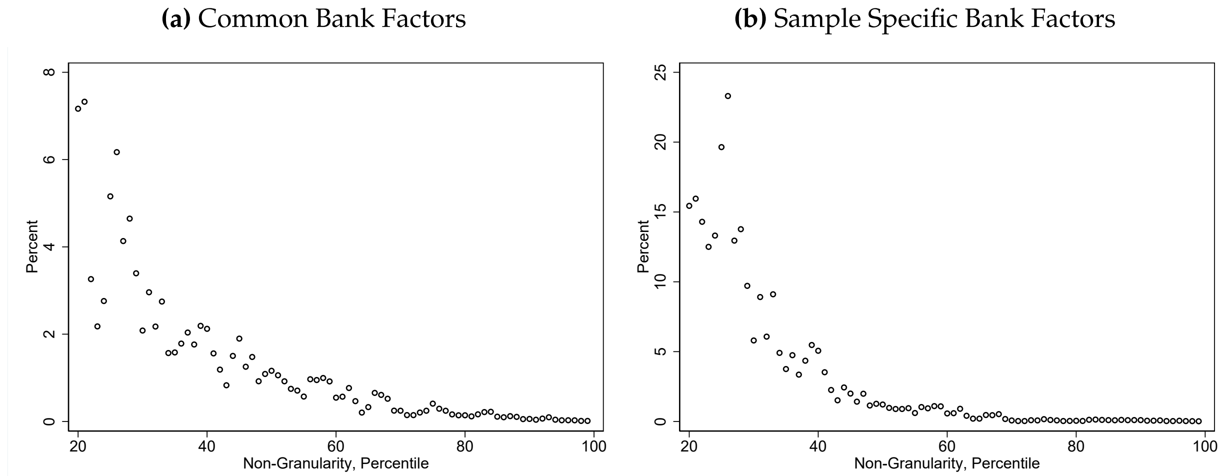
Overall, all of the above is highly indicative of a "pecking order" of credit relationships: banks adjust lending conditions with their non-granular borrowers in order to compensate for portfolio losses stemming from their granular corporate clients.

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 *P*th percentile of the loan share distribution, which is pooled over all banks and years. Percentiles $\mathrm{P} = 20, 21, \ldots, 99$ are shown on the x-axes and the y-axes show point estimates and 90% confidence bands for each respective case.

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 adding either the granular credit shock or bank-time FE, relative to a baseline estimation of equation (12) with neither of these controls. The x-axes represents different sub-sample regressions, where the estimation of equation (12) 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 *p*th 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 (12) 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.

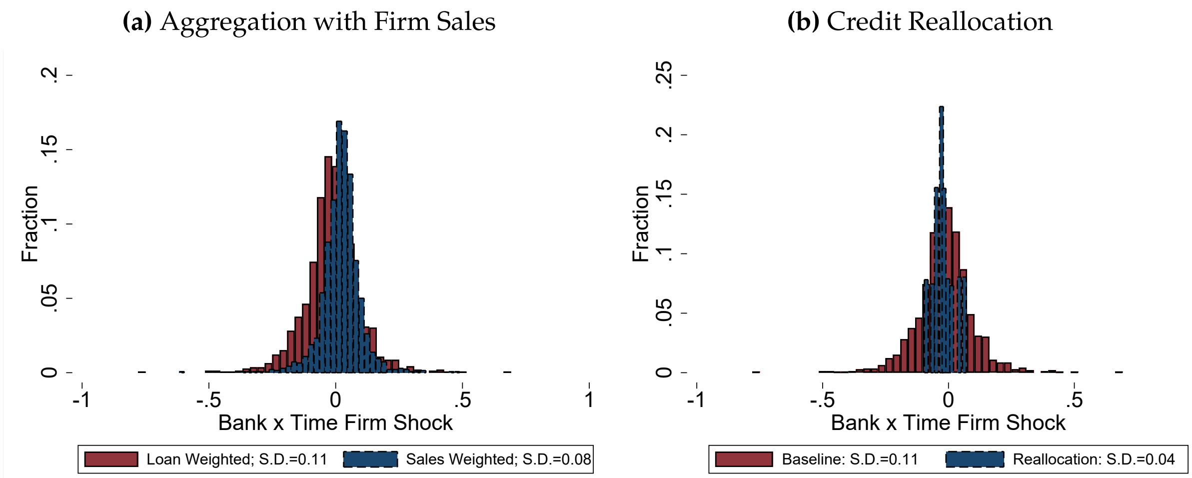
4.5 Quantification and Counterfactuals

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, 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. We do so by comparing the R^2 contribution of generic bank-time factors to the contribution of our granular shock in the estimation of equation (12), with loan-level credit growth as the dependent variable. By measuring the R^2 contribution, we are able to quantify how much granular shocks explain in terms of variation in loan-level credit growth, compared to an aggregate, generic bank x time factor. 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 (12) with neither of these controls. We perform this exercise 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

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.

subsequently use those fixed effects as bank supply controls in the sub-sample regressions. The underlying implicit assumption is that the generic bank supply factor is similar across all firms, irrespective of the size of the loan. In panel (b) we relax this assumption by re-estimating 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 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

Table 8: 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.

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 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 8 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. Importantly, they also abstract from the underlying origins of concentration, which are essential for evaluating the feasibility and desirability of alternative allocations. In practice, loan concentration may arise from a variety of sources: firm size distribution, specialization and asymmetric information, home bias and behavioral biases, among others. Some of these mechanisms—for instance, banks specializing in firms or sectors where they possess superior screening or monitoring capabilities—may reflect a form of constrained optimality, where concentration is the outcome of rational profit-maximizing behavior under frictions. In contrast, other sources, such as behavioral biases, may be more consistent with inefficient or suboptimal allocations. We discuss these potential origins of large exposures in more detail in Section G.

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.

Table 9: Loan Concentration Measures: International Comparison

					Loan Herfindahl Index		Share of 10% Largest Loans		Share of 5 Largest Loans	
Country	Source	Currency	Coverage	Obs.	Mean	Median	Mean	Median	Mean	Median
Norway	**This paper**	**NOK**	**2003-2015**	**1,380**	**0.10**	**0.07**	**0.54**	**0.52**	**0.51**	**0.49**
EU (average)	**AnaCredit**	**EUR**	**2019-2024**	**19 countries**	**0.12**	**0.07**	**0.53**	**0.53**	**0.47**	**0.43**
Austria	AnaCredit	EUR	2019-2024	2,954	0.06	0.02	0.49	0.50	0.34	0.22
Belgium	AnaCredit	EUR	2019-2024	640	0.18	0.14	0.49	0.49	0.62	0.71
Germany	AnaCredit	EUR	2019-2024	5,936	0.05	0.01	0.53	0.55	0.24	0.13
Spain	AnaCredit	EUR	2019-2024	1,324	0.11	0.05	0.54	0.53	0.44	0.40
France	AnaCredit	EUR	2019-2024	1,906	0.09	0.03	0.54	0.57	0.38	0.28
Ireland	AnaCredit	EUR	2019-2024	301	0.20	0.15	0.48	0.45	0.62	0.72
Italy	AnaCredit	EUR	2019-2024	1,850	0.08	0.01	0.53	0.55	0.32	0.11
Lithuania	AnaCredit	EUR	2019-2024	174	0.09	0.04	0.50	0.46	0.41	0.33
Latvia	AnaCredit	EUR	2019-2024	119	0.13	0.06	0.53	0.49	0.53	0.46
Malta	AnaCredit	EUR	2019-2024	72	0.07	0.03	0.51	0.54	0.37	0.31
Portugal	AnaCredit	EUR	2019-2024	890	0.07	0.02	0.56	0.57	0.32	0.19
Slovenia	AnaCredit	EUR	2019-2024	222	0.12	0.06	0.53	0.53	0.50	0.45
Slovakia	AnaCredit	EUR	2019-2024	282	0.16	0.11	0.54	0.55	0.59	0.64
Cyprus	AnaCredit	EUR	2019-2024	122	0.18	0.11	0.62	0.61	0.57	0.61
Estonia	AnaCredit	EUR	2019-2024	98	0.10	0.05	0.60	0.63	0.47	0.38
Finland	AnaCredit	EUR	2019-2024	1,097	0.07	0.03	0.53	0.53	0.34	0.26
Greece	AnaCredit	EUR	2019-2024	212	0.15	0.06	0.54	0.55	0.49	0.40
Luxembourg	AnaCredit	EUR	2019-2024	440	0.20	0.16	0.48	0.46	0.68	0.79
Netherlands	AnaCredit	EUR	2019-2024	773	0.17	0.14	0.46	0.43	0.64	0.72

Notes: This table presents loan concentration measures across countries. The Loan Herfindahl Index measures the concentration of loan portfolios, with higher values indicating greater concentration. The Share of 10% Largest Loans and Share of 5 Largest Loans represent the proportion of total lending attributed to the largest loans in each bank's portfolio. Norwegian data comes from this paper's dataset covering 2003-2015, while European data is sourced from AnaCredit covering 2019-2024. Observations refer to bank-year observations.

5 Discussion and Supplementary Results

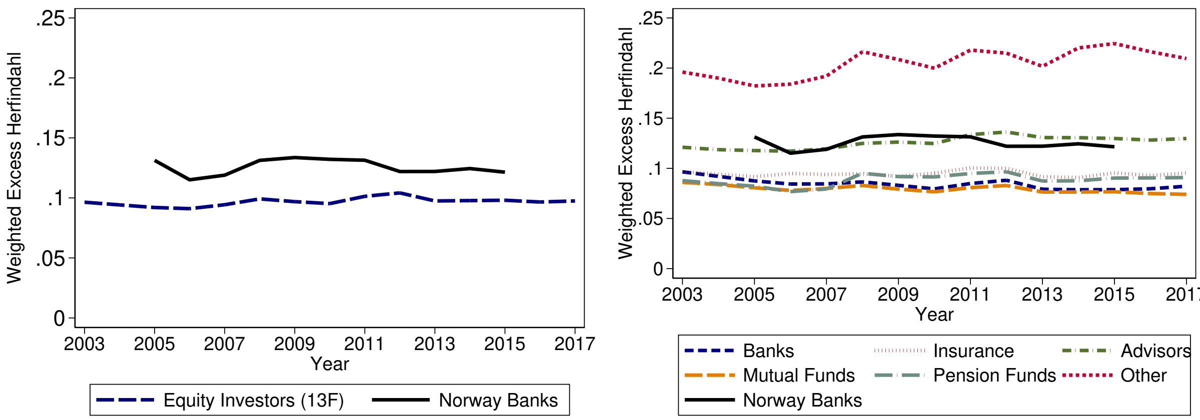
In this section, we expand on several issues that are relevant for our analysis. First, we argue for the external validity of our empirical approach and findings. Second, we discuss the production networks literature and show that our spillover results are not driven by firm-side inter-connectedness. 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 loan shares is important for the transmission of idiosyncratic shocks to portfolio-level outcomes of the lender.

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

(a) Aggregate Data **(b)** Investor Types



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.

To assess the degree of generalizability of our methodology and results to other settings, we compute measures of credit concentration on available loan-level data from other countries. Specifically, we use data from AnaCredit—a comprehensive credit register covering all EUR denominated loans above 25′000 Euros across both euro-area and non-euro-area European countries (Altavilla et al., 2020, 2024). The results are shown in Table 9. The table illustrates that credit concentration in our sample is on par with the EU-average and is, in fact, considerably *lower* than in major EU economies such as Germany. These results suggest that the degree of credit concentration in our sample is not something that is particular to Norway, but rather a common feature across banking systems. Furthermore, this implies that granular credit risk potentially extends to many other geographies and contexts.

Consistent with this, Baena et al. (2022) quantify the pass-through of estimated idiosyncratic firm performance shocks to bank portfolio outcomes in the context of France 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.

Bank-dependency has diminished over the past decades in some countries, e.g. the U.S. (Buchak et al., 2024). 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? To complement our empirical findings for Norwegian banks, we perform an additional test of external validity.[30] 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: $\mathrm{eHHI}_{i,t} = \sqrt{\sum_j s_{i,j,t}^2 - \frac{1}{N_{i,t}}}$ 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).

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.

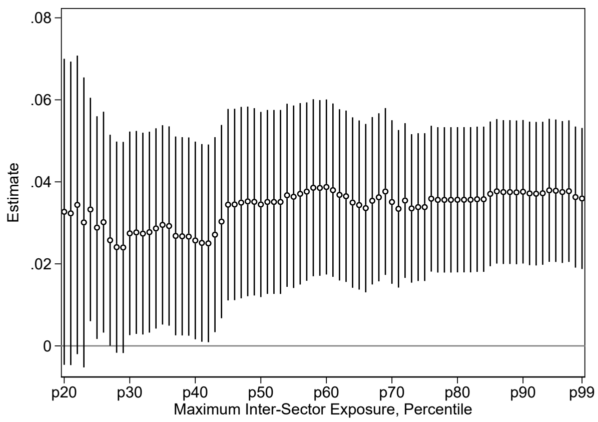
5.2 Network Effects

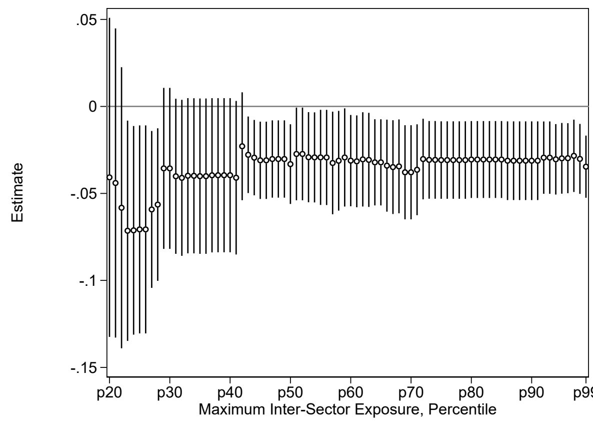
An important literature emphasizes the role of networks in the amplification and propagation of idiosyncratic financial shocks (Huremovic et al., 2025; Dewachter et al., 2020; Elliott et al., 2021). In paper that is closely related to ours, Huremovic et al. (2025) show that bank credit supply shocks 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 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

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

Figure 9: Firm Spillovers: Accounting for Production Networks





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 6 Column (3). In the right panel estimation results are obtained from running the same specification as in Table 7 Column (4).

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 6 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 7 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. (2025) 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, 2025). 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.[31] 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-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.[32] Third, the pass-through is twice as large for banks with

[31] 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.

[32] 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

Table 10: Bank Outcomes - Heterogeneity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent Variable: Bank Return on Loans (RoA)						
Lagged 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.

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.[33] 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).[34] In order to 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

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.

[33] 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.

[34] 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. (2023).

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.

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 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.[35] 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. Appendix G provides a detailed discussion of the origins of large exposures with potential implications for our results. Finally, Appendix H lays out our theoretical model, which provides an analytical motivation for empirical analysis.

[35] Banks could potentially pre-insure against granular borrower shocks by charging higher interest mark-ups 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 Jiménez et al. (2014), are better equipped at addressing this concern.

6 Conclusion

This paper has developed a bottom-up causal quantification of *single-name credit concentration risk* on bank-level outcomes and on the economy. While the previous literature has primarily 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.

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 (2021, 2024). 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 detailed dataset we can estimate the parameters of the Pareto distribution governing the distribution of loans and confirm its granularity.

A Appendix

Table A1: 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 = 9.98 NOK as of October 2, 2025. Firm shocks are estimated according to specification 1. 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.

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Online Appendix for "Granular Credit Risk"

(Not for Publication)

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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 (1) 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:

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

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 ($\delta^{x\prime}_{j,t} \eta^x_t$ 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 (2024), 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

[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.

are performed 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

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

[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.

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 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 1. Rows (1)-(3) show results for the three new shock measures. Recall that baseline estimates from Table 1 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 2 from main text. Recall that baseline estimates from Table 2 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

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) $\text{GIV}^{\check{\epsilon}}_{i,t}$	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) $\text{GIV}^{u^1}_{i,t}$	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) $\text{GIV}^{u^2}_{i,t}$	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 $\check{\bar{\epsilon}}_{i,t}$, 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.

shock measure $\epsilon_{j,t}$ itself, we keep $\epsilon_{j,t}$ as the shock variable but build the Granular IV based on the three new shocks $\text{GIV}^{\check{\epsilon}}_{i,t}$, $\text{GIV}^{u^1}_{i,t}$, and $\text{GIV}^{u^2}_{i,t}$. 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

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.

factors (to obtain $\check{\epsilon}_{j,t}$) 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 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]

[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.

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 Gabaix and Koijen (2024). 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

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.

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 quantitatively unchanged compared to the results reported in Table 2 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:

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

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

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

In words, $Z^{SS}_{i,t}$ 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 $Z^{GIV}_{i,t}$ and $Z^{SS}_{i,t}$ 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 (2024), 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:

$$\begin{aligned}
\mathrm{Cov}(\mathrm{Z}^{\mathrm{GIV}}, \bar{\epsilon}) &= \mathrm{Cov}(\sum_{\mathrm{j}}^{\mathrm{N}} \tilde{\mathrm{s}}_{\mathrm{j}}\mathrm{u}_{\mathrm{j}}, \eta + \sum_{\mathrm{j}}^{\mathrm{N}} \mathrm{s}_{\mathrm{j}}\mathrm{u}_{\mathrm{j}}\epsilon_{\mathrm{j}}) && \text{(B6)} \\
&= \mathrm{Cov}(\sum_{\mathrm{j}}^{\mathrm{N}} \tilde{\mathrm{s}}_{\mathrm{j}}\mathrm{u}_{\mathrm{j}}, + \sum_{\mathrm{j}}^{\mathrm{N}} \mathrm{s}_{\mathrm{j}}\mathrm{u}_{\mathrm{j}}\epsilon_{\mathrm{j}}) && \text{(B7)} \\
&= \sum_{\mathrm{j}}^{\mathrm{N}} \sum_{\mathrm{i}}^{\mathrm{N}} \tilde{\mathrm{s}}_{\mathrm{j}}\mathrm{s}_{\mathrm{i}}\mathrm{Cov}(\mathrm{u}_{\mathrm{j}}, \mathrm{u}_{\mathrm{i}}) && \text{(B8)}
\end{aligned}$$

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

$$\mathrm{Cov}(\mathrm{Z}^{\mathrm{GIV}}, \bar{\epsilon}) = \sigma_{\mathrm{u}}^2 \sum_{\mathrm{j}}^{\mathrm{N}} \tilde{\mathrm{s}}_{\mathrm{j}}\mathrm{s}_{\mathrm{j}} \tag{B9}$$

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

$$\mathrm{eHHI} := \sum_{\mathrm{j}}^{\mathrm{N}} \tilde{\mathrm{s}}_{\mathrm{j}}\mathrm{s}_{\mathrm{j}} = \sum_{\mathrm{j}}^{\mathrm{N}} \tilde{\mathrm{s}}_{\mathrm{j}}^2 - 1/\mathrm{N} \tag{B10}$$

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

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

Dividing through by σ_{u}^2 and noting that $\sum \tilde{\mathrm{s}}_{\mathrm{j}}^2 = \mathrm{eHHI}$ and $\sum \mathrm{s}_{\mathrm{j}}^2 = \mathrm{HHI}$ we get that:

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

which is the equation shown in Section 3.3 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 follow two distinct approaches. First, we do a purely manual validation of some of the most extreme shock realizations to gauge whether they capture idiosyncratic events. Second, we apply two complementary machine learning approaches on *all* Norwegian newspapers and all shocks in our sample to automatically substantiate that they are indeed idiosyncratic.

C.1 Manual inspection of the 1st percentile of the shock distribution

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

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

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.

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 $\epsilon_{\mathrm{j,t}}$ 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).

C.2 Machine learning approach on the universe of shocks

Our second approach utilizes the full sample of shocks. To gather textual information related to these shocks, we search through all Norwegian newspapers by accessing the National Library of Norway. Conveniently, the National Library provides digitized versions of all Norwegian newspapers, updated daily. For each firm-year observation, we search for mentions of the firm across all newspapers. When a match is found, we extract a 25-word string from the relevant section of the newspaper in which the firm is mentioned.[7] If multiple strings are found for a given firm-year, we concatenate all such strings into a single text sequence. Of the 293,415 firm-year pairs searched in the news database of the national library, we find that firms are mentioned in the news during their respective years in 124,620 instances. We refer to this subset as our narrative sample—i.e., the sample for which we have associated text data.

We analyze the narrative sample using two complementary approaches, with the ultimate objective of verifying that the shocks are indeed idiosyncratic. First, we employ a dictionary-based method, wherein we identify terms that are indicative of either positive or negative idiosyncratic firm-level performance shocks. The dictionaries used for this purpose are presented in Table C1. In the table we show the actual Norwegian dictionary used, together with an english translation. Negative modifiers are words that, when appearing in the same 25-word sentence as a positive word, negate its classification as positive. Since identifying positive idiosyncratic sentences is not straightforward, we consider two alternative versions of the positive dictionary, labeled *Case 1* and *Case 2*.

Second, we prompt a large language model (LLM), using the instructions outlined in Figure C1, to generate assessments of whether a shock is idiosyncratic and whether it is positive or negative. To ensure that the LLM interprets the term idiosyncratic in line with our usage, we instruct it to provide its own definition based on the prompt in Figure C1. The resulting definition, shown in Figure C2, is reassuringly consistent with our intended concept of idiosyncratic.

As shown in Figure C1, we also prompt the LLM to provide keywords that justify the assigned probability of a shock being idiosyncratic. For shocks with an idiosyncratic probability of at least 80%, Figure C3 presents word clouds based on the associated text strings. These word clouds typically feature terms such as “fire” or “theft” for negative

[7] The 25-word limit reflects a capacity constraint imposed by the National Library.

````
USER_TEMPLATE = """
    You are reading newspaper coverage of a company. Given the text below, you should assess whether at least one of the sentences describes an idiosyncratic shock, a positive or a negative event
    for the company.

    Definitions:
    - Idiosyncratic shock: A shock that is peculiar, distinctive, strange, or that only applies to the specific company in question.
    - Negative shock: Something that is disadvantageous for the company and/or sector.
    - Positive shock: Something that is advantageous for the company and/or sector.

    Text:
    \"\"\"{text}\"\"\"

    Answer ONLY with a complete and valid JSON in markdown format, like this: `{{...}}`.
    No explanations, no extra text, no lines before or after.

    JSON format:
    ```json
    {{
    "idiosync_shock": decimal probability between 0 and 1,  // 1 = completely certain that an idiosyncratic shock is described, 0 = completely certain that an idiosyncratic shock is NOT described.
    "positive_shock": decimal probability between 0 and 1,  // 1 = completely certain that a positive shock is described, 0 = completely certain that a positive shock is NOT described.
    "negative_shock": decimal probability between 0 and 1,  // 1 = completely certain that a negative shock is described, 0 = completely certain that a negative shock is NOT described.
    "idiosync_keywords": three keywords in English that describe the shock, or 'Noise' if probability is low.
    "positive_keywords": three keywords in English that describe the shock, or 'Noise' if probability is low.
    "negative_keywords": three keywords in English that describe the shock, or 'Noise' if probability is low.
    }}
    """
````

Figure C1: LLM-prompt to identify and describe idiosyncratic shocks

Notes: This figure is a screenshot of the prompt we used to estimate the likelihood that a shock is idiosyncratic using an LLM. The original prompt has been translated to English.

shocks, and "award" or "contract" for positive ones. We interpret this as strong evidence supporting our conjecture that the estimated idiosyncratic shocks capture events with a genuinely firm-specific origin.[8]

In both approaches, we proceed by focusing on shocks in the narrative sample for which are likely to be idiosyncratic, i.e. they have at least one match in the words defined in the dictionary-based approach, or the LLM assigns a probability that it is idiosyncratic greater to or equal to 80 %. For this subsample of the narrative sample, we re-estimate the baseline loan-level regressions.

The results for the LLM approach are displayed in Table C2, and show that the transmission of shocks to loan returns remains large. Likewise, results based on the dictionary tagging are reported in Tables C3 and C4, and show similar patterns although slightly lower point estimates. A general tendency is that estimates become more noisy, compared with the baseline results, and increasingly so as we saturate the model with fixed effects. This is due to the fact that the narrative approaches in many instances fail to tag firms. Importantly, failure to tag should not be interpreted as an indication of no shock occurrence, but rather reflecting the noisy nature of newspaper text extractions.

[8]Note that newspapers predominantly report on the consequences of shocks. As a result, the text strings often contain generic terms such as "bankruptcy", "closure", "success", and "expansion". To provide more direct evidence on the causes of idiosyncratic shocks, we exclude commonly used outcome-related words. We also exclude two additional terms—"specific" and "local"—which, although suggestive of idiosyncratic shocks, are too generic to inform their underlying causes. These terms are, however, far less prominent than the outcome-related words.
````

NBGPT

An **idiosyncratic shock** is an event or impact that is **unique** and **specific** to a particular business, unrelated to broader economic, industry-related, or external factors. This shock is unexpected and distinct, affecting only the specific company without influencing multiple actors within the same market or industry.

Examples of idiosyncratic shocks might include:

- The sudden resignation of a key leader in the company.
- The discovery of a unique scandal or fraud tied to the business.
- A shortage of raw materials that are exclusively available to this business.
- A sudden technological innovation or breakthrough developed only by the company, not available to competitors.

It differs from **systemic shocks**, which have an impact on the entire economy or industries as a whole.

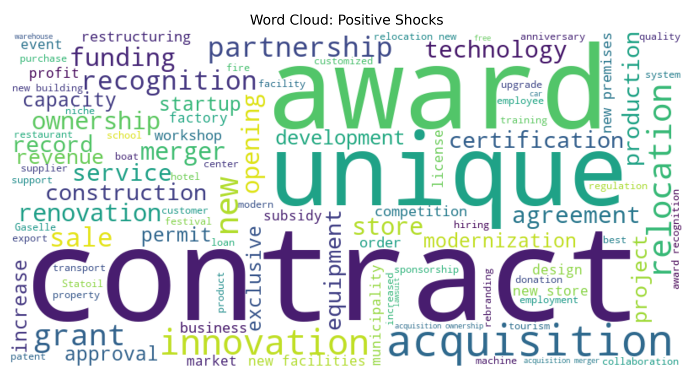
Figure C2: LLM response to the prompt: "Define an idiosyncratic shock based on the previous prompt", where the previous prompt is shown in Figure C1.

Notes: This figure is a screenshot of the LLMs answer on how it would 'Define an idiosyncratic shock based on the previous prompt", where "previous prompt" refers to the prompt used to estimate the likelihood that a shock is idiosyncratic using an LLM and shown in Figure C1. The original prompt has been translated to English.

Figure C3: Word clouds based on the LLM-based description of positive and negative idiosyncratic shocks

(a) Negative shocks

(b) Positive shocks



Notes: This figure shows the LLM-assigned keywords to shocks it tagged as idiosyncratic, negative and with an estimated negative shock (left panel) or idiosyncratic, positive and with an estimated positive shock (right panel). We define shocks as tagged as idiosyncratic if the LLM assigns a probability of the shock being idiosyncratic of at least 80 % We define a shock as either negative or positive if the LLM assigns a probability of that event of at least 80 %.

Table C1: Keyword dictionaries for firm-specific event tagging

Positive phrases (case 1):
børsnotering (*stock exchange listing*), gjennombrudd (*breakthrough*), innovasjon (*innovation*), lansering (*launch*), løyve (*license*), markedsgjennombrudd (*market breakthrough*), monopol (*monopoly*), ny kontrakt (*new contract*), nyvinning (*invention*), nysatsing (*new initiative*), patent (*patent*), prisvinnende (*award-winning*), sertifikat (*certificate*), sertifisering (*certification*), tildelt (*granted*), utmerkelse (*recognition*)
Positive phrases (case 2):
vekst (*growth*), rekord (*record*), salget øker (*sales increasing*), godt salg (*strong sales*), rekordomsetning (*record revenue*), høy etterspørsel (*high demand*), oppgang (*upswing*), ny kontrakt (*new contract*), prisvinnende (*award-winning*), sertifisering (*certification*), tildelt (*granted*), utmerkelse (*recognition*), suksess (*success*), utvider (*expanding*), lansering (*launch*), nysatsing (*new initiative*), styrker (*strengthening*), opptur (*upturn*), omsetningsvekst (*revenue growth*), inntektsøkning (*income increase*), beste resultat (*best result*), markedsgjennombrudd (*market breakthrough*), ny fabrikk (*new factory*), børsnotering (*stock exchange listing*), sertifikat (*certificate*), klimapris (*climate award*), miljøsertifisering (*environmental certification*), ny kunde (*new customer*), ny avtale (*new agreement*), patent (*patent*), innovasjon (*innovation*), monopol (*monopoly*), løyve (*license*), gjennombrudd (*breakthrough*)
Negative phrases:
underslag (*embezzlement*), brann (*fire*), vannskade (*water damage*), rettssak (*lawsuit*), anmeldt (*reported*), tilsyn (*inspection*), ulykke (*accident*), korrupsjon (*corruption*), straff (*penalty*), klage (*complaint*), tilbakekalling (*recall*), avvik (*non-compliance*), stengt (*closed*), mattilsynet (*Norwegian Food Safety Authority*), advarsel (*warning*), straffbart (*criminal offense*), krenkelse (*violation*), beslag (*seizure*), lukt (*odor*), nekte (*refusal*), ulovlig (*illegal*), skandale (*scandal*), mangler (*deficiencies*), driftstans (*operational stoppage*), produksjonsstans (*production halt*), ødelagt (*destroyed*), ødeleggelse (*destruction*), datafeil (*data error*), systemfeil (*system error*), havari (*breakdown*), innbrudd (*burglary*), tyveri (*theft*)
Negative modifiers:
dårlig (*poor*), svak (*weak*), liten (*small*), negativ (*negative*), fallende (*declining*), nedgang (*downturn*), feilende (*failing*)

Table C2: Loan Outcomes on LLM subsample

	(1)	(2)	(3)
	Dep. Var.: Return on Loan		
Firm Shock: $\epsilon_{j,t}$	0.218	0.295	1.140
	(0.098)	(0.202)	(0.353)
Observations	5610	2708	1121
Bank x Industry x Year FE	-	✓	-
Bank x Industry x Year x Loan-type x County FE	-	-	✓

Notes: This table reports loan level results on the subsample of firms with $\epsilon_{j,t} < 0(> 0)$ for which the LLM approach assigns a 80 percent probability that the shock is idiosyncratic negative (positive) .

Table C3: Loan Outcomes on Dictionary Subsample (Case 1)

	(1)	(2)	(3)
	Dep. Var.: Return on Loan		
Firm Shock: $\epsilon_{j,t}$	0.208	0.204	0.184
	(0.07)	(0.102)	(0.16)
Observations	15616	10480	6467
Bank x Industry x Year FE	-	✓	-
Bank x Industry x Year x Loan-type x County FE	-	-	✓

Notes: This table reports loan level results on the subsample of firms for which $\epsilon_{j,t} < 0(> 0)$ is backed up by a negative (positive) dictionary tag.

Table C4: Loan Outcomes on Dictionary Subsample (Case 2)

	(1)	(2)	(3)
	Dep. Var.: Return on Loan		
Firm Shock: $\epsilon_{j,t}$	0.252	0.312	0.217
	(0.065)	(0.094)	(0.118)
Observations	21814	15631	10250
Bank x Industry x Year FE	-	✓	-
Bank x Industry x Year x Loan-type x County FE	-	-	✓

*Notes:*This table reports loan level results on the subsample of firms for which $\epsilon_{j,t} < 0(> 0)$ is backed up by a negative (positive) dictionary tag.

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 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

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.

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 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 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.

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.

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[9]. 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.

[9]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.

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

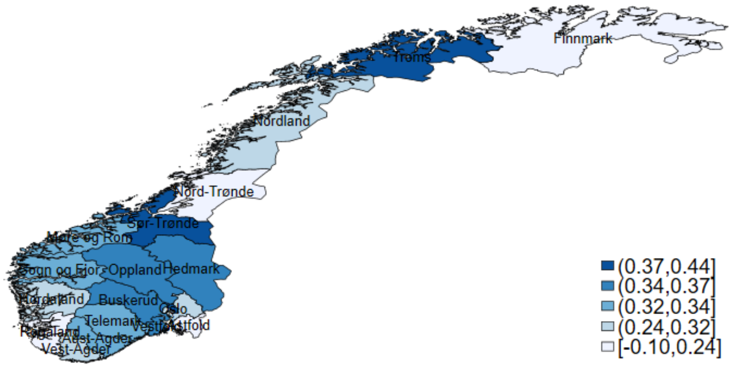
	(1)	(2)	(3)	(3)	(4)	(5)
	Dependent Variable: Return on Loan					
	All Firms	Manufacturing	Mining	Construction	Real Estate	Agriculture
Firm Shock	0.335	0.356	0.401	0.414	0.064	0.215
	(0.016)	(0.050)	(0.251)	(0.040)	(0.034)	(0.055)
Bank x Year x County FE	✓	✓	✓	✓	✓	✓
Observations	330490	34232	1097	60169	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.

D.5 Loan-level Asymmetric Effects

In Section 3.3 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 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

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*).

negative shocks.

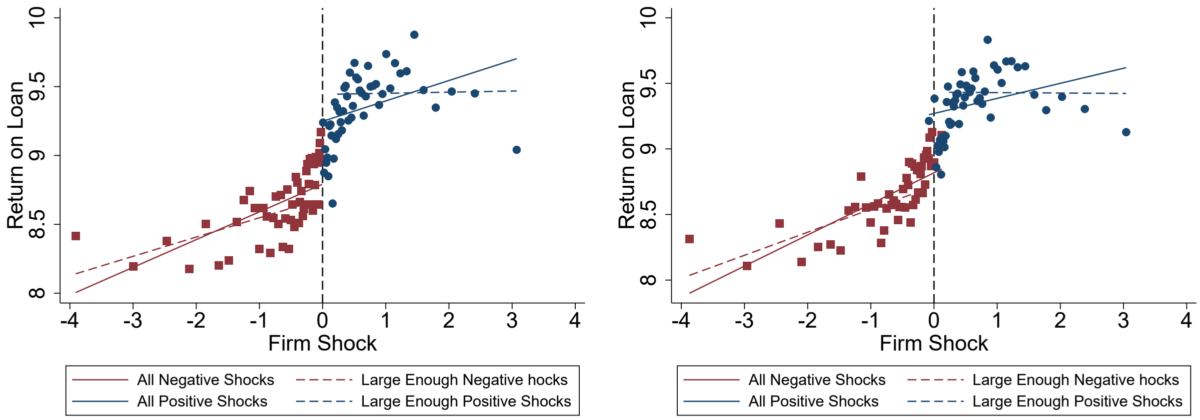
Figure D2 reports binned scatter plots for the relationship between loan-level returns on loans and $\epsilon_{j \in \mathbb{P}(i,t)}$. The plots are constructed in a similar fashion as described in detail in Section 4.2. Panel (a) shows the raw specifications without any fixed effects while panel (b) 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.

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 Jiménez et al. (2014). Given the nature of our data, it is

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.

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.

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.

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.

Table D6: Impact of Aggregate Shocks

	(1)	(2)	(3)	(4)
Granular Credit Shock	0.087	0.087	0.117	0.117
	(0.044)	(0.044)	(0.042)	(0.042)
Sectoral shock		0.066		0.161
		(0.061)		(0.064)
Log(GDP)			0.186	0.252
			(0.077)	(0.084)
Log(Oil Price)			0.511	0.511
			(0.030)	(0.029)
Bank FE	✓	✓	✓	✓
Year FE	-	-	-	-
Bank Controls	✓	✓	✓	✓
R^2	0.141	0.142	0.254	0.260
Observations	1211	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 column we use a portfolio-weighted sectoral shock, where the sectoral shock is the sector x year fixed effect from a firm performance regression in equation (1) (3)-(4) 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.

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 research.

D.7 Impact of Aggregate Shocks

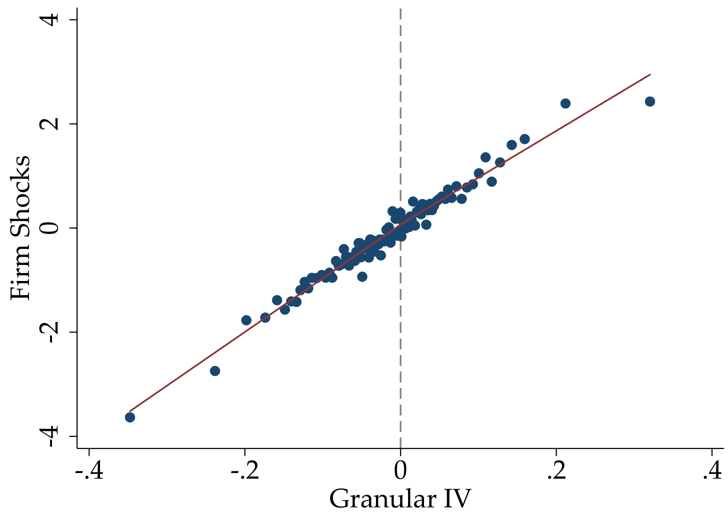
In this paper our primary focus is on the effect of idiosyncratic firm shocks on banks and the broader economy. But how do idiosyncratic shocks compare to aggregate risk? Section 4.3 demonstrates that idiosyncratic borrower-level risk is not insured in practice, but the margin of adjustment when it comes 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 2 but without year fixed effects. In columns (2)-(4) the main regressors are now (standardized) sector x year fixed effects from equation (1), real GDP and oil prices, respectively. The most restrictive specification is in column (4), where all of the aggregate variables are included. The point estimate of the sectoral shock is slightly larger (0.161 vs. 0.117), whereas the point estimates for GDP and oil prices are greater by factors of 2 and 5, respectively. Nevertheless, these "aggregate" factors 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.

D.8 Supplementary Figures and Tables

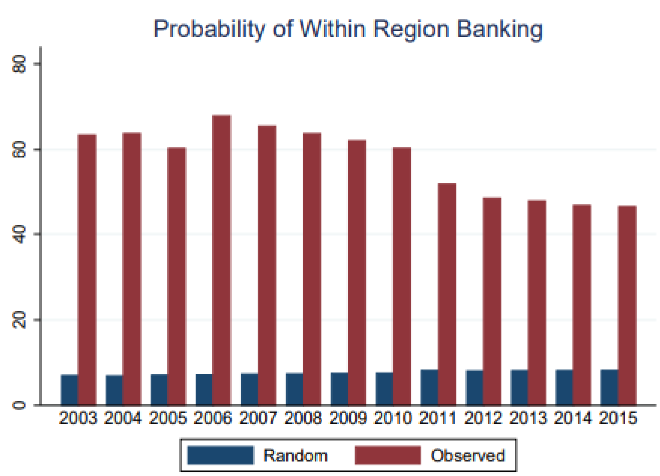
In this section we present supplementary figures and tables that complement our main results and text. Figure D3 plots the relationship between the granular instrument $\mathrm{GIV}_{i,t}$ and the weighted firm shock $\bar{\epsilon}_{i,t}$: the test of the first stage. Figure D4 demonstrates the probability 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 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, $\text{GIV}_{i,t}$. On the vertical axis we have the idiosyncratic firm shock which is loan size-weighted and aggregated to the level of a bank. Idiosyncratic firm shocks are extracted from specification 1. The granular instrument (horizontal axis) is constructed based on equation (7). Correlation between the two variables is 0.863.

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) Writedowns_t	(2) Writedowns_t	(3) Writedowns_{t+1}	(4) Writedowns_{t+1}	(5) Sharpe_t	(6) Sharpe_t
Granular Credit Shock	-0.016	-0.015	-0.021	-0.020	0.057	0.052
	(0.009)	(0.011)	(0.011)	(0.013)	(0.069)	(0.037)
Bank FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Bank Controls	✓	✓	✓	✓	✓	✓
Instrumented by GIV	-	✓	-	✓	-	✓
Observations	1184	1184	1077	1077	1206	1206
R^2	0.937	0.071	0.936	0.067	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 in odd numbers are standard OLS, while in columns in even numbers relies on the GIV. 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 1 and 2, 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

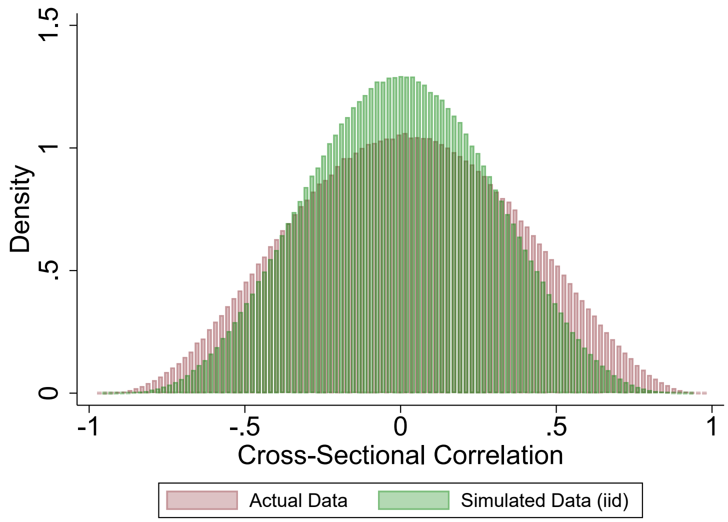
In this section, we provide several additional robustness checks. First, we test robustness with respect to the Great Financial Crisis (GFC). Second, we check that idiosyncratic firm shocks have a pairwise correlation of approximately zero. Third, we conduct several placebo tests at various levels of aggregation to lend further support to our baseline results. Third, 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. We also present spillover estimates using alternative identification techniques and outcomes, and replicate the main results replacing idiosyncratic firm value-added shocks with sales shocks.

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 1. For the simulated data the estimated firm shocks are replaced by draws from a standard normal distribution.

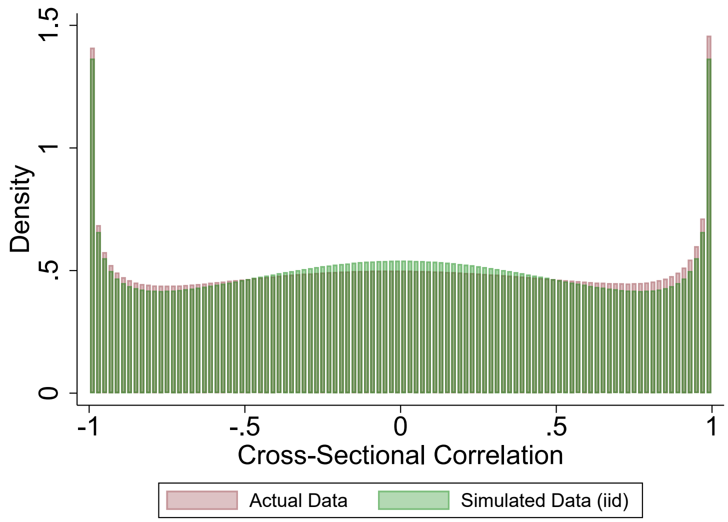
E.2 Pairwise Correlations Tests

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 1. 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.[10] 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

[10]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 1 column (3) and Table 2 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.

remarkably 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.[11]

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 1. The results from using these drawn shocks for the loan-

[11] 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

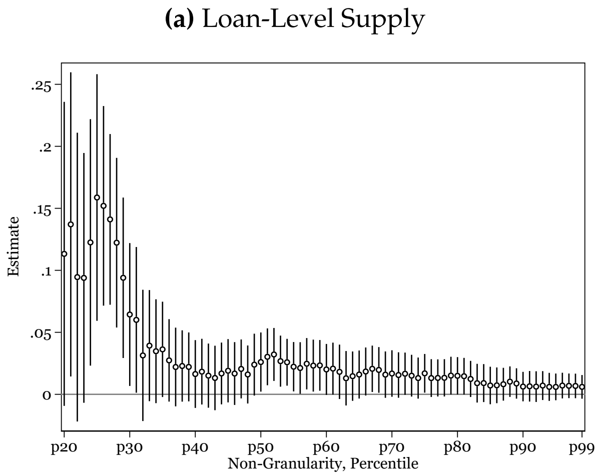
	Borrower Level	Bank Level	Firm Industry Level	County Level
Autoregressive Coef.	0.318	0.122	0.241	0.223
Standard Deviation	0.267	0.107	0.254	0.251

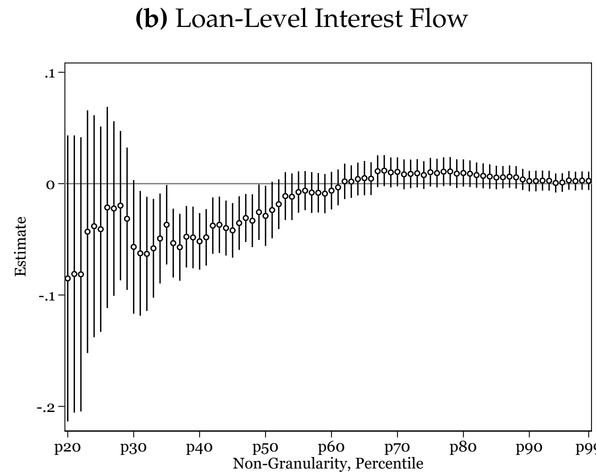
Notes: This table reports parameter estimates of a linear unbalanced panel fixed effects model with a disturbance that follows an autoregressive process of order 1. Estimates for the autoregressive coefficient and the standard deviation of the error term are reported. Columns report results for various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

E.5 Alternative Spillover Estimation

In this section, we conduct two robustness checks on the baseline spillover effects of granular shocks to firm credit and interest rates, as reported in Figure 5, panels (a) and (b)

Figure E7: Spillovers from Granular Credit Shocks: All Firms



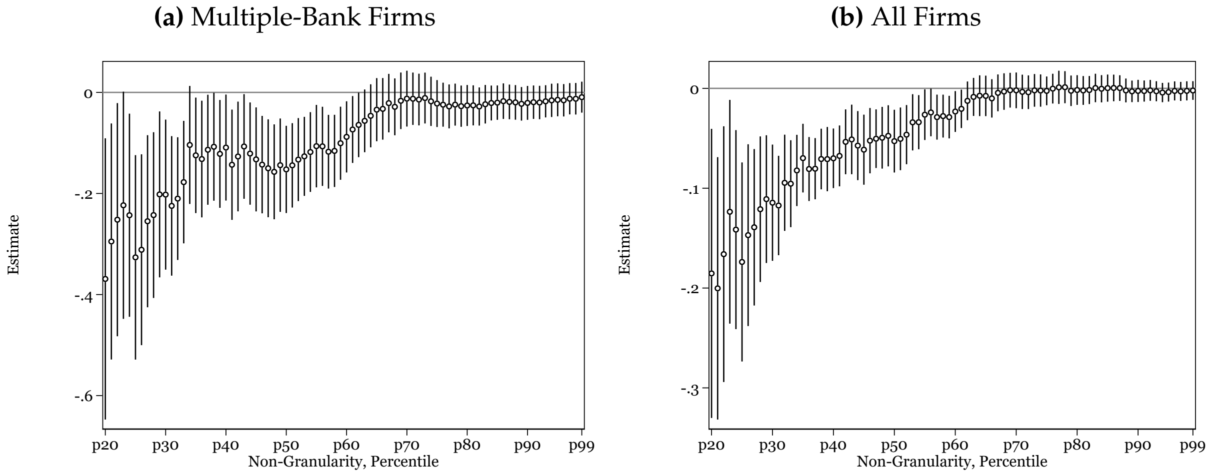


Notes: This figure reports the result from a robustness check of panel (a) and (b) in Figure 5, where we remove firm-year FE.

The first robustness check addresses the inherent tension in the Khwaja and Mian (2008) methodology between identification and generalizability. Specifically, when conditioning on firms with multiple bank relationships, the estimated effects are identified from a selected subset of firms, raising the question of whether these effects extend to the broader firm population. To examine this concern, we expand the sample to include all firms by omitting time-varying firm fixed effects. Instead, in the spirit of Degryse et al. (2019), we introduce a more granular set of time-varying fixed effects. The rationale is that by saturating the model with detailed controls, we can still account for firm-specific demand shocks even without firm-time fixed effects. In Figure 5, panels (a) and (b), the baseline specification includes year × industry × county × firm fixed effects, along with separate time-invariant bank fixed effects. In the robustness specification, we replace these with interactions of year × industry × municipality × firm rating, and include time-invariant firm and bank fixed effects. This adjustment allows for more precise control of local economic conditions – given that Norway has approximately 360 municipalities compared to just 20 counties – and ensures comparability among firms with similar recent performance through the inclusion of firm rating fixed effects.

The results from these regressions are presented in Figure E7 and demonstrate that our baseline findings in Figure 5 are robust to extending the sample beyond firms with multiple bank relationships. Notably, the number of observations increases from 212 to 9,091 at the 20th percentile cutoff and from 3,443 to 34,068 at the 50th percentile cutoff. This robustness provides strong evidence that the estimated effects are not confined to the

Figure E8: Spillovers from Granular Credit Shocks: Imputed Loan Rate



Notes: This figure reports the result when replacing the the dependent variable in panel (b) of Figure 5 with the log change in imputed loan rates. Panel (a) reports results using firms with multiple-bank relationships, while panel (b) reports results when using all firms as in panel (b) of Figure E7.

subset of multiple-bank firms, but are instead generalizable to the broader firm population.

The second robustness check relates to the price measure used in panel (b) of Figure 5. Specifically, there we rely on the level of interest expenses, which reflects both the loan rate (price) and the volume of debt (quantity). This choice imposes a conservative test for identifying bank supply shocks: all else equal, an increase in borrowing should lead to higher interest expenses. Therefore, observing a positive response in quantities alongside a flat or negative response in interest expenses provides strong evidence consistent with supply-driven credit shocks

We illustrate this point by replacing the log change in interest expenses with the log change in imputed loan rates (imputed as described in Section 2 and used in 4.1).[12] The resulting interest rate response is shown in Figure E8 and reveals a clearly significant negative effect among non-granular firms. This finding corroborates our interpretation that the granular bank-level credit shock operates as a supply shock for non-granular firms.

E.6 Firm Sales Shocks

To alleviate concerns about measurement error in value added, this section provides a robustness check of the main results where we estimate firm performance shocks using

[12] This is equivalent to using the log difference ΔInterest Flow $-$ ΔLoans as the dependent variable.

Table E13: Robustness to sales shocks

	(1)	(2)	(3)	(4)
	Loan-Level	Bank-Level		
Firm Shock	0.426	0.069	-0.129	0.215
	(0.019)	(0.034)	(0.098)	(0.079)
All Controls	✓	✓	✓	✓
Observations	283279	1209	549	652

Notes: Using firm sales shocks, this table replicate the results for loan-level returns in column 4 in Table 1, and bank-level returns in columns 6-8 in Table 2 in the main text.

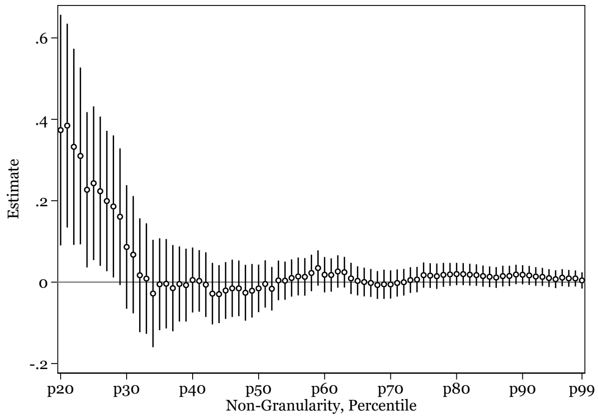
log sales as dependent variable, which is likely less prone to measurement error than value-added. Hence, we replace the dependent variable in equation 1 in the main text with firm sales.

Table E13 show that also this shock measure impacts both loan returns and bank level returns. In column (1) we replicate the the most saturated loan-level returns regression in the main text (reported in column 4 in Table 1), while in columns (2)-(4) we replicate columns (6)-(8) from Table 2 in the main text. In particular the sales shock replicates the magnitude and significance of negative shocks at the bank level, while we find no systematic relationship between positive granular firm shocks and bank-level loan returns.

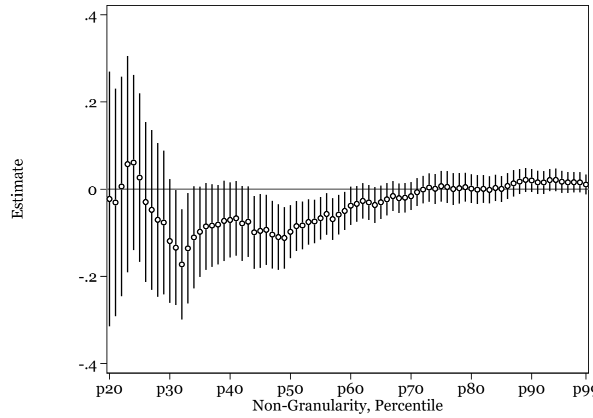
Furthermore, in Figure E9 we show that using the sale-based shock measure, the spillovers to firm-level credit and interest rate remain similar to results reported in the main text.

Figure E9: Spillovers from Granular Credit Shocks: Sales Robustness

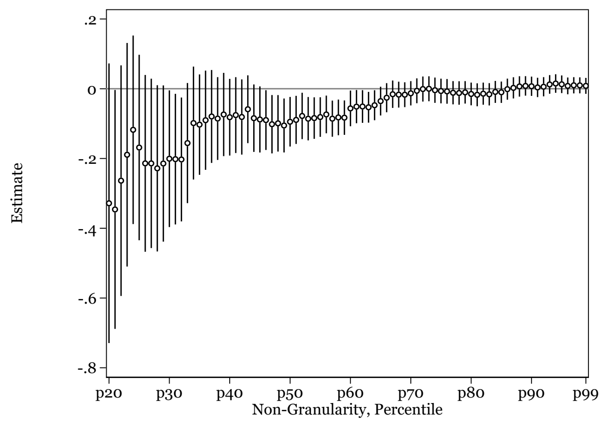
(a) Loan-Level Supply



(b) Loan-Level Interest Flow



(c) Loan-Level Interest rates



Notes: This figure reports the result from a robustness check of panel (a) and (b) in Figure 5, using granular credit shocks derived from idiosyncratic firm sales shocks. In panel (a) we report spillovers to firm credit, in panel (b) spillovers to firm interest payments, and in (c) spillovers to imputed firm loan rates (imputed loan rates computed as in Figure E8 .

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 F14), credit spillovers (Tables F15 and F16), capital growth (Table F17) and firm defaults (Table F18). Importantly, we control for the average shock of all other firms in every bank's portfolio.

Table F14: 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 F15: 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 2. Standard errors (in parentheses) are double clustered at the bank and firm level.

Table F16: 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 2. Standard errors (in parentheses) are double clustered at the bank and firm level.

Table F18: 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 F17: 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 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 H 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 H 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 3.3 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.

H 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.[13] 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

[13] As noted in Appendix G, other frictions would have to be added to fully account for the data.

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.

H.1 Model

Suppose there are N firms in the economy[14]. 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:

$$\frac{\Delta L_{i,t+1}}{L_{it}} = \sigma_i \epsilon_{i,t+1} \tag{H1}$$

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:

$$D_t = \sum_i^N L_{it} \tag{H2}$$

and growth of financial debt in the economy is

$$\frac{\Delta D_{t+1}}{D_t} = \sum_i^N \sigma_i \frac{L_{it}}{D_t} \epsilon_{i,t+1} \tag{H3}$$

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:

$$\sigma_D = \Big[\sum_i^N \sigma \Big(\frac{L_{it}}{D_t}\Big)^2 \Big]^{\frac{1}{2}} \tag{H4}$$

It is clear from equation H4 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:

$$\mathbb{P}(y > x) = (1 + x)^{-\alpha} \tag{H5}$$

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

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}:

$$L_{it} = y_{it}^{\lambda_i} \tag{H6}$$

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:

$$\mathbb{P}(L > x) \sim (1 + x^{\tau})^{-\alpha} \tag{H7}$$

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 H.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.

H.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 (H6) and then take the median of the resulting distribution. We conduct this step for all three definitions of size as well. As a result, we have three estimates for $\alpha\tau$ - the sufficient statistic that determines the speed of decay of σ_D.

Table H1 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.

Table H1: 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 H. 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.

H.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:

$$\lim_{x\to\infty} B(tx)/B(x) = \frac{\lim B(tx)}{\lim B(x)} = 1 \tag{H8}$$

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

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

And $s_n = \sum_i^N L_i$. Thus:

$$\lim_{N\to\infty}\left(N^{\frac{1}{\alpha\tau}}\right)^{-1}\sum_i^N L_i \xrightarrow{d} \eta \sim \text{Lévy}(\alpha\tau) \tag{H9}$$

In the remainder of the proof, we apply equation (H9) to the case of constant σ, i.e. when firm-liability volatility is constant over time and not correlated cross-sectionally. When $\alpha\tau > 2$, standard Lindeberg-Lévy applies. When $1 < \alpha\tau < 2$, the loan portfolio Herfindahl decays according to:

$$N^{1-\frac{1}{\alpha\tau}}\frac{\left(N^{\frac{-2}{\alpha\tau}}\sum_i^N L_i^2\right)^{1/2}}{N^{-1}\sum_i^N L_i} \xrightarrow{d} \frac{\text{Lévy}^{1/2}}{\mathbb{E}(L)} \tag{H10}$$

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

$$\sigma_D \sim \frac{1}{N^{1-1/(\alpha\tau)}}\text{Lévy}^{1/2}\sigma \tag{H11}$$

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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