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348

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December 2017

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Shock Propagation and Banking Structure*

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Sveriges Riksbank Working Paper Series
No. 348

December 2017

Abstract

We conjecture that lenders' decisions to provide liquidity are affected by the extent to which they internalize negative spillovers. We show that lenders with a large share of loans outstanding in an industry provide liquidity to industries in distress when spillovers are expected to be strong, because fire sales are likely to ensue. Lenders with a large share of outstanding loans also provide liquidity to customers and suppliers of industries in distress, especially when the disruption of supply chains is expected to be costly. Our results suggest a novel channel explaining why credit concentration may favor financial stability.

Keywords: syndicated loans, bank concentration, supply chains, fire sales, externalities

JEL classification: E23, E32, E44, G20, G21, L14

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*We thank Jung-Hyun Ahn, Laurent Bach, Vasco Carvalho, Filippo Ippolito, Rustom Irani, Jakub Kastl, José Liberti, Mitchell Petersen, Simon Rother, Anthony Saunders, Bogdan Stacescu, Sascha Steffen, Neeltje Van Horen, Emily Williams and Liu Yang, as well as participants at various conferences and seminars for helpful comments. Giannetti acknowledges financial support from the Bank of Sweden Tercentenary Foundation. The opinions expressed in this article are the sole responsibility of the author(s) and should not be interpreted as reflecting the views of Sveriges Riksbank.

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1 Introduction

Interconnections between different firms and industries are known to lead to the propagation and amplification of shocks throughout the economy in a way that can drive aggregate fluctuations (Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012)). Interconnections may also lead to credit market freezes because lenders fearing poor firm performance if interconnected firms fail to receive credit may refrain from providing new loans (Bebchuk and Goldstein (2011)). This paper argues that the extent to which cascade effects due to interconnections propagate, and credit markets freeze, depends on the structure of the banking system and the lenders' share of the loans outstanding in an industry.

Our argument is as follows. Negative shocks and industry distress often lead to asset fire sales. Through this channel, negative shocks affecting one borrower may deplete the balance sheets of other firms in the same industry (Lang and Stulz (1992), Benmelech and Bergman (2011), Carvalho (2015)). Shocks may also ripple through the supply chain (Hertzel, Li, Officer, and Rodgers (2008); Barrot and Sauvagnat (2016)), magnifying the initial shock to the industry in distress through the disruption of input supply and demand. Ultimately, these spillover effects are expected to adversely affect lenders of the distressed industry not only because the propagation of shocks may impair the value of the loans they have retained, but also because it may disrupt future business with firms in the distressed industry.

Lenders anticipate that fire sales and cascade effects along the supply chain are less likely to ensue if they directly or indirectly provide liquidity to firms affected by large negative shocks and distress. We hypothesize that a lender's decision to provide liquidity depends on the extent to which the lender internalizes any adverse spillover effects of negative shocks. Lenders that issued a larger share of the loans outstanding in an industry are likely to have retained a larger share of the outstanding loans and to expect higher profits from future business with firms in the industry. Anticipating that liquidity provision will enable them to preserve future business and to limit the effect of costly defaults on outstanding loans, high-market-share lenders may have stronger incentives to provide credit in times of distress.

We find that lenders that have a large share of the loans outstanding in an industry in distress are more likely to extend credit to firms in that industry, especially if the industry is prone to fire sales, as proxied by the presence of industry-specific assets or a large fraction of long-term loans maturing around the time of distress. We also find that lenders that are prominent providers of credit to an industry in distress are more likely to initiate new loans to firms upstream and downstream. These effects are largely driven by industries in which firms have strong relationships with their customers and suppliers. In particular, by propping up the distressed industry's customers, lenders may help to boost the sales of the distressed (upstream) industry, thereby mitigating fire sales and increasing borrowers' ability to repay their loans.

High-market-share lenders also provide credit to suppliers of distressed industries. Suppliers are more likely to experience negative liquidity shocks if downstream firms make late payments or default on their obligations. As a consequence, they may experience distress and even failure (Boissay and Gropp (2013), Jacobson and von Schedvin (2015)). However, suppliers' financial health and continued provision of inputs and other products are important for the performance of their customers (Bernard, Moxnes, and Saito (2015); Barrot and Sauvagnat (2016)), especially if they are in industries with strong relationships along the supply chain. Thus, high-market-share lenders initiate new loans to suppliers of industries in distress to reduce shock propagation and amplification.

Overall, high-market-share lenders' liquidity provision along the supply chain stabilizes distressed industries. As we show, industries in which loan provision is more concentrated experience fewer bankruptcies, possibly thanks to intra-industry mergers that high-market-share lenders appear to favor following distress. In addition, we find that industries in distress enjoy better long-term stock market performance, which suggests that the observed bank lending behavior is at least on average efficient.

All of our results are obtained after absorbing bank-level supply and industry-level demand shocks using bank-time and industry-time fixed effects, respectively. Thus, our estimates capture the differential propensity of banks that are important to an industry to provide new loans in case of distress. We mitigate any lingering concerns that a lender's market share may be spuriously correlated with its propensity to grant new loans by exploiting exogenous variation in industry market shares due to recent bank mergers, similarly to Favara and Giannetti (2017) and Garmaise and Moskowitz (2006).

Bank mergers are unlikely to be driven by bank lending to particular industries in the syndicated loan market, as banks active in the syndicated loan market are very large and each industry in the syndicated loan market is small with respect to their balance sheets. While in principle, high-market-share banks may be able to provide particular services and face greater loan demand from distressed industries, this is less likely to be the case if the market share is the result of recent bank mergers, as banks are unlikely to have acquired the expertise necessary to provide these services. It is therefore comforting that the instrumental-variable estimates support the causal interpretation of our findings.

We also document a number of cross-sectional effects that are consistent with the causal mechanism underlying our hypothesis. Banks are significantly more likely to lend to customers of distressed industries if these customers are less leveraged than firms in the distressed industry. In this manner, banks generate liquidity for their borrowers in the distressed industry without further increasing their leverage. Banks also lend more to customers of distressed industries if these customers are highly concentrated. Banks thus optimize the extent to which they internalize the externalities created by financial distress along the supply chain by focusing on strategically important firms.

Finally, we investigate alternative mechanisms that may lead to our findings. For instance, one may wonder whether a lender's share of the loans outstanding in an industry captures the exposure of the lender's portfolio to the industry (i.e., the industry's share of the bank's loan portfolio). As Acharya, Hasan, and Saunders (2006) and Loutskina and Strahan (2011) show, less diversified lenders may be better informed. Therefore, our measure of a lender's share of the loans outstanding in an industry could be related to an informational advantage, which may explain the lender's willingness to extend loans to borrowers in distressed industries.

While we do not deny that better information may enable lenders to internalize externalities, an explanation based on portfolio concentration and information asymmetry alone cannot account for the cross-sectional effects that we document.

First, in our data the correlation between a lender's market share and the share of the industry in the lender's portfolio is close to zero. Second, we find no evidence that a lender's portfolio exposure to an industry, a common indicator of banks' expertise, positively affects its propensity to extend new loans to borrowers in distressed industries. Third, if banks' liquidity provision was driven exclusively by an informational advantage, it would be difficult to explain why banks are more inclined to provide liquidity to industries prone to fire sales, such as industries with more fixed assets. This is because the presence of fixed assets is generally associated with a lower degree of information asymmetry (e.g., Rajan and Zingales (1995) and Titman and Wessels (1988)). Fourth, exogenous variation in market shares due to recent mergers is unlikely to capture lenders' informational advantage. Finally, we document that lenders provide liquidity to new borrowers in distressed industries, and not only to borrowers that they engaged with in the recent past and that they are expected to know better.

Our paper is related to several strands of literature. First, we contribute to the banking literature. Existing work focuses on the effect of bank and relationship characteristics in the transmission of economic shocks. Typically, foreign banks are believed to be fickle lenders (Giannetti and Laeven (2012)), while a close relationship with a bank guarantees stable funding when negative shocks occur (Bolton, Freixas, Gambacorta, and Mistrulli (2016); Liberti and Sturgess (2016)). We recognize that bank lending decisions affect borrowers' health, and may feed back to lenders' balance sheets. Some lenders – notably banks with a high fraction of the loans outstanding in an industry – may therefore take into account these feedback effects in their lending decisions.

This point is related to Favara and Giannetti (2017), who show that lenders that have retained a high fraction of outstanding mortgages are more likely to renegotiate defaulting mortgages and, thus, mitigate the effects of negative shocks on real estate prices. To the best of our knowledge, we are the first to recognize that the internalization of externalities may affect not only loan renegotiations but also the provision of new loans to distressed industries and along the supply chain.

Our paper also relates to the literature that explores the effects of bank loan concentration on bank-firm relationships (Petersen and Rajan (1995)), loan supply (Garmaise and Moskowitz (2006)), and the transmission of monetary policy to mortgage rates (Scharfstein and Sunderam (2016)). All of these papers study the effects of market power on loan contract terms. We focus, instead, on the role of concentration of the loans outstanding in an industry for lenders' incentives to provide liquidity during distress. By showing that concentrated lenders are more prone to provide liquidity, we also present an alternative interpretation of the view that competition in the credit market erodes financial stability because it distorts lenders' risk-taking incentives by lowering their profit margins (Keeley (1990)).

Finally, we contribute to the literature on forced sales of real and financial assets (Shleifer and Vishny (1992), Shleifer and Vishny (2011)). Forced asset sales may reduce the value of collateral and impair the balance sheets of other borrowers (Benmelech and Bergman (2011)). Our paper shows that when industry conditions are poor, certain lenders are more inclined to extend new loans, potentially mitigating the initial effects of forced asset sales.

2 Data Description and Variable Definitions

This section describes the construction of the dataset and the most important variables in our analysis. Our main data source is DealScan, which covers syndicated loan issuance (both credit lines and term loans). While syndicated lending is only a fraction of banks' total lending, in the absence of data on other credit transactions, it is commonly used to evaluate bank lending policies and their real effects (e.g., Ivashina and Scharfstein (2010)). Importantly, the evidence of real effects that we uncover in Section 7 indicates that the effects we highlight are salient.

We focus on all completed syndicated loans granted to publicly listed or privately held

U.S. firms. While our most comprehensive sample period is $1990-2013$, in some of our tests we focus on the period from 1997 to 2013, because we are able to identify relationships over the supply chain starting only from 1997. As is customary, we drop all public-service, energy and financial-services firms, and identify bank-industry lending relationships by focusing on the lead arrangers of syndicated loans. We hand-match each lead arranger to its respective bank-holding company.

We measure bank lending as the dollar amount of loans for which a bank serves as lead arranger. We proceed in this way, instead of apportioning the share of a loan provided by the various participants of a syndicated loan, because loan-share data have relatively poor coverage in DealScan. Our proxies, based on the total number and volume of loans originated by a lead bank, allow us to capture a bank's share of profits in different industries, which should ultimately govern a lender's incentives to internalize externalities – the focal point of our analysis. To mitigate any lingering doubts, we correlate the market share of a lender in an industry to the average share of the loan that it retains as a lead bank in that industry. We find no relation. As will be clearer later, this implies that considering actual loan shares (in $ amounts) retained by a lead arranger would leave our findings unaffected (because it would be equivalent to dividing the dependent variable by a constant).

Since our objective is to explore whether lender j's (past) market share in industry i affects its propensity to provide credit to firms in industry i at time t, we aggregate data at the bank-industry-time level ijt. The main reason for aggregating the loan-level information is that, as we will show, changes in the loan supply are mainly driven by changes in the number of loans that are issued. Thus, changes in the total amount of loans that are extended are a better proxy for changes in the supply of credit than changes in the amount of each loan that has been granted. We aggregate the data at the half-year frequency in order to capture time-varying industry conditions. Using six-month periods also allows lenders to react to industry conditions as it typically takes several months to issue a syndicated loan.

To detect industry distress, we rely on historical industry stock returns from CRSP. In the spirit of Opler and Titman (1994) and Dinc, Erel, and Liao (2017), we define *Industry*

$distress_{it-1}$ as a binary variable that takes the value of one if industry i experienced a cumulative median stock return of less than -10% in the previous half-year $t-1$.

Our conjecture is that banks' incentives to internalize potential externalities derive from their share of the loans outstanding in an industry in distress. We define $\textit{Market share}_{ijt-2}$ as the proportion of bank j's total loan volume granted to industry i over the aggregate loan volume of industry i in $t-2$, that is, prior to any potential industry shock. Both the bank's and the industry's loan volumes are measured over the previous six years (that is, the previous six-month periods from $t-13$ to $t-2$), because the average maturity of syndicated loans is six years.

We contrast a bank's market share to the share of an industry in a bank's loan portfolio, a commonly used proxy for a bank's informational advantage in an industry. The difference between $\textit{Portfolio share of industry}_{ijt-2}$ and $\textit{Market share}_{ijt-2}$ is the denominator. We define the former to be equal to the proportion of bank j's total loan volume to industry i over the aggregate loan volume granted by bank j over the previous six years. Consistent with our argument that $\textit{Portfolio share of industry}_{ijt-2}$ and $\textit{Market share}_{ijt-2}$ capture different bank characteristics, their correlation is extremely close to zero (0.002).

To focus on banks that have an interest in an industry, the sample is limited to bank-industry (ij) pairs with non-zero loans in at least three half-years.[1] If a lender that satisfies this condition does not issue any loan to an industry in a six-month period, we include this as a zero-loan observation. Thus, our dataset comprises 48 observations (for each half-year from the first half of 1990 to the second half of 2013) for each bank-industry pair.

In order to test our maintained hypothesis that banks with a larger market share internalize any externalities created by financial distress, we also consider customer and supplier relationships. We identify supplier-customer relationships at the industry level using input-output tables from the U.S. Bureau of Economic Analysis (BEA), because contagion effects are known to spread beyond reliant suppliers and major customers to firms in their re-

[1] Results would be similar if we included all bank-industry pairs, but this would yield a larger number of zeros in our dataset.

spective industries (Hertzel, Li, Officer, and Rodgers (2008); Carvalho, Nirei, Saito, and Tahbaz-Salehi (2016)). The BEA provides annual tables for the use of commodities by industries, before redefinitions (producers' prices), for 71 summary industries for the period from 1997 to 2013, which constrains our sample period. We match the BEA's input-output tables with information about borrower firms in the DealScan database. To do so, we translate the BEA's industry codes to SIC codes, available for each borrower in DealScan, using a conversion table attained from the BEA.[2]

For each one of the 71 BEA industries, we identify suppliers and customers of an industry as the top supplier and customer industries, respectively, other than the industry itself. While a large component of supplier-customer relationships may occur within the same industry, other mechanisms, such as the desire to avoid fire sales, may induce high-market-share lenders to provide credit directly to the industry in distress. Therefore, to isolate lending to supplier and customer industries, we consider the top supplier and customer industries other than the distressed industry.

When we explore banks' liquidity provision over the supply chain, we measure supplier and customer distress as well as a lender's market share in, or portfolio share of, the industries of the main suppliers and customers using variables defined analogously to $\textit{Industry distress}_{it-1}$, $\textit{Market share}_{ijt-2}$, and $\textit{Portfolio share of industry}_{ijt-2}$. We refer to these variables as $\textit{Supplier distress}_{it-1}$, $\textit{Customer distress}_{it-1}$, $\textit{Supplier share}_{ijt-2}$, $\textit{Customer share}_{ijt-2}$, $\textit{Portfolio share of supplier}_{ijt-2}$, and $\textit{Portfolio share of customer}_{ijt-2}$.

We differentiate industries along a number of dimensions. First, we conjecture that if banks indeed internalize externalities arising from industry distress, they should have stronger incentives to initiate new loans if the industry is prone to fire sales. This is more likely to be the case in industries with less redeployable assets.

We use two alternative measures of asset specificity. Our first measure follows Kung and Kim (2017), who use the 1997 BEA capital-flow table which breaks down expenditures on new equipment, software, and structures by 180 assets for 123 industries. We define

[2] https://www.census.gov/eos/www/naics/concordances/concordances.html

Specific$_i$ as a time-invariant indicator for whether the industry in question is among the bottom-quintile industries in terms of asset redeployability. In addition, we define a second proxy for asset specificity, *Specific (alternative)*$_{it}$, as a time-varying indicator for whether the industry in question is among the top-quintile industries in terms of the ratio of machinery and equipment to total assets in year t. This proxy measures an industry's asset tangibility, and is widely used in the literature to capture how prone an industry is to fire sales (see Acharya, Bharath, and Srinivasan (2007)).

Second, we consider that firms' liquidity needs are stronger and the negative effects of distress are likely to be amplified when a larger proportion of firms in the industry has long-term debt maturing around the time of distress (Carvalho (2015)). To capture this empirically, we use the one-year lag of the ratio of long-term debt due within one year in the industry, a variable that is determined when long-term debt was issued, i.e., well before the date at which we measure industry distress. We define *Liquidity needs*$_{it}$ as an indicator for whether industry i is among the top-quintile industries in terms of the ratio of long-term debt maturing in one year from $t-1$ over total long-term debt in $t-1$, and include the relevant interaction effects in our regressions.

Finally, high-market-share banks' incentives to initiate new loans to customers and suppliers of industries in distress should depend on the extent to which customers and suppliers entertain close relationships, as defaults and other problems may cause larger costs in these industries due to the disruption of valuable relationships. To detect such relationship industries, we use the list of industries in Cremers, Nair, and Peyer (2008). We define *Relationship industries*$_i$ as an indicator for whether industry i and its customer or supplier industry are relationship industries. The intuition behind this classification, described in detail by Cremers, Nair, and Peyer (2008) and widely used in the literature, is that in industries that sell durable goods, firms are likely to interact repeatedly with their trade partners to provide maintenance and service. Therefore, service interruptions are expected to cause large costs.

Summary statistics. In Table 1, we present summary statistics for our main variables. After merging the BEA input-output tables with industries borrowing in the syndicated loan market, as recorded in DealScan, our sample (from 1997 to 2013) includes 57 industries and 211 banks. On average, each industry obtains credit from 44 banks, whereas each bank covers 12 industries. In total, our sample includes 2,516 bank-industry relationships.

Our bank-industry-half-year structure includes observations associated with zero loans issued in an industry. We find that 21% of the 116,662 observations from 1990 to 2013 are associated with non-zero loans. In the whole sample, the average bank's market share in a given industry, and in supplier and customer industries is 2 to 3%.[3] There is, however, large variation in lenders' market shares, and some industries have a unique lender in certain periods. On average, $\textit{Portfolio share of industry}_{ijt-2}$, $\textit{Portfolio share of supplier}_{ijt-2}$, and $\textit{Portfolio share of customer}_{ijt-2}$ are somewhat higher, as the denominator is replaced by the aggregate loan volume granted by bank j.

Finally, based on our definition of industry distress, about 21% of all observations are associated with industry-level shocks.

3 Empirical Methodology

Our objective is to test whether banks with a large market share in an industry are more inclined to extend loans to the industry, its suppliers, or its customers when the industry experiences distress. We start by exploring how bank j's propensity to lend to industry i in half-year t following industry distress varies depending on bank j's past market share in industry i. Therefore, our baseline regression specification is:

$$y_{ijt} = \beta_1 \textit{Market share}_{ijt-2} \times \textit{Industry distress}_{it-1} + \beta_2 \textit{Market share}_{ijt-2} + \mu_{ij} + \theta_{it} + \psi_{jt} + \epsilon_{ijt},$$

where the outcome, y_{ijt}, is either the total loan volume that industry i attains from bank j in period t, or an indicator variable for whether bank j grants any loan to industry i in

[3] Note that the number of observations for $\textit{Market share}_{ijt-2}$, $\textit{Supplier share}_{ijt-2}$, and $\textit{Customer share}_{ijt-2}$ varies because (i) we have supply-chain data starting only in 1997 and (ii) we consider observations for which the denominator of these shares is zero as missing.

period t; *Market share*$_{ijt-2}$ is bank j's market share of loans in industry i in period $t-2$; *Industry distress*$_{it-1}$ is an indicator variable for whether industry i was in distress in period $t-1$; and μ_{ij}, θ_{it}, and ψ_{jt} denote bank-industry, industry-period, and bank-period fixed effects, respectively. Standard errors are clustered at the bank level.

In particular, θ_{it} captures all time-varying unobserved heterogeneity at the industry level, including an industry's demand for loans.[4] ψ_{jt} captures all time-varying unobserved heterogeneity across banks, such as shocks to credit supply or other bank-level changes. For instance, ψ_{jt} captures that weakly capitalized banks may want to provide liquidity to *any* of the current clients in distress in order not to recognize previous bad loans.

The coefficient of interest is β_1, which reflects to what extent a bank's previous market share in an industry increases the bank's propensity to grant new loans to that industry after it enters distress.

We also extend this framework to study banks' propensity to lend to the customers and suppliers of industries in distress. By replacing *Market share*$_{ijt-2}$ with *Supplier share*$_{ijt-2}$ or *Customer share*$_{ijt-2}$, and *Industry distress*$_{it-1}$ by the corresponding indicators of distress in suppliers' and customers' industries, respectively, β_1 captures banks' propensity to lend to the customers and suppliers of an industry in distress.

By absorbing any supply shocks affecting bank j and any demand shocks affecting industry i, our empirical framework allows us to identify the differential propensity of bank j to lend to industry i in distress (and industry i's customers and suppliers), using as controls other banks with different market shares in the same industry i, as well as bank j's propensity to lend to other industries, not in distress, in which it has a similar market share. Thus, our fixed-effects structure allows us to exclude a wide range of alternative explanations, which could lead to a spurious correlation between a bank's market share and its lending decisions. In Section 4.2, we introduce an instrumental-variable methodology to further address any lingering doubts.

[4] Industry-period fixed effects subsume *Industry distress*$_{it-1}$.

4 Bank Lending to Distressed Industries

We now turn to our estimation results for bank lending to industries in distress, discuss their robustness, and present additional findings that shed light on the underlying mechanism.

4.1 Baseline Specifications

Table 2 tests whether lenders that over the past six years provided a larger share of an industry's loans are more inclined to lend to this industry when it experiences distress. Panel A shows that banks with a large market share generally extend more loans. This tendency, however, is drastically accentuated during periods of industry distress. The estimates are both statistically and economically significant. In column 1 of Panel A, increasing a bank's market share by one standard deviation (0.055) increases the volume of new loans by 24.6% (= 0.055 × 4.468) following industry distress.

The tendency of high-market-share banks to lend to industries in distress does not depend on the fact that certain banks lend more than others to all industries, as we include bank-period fixed effects throughout the analysis. The effect is also not driven by industries in distress borrowing more, as our estimates are robust when we include industry-period fixed effects in column 2. The coefficient of interest on the interaction term $\textit{Market share}_{ijt-2} \times \textit{Industry distress}_{it-1}$ remains significant even after controlling for bank-industry fixed effects (column 3). The estimated coefficient on the interaction term capturing the propensity of banks with different market shares to lend to industries in distress is smaller, but it still implies an economically relevant 9.9% (= 0.055 × 1.805) increase in the propensity to lend following a one-standard-deviation increase in $\textit{Market share}_{ijt-2}$. Hereafter, we use the most conservative specification in column 3 – with bank-industry, bank-period, and industry-period fixed effects – as our baseline specification.

The higher propensity of banks with large market shares to lend to distressed industries is driven by the number of new loans rather than by the size of each loan. In column 4, the interaction term $\textit{Market share}_{ijt-2} \times \textit{Industry distress}_{it-1}$ is not significant when we consider as dependent variable the individual loan amount, computed as the logarithm of the average size of the loans issued to an industry during period t. Thus, on average, lenders with high market shares do not grant larger loans when an industry is in distress in comparison to normal times. In contrast, we continue to find a higher propensity of high-market-share banks to lend to industries in distress if we use as dependent variable an indicator capturing any new loans granted to industry i by bank j during period t (column 5).[5]

This evidence is consistent with the idea that banks with a large market share in an industry provide liquidity to internalize the externalities of financial distress. However, bank-firm relationships could be closer in industries with higher loan concentration. Relationship banks are, in turn, known to lend to their clients in distress (Bolton, Freixas, Gambacorta, and Mistrulli (2016)), even if they do not internalize any externalities. To evaluate the merit of this alternative explanation, in Panel B, we repeat the tests from Panel A, and exclude any loans granted by banks that already entertained a relationship with the borrower.

For this purpose, we redefine the dependent variables to exclude loans to firms in industry i to which bank j lent in the previous six years. The remaining loans are unlikely to have been granted to borrowers with a close relationship with bank j or to have been renegotiated. It still emerges that banks with a higher market share issue more loans to borrowers in distressed industries. This indicates that our findings are not driven by close relationships in high-market-share industries. In addition, banks do not appear to merely provide liquidity by renegotiating loans to existing borrowers, an occurrence that is hard to distinguish from new loan issuance in DealScan (Roberts (2015)), but that would be fully consistent with banks' propensity to internalize the negative spillovers of industry distress.

Importantly, this test also allows us to rule out another potential explanation for high-market-share banks' propensity to lend to industries in distress. Troubled banks may have incentives to allocate credit to severely impaired borrowers in order to avoid the realization of losses on their own balance sheets (Peek and Rosengren (2005), Giannetti and Simonov (2013)). Since high-market-share banks exhibit a higher propensity to lend to industries in

[5] Given the structure of the syndicated loan market, there is rarely more than one loan granted by a given bank to an industry during a six-month period.

distress even when we exclude current borrowers, their behavior cannot be driven exclusively by the desire to avoid the negative direct effect of firm defaults on their balance sheets. Rather, banks lending to firms with which they previously did not entertain relationships appear to take into account the indirect effects of those firms' well-being on the industry as a whole, including current borrowers.

In Panel C, we evaluate whether our results may be driven by the recent financial crisis. Given the way we define industry distress, episodes of industry distress could be correlated with bank distress. This gives rise to the possibility that instead of providing liquidity to distressed industries, banks rebalance their portfolios towards their core activities (Giannetti and Laeven (2012)), which in our case may comprise lending to the high-market-share industries. A conservative way of ruling out such competing explanation is to omit the financial crisis – from 2008 until the first half of 2010 – from our sample.[6] In Panel C, our estimates remain invariant, implying that the financial crisis does not drive our estimates. Our findings that banks internalize externalities could, however, potentially explain why banks are found to rebalance to core activities when they experience distress.

Finally, we consider that high-market-share banks may be particularly suitable for granting loans which require additional non-loan services, such as loans related to mergers and acquisitions (M&A). Mergers and acquisitions may also be more likely to occur when industries are in distress and need to restructure, giving an alternative mechanism for why high-market-share banks may grant more loans to industries in distress. However, Panel D shows that excluding loans related to M&A activities leaves our results qualitatively and quantitatively unaffected. This suggests that the propensity of high-market-share banks to lend to distressed industries is unlikely to be driven by the fact that these banks are able to provide specific services, at least the ones connected to M&A activities.

Below, we introduce an instrumental-variable methodology, which helps us to further address the potential criticism that high-market-share lenders may be special, for instance because they face higher demand for credit when industries are in distress.

[6] Thus, the last observation for $Industry\ distress_{it-1}$ before the omitted period is measured over the first half of 2007, and its first observation after the crisis is measured over the first half of 2010.

4.2 Exogenous Variation in Market Shares Due to Bank Mergers

The economic mechanism we propose is that the desire to avoid potential externalities stemming from defaults and more firms entering dire straits prompts high-market-share banks to grant new loans to industries in distress. We do not deny that banks may know better the industries in which they have high market shares. While their knowledge may be a prerequisite for lending in times of distress, we argue that high-market-share banks are more inclined to provide liquidity if negative shocks may cause externalities.

However, one may wonder whether our results are uniquely driven by high-market-share lenders' informational advantage. In this subsection, we introduce an instrumental-variable methodology to address this concern. In the next subsection, we present additional cross-sectional evidence in support of our hypothesis.

To yield exogenous variation in market shares, arguably unrelated to lenders' informational advantage or their ability to provide other, non-loan services to borrowers, we follow Favara and Giannetti (2017) and Garmaise and Moskowitz (2006), and exploit mergers between banks that are active in the syndicated loan market. We detect mergers between any two banks in DealScan using the SDC M&A database in conjunction with any mergers that we identify through a LexisNexis news search. Our instrument for $\textit{Market share}_{ijt-2}$ is defined to be equal to the sum of the two merging banks' historical market shares in industry i in $t-3$, starting in period $t-2$ which is when a merger between bank j and another bank is completed.

In this manner, we only exploit variation in banks' market shares that is due to recent mergers. That is, we identify a treatment effect using incremental increases in market shares, irrespective of the level of historical market shares of the merging banks. This renders it unlikely that our treatment effect is due to any pre-merger private information of the banks involved.

Our instrument is likely to satisfy the exclusion restriction, because banks active in the syndicated loan market are large and each industry in the syndicated loan market constitutes only a small portion of banks' balance sheets. Thus, it is not plausible that mergers occur because of the anticipation of fire sales in case of financial distress. In addition, our instrument captures variation in market shares arising from recent mergers which are therefore unlikely to have led to an informational advantage or any particular expertise in providing services to an industry, which goes beyond the expertise of the merging banks.

The first two columns of Table 3 display the first-stage results, and show that our instrument is highly statistically significant. Hence, there are no concerns about our instrument being weak. The last two columns of Table 3 present the second-stage estimates, using as dependent variables the logged total amount of all loans and an indicator for any loans granted (as in columns 3 and 5 of Table 2). The estimates are qualitatively and quantitatively robust, suggesting that even the high-market-share banks that are least likely to have gained an informational advantage are prone to extend new loans to industries in distress.

4.3 Cross-sectional Effects

To provide more direct evidence on our proposed mechanism, we consider industries prone to fire sales, in which the negative externalities of distress are expected to be higher. If high-market-share lenders indeed internalize externalities, we would expect them to be particularly inclined to provide new loans to these industries when they are in distress.

Distress is more likely to result in fire sales in industries in which assets are highly specific and less redeployable, because most of the potential buyers are in the same industry and are likely to be financially constrained by the time the industry enters distress and asset sales occur. In Table 4, we re-estimate the specifications from columns 3 and 5 of Table 2, differentiating industries by their level of asset specificity. We measure asset specificity using two alternative widely-used proxies: the industry's level of asset redeployability from Kung and Kim (2017) and the industry's asset tangibility, used for instance by Acharya, Bharath, and Srinivasan (2007) to capture an industry's propensity to fire sales. Consistent with our maintained hypothesis, we find that high-market-share banks' propensity to grant new loans to industries in distress increases with industries' asset specificity. This is indicated by the coefficient on the triple-interaction term, which is positive and significant regardless of whether we consider industries with low levels of asset redeployability (columns 1 and 2) or industries with a high ratio of tangible assets (columns 3 and 4).

Importantly, industries with high tangible assets, having relatively more collateral to pledge, are considered to be less subject to asymmetric information (e.g., Rajan and Zingales (1995) and Titman and Wessels (1988)). Therefore, these results support the idea that the effect of a bank's market share on loan provision to distressed industries is unlikely to be driven by any informational advantage.

We also consider that industry downturns are more likely to result in fire sales when firms are financially constrained (Shleifer and Vishny (1992)). Firms' liquidity needs tend to be stronger and to cause larger negative externalities for other firms when a larger proportion of firms in the industry has long-term debt maturing around the time of distress (Carvalho (2015)). Extending this idea to our hypothesis, we would expect that to limit shock amplification, high-market-share lenders would want to provide liquidity precisely to industries with higher liquidity needs and greater exposure to the amplification of the initial shock.

Consistent with the mechanism underlying our hypothesis, columns 5 and 6 of Table 4 show that high-market-share banks extend more loans to industries in distress with a high proportion of long-term debt maturing, that is, to industries in which the initial shock is more likely to be amplified by firms' liquidity constraints and fire sales.

4.4 Which Shocks Matter?

In most of our analysis, we consider an industry to be in distress if the median return in the industry during a six-month period is below -10%. Table 5 shows that our results are robust to a number of variations. For instance, in Panel A, we consider an industry to be in distress if the mean return, rather than the median return, is below -10%. Our results are invariant.

In the remaining panels of Table 5, we consider alternative definitions of shocks to shed further light on the mechanism leading high-market-share banks to provide credit to industries in distress.

If the observed bank lending behavior is indeed driven by the desire to avoid negative externalities of distress, we would expect high-market-share lenders' tendency to provide credit to industries in distress to be more pronounced after temporary shocks. In this case, industries are expected to recover, and may be able to do so more promptly if they can avoid defaults, fire sales, and supply-chain disruptions. Following permanent shocks, firm exit and radical change may be optimal, and it is not clear that providing liquidity may benefit bank profits. Thus, to the extent that they are able to distinguish ex ante between permanent and transitory shocks, high-market-share lenders should not provide credit if the shocks are permanent.

In Panel B, we define a shock as permanent if the industry's median return is still below -10% three years after the initial distress period. We label all remaining episodes of industry distress as transitory.[7] High-market-share banks appear to lend more to industries in distress only after transitory shocks. This suggests that high-market-share lenders support industries in distress only when they expect distress to be temporary. This finding also suggests that high-market-share banks' behavior is not due to loan evergreening, as in that case lenders would want to keep afloat their borrowers irrespective of their capacity to recover. Overall, our evidence suggests that banks' tendency to internalize externalities may benefit the economy, an issue that we revisit in Section 7.

Our results show how lenders react to systemic shocks that affect a large majority of firms in the industry and are, therefore, more likely to lead to negative externalities. In Panel C, we consider banks' lending decisions following more idiosyncratic shocks, which we define as six-month periods in which the average return of the top-three firms in an industry (in terms of their sales) is below -10%. This definition does not require any widespread industry

[7] While industry performance depends on bank behavior, our stark definition of permanent shocks is likely to capture structural changes, such as increased competition from emerging economies, which permanently affect an industry's performance.

distress. We find no evidence that high-market-share banks are more inclined to lend when industry distress is limited to a few firms in the industry. If industry distress is not systemic, we expect externalities to be less likely to ensue as other firms in the industry can purchase the ailing firms' assets, thereby avoiding fire sales. This evidence lends further support to our maintained hypothesis that high-market-share banks provide liquidity if industry distress is widespread and the intervention is, thus, necessary to avoid negative externalities.

5 Bank Lending to Customers and Suppliers of Distressed Industries

In this section, we consider banks' ability to internalize potential externalities from industry distress over the supply chain.

5.1 Main Results

So far, our evidence suggests that high-market share banks tend to internalize any externalities that distress may generate within an industry. However, externalities are not confined to the industry in distress, but are known to spread over the supply chain and may amplify the effect of the initial shock to the distressed industry. Supply-chain disruptions may in turn have negative feedback effects on the balance sheets of lenders that are highly exposed to industries in distress. Firms in distress are likely to default on their suppliers, potentially leading to further defaults. The spreading of financial problems to upstream industries may worsen the problems of industries in distress, because firms are highly dependent on their suppliers. Therefore, high-market-share lenders have an incentive to extend new loans to the suppliers of industries in distress in an attempt to limit the propagation of the initial shock, and to avoid negative feedback effects on the distressed industry and ultimately their own profits.

Table 6 presents supporting evidence for this conjecture. In column 1, we find that banks that have a large market share in an industry (customer) in distress are more likely to grant new loans to the suppliers of that industry. The magnitude of the coefficient on *Customer* $share_{ijt-2} \times$ *Customer* $distress_{it-1}$ is even larger than the corresponding coefficients in column 3 of Table 2. As in Table 2, the effect is driven entirely by new loans to the industry, i.e., the extensive margin (column 3) rather than the intensive margin (column 2).

Importantly, this result does not depend on the fact that banks with a large market share in the customers' industry also have a large market share in upstream industries. In columns 4 and 5, we control for *Market* $share_{ijt-2} \times$ *Industry* $distress_{it-1}$ and *Market* $share_{ijt-2}$ to capture this effect. The magnitude of the coefficient on *Customer* $share_{ijt-2} \times$ *Customer* $distress_{it-1}$ is invariant, and remains highly statistically significant.

High-market-share lenders may also be inclined to extend new loans to distressed industries' customers in order to prop up the demand for their clients' products. More than that, since distressed industries may cut the amount of trade credit they are able to offer to their customers, liquidity provision to customers may be particularly important to sustain demand. To test this, in Table 7, we re-estimate all specifications from Table 6, but replace *Customer* $share_{ijt-2}$ and *Customer* $distress_{it-1}$ by *Supplier* $share_{ijt-2}$ and *Supplier* $distress_{it-1}$. The results confirm that banks with a large market share in an industry (supplier) in distress grant new loans to its customers.

Again, the internalization of externalities over the supply chain does not appear to depend on the correlation of banks' market shares in upstream and downstream industries. In columns 4 and 5, where we additionally control for *Market* $share_{ijt-2} \times$ *Industry* $distress_{it-1}$ and *Market* $share_{ijt-2}$, the magnitude of the coefficient on *Supplier* $share_{ijt-2} \times$ *Supplier* $distress_{it-1}$ remains largely invariant, even though in column 4 the coefficient, with a p-value of 15%, is not statistically significant at conventional levels.

Lenders' incentives to internalize externalities stemming from financial distress along the supply chain should be stronger in industries in which firms maintain long-term relationships with their trade partners, as these are likely to be hard to replace. Following Cremers, Nair, and Peyer (2008), we classify industries that provide durable goods or services as industries in which trade partners are more likely to establish long-term relationships. Therefore, any externalities caused by financial distress should be more severe if both the distressed industry and its upstream or downstream industry are relationship industries.

We conjecture that the effect of lenders' market shares on new loans to the suppliers and customers of industries in distress should be more pronounced in relationship industries. In Table 8, we find that this is indeed the case: in columns 1 and 2, the tendency of high-market-share lenders to provide credit to the suppliers of industries in distress is highest when both customers and suppliers are in relationship industries. Columns 3 and 4 show a similar tendency for the customers of industries in distress.

5.2 To Which Customers Do Banks Extend New Loans?

In the following tests, we explore the strategic dimension of banks' decision to extend new loans to distressed industries' customers. First, banks may decide to lend to a distressed industry or to its customers in order to maximize the effectiveness of their liquidity provision and at the same time to minimize costs arising from financial frictions and credit risk. For instance, extending new loans to an industry in distress may be particularly costly if the industry already has high leverage, because situations of debt overhang may arise. In this case, indirectly providing liquidity to customers, which would increase their input purchases, may be optimal from a lender's point of view.

To explore this, we re-run the first three specifications of Table 7, and add an interaction term with *Relative leverage*$_{it}$, which is a ratio comparing the leverage of an industry with that of its customer industry.

Our estimates in the first column of Table 9 show that high-market-share banks' tendency to lend to the customers of an (upstream) industry in distress is more pronounced if the industry in distress has high leverage in comparison to its customer industry. By providing loans to the customers, lenders can increase the sales in a distressed industry and, thus, provide liquidity without having to further increase its leverage and the financial frictions associated with high debt. As before, the effect is driven by the extensive margin (in column 3) rather than the intensive margin (in column 2).

In Table 10, we provide further evidence for the strategic nature of banks' decision to provide credit to customers of distressed industries. Namely, we document that high-market-share banks are more likely to extend new loans to the customers of an industry in distress if these customers are highly concentrated. In this case, one or few loans are likely to generate large sales for the distressed upstream industry, while in dispersed customer industries many loans may be necessary, increasing lenders' cost of limiting contagion.

In summary, our evidence suggests that banks optimize their efforts to internalize externalities along the supply chain by focusing on strategically important customers.

5.3 Mechanisms

This subsection discusses why banks may benefit from providing liquidity to industries in distress. Industry distress may feed back on profits of high-market-share banks for several reasons. First, banks' balance sheets may be directly exposed to distressed industries if the lead banks have retained a large proportion of the loans they issued. Banks' net worth could therefore be negatively affected by defaults, giving high-market-share banks, whose balance sheets are more exposed, incentives to provide liquidity and thereby avoid defaults.

Columns 1 and 2 of Table 11 provide evidence in support of this mechanism. As discussed in Section 2, due to the relatively poor coverage of loan shares, we are unable to define $\textit{Market share}_{ijt-2}$ using the amount of loans retained by the lead bank. However, we can identify industries in which syndicated loans have few participants, suggesting that the lead arrangers retain a larger share of the loans in such industries. The dummy $\textit{Retention}_{it-2}$ captures industries whose average number of participants across syndicates places them in the bottom quintile of all industries. The positive and significant coefficient on the respective triple interaction suggests that high-market-share banks are more inclined to provide loans to distressed industries in which they are likely to have retained a large exposure on their balance sheets.

Second, high-market-share banks may support industries in distress to preserve their profits from these industries. Some of these profits derive from underwriting activities, because banks tend to also serve the debt- and equity-underwriting needs of firms in the industries in which they have high market shares (in terms of credit). Using SDC data and hand-matching underwriters with lead arrangers in DealScan, we define *Underwriting market share*$_{ijt-2}$ as the proportion of debt- and equity-underwriting mandates of bank j in industry i over the previous six years, similarly to *Market share*$_{ijt-2}$. In this manner, we yield a correlation between the two market shares of 0.47. Furthermore, columns 3 and 4 of Table 11 show that banks with higher underwriting market shares indeed tend to provide more loans to industries in distress. A one-standard-deviation increase in *Underwriting market share*$_{ijt-2}$ increases the volume of new loans by 6.0% (= 0.046×1.294, see column 3) following distress.

Finally, high-market-share banks may also be inclined to support industries in distress if they are able to charge more for their loans. Table 12 explores whether *Market share*$_{ijt-2}$ is positively associated with two measures of the average cost of loans in the respective industries.

In the first column, we use as outcome variable the logged average all-in-drawn spread of all loans granted to industry i by bank j during a 12-month period. In the second column, we use as an alternative measure the total cost of borrowing, as defined in Berg, Saunders, and Steffen (2016). In the last two columns, we test whether the spread on future loans is higher when lenders have a high market share and the industry has experienced distress in the past 24 months, rather than 12 months. We do not find any evidence that loan spreads charged by high-market-share banks increase following industry distress. However, high-market-share lenders charge higher interest rates and fees, suggesting that these banks have economic incentives to lend to industries in which they have larger market shares, albeit not differentially so in times of distress versus normal times (columns 2 and 4).

In summary, it appears that high-market-share banks do have stronger incentives to avoid the externalities created by industry distress, because the amplification of the initial shock would feed back on their balance sheets and jeopardize future profits.

6 Alternative Explanations: The Role of Bank Diversification

Throughout the paper, we have interpreted the effects of *Market share*$_{ijt-2}$, *Customer share*$_{ijt-2}$, and *Supplier share*$_{ijt-2}$ to depend on banks' ability to internalize externalities. However, banks' market shares in distressed industries may also be correlated with their informational advantage in extending loans to such industries.

In Tables 3 and 4, we have already presented evidence suggesting that loan provision to distressed industries is unlikely to be driven by any informational advantage. In addition, Table 13 explores whether patterns similar to the ones we have highlighted so far emerge when we use a bank's *Portfolio share*$_{ijt-2}$. This variable captures the extent to which a lender's portfolio is exposed to a given industry, and is considered to be positively correlated with banks' informational advantage in extending loans to an industry (Acharya, Hasan, and Saunders (2006); Loutskina and Strahan (2011)).

After re-estimating the regression specification in the third column of Table 2 as well as the ones in the first column of Tables 6 and 7, we find that *Portfolio share*$_{ijt-2}$ does not positively affect the extension of new loans to borrowers in distressed industries, or to their suppliers and customers. If anything, in column 1, high-portfolio-share banks lend less to industries in distress, possibly because higher balance-sheet exposure may impair bank health.

We continue to find no effect of *Portfolio share*$_{ijt-2}$ on the extension of new loans to industries in distress when we define *Underwriting portfolio share*$_{ijt-2}$ similarly to *Underwriting market share*$_{ijt-2}$ in column 4. These findings demonstrate that the effects we uncover are tied to the proportion of loans outstanding in an industry and banks' expectations regarding future profits, rather than to banks' diversification, and further corroborate the idea that lenders internalize the externalities associated with distress.

7 Real Effects

To evaluate the economic consequences of the patterns in bank lending that we find, we examine whether a higher concentration of loans outstanding in an industry alleviates the consequences of distress.

To test this, we start by conjecturing that distress in industries with a high credit concentration is less likely to be associated with adverse real outcomes, such as bankruptcies. We estimate industry-level regressions at the half-year frequency, and use as dependent variable an indicator for whether there have been any delistings due to liquidations and bankruptcies in industry i in period t. As before, we use as explanatory variable an indicator for industry distress, *Industry distress*$_{it-1}$. In addition, we define a measure of credit concentration, *Market HHI*$_{it-2}$, as the Herfindahl index of banks' market shares in industry i over the previous six years, that is, from $t-13$ to $t-2$, analogously to *Market share*$_{ijt-2}$. This measure of concentration varies between 0 and 1, with a higher value indicating higher concentration in the credit provision to an industry.

In the first column of Table 14, periods of industry distress are associated with a 21-percentage-point increase in the probability of industry-wide delistings due to liquidations and bankruptcies. However, this effect is attenuated in industries with a high credit concentration, as the coefficient on the interaction between *Market HHI*$_{it-2}$ and *Industry distress*$_{it-1}$ is negative and significant. The effect remains robust after including industry fixed effects in column 2. Conversely, the previously negative coefficient on *Market HHI*$_{it-2}$ becomes insignificant, possibly because credit concentration does not vary considerably within industries over time.

The attenuating effect of credit concentration on industry delistings following distress is not only statistically but also economically significant. A one-standard-deviation increase in *Market* HHI_{it-2} of 0.124 corresponds to a decrease in the likelihood of industry-wide delistings by 4.76 percentage points ($= 0.124 \times 0.384$) following industry distress, a large effect considering that the probability of delisting is 0.304 in our sample.

As delistings are longer-term consequences of industry distress, in columns 4 and 5, we double the horizon of our dependent variable from six months to one year after industry distress. The coefficients of the interaction term are virtually unaltered. In columns 3 and 6, we use the market share of the top lender in industry i over the past six years as an alternative measure of concentration. Our results remain largely robust.

Fewer delistings due to liquidations and bankruptcies in distressed industries appear to be achieved, at least partly, through an increase in intra-industry mergers. We consider the number of intra-industry mergers, standardized by the number of successful mergers initiated by acquirers in that industry, to account for the industry's propensity to be involved in M&A activities. Table 15 shows that while bank concentration generally does not favor intra-industry mergers, the number of intra-industry mergers in an industry increases especially in the six months following industry distress. In column 1, following industry distress, a one-standard-deviation increase in *Market* HHI_{it-2} is associated with an increase in the proportion of intra-industry mergers by 7.94 percentage points ($= 0.124 \times 0.640$). The effect is qualitatively similar but not always significant at conventional levels when we consider the first twelve, rather than six, months after industry distress.

Fewer delistings and more intra-industry mergers in distressed industries are not necessarily efficient, and may actually decrease an industry's overall performance, if they allow non-viable "zombie" firms to survive, as highlighted by Caballero, Hoshi, and Kashyap (2008). To evaluate whether the behavior of high-market-share banks is efficient, we investigate whether the long-run abnormal performance of industries following distress is related to the level of credit concentration.

To this end, we adopt a calendar-time-portfolio approach (see Fama (1998)), using monthly industry stock returns. We build two portfolios for industries in distress that are in the top and bottom quintiles of the distribution of the industry credit concentration over six years prior to distress, as captured by $Market\ HHI_{it-2}$. We estimate industry abnormal performance (alpha) using weighted least squares with weights that account for the fact that monthly returns are more precisely estimated when more industries enter the respective portfolios (see Malmendier, Opp, and Saidi (2016)).

Table 16 displays the long-run abnormal monthly returns (%) over three, five, and seven years for the two types of portfolios in the first two columns. The last column reports the abnormal return of a portfolio that is long in the top quintile of the credit-concentration distribution and short in the bottom quintile.[8]

We find that industries in distress generally experience negative abnormal returns in the long run, but significantly less so if they have high levels of credit concentration (column 3). The long-short difference amounts to approximately 4% (= 0.332% $\times$ 12) per annum over three years. After seven years, the long-short difference remains positive, at 3% (= 0.250% $\times$ 12) per annum.

This evidence complements our findings in Table 14 and suggests that industries with a high credit concentration experience fewer liquidations and bankruptcies following industry distress, and that the surviving stocks indeed outperform those in distressed industries with a low credit concentration. Thus, the behavior of banks in industries with a high concentration of outstanding loans appears to be efficient overall and to improve industry performance.

8 Conclusion

In this paper, we argue that lenders' propensity to provide liquidity depends on whether they internalize potential feedback effects of negative shocks. We find that lenders with a larger share of the loans outstanding in an industry in distress are more likely to provide credit, especially if the industry is prone to fire sales. Lenders with a larger share of outstanding

[8] Note that the alpha estimate in the third column is generally not exactly equal to the difference between the alpha estimates in the first and second column, because the number of industries in a given portfolio month is not constant across the two portfolios, for which we account by weighting observations as indicated in Appendix A of Malmendier, Opp, and Saidi (2016).

loans are also more likely to provide loans to suppliers and customers of industries in distress, and particularly so when the disruption of supply chains would be more costly.

Our results show that the concentration of outstanding loans impacts to what extent industry shocks are transmitted along the supply chain and become systemic. In this respect, we present evidence of a new channel for why concentration in the credit market may enhance financial stability.

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9 Tables

Table 1: **Summary Statistics**

Bank-industry-half-year level	Mean	Std. dev.	Min	Max	N
Number of bank-industry pairs					2,516
Number of industries					57
Number of banks					211
Loan volume in 2015 \$bn	0.313	1.849	0.000	102.715	116,662
Any loan $\in \{0,1\}$	0.210	0.408	0	1	116,662
Market share $\in [0,1]$	0.020	0.055	0	1	116,662
Supplier share $\in [0,1]$	0.025	0.057	0	1	39,210
Customer share $\in [0,1]$	0.026	0.058	0	1	43,916
Underwriting market share $\in [0,1]$	0.015	0.046	0	1	116,662
Portfolio share of industry $\in [0,1]$	0.042	0.127	0	1	116,662
Portfolio share of supplier $\in [0,1]$	0.038	0.081	0	1	39,210
Portfolio share of customer $\in [0,1]$	0.025	0.058	0	1	43,916
Underwriting portfolio share $\in [0,1]$	0.017	0.066	0	1	116,662
Industry distress $\in \{0,1\}$	0.206	0.404	0	1	116,662
Supplier distress $\in \{0,1\}$	0.199	0.399	0	1	39,210
Customer distress $\in \{0,1\}$	0.210	0.407	0	1	43,916
Specific $\in \{0,1\}$	0.200	0.400	0	1	116,662
Specific (alternative) $\in \{0,1\}$	0.146	0.353	0	1	109,364
Liquidity needs $\in \{0,1\}$	0.217	0.412	0	1	116,662
Relationship industry $\in \{0,1\}$	0.500	0.500	0	1	65,320
Retention $\in \{0,1\}$	0.201	0.401	0	1	116,662
Avg. spread in bps ($\neq 0$)	246.495	145.618	1.5	1,480	23,508
Avg. total cost of borrowing in bps ($\neq 0$)	134.856	116.354	4.616	924.600	10,647
Market HHI $\in [0,1]$	0.171	0.124	0	1	2,633

Notes: *Market share*$_{ijt-2}$ is the proportion of bank j's total loan volume to industry i over the aggregate loan volume in industry i, measured over the past six years (i.e., twelve half-year periods from $t-13$ to $t-2$). *Supplier share*$_{ijt-2}$ is the proportion of bank j's total loan volume to industry i's supplier industry over the aggregate loan volume in industry i's supplier industry, measured over the past six years (i.e., twelve half-year periods from $t-13$ to $t-2$). *Customer share*$_{ijt-2}$ is the proportion of bank j's total loan volume to industry i's customer industry over the aggregate loan volume in industry i's customer industry, measured over the past six years (i.e., twelve half-year periods from $t-13$ to $t-2$). *Underwriting market share*$_{ijt-2}$ is the proportion of bank j's total number of debt and equity underwriting mandates in industry i over the aggregate number of debt and equity issuances in industry i, measured over twelve half-year periods (i.e., six years) from $t-13$ to $t-2$. *Portfolio share of industry*$_{ijt-2}$ is the proportion of bank j's total loan volume to industry i over the aggregate loan volume granted by bank j, measured over twelve half-year periods (i.e., six years) from $t-13$ to $t-2$. *Portfolio share of supplier*$_{ijt-2}$ is the proportion of bank j's total loan volume to industry i's supplier industry over the aggregate loan volume granted by bank j, measured over twelve half-year periods (i.e., six years) from $t-13$ to $t-2$. *Portfolio share of customer*$_{ijt-2}$ is the proportion of bank j's total loan volume to industry i's customer industry over the aggregate loan volume granted by bank j, measured over twelve half-year periods (i.e., six years) from $t-13$ to $t-2$. *Underwriting portfolio share*$_{ijt-2}$ is the proportion of bank j's total number of debt and equity underwriting mandates in industry i over the aggregate number of underwriting mandates of bank j across industries, measured over twelve half-year periods (i.e., six years) from $t-13$ to $t-2$. *Industry distress*$_{it-1}$ is an indicator variable for whether the cumulative median stock return of industry i was less than -10% in the previous half-year $t-1$. *Supplier distress*$_{it-1}$ is an indicator variable for whether the cumulative median stock return of industry i's supplier industry was less than -10% in the previous half-year $t-1$. *Customer distress*$_{it-1}$ is an indicator variable for whether the cumulative median stock return of industry i's customer industry was less than -10% in the previous half-year $t-1$. *Specific*$_i$ is an indicator for whether industry i is among the bottom 20% industries in terms of asset redeployability, as defined in Kung and Kim (2017). *Specific (alternative)*$_{it}$ is an indicator for whether industry i is among the top 20% industries in terms of the ratio of machinery and equipment to total assets in year t. *Liquidity needs*$_{it}$ is an indicator for whether industry i is among the top 20% industries in terms of the ratio of long-term debt maturing in one year from $t-1$ over total long-term debt in $t-1$. *Relationship industry*$_i$ is an indicator for whether industry i is a relationship industry, as defined in Cremers, Nair, and Peyer (2008). *Retention*$_{it-2}$ is an indicator for whether industry i is among the bottom 20% industries in terms of the average number of participants across all syndicated loans from $t-13$ to $t-2$. Spread refers to the all-in-drawn spread, which is the sum of the spread over LIBOR and any annual fees paid to the lender syndicate. The total cost of borrowing is from Berg, Saunders, and Steffen (2016). *Market HHI*$_{it-2}$ measures the credit concentration in industry i over twelve half-year periods (i.e., six years) from $t-13$ to $t-2$, across all banks that provide credit to industry i in the sample described in Table 14.

Table 2: **Bank Lending to Industries in Distress**

	ln(1+Loan volume)			ln(Avg. loan size)	Any loan
Sample	All	All	All	Loan vol. $\neq 0$	All
Panel A: Regression sample from 1990 to 2013					
	(1)	(2)	(3)	(4)	(5)
Market share × Ind. distress	4.468***	3.136***	1.805**	-0.193	0.097**
	(1.294)	(0.934)	(0.838)	(0.213)	(0.043)
Market share	8.369***	12.654***	4.870***	-0.198	0.221***
	(1.622)	(1.271)	(0.927)	(0.374)	(0.049)
Industry distress	-0.070				
	(0.069)				
Bank-industry FE	N	N	Y	Y	Y
Bank-period FE	Y	Y	Y	Y	Y
Industry-period FE	N	Y	Y	Y	Y
N	113,494	113,470	113,470	24,292	113,470
Panel B: Regression sample from 1990 to 2013, no relationship loans					
	(1)	(2)	(3)	(4)	(5)
Market share × Ind. distress	3.365**	3.358**	2.796**	-0.014	0.143**
	(1.325)	(1.376)	(1.236)	(0.605)	(0.065)
Market share	21.771***	21.019***	11.376***	-1.990***	0.634***
	(3.732)	(3.510)	(2.819)	(0.391)	(0.144)
Industry distress	0.002				
	(0.069)				
Bank-industry FE	N	N	Y	Y	Y
Bank-period FE	Y	Y	Y	Y	Y
Industry-period FE	N	Y	Y	Y	Y
N	59,444	59,425	59,412	11,026	59,412
Panel C: Regression sample from 1990 to 2013, excluding 2008 to first half of 2010					
	(1)	(2)	(3)	(4)	(5)
Market share × Ind. distress	4.090***	3.050***	2.511***	-0.412*	0.131***
	(1.275)	(1.060)	(0.933)	(0.229)	(0.048)
Market share	8.855***	12.643***	4.746***	-0.162	0.214***
	(1.473)	(1.320)	(0.872)	(0.388)	(0.044)
Industry distress	-0.068				
	(0.079)				
Bank-industry FE	N	N	Y	Y	Y
Bank-period FE	Y	Y	Y	Y	Y
Industry-period FE	N	Y	Y	Y	Y
N	101,664	101,645	101,645	22,542	101,645
Panel D: Regression sample from 1990 to 2013, no acquisition loans					
	(1)	(2)	(3)	(4)	(5)
Market share × Ind. distress	4.604***	2.908***	1.636**	-0.175	0.089**
	(1.461)	(0.969)	(0.769)	(0.212)	(0.038)
Market share	10.191***	15.374***	5.411***	0.148	0.249***
	(2.158)	(1.796)	(0.793)	(0.346)	(0.042)
Industry distress	-0.021				
	(0.079)				
Bank-industry FE	N	N	Y	Y	Y
Bank-period FE	Y	Y	Y	Y	Y
Industry-period FE	N	Y	Y	Y	Y
N	94,988	94,964	94,939	21,789	94,939

Notes: The unit of observation is the bank-industry-half-year level ijt, based on the sample of all completed syndicated loans from 1990 to 2013 granted to industry i for which bank j served as a lead arranger in half-year t. In Panels A, B, and D, the sample comprises the years 1990 to 2013. In Panel C, the sample omits the period from 2008 until (and including) the first half of 2010. Furthermore, the sample is limited to bank-industry (ij) pairs with non-zero loans in at least three half-years, whereas the remaining periods are included as zero-loan observations. In Panels A and C, the dependent variable in the first three columns is the logarithm of the total volume of all loans granted to industry i by bank j in period t plus one. In the fourth column, the dependent variable is the logged average size of loans granted to industry i by bank j in period t, and the sample is limited to non-zero loans granted to industry i by bank j in period t. In Panels A and C, the dependent variable in the fifth column is an indicator capturing whether *any* loans were granted to industry i by bank j in period t. For all dependent variables in Panel B, we additionally exclude the volume of all loans granted to firms in industry i to which bank j already lent anytime from $t-13$ to $t-2$ (relationship loans). As a result, we also drop observations in which all loans to industry i consist entirely of relationship loans. For all dependent variables in Panel D, we exclude the volume of loans with the following DealScan purposes, to which we refer as acquisition loans: "LBO," "MBO," "Merger," "Proj. finance," or "Takeover". As a result, we also drop observations in which all loans to industry i consist entirely of acquisition loans. $\textit{Market share}_{ijt-2}$ is the proportion of bank j's total loan volume to industry i over the aggregate loan volume in industry i, measured over twelve half-year periods (i.e., six years) from $t-13$ to $t-2$. $\textit{Industry distress}_{it-1}$ is an indicator variable for whether the cumulative median stock return of industry i was less than -10% in the previous half-year $t-1$. Public-service, energy, and financial-services industries are dropped. Robust standard errors, clustered at the bank level, are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 3: **Bank Lending to Industries in Distress: Instrumental-variable Estimates**

	Market share	Market share × Industry distress	ln(1+Loan volume)	Any loan
	(1)	(2)	(3)	(4)
Merger-implied market share × Ind. distress	0.018	0.504***		
	(0.015)	(0.080)		
Merger-implied market share	0.207***	-0.041***		
	(0.064)	(0.012)		
Market share × Industry distress (instrumented)			5.696*	0.277*
			(3.087)	(0.147)
Market share (instrumented)			-24.142**	-1.037**
			(9.384)	(0.496)
Bank-industry FE	Y	Y	Y	Y
Bank-period FE	Y	Y	Y	Y
Industry-period FE	Y	Y	Y	Y
F-statistic	7.83	21.95		
N	43,849	43,849	43,849	43,849

Notes: The unit of observation is the bank-industry-half-year level ijt, based on the sample of all completed syndicated loans from 1990 to 2013 granted to industry i for which bank j served as a lead arranger in half-year t. Furthermore, the sample is limited to bank-industry (ij) pairs with non-zero loans in at least three half-years, whereas the remaining periods are included as zero-loan observations, and it is limited to banks that merged with at least one another bank anytime during the sample period. The two first-stage regressions (for two instruments) are given in the first two columns. *Merger-implied market share*$_{ijt-2}$ is equal to the sum of the two merging banks' market shares in industry i in $t-3$ starting in period $t-2$, which is when a merger between bank j and another bank is completed. The dependent variable of the second stage in the third column is the logarithm of the total volume of all loans granted to industry i by bank j in period t plus one. The dependent variable of the second stage in the last column is an indicator capturing whether *any* loans were granted to industry i by bank j in period t. *Market share*$_{ijt-2}$ is the proportion of bank j's total loan volume to industry i over the aggregate loan volume in industry i, measured over twelve half-year periods (i.e., six years) from $t-13$ to $t-2$. We instrument this variable by *Merger-implied market share*$_{ijt-2}$. *Industry distress*$_{it-1}$ is an indicator variable for whether the cumulative median stock return of industry i was less than -10% in the previous half-year $t-1$. Public-service, energy, and financial-services industries are dropped. Robust standard errors, clustered at the bank level, are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 4: **Cross-sectional Differences in Industry Propensities to Fire Sales**

	ln(1+Loan volume)	Any loan	ln(1+Loan volume)	Any loan	ln(1+Loan volume)	Any loan
Specificity measure	Low asset redeployability		High M&E/assets			
Sample period	1997 – 2013		1990 – 2013		1990 – 2013	
	(1)	(2)	(3)	(4)	(5)	(6)
Market share × Industry distress × Specific	5.870**	0.258**	6.564***	0.299***		
	(2.296)	(0.112)	(1.589)	(0.075)		
Market share × Industry distress × Liquidity needs					7.724**	0.383**
					(3.516)	(0.172)
Market share × Industry distress	2.042	0.112	-0.857	-0.030	0.067	0.017
	(1.509)	(0.072)	(0.937)	(0.046)	(1.177)	(0.060)
Market share × Specific	0.433	0.003	-5.101**	-0.182		
	(2.032)	(0.111)	(2.408)	(0.114)		
Market share × Liquidity needs					0.482	0.002
					(2.517)	(0.117)
Market share	0.058	-0.016	6.053***	0.248***	4.780***	0.211***
	(1.361)	(0.069)	(1.400)	(0.074)	(1.506)	(0.077)
Bank-industry FE	Y	Y	Y	Y	Y	Y
Bank-period FE	Y	Y	Y	Y	Y	Y
Industry-period FE	Y	Y	Y	Y	Y	Y
N	80,392	80,392	106,202	106,202	108,428	108,428

Notes: The unit of observation is the bank-industry-half-year level ijt, based on the sample of all completed syndicated loans from 1990 (1997 in the first two columns) to 2013 granted to industry i for which bank j served as a lead arranger in half-year t. Furthermore, the sample is limited to bank-industry (ij) pairs with non-zero loans in at least three half-years, whereas the remaining periods are included as zero-loan observations. The dependent variable in the first, third, and fifth column is the logarithm of the total volume of all loans granted to industry i by bank j in period t plus one. The dependent variable in the second, fourth, and sixth column is an indicator capturing whether *any* loans were granted to industry i by bank j in period t. $\textit{Market share}_{ijt-2}$ is the proportion of bank j's total loan volume to industry i over the aggregate loan volume in industry i, measured over twelve half-year periods (i.e., six years) from $t-13$ to $t-2$. $\textit{Industry distress}_{it-1}$ is an indicator variable for whether the cumulative median stock return of industry i was less than -10% in the previous half-year $t-1$. In the first two columns, $\textit{Specific}_i$ is an indicator for whether industry i is among the bottom 20% industries in terms of asset redeployability, as defined in Kung and Kim (2017). In the third and fourth column, $\textit{Specific}_{it}$ is an indicator for whether industry i is among the top 20% industries in terms of the ratio of machinery and equipment to total assets in year t. $\textit{Liquidity needs}_{it}$ is an indicator for whether industry i is among the top 20% industries in terms of the ratio of long-term debt maturing in one year from $t-1$ over total long-term debt in $t-1$. Public-service, energy, and financial-services industries are dropped. Robust standard errors, clustered at the bank level, are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 5: **Alternative Definitions of Industry Distress**

	ln(1+Loan volume)			ln(Avg. loan size)	Any loan
Sample	All	All	All	Loan vol. $\neq 0$	All
Panel A: Regression sample from 1990 to 2013, mean returns					
	(1)	(2)	(3)	(4)	(5)
Market share × Ind. distress	5.462***	3.995***	2.591**	-0.179	0.146**
	(1.715)	(1.305)	(1.246)	(0.242)	(0.062)
Market share	8.395***	12.662***	4.832***	-0.205	0.218***
	(1.594)	(1.286)	(0.983)	(0.386)	(0.052)
Industry distress	-0.449***				
	(0.089)				
Bank-industry FE	N	N	Y	Y	Y
Bank-period FE	Y	Y	Y	Y	Y
Industry-period FE	N	Y	Y	Y	Y
N	113,494	113,470	113,470	24,292	113,470
Panel B: Regression sample from 1990 to 2013, transitory vs. permanent shocks					
	(1)	(2)	(3)	(4)	(5)
Market share × Transitory shock	6.000***	4.671***	2.700**	-0.033	0.142**
	(2.056)	(1.494)	(1.137)	(0.307)	(0.057)
Market share × Permanent shock	2.748	1.228	0.508	-0.342	0.032
	(1.663)	(1.636)	(1.172)	(0.281)	(0.060)
Market share	8.365***	12.660***	4.888***	-0.200	0.222***
	(1.627)	(1.272)	(0.922)	(0.374)	(0.049)
Transitory shock	-0.019				
	(0.097)				
Permanent shock	-0.085				
	(0.081)				
Bank-industry FE	N	N	Y	Y	Y
Bank-period FE	Y	Y	Y	Y	Y
Industry-period FE	N	Y	Y	Y	Y
N	113,494	113,470	113,470	24,292	113,470
Panel C: Regression sample from 1990 to 2013, mean returns of top-3 firms					
	(1)	(2)	(3)	(4)	(5)
Market share × Non-system. distress	-2.720	-2.844	-1.143	-0.394	-0.030
	(1.846)	(1.825)	(1.530)	(0.315)	(0.081)
Market share	13.231***	15.274***	5.457***	-0.094	0.234***
	(1.812)	(2.098)	(1.608)	(0.391)	(0.086)
Non-systemic distress	-0.347***				
	(0.066)				
Bank-industry FE	N	N	Y	Y	Y
Bank-period FE	Y	Y	Y	Y	Y
Industry-period FE	N	Y	Y	Y	Y
N	105,832	105,832	105,832	22,973	105,832

Notes: The unit of observation is the bank-industry-half-year level ijt, based on the sample of all completed syndicated loans from 1990 to 2013 granted to industry i for which bank j served as a lead arranger in half-year t. Furthermore, the sample is limited to bank-industry (ij) pairs with non-zero loans in at least three half-years, whereas the remaining periods are included as zero-loan observations. The dependent variable in the first three columns is the logarithm of the total volume of all loans granted to industry i by bank j in period t plus one. In the fourth column, the dependent variable is the logged average size of loans granted to industry i by bank j in period t, and the sample is limited to non-zero loans granted to industry i by bank j in period t. The dependent variable in the fifth column is an indicator capturing whether *any* loans were granted to industry i by bank j in period t. *Market share*$_{ijt-2}$ is the proportion of bank j's total loan volume to industry

i over the aggregate loan volume in industry i, measured over twelve half-year periods (i.e., six years) from $t-13$ to $t-2$. In Panel A, *Industry distress*$_{it-1}$ is an indicator variable for whether the cumulative *average* stock return of industry i was less than -10% in the previous half-year $t-1$. In Panel B, *Transitory shock*$_{it-1}$ is an indicator variable for whether the cumulative median stock return of industry i was less than -10% in the previous half-year $t-1$, but no longer below -10% after three more years. In contrast, *Permanent shock*$_{it-1}$ is an indicator variable for whether the cumulative median stock return of industry i was less than -10% in the previous half-year $t-1$, and remained below -10% after three more years. In Panel C, *Non-systemic distress*$_{it-1}$ is an indicator variable for whether the cumulative average stock return of the top-3 firms (in terms of sales) in industry i was less than -10% in the previous half-year $t-1$. Public-service, energy, and financial-services industries are dropped. Robust standard errors, clustered at the bank level, are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 6: **Bank Lending to Distressed Industries' Suppliers**

	ln(1+Loan volume)	ln(Avg. loan size)	Any loan	ln(1+Loan volume)	Any loan
Sample	All	Loan volume $\neq 0$	All	All	All
	(1)	(2)	(3)	(4)	(5)
Customer share × Customer distress	2.994**	-0.240	0.151**	3.036**	0.153**
	(1.485)	(0.423)	(0.067)	(1.502)	(0.068)
Customer share	2.996	0.239	0.131	2.889	0.127
	(2.311)	(0.321)	(0.104)	(2.174)	(0.098)
Market share × Industry distress				2.687	0.132
				(2.264)	(0.111)
Market share				0.125	-0.017
				(2.029)	(0.106)
Bank-industry FE	Y	Y	Y	Y	Y
Bank-period FE	Y	Y	Y	Y	Y
Industry-period FE	Y	Y	Y	Y	Y
N	43,058	13,074	43,058	43,058	43,058

Notes: The unit of observation is the bank-industry-half-year level ijt, based on the sample of all completed syndicated loans from 1997 to 2013 granted to industry i for which bank j served as a lead arranger in half-year t. Furthermore, the sample is limited to bank-industry (ij) pairs with non-zero loans in at least three half-years, whereas the remaining periods are included as zero-loan observations. The dependent variable in the first and fourth column is the logarithm of the total volume of all loans granted to industry i by bank j in period t plus one. In the second column, the dependent variable is the logged average size of loans granted to industry i by bank j in period t, and the sample is limited to non-zero loans granted to industry i by bank j in period t. The dependent variable in the third and fifth column is an indicator capturing whether *any* loans were granted to industry i by bank j in period t. *Customer share*$_{ijt-2}$ is the proportion of bank j's total loan volume to industry i's customer industry over the aggregate loan volume in industry i's customer industry, measured over twelve half-year periods (i.e., six years) from $t-13$ to $t-2$. *Customer distress*$_{it-1}$ is an indicator variable for whether the cumulative median stock return of industry i's customer industry was less than -10% in the previous half-year $t-1$. *Market share*$_{ijt-2}$ is the proportion of bank j's total loan volume to (supplier) industry i over the aggregate loan volume in industry i, measured over twelve half-year periods (i.e., six years) from $t-13$ to $t-2$. *Industry distress*$_{it-1}$ is an indicator variable for whether the cumulative median stock return of (supplier) industry i was less than -10% in the previous half-year $t-1$. Public-service, energy, and financial-services industries are dropped. Robust standard errors, clustered at the bank level, are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 7: **Bank Lending to Distressed Industries' Customers**

	ln(1+Loan volume)	ln(Avg. loan size)	Any loan	ln(1+Loan volume)	Any loan
Sample	All	Loan volume $\neq 0$	All	All	All
	(1)	(2)	(3)	(4)	(5)
Supplier share × Supplier distress	2.314*	0.002	0.119**	1.970	0.102*
	(1.216)	(0.355)	(0.058)	(1.339)	(0.063)
Supplier share	0.073	-0.328	-0.011	-0.012	-0.014
	(2.959)	(0.249)	(0.143)	(2.834)	(0.137)
Market share × Industry distress				3.895**	0.190**
				(1.806)	(0.089)
Market share				0.052	-0.015
				(2.217)	(0.114)
Bank-industry FE	Y	Y	Y	Y	Y
Bank-period FE	Y	Y	Y	Y	Y
Industry-period FE	Y	Y	Y	Y	Y
N	38,348	11,553	38,348	38,348	38,348

Notes: The unit of observation is the bank-industry-half-year level ijt, based on the sample of all completed syndicated loans from 1997 to 2013 granted to industry i for which bank j served as a lead arranger in half-year t. Furthermore, the sample is limited to bank-industry (ij) pairs with non-zero loans in at least three half-years, whereas the remaining periods are included as zero-loan observations. The dependent variable in the first and fourth column is the logarithm of the total volume of all loans granted to industry i by bank j in period t plus one. In the second column, the dependent variable is the logged average size of loans granted to industry i by bank j in period t, and the sample is limited to non-zero loans granted to industry i by bank j in period t. The dependent variable in the third and fifth column is an indicator capturing whether *any* loans were granted to industry i by bank j in period t. *Supplier share*$_{ijt-2}$ is the proportion of bank j's total loan volume to industry i's supplier industry over the aggregate loan volume in industry i's supplier industry, measured over twelve half-year periods (i.e., six years) from $t-13$ to $t-2$. *Supplier distress*$_{it-1}$ is an indicator variable for whether the cumulative median stock return of industry i's supplier industry was less than -10% in the previous half-year $t-1$. *Market share*$_{ijt-2}$ is the proportion of bank j's total loan volume to (customer) industry i over the aggregate loan volume in industry i, measured over twelve half-year periods (i.e., six years) from $t-13$ to $t-2$. *Industry distress*$_{it-1}$ is an indicator variable for whether the cumulative median stock return of (customer) industry i was less than -10% in the previous half-year $t-1$. Public-service, energy, and financial-services industries are dropped. Robust standard errors, clustered at the bank level, are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 8: **Bank Lending to Distressed Industries' Suppliers and Customers: Relationship Industries**

	ln(1+Loan volume) (1)	Any loan (2)	ln(1+Loan volume) (3)	Any loan (4)
Customer share × Customer distress × Relationship industries	6.931**	0.372**		
	(2.929)	(0.164)		
Customer share × Customer distress	1.466	0.068		
	(1.848)	(0.087)		
Customer share × Relationship industries	-0.826	-0.081		
	(2.908)	(0.138)		
Customer share	3.307	0.160		
	(3.110)	(0.142)		
Supplier share × Supplier distress × Relationship industries			7.059*	0.314*
			(3.911)	(0.190)
Supplier share × Supplier distress			-0.491	-0.005
			(1.932)	(0.090)
Supplier share × Relationship industries			-2.664	-0.139
			(2.169)	(0.114)
Supplier share			0.952	0.035
			(3.210)	(0.157)
Bank-industry FE	Y	Y	Y	Y
Bank-period FE	Y	Y	Y	Y
Industry-period FE	Y	Y	Y	Y
N	43,058	43,058	38,348	38,348

Notes: The unit of observation is the bank-industry-half-year level ijt, based on the sample of all completed syndicated loans from 1997 to 2013 granted to industry i for which bank j served as a lead arranger in half-year t. Furthermore, the sample is limited to bank-industry (ij) pairs with non-zero loans in at least three half-years, whereas the remaining periods are included as zero-loan observations. The dependent variable in the first and third column is the logarithm of the total volume of all loans granted to industry i by bank j in period t plus one. The dependent variable in the second and fourth column is an indicator capturing whether *any* loans were granted to industry i by bank j in period t. *Customer share*$_{ijt-2}$ is the proportion of bank j's total loan volume to industry i's customer industry over the aggregate loan volume in industry i's customer industry, measured over twelve half-year periods (i.e., six years) from $t-13$ to $t-2$. *Customer distress*$_{it-1}$ is an indicator variable for whether the cumulative median stock return of industry i's customer industry was less than -10% in the previous half-year $t-1$. *Supplier share*$_{ijt-2}$ is the proportion of bank j's total loan volume to industry i's supplier industry over the aggregate loan volume in industry i's supplier industry, measured over twelve half-year periods (i.e., six years) from $t-13$ to $t-2$. *Supplier distress*$_{it-1}$ is an indicator variable for whether the cumulative median stock return of industry i's supplier industry was less than -10% in the previous half-year $t-1$. *Relationship industries*$_i$ is an indicator for whether industry i and its customer or supplier industries are relationship industries, as defined in Cremers, Nair, and Peyer (2008). Public-service, energy, and financial-services industries are dropped. Robust standard errors, clustered at the bank level, are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 9: **Bank Lending to Distressed Industries' Customers: Relative Leverage**

	ln(1+Loan volume)	ln(Avg. loan size)	Any loan
Sample	All	Loan volume $\neq 0$	All
	(1)	(2)	(3)
Supp. share × Supp. distress × Relative leverage	3.981**	0.334	0.194**
	(1.567)	(0.372)	(0.081)
Supplier share × Supplier distress	-2.598	-0.527	-0.112
	(1.861)	(0.684)	(0.095)
Supplier share × Relative leverage	2.680**	-0.352	0.121*
	(1.185)	(0.296)	(0.062)
Supplier share	-1.546	0.169	-0.085
	(4.433)	(0.513)	(0.214)
Bank-industry FE	Y	Y	Y
Bank-period FE	Y	Y	Y
Industry-period FE	Y	Y	Y
N	36,334	10,946	36,334

Notes: The unit of observation is the bank-industry-half-year level ijt, based on the sample of all completed syndicated loans from 1997 to 2013 granted to industry i for which bank j served as a lead arranger in half-year t. Furthermore, the sample is limited to bank-industry (ij) pairs with non-zero loans in at least three half-years, whereas the remaining periods are included as zero-loan observations. The dependent variable in the first column is the logarithm of the total volume of all loans granted to industry i by bank j in period t plus one. In the second column, the dependent variable is the logged average size of loans granted to industry i by bank j in period t, and the sample is limited to non-zero loans granted to industry i by bank j in period t. The dependent variable in the third column is an indicator capturing whether *any* loans were granted to industry i by bank j in period t. $\textit{Supplier share}_{ijt-2}$ is the proportion of bank j's total loan volume to industry i's supplier industry over the aggregate loan volume in industry i's supplier industry, measured over twelve half-year periods (i.e., six years) from $t-13$ to $t-2$. $\textit{Supplier distress}_{it-1}$ is an indicator variable for whether the cumulative median stock return of i's supplier industry was less than -10% in the previous half-year $t-1$. $\textit{Relative leverage}_{it}$ is the ratio between the average leverage of industry i's (distressed) supplier industry and the average leverage of industry i in period t. Public-service, energy, and financial-services industries are dropped. Robust standard errors, clustered at the bank level, are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 10: **Bank Lending to Distressed Industries' Customers: Customer HHI**

	ln(1+Loan volume)	ln(Avg. loan size)	Any loan
Sample	All	Loan volume $\neq 0$	All
	(1)	(2)	(3)
Supp. share × Supp. distress × Customer HHI	10.701*	-4.010**	0.581**
	(5.846)	(1.729)	(0.286)
Supplier share × Supplier distress	0.938	0.565	0.041
	(1.083)	(0.394)	(0.058)
Supplier share × Customer HHI	5.789	2.512*	-0.023
	(9.545)	(1.421)	(0.473)
Supplier share	-0.844	-0.681***	-0.009
	(3.258)	(0.241)	(0.159)
Bank-industry FE	Y	Y	Y
Bank-period FE	Y	Y	Y
Industry-period FE	Y	Y	Y
N	38,348	11,533	38,348

Notes: The unit of observation is the bank-industry-half-year level ijt, based on the sample of all completed syndicated loans from 1997 to 2013 granted to industry i for which bank j served as a lead arranger in half-year t. Furthermore, the sample is limited to bank-industry (ij) pairs with non-zero loans in at least three half-years, whereas the remaining periods are included as zero-loan observations. The dependent variable in the first column is the logarithm of the total volume of all loans granted to industry i by bank j in period t plus one. In the second column, the dependent variable is the logged average size of loans granted to industry i by bank j in period t, and the sample is limited to non-zero loans granted to industry i by bank j in period t. The dependent variable in the third column is an indicator capturing whether *any* loans were granted to industry i by bank j in period t. $\textit{Supplier share}_{ijt-2}$ is the proportion of bank j's total loan volume to industry i's supplier industry over the aggregate loan volume in industry i's supplier industry, measured over twelve half-year periods (i.e., six years) from $t-13$ to $t-2$. $\textit{Supplier distress}_{it-1}$ is an indicator variable for whether the cumulative median stock return of i's supplier industry was less than -10% in the previous half-year $t-1$. $\textit{Customer HHI}_{it}$ measures the sales concentration of industry i as customers to their (distressed) suppliers in period t. Public-service, energy, and financial-services industries are dropped. Robust standard errors, clustered at the bank level, are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 11: **Retention of Loans and Non-loan Exposure**

	ln(1+Loan vol.) (1)	Any loan (2)	ln(1+Loan vol.) (3)	Any loan (4)
Market share × Ind. distress × Retention	4.867**	0.235*		
	(2.341)	(0.124)		
Market share × Industry distress	0.958	0.056		
	(0.784)	(0.040)		
Market share × Retention	-2.179	-0.057		
	(1.812)	(0.098)		
Market share	5.273***	0.231***		
	(0.997)	(0.053)		
Underwriting market share × Ind. distress			1.294*	0.074*
			(0.746)	(0.041)
Underwriting market share			3.596**	0.122
			(1.493)	(0.076)
Bank-industry FE	Y	Y	Y	Y
Bank-period FE	Y	Y	Y	Y
Industry-period FE	Y	Y	Y	Y
N	113,470	113,470	113,470	113,470

Notes: The unit of observation is the bank-industry-half-year level ijt, based on the sample of all completed syndicated loans from 1990 to 2013 granted to industry i for which bank j served as a lead arranger in half-year t. Furthermore, the sample is limited to bank-industry (ij) pairs with non-zero loans in at least three half-years, whereas the remaining periods are included as zero-loan observations. The dependent variable in the first and third column is the logarithm of the total volume of all loans granted to industry i by bank j in period t plus one. The dependent variable in the second and fourth column is an indicator capturing whether *any* loans were granted to industry i by bank j in period t. *Market share*$_{ijt-2}$ is the proportion of bank j's total loan volume to industry i over the aggregate loan volume in industry i, measured over twelve half-year periods (i.e., six years) from $t-13$ to $t-2$. *Industry distress*$_{it-1}$ is an indicator variable for whether the cumulative median stock return of industry i was less than -10% in the previous half-year $t-1$. *Retention*$_{it-2}$ is an indicator for whether industry i is among the bottom 20% industries in terms of the average number of participants across all syndicated loans from $t-13$ to $t-2$. *Underwriting market share*$_{ijt-2}$ is the proportion of bank j's total number of debt and equity underwriting mandates in industry i over the aggregate number of debt and equity issuances in industry i, measured over twelve half-year periods (i.e., six years) from $t-13$ to $t-2$. Public-service, energy, and financial-services industries are dropped. Robust standard errors, clustered at the bank level, are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 12: **Impact on Cost of Debt**

	ln(Spread)	ln(TCB)	ln(Spread)	ln(TCB)
Horizon	After 12 months		After 24 months	
Sample	Loan volume $\neq 0$			
	(1)	(2)	(3)	(4)
Market share × Industry distress	-0.053	0.119	-0.150	-0.144
	(0.126)	(0.290)	(0.127)	(0.209)
Market share	-0.022	0.382**	-0.006	0.384**
	(0.108)	(0.144)	(0.139)	(0.162)
Bank-industry FE	Y	Y	Y	Y
Bank-period FE	Y	Y	Y	Y
Industry-period FE	Y	Y	Y	Y
N	23,176	9,236	23,245	9,071

Notes: The unit of observation is the bank-industry-half-year level ijt, based on the sample of all completed syndicated loans from 1990 to 2013 granted to industry i for which bank j served as a lead arranger in half-year t. Furthermore, the sample is limited to periods with non-zero loans granted to industry i by bank j. The dependent variable in the first and third column is the logged average all-in-drawn spread of all loans granted to industry i by bank j in period $t+1$ (12 months after the industry shock) and in period $t+3$ (24 months after the industry shock), respectively, where the all-in-drawn spread is the sum of the spread over LIBOR and any annual fees paid to the lender syndicate. The dependent variable in the second and fourth column is the logged average total cost of borrowing, as defined in Berg, Saunders, and Steffen (2016), of all loans granted to industry i by bank j in period $t+1$ (12 months after the industry shock) and in period $t+3$ (24 months after the industry shock), respectively. *Market share*$_{ijt-2}$ is the proportion of bank j's total loan volume to industry i over the aggregate loan volume in industry i, measured over twelve half-year periods (i.e., six years) from $t-13$ to $t-2$. *Industry distress*$_{it-1}$ is an indicator variable for whether the cumulative median stock return of industry i was less than -10% in the previous half-year $t-1$. Public-service, energy, and financial-services industries are dropped. Robust standard errors, clustered at the bank level, are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 13: **Distressed Industries' Shares in Banks' Loan Portfolios**

	ln(1+Loan volume)			
Sample period	1990 – 2013	1997 – 2013	1997 – 2013	1990 – 2013
	(1)	(2)	(3)	(4)
Portfolio share of industry × Industry distress	-1.229**			
	(0.468)			
Portfolio share of industry	1.611***			
	(0.377)			
Portfolio share of supplier × Supplier distress		-1.595		
		(1.248)		
Portfolio share of supplier		0.798		
		(1.006)		
Portfolio share of customer × Cust. distress			0.352	
			(2.361)	
Portfolio share of customer			1.296	
			(0.920)	
Underwriting portfolio share × Ind. distress				0.525
				(0.660)
Underwriting portfolio share				1.220**
				(0.549)
Bank-industry FE	Y	Y	Y	Y
Bank-period FE	Y	Y	Y	Y
Industry-period FE	Y	Y	Y	Y
N	113,470	38,348	43,058	113,470

Notes: The unit of observation is the bank-industry-half-year level ijt, based on the sample of all completed syndicated loans from 1990 (1997 in the second and third column) to 2013 granted to industry i for which bank j served as a lead arranger in half-year t. Furthermore, the sample is limited to bank-industry (ij) pairs with non-zero loans in at least three half-years, whereas the remaining periods are included as zero-loan observations. The dependent variable is the logarithm of the total volume of all loans granted to industry i by bank j in period t plus one. *Portfolio share of industry*$_{ijt-2}$ is the proportion of bank j's total loan volume to industry i over the aggregate loan volume granted by bank j, measured over twelve half-year periods (i.e., six years) from $t-13$ to $t-2$. *Industry distress*$_{it-1}$ is an indicator variable for whether the cumulative median stock return of industry i was less than -10% in the previous half-year $t-1$. *Portfolio share of supplier*$_{ijt-2}$ is the proportion of bank j's total loan volume to i's supplier industry over the aggregate loan volume granted by bank j, measured over twelve half-year periods (i.e., six years) from $t-13$ to $t-2$. *Supplier distress*$_{it-1}$ is an indicator variable for whether the cumulative median stock return of industry i's supplier industry was less than -10% in the previous half-year $t-1$. *Portfolio share of customer*$_{ijt-2}$ is the proportion of bank j's total loan volume to industry i's customer industry over the aggregate loan volume granted by bank j, measured over twelve half-year periods (i.e., six years) from $t-13$ to $t-2$. *Customer distress*$_{it-1}$ is an indicator variable for whether the cumulative median stock return of industry i's customer industry was less than -10% in the previous half-year $t-1$. *Underwriting portfolio share*$_{ijt-2}$ is the proportion of bank j's total number of debt and equity underwriting mandates in industry i over the aggregate number of underwriting mandates of bank j across industries, measured over twelve half-year periods (i.e., six years) from $t-13$ to $t-2$. Public-service, energy, and financial-services industries are dropped. Robust standard errors, clustered at the bank level, are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 14: **Industry-wide Credit Concentration and Firm Exit**

	Any bankruptcy-related delisting in industry					
Horizon	After 6 months			After 12 months		
HHI measure	All banks		Top 1	All banks		Top 1
	(1)	(2)	(3)	(4)	(5)	(6)
Market HHI × Ind. distress	-0.456***	-0.384**	-0.244*	-0.392**	-0.330**	-0.252*
	(0.166)	(0.156)	(0.145)	(0.168)	(0.132)	(0.137)
Market HHI	-0.635***	-0.011	-0.059	-0.648***	-0.012	-0.046
	(0.150)	(0.084)	(0.095)	(0.149)	(0.082)	(0.093)
Industry distress	0.210***	0.142***	0.150***	0.191***	0.123***	0.141***
	(0.045)	(0.042)	(0.054)	(0.047)	(0.036)	(0.052)
Industry FE	N	Y	Y	N	Y	Y
Time FE	Y	Y	Y	Y	Y	Y
N	2,633	2,633	2,633	2,579	2,579	2,579

Notes: The unit of observation is the industry-half-year level it. Furthermore, the sample is limited to industries with more than 50 non-zero loan observations across all bank relationships over 14 years from 1990 to 2013. The dependent variable is an indicator variable for whether there is any exit in industry i in half-year t (in the first three columns) or $t+1$ (in the last three columns). We use the following CRSP delisting codes to identify exits: any type of liquidation (400-490); price fell below acceptable level; insufficient capital, surplus, and/or equity; insufficient (or non-compliance with rules of) float or assets; company request, liquidation; bankruptcy, declared insolvent; delinquent in filing; non-payment of fees; does not meet exchange's financial guidelines for continued listing; protection of investors and the public interest; corporate governance violation; and delist required by Securities Exchange Commission (SEC). $\textit{Market HHI}_{it-2}$ measures the credit concentration in industry i over twelve half-year periods (i.e., six years) from $t-13$ to $t-2$, across all banks that provide credit to industry i (in all columns but the third and sixth column). In columns 3 and 6, the measure of concentration is the market share of the top lender to industry i from $t-13$ to $t-2$. $\textit{Industry distress}_{it-1}$ is an indicator variable for whether the cumulative median stock return of industry i was less than -10% in the previous half-year $t-1$. Public-service, energy, and financial-services industries are dropped. Robust standard errors, clustered at the industry level, are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 15: **Industry-wide Credit Concentration and Intra-industry Mergers**

	Proportion of intra-industry mergers as acquirer					
Horizon	After 6 months			After 12 months		
HHI measure	All banks		Top 1	All banks		Top 1
	(1)	(2)	(3)	(4)	(5)	(6)
Market HHI × Ind. distress	0.640**	0.417*	0.293*	0.385*	0.164	0.007
	(0.244)	(0.209)	(0.149)	(0.228)	(0.227)	(0.174)
Market HHI	-0.391***	-0.187	-0.111	-0.332**	-0.115	0.005
	(0.138)	(0.180)	(0.131)	(0.154)	(0.195)	(0.139)
Industry distress	-0.113**	-0.088**	-0.104**	-0.081	-0.056	-0.033
	(0.046)	(0.039)	(0.046)	(0.053)	(0.041)	(0.050)
Industry FE	N	Y	Y	N	Y	Y
Time FE	Y	Y	Y	Y	Y	Y
N	2,508	2,508	2,508	2,459	2,459	2,459

Notes: The unit of observation is the industry-half-year level it. Furthermore, the sample is limited to industries with more than 50 non-zero loan observations across all bank relationships over 14 years from 1990 to 2013, and to observations with non-zero takeovers in a given period. The dependent variable is the fraction, from 0 to 1, of intra-industry mergers over the total transaction volume of takeovers where industry i is the acquirer in half-year t (in the first three columns) or $t+1$ (in the last three columns). *Market* HHI_{it-2} measures the credit concentration in industry i over twelve half-year periods (i.e., six years) from $t-13$ to $t-2$, across all banks that provide credit to industry i (in all columns but the third and sixth column). In columns 3 and 6, the measure of concentration is the market share of the top lender to industry i from $t-13$ to $t-2$. *Industry* $distress_{it-1}$ is an indicator variable for whether the cumulative median stock return of industry i was less than -10% in the previous half-year $t-1$. Public-service, energy, and financial-services industries are dropped. Robust standard errors, clustered at the industry level, are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 16: **Credit Concentration and Long-run Abnormal Returns of Industries following Distress**

Alpha (in % per month)	Top-quintile credit concentration	Bottom-quintile credit concentration	Long-short
Three years	-0.855***	-1.121***	0.332**
	(0.170)	(0.129)	(0.156)
N	288	287	287
Five years	-0.810***	-1.050***	0.293**
	(0.159)	(0.121)	(0.132)
N	288	287	287
Seven years	-0.771***	-0.980***	0.250**
	(0.157)	(0.116)	(0.118)
N	288	287	287

Notes: Fama and French (1993) three-factor-model calendar-time portfolio estimates of alpha (in percent per month) are based on weighted-least-squares (WLS) regressions from 1990 to 2013 of the monthly premium of a given portfolio relative to the one-month Treasury rate (as dependent variable) on the monthly market premium, small minus big market capitalization excess return, and high minus low book-to-market ratio excess return. We form equal-weight portfolios of industries that in the past n years, where n varies from three to five and seven (across rows), had a cumulative median stock return of less than -10% in the previous half-year, and were in the top (first column) or bottom (second column) quintile of the distribution in terms of the industry-level credit concentration over six years prior to industry distress across all banks in a given industry (see definition of $Market\ HHI_{it-2}$ in Table 14). In the last column, long-short portfolios are long in the top quintile of said distribution and short in the bottom quintile. N is the number of months with non-empty portfolios. Observations are weighted efficiently as a function of the number of industries in a given portfolio in month t, as in Malmendier, Opp, and Saidi (2016). Robust standard errors are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

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