Shock Absorbers and Transmitters: The Dual Role of Bank Specialization*

Rajkamal Iyer
Imperial College London & CEPR

Sotirios Kokas
University of Essex

Alexander Michaelides
Imperial College London & CEPR

José-Luis Peydró
Imperial College London & CEPR

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Abstract

How does bank lending specialization amplify industry-specific shocks? After a negative shock, banks specializing in an affected industry increase their lending primarily to more profitable firms in that sector, expecting higher loan yields. As a result, banks cut their lending disproportionately to unrelated and non-affected industries. Firms in unrelated sectors experiencing a reduction in credit compensate by raising funds externally. However, when financing conditions are tight, these shocks translate into aggregate real effects for unrelated industries. In effect, industry-specific shocks can be passed on to other unrelated industries through bank specialization in bad times, thereby amplifying the initial shock.

Keywords: Bank specialization, industry-specific shocks, real effects, credit growth, financial frictions.

JEL Classification: G20, G21

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1 Introduction

Economic shocks at the individual firm level may lead to aggregate fluctuations through real and financial channels. On the real side, idiosyncratic shocks to large firms can generate aggregate shocks (Gabaix, 2011; Gabaix and Koijen, 2021), and also lead to spillovers via input-output production linkages (Acemoglu, Carvalho, Ozdaglar and Tahbaz-Salehi, 2012; Carvalho, 2014). On the financial side, micro shocks can propagate between firms through, for instance, a financial network arising from trade credit linkages (Costello, 2020); or due to linkages via banking intermediaries leading to aggregate fluctuations (Allen and Gale, 2000; Chodorow-Reich, 2014; Iyer, Peydró, da Rocha-Lopes and Schoar, 2014). However, banks might play a much more important role in the transmission of negative sector-specific shocks - beyond the mechanical effect of financial linkages - due to their monitoring and screening functions (Fama, 1980; Diamond, 1984; Levine, 2005). The lending specialization of individual banks in specific sectors that arises due to their monitoring and screening of borrowers, in combination with financing frictions, could be crucial in determining whether and how shocks are transmitted (Acharya, Hasan and Saunders, 2006; Paravisini, Rappoport and Schnabl, 2015; Federico, Hassan and Rappoport, 2020). However, despite its importance, there is scant evidence on how bank lending specialization affects the transmission of industry-specific shocks.

In this paper we analyze whether banks' lending specialization affects the propagation of sector-specific shocks to the economy. Specifically, in the presence of negative sector-specific shocks, we investigate how bank lending specialization affects credit supply not only to sectors that banks specialize in but also crucially to unrelated (unaffected) sectors. Conceptually, the answer is not clear-cut. On the one hand, if there is a negative shock to an industry, more specialized banks with higher exposure to that industry will have lower profits (hence lower capital), thereby reducing lending, including to the negatively affected sector (Freixas and Rochet, 2008). On the other hand, as the negatively affected sector has less funding, loan pricing can increase sufficiently to make it attractive for banks specializing in that sector to lend more and secure a higher yield relative to lending to firms in other sectors (for a very related argument, see Stein, 2013). In this scenario, specialized banks will reallocate credit towards the negatively affected sector and constrain the unaffected sectors' growth opportunities.[1]

[1] A related but different mechanism is zombie lending (Caballero, Hoshi and Kashyap, 2008) as, in this case, banks will lend to the firms in the negatively affected sector but not to obtain higher profits but to

To examine the role bank specialization plays in providing credit supply in the presence of industry-specific shocks, we use granular data for bank loans from the U.S. syndicated loan market.[2] We define a negative economic shock at the industry level by using episodes where the industry median stock return is lower than -10%.[3] Our measure of bank specialization is the fraction of a bank's credit given to a specific sector relative to a bank's total credit portfolio (Paravisini, Rappoport and Schnabl, 2015). Bank sectoral specialization captures the importance of a sector for a bank and ranges from zero (no lending to a sector) to one (perfect specialization in a sector). Finally, we measure each bank's exposure to the negative shock by using the size of the shock to a sector and the relative exposure of the bank's portfolio to the sector.

The main empirical findings can be summarized as follows. We find that if a sector experiences a negative shock, banks that specialize in lending to the sector increase their flow of credit to firms in the affected sector relative to non-specialized banks.[4] In terms of magnitude, a one standard deviation increase in the bank's exposure to the distressed sector increases total credit to the firms in the affected sector by approximately 5%. This result holds even when we control for other measures like industries' credit concentration.

Zombie lending does not drive the results. We find that the increased lending to the affected sector is primarily focused on firms with better profitability outcomes up to three years after the loan origination (ex-post). Importantly, this effect holds not only for high capitalized banks but also for low capitalized banks. In addition, we find that banks do not provide lending to firms with ex-ante lower profitability outcomes one year before the loan origination. Thus, the results suggest that an increase in lending to the affected sector is not an artifact of zombie lending but in line with specialized banks lending to profitable firms (consistent with better screening and monitoring) in the negatively affected sector.

Our results suggest that specialized banks increase credit supply to affected sectors to obtain a higher loan yield. We provide evidence that the loan interest rate charged by specialized banks for lending to the affected sectors is higher than that to the other unaffected sectors, and the effects tend to be stronger for under-capitalized banks. Thus,

delay loan defaults.

[2]We exclude term loans B because banks usually hold none of these loans after the syndication. Term loans B are structured specifically for institutional investors and almost entirely sold off in the secondary market (Irani, Iyer, Meisenzahl and Peydró, 2020).

[3]In addition, as discussed later in the paper, we use an alternative definition to measure negative shocks based on unexpected oil price movements for oil-dependent sectors.

[4]Also, we show that specialized banks sustain a higher loan supply in absolute terms (not only relative to the non-specialize banks) when sectors experience an adverse shock.

post a negative shock, specialized banks get higher returns (6 bps) from lending to affected sectors as compared to unaffected sectors. Furthermore, when we compare the loan rates charged by non-specialized banks for lending to the affected sectors, we find that they are higher than those offered by specialized banks. That is, after the negative shock, specialized banks provide more lending volume and at a relatively lower price than non-specialized banks. This suggests that an increase in credit supply to firms in the affected sector is not purely an artifact of more credit demand by firms borrowing from specialized banks.

Does the higher credit from specialized banks to the affected sectors change lending conditions to the unaffected sector? We find that firms in unaffected sectors that have an outstanding loan with a bank that has a higher exposure to sectors hit by negative shocks -through specialized lending- experience a reduction in credit. Economically, one standard deviation increase in the bank's lending specialization in an exposed sector decreases lending in a non-affected firm by 2.3%. That is, at the same time that specialized banks are increasing lending to affected sectors, these banks are decreasing lending to non-affected sectors.[5] Furthermore, we provide evidence that for the pass-through to unaffected sectors to occur, the industry shock must be of a sufficiently high magnitude, and the bank must have high specialization in the affected sectors.

We use several approaches to address the concern that the results could be driven by credit demand. First, we saturate the loan level specifications with granular bank-time, firm-time, and bank-firm fixed effects (Khwaja and Mian, 2008; Jiménez, Ongena, Peydró and Saurina, 2012, 2014). These fixed effects control for a wide range of unobserved factors such as a bank's time-varying unobserved overall bank (credit supply) conditions, a firm's time-varying overall unobserved firm conditions (fundamentals, including overall demand for credit), and bank-firm matching. Second, we use the unexpected oil price movements for oil-dependent sectors to identify industry distress episodes as oil-price trends can be orthogonal to industries financial health (Hamilton and Wu, 2014; Kilian and Murphy, 2014; Kilian and Vigfusson, 2017). Finally, we control for coincident demand fluctuations between sectors as a negative shock to a sector can spread over the production network and affect their related suppliers or customers. Specifically, we use the input-output table from the U.S. Bureau of Economic Analysis (BEA) and include only unrelated sectors (Costello,

[5] To elaborate on this, there is no difference between the lending behavior of exposed banks to affected and unaffected sectors prior to the downturn to the industries that banks are specialized in. Only after the downturn has occurred do exposed banks exhibit a change in their lending behavior.

2020).

To further understand whether firms in unaffected sectors can compensate for the loss in credit with other banks and nonbanks, as well as to analyze the associated real effects (if any), we aggregate the loan-level data at the firm level. We examine several firm outcomes like bank credit, total debt, investment, size, employment, and sales. We find that, on average, firms in the unaffected sector do not experience any significant change in their total bank credit, total debt and employment. This suggests that even when these firms experience a reduction in credit from the specialized banks that have exposure to the affected sectors, they can fully compensate for the shortfall in credit by borrowing from other financial intermediaries. However, during periods of financial turmoil like the global financial crisis or when aggregate financing frictions are high (following Gilchrist and Zakrajšek, 2012, shocks), higher credit supply by specialized banks to the affected sector has an effect on total debt availability to firms in unrelated sectors. In periods when financing frictions are high, firms in unaffected sectors witness an overall reduction in their bank credit, total debt, and also employment, sales and size.[6]

The above results suggest that there is a transmission of negative industry-specific shocks from firms in affected sectors to firms in unaffected sectors due to the lending specialization of common lenders. However, an important question that arises is whether these results also hold at the aggregate industry level.

We aggregate the loan-level data at the bank-industry-time level to shed light on this. We find that banks more exposed to affected sectors allocate lower amounts of credit to the unaffected sectors in their portfolio. As the data set for this analysis is aggregated at the bank-industry level, we lose the advantage of using granular fixed effects to control for confounding factors. For this stage, we adopt an IV approach. We exploit changes in bank exposure to affected sectors that stem from bank mergers (Favara and Giannetti, 2017). Results from the IV strategy are similar to the bank-firm level results.

We then analyze whether the results still hold when we aggregate across all firms (and banks) within an industry. Specifically, we examine whether the reduction in credit for the unaffected sectors translates into an aggregate reduction in credit growth at the industry level. We construct a measure at the industry level to capture the bank's exposure to affected sectors and evaluate whether greater banks' exposure to affected sectors has an effect on aggregate industry lending and has real effects at the industry level. We find that

[6]We exclude the global financial crisis period for robustness, to ensure that the firm outcomes are not driven by the fact that during the global financial crisis many sectors were in distressed.

during good times there is no drop in credit supply. However, consistent with the firm-level results documented before, we find a reduction in bank credit and industry-level outcomes (external debt, size, and employment) during periods of financial turmoil (global financial crisis or financing frictions exploiting Gilchrist-Zakrajśek shocks).

Our paper contributes to the literature on bank specialization. Many researchers have analyzed the role that geographical specialization plays for credit reallocation after a funding shock (for instance, Carey, Post and Sharpe, 1998; Paravisini, Rappoport and Schnabl, 2015; Cortés and Strahan, 2017; Chakraborty, Goldstein and MacKinlay, 2020, among others). Our paper adds to this literature by documenting how banks increase their lending to sectors they specialize in following a negative industry-specific shock and cutting back on credit to unrelated sectors. Our paper also provides novel evidence on the internal reallocation of banks' portfolio post a negative shock due to specialization in lending. Because specialized banks get higher loan yields in the negatively affected industries in which they are specialized, they increase credit supply in firms in this sector while cutting in other sectors, that is, we show financial contagion due to bank specialization.

An important literature examines how and to what extent the contraction in bank lending affects non-financial firms (Ivashina and Scharfstein, 2010; Chodorow-Reich, 2014; Iyer, Peydró, da Rocha-Lopes and Schoar, 2014; Giannetti and Saidi, 2019; Costello, 2020; Galaasen, Jamilov, Juelsrud and Rey, 2020). However, the prior literature focuses on the effect of the propagation of financial shocks via a bank-firm relationship mechanism. We add to this literature by considering whether non-financial shocks (for example, arising from sudden changes in consumer demand in an industry) can have spillover effects on unrelated and unaffected firms through the banks' industry specialization. We find that specialized banks are more likely to cut back on credit to unrelated sectors because they increase lending in the negatively affected sectors in which banks are specialized. This evidence suggests an asymmetry in portfolio reallocation by banks, which have important real effects when financial constraints are important

The paper closest to ours is by Giannetti and Saidi (2019), which analyzes the extent to which the internalization of negative spillovers of industry downturns depends on the structure (concentration) of the banking system. They find that banks increase lending to firms in affected sectors because banks internalize the negative spillovers due to potential fire sales (arising from their market shares). Our focus differs from theirs in two important ways. First, we show the importance of banks' lending specialization instead of bank concentration in increasing lending within firms in affected sectors. Second, we also analyze the negative externalities that arise for firms in unaffected and unrelated sectors due to banks' specialization and incentives to increase lending in negatively affected sectors.

The rest of the paper is structured as follows. Section 2 discusses the empirical methodology. Section 3 presents the data and the approach that we use to measure the main variables of interest. The results from the estimation and additional analyses are presented in Section 4. Section 5 concludes.

2 Empirical Methodology

To empirically test whether banks experiencing an industry-level shock reduce credit supply toward firms in non-affected industries, we use regression analysis at three aggregation levels. We start our analysis at the loan level to isolate loan supply from loan demand. We next aggregate at the firm level to investigate the effect of shocks on firm outcomes, and we then aggregate at the bank-industry level to investigate whether the common lenders' linkages between sectors can serve as the transmission channel for these shocks. Finally, we aggregate at the industry level to investigate the real effects on aggregate economic outcomes.

2.1 Loan level

We follow Smolyansky (2019) to capture industry spillovers, and our estimation relies on the Khwaja and Mian (2008) approach. Specifically, we test whether banks' sector specialization has an effect on loan supply to firms that operate in sectors unaffected by a non-financial shock by estimating the following loan specification:

$$Ln(amount)_{l,b,f,t} = \alpha_{f,t} + \alpha_{b,t} + \alpha_{b,f} + \beta * Exposure_{b,t-1} + \gamma_1 * X_{l,t} + \epsilon_{l,b,f,t} \ . \quad (1)$$

The dependent variable is the natural logarithm of the loan amount (l) that bank b lends to firm f operating in non-affected industries at time t (semi-annual frequency). $Exposure_{b,t-1}$ measures the bank's specialization in industries that experience distress episodes ($Exposure^{Dist}_{b,t-1}$) or unanticipated oil price shocks ($Exposure^{Oil}_{b,t-1}$).[7] Importantly, we measure bank specialization before a sector experiences a non-financial shock. X is a vector of loan controls, $\alpha_{f,t}$, $\alpha_{b,t}$ and $\alpha_{b,t}$ denote firm-time, bank-time and bank-firm fixed

[7] The variables are defined in section 3.

effects as described below, and $\epsilon_{l,b,f,t}$ is a stochastic disturbance. We double cluster our standard errors at the bank and firm level to account for serial correlation within firm and bank across time.

In equation (1), β is the main coefficient of interest and captures the marginal effect of lending to firms that operate in unaffected sectors from banks specialising in affected (distressed or oil shock) sectors. Identifying a spillover in credit supply to one sector due to a shock occurring in another sector is empirically challenging. The main difficulty is that while some sectors are affected, other sectors that do not, are also likely to experience coincident fluctuations in economic conditions. Such fluctuations would affect credit demand and the creditworthiness of firms that operate in these sectors, and so alter bank incentives to lend in non-affected sectors independent of any contemporaneous shock occurring elsewhere. Therefore, the main empirical challenge is to control for simultaneous variation in lending opportunities between affected and non-affected sectors.

Even though such variation is not directly observable, the richness of our dataset allows us to control for it at a highly granular level. To do so, we follow Jiménez, Ongena, Peydró and Saurina (2012, 2014) and isolate simultaneous changes in credit supply and firm demand by inserting sequentially bank-year, firm-year and bank-firm fixed effects. These fixed effects control for time-varying unobservable bank fundamentals (credit supply), firm fundamentals including overall demand for credit and bank-firm matching.

Another concern is that adverse shocks can spread over the supply chain as firms in distress can affect their related suppliers or clients, for example, via a trade credit mechanism, (see for instance Costello, 2020), or via lower quality of inputs, (see for instance Acemoglu, Akcigit and Kerr, 2016). Thus, relationship banks can smooth the initial shock to other unaffected but related sectors as suppliers and clients can default and reduce their supply and demand of inputs. Were this to occur, it would give a false impression that credit has not been reallocated. To address this potential confound, we identify the supplier and customer relationships using input-output tables from the U.S. Bureau of Economic Analysis (BEA) and include only unrelated sectors.[8]

[8] The BEA provides annual tables on the industry use of commodities at producers' prices for a wide range of industries (for instance, Carvalho, 2014; Acemoglu, Akcigit and Kerr, 2016).

2.2 Firm level

In the loan-level analysis, we observe whether banks propagate sector-specific shocks to other unaffected sectors via linkages arising due to common lenders. However, the analysis cannot uncover a potential substitution effect and remains silent about firm outcomes (real effects). For instance, whether unaffected firms can compensate for the loss of credit, they will average out credit spillovers leaving firm aggregates unchanged in normal times, yielding at least a weak propagation mechanism.

To test for the substitution and real effects, we aggregate the loan-level data at the firm level and estimate the following regression only for unaffected and unrelated firms:

$$Ln(Y)_{f,t} = \alpha_t + \alpha_f + \beta * Exposure_{f,t-1} + \gamma_1 * X_{f,t} + \epsilon_{f,t} \ . \tag{2}$$

In the baseline regression of equation (2), the dependent variable is the natural logarithm of the loan amount that an unaffected firm f at time t (semi-annual frequency) receives in total.[9] To analyze the real effects, we also use as a dependent variable the investment, total debt, size, employment and sales. We aggregate the exposure variable at the firm-level and is defined as a weighted sum approach based on the shares that each bank holds within a firm. $X_{f,t}$ is a vector of time-varying firm-level control variables and $\epsilon_{f,t}$ is a stochastic disturbance at the firm-time level. We double cluster our standard errors at the firm and time level.

2.3 Bank-industry level

To evaluate whether common lenders between sectors is the linkage that can amplify the propagation of non-financial shocks affecting a specific sector, we aggregate the loan-level data to a bank-industry level.[10] We estimate the following regression only for unaffected and unrelated sectors:

$$\Delta Ln(amount)_{b,s,t} = \alpha_b + \alpha_{s,t} + \alpha_{b,s} + \beta * Exposure_{b,t-1} + \gamma_1 * X_{b,t} + \epsilon_{b,s,t} \ . \tag{3}$$

The dependent variable is the incremental change in the value of lending done by bank b in a two-digit SIC code s at time t. $X_{b,t}$ is a vector of time-varying bank-level control

[9] We use the natural logarithm of the levels and not the growth because we want to analyze whether lending and firm outcomes are abnormally lower in levels and not the incremental changes when a firm is unaffected, and a bank has high exposure in affected sectors.

[10] We sum all bank lending amounts across all firms within two-digit SIC codes.

variables, α_b, $\alpha_{s,t}$ and $\alpha_{b,s}$ are a set of bank, industry-time and bank-industry fixed effects. $\epsilon_{b,s,t}$ is a stochastic disturbance at the bank-industry level and we cluster our standard errors at the bank and industry level.

A potential concern about endogeneity in estimating equation (3) is that demand in unaffected sectors can coincide with local shocks in affected sectors. To this end, we include change in lending growth and industry-time fixed effects to filter out unobserved variation in sector-specific lending demand by comparing lending to unaffected sectors by banks with an exposure to affected sectors. In addition, we mitigate any lingering simultaneity concerns that bank specialization may be endogenous to the propensity to grant new loans, or to the structure of loan syndicates, by exploiting changes in credit market specializations that stem from bank mergers (Favara and Giannetti, 2017; Giannetti and Saidi, 2019). To this end, we use information on bank mergers where both banks are active in the syndicated loan market in the year before the merger. Specifically, we instrument a bank's specialization with information from the acquired bank in the last pre-merger quarter. This instrument is likely to satisfy the exclusion and relevance restrictions because it affects only peers' activities. Our results are fully robust to this IV strategy.

2.4 Industry level

Finally, in order to investigate aggregate real effects of exposed banks, we aggregate the data at the industry level. In our setting, we estimate the following regression only for <u>unaffected and unrelated sectors</u>:

$$\Delta Ln(Y)_{s,t} = \alpha_s + \alpha_t + \beta * Exposure_{s,t-1} + \gamma_1 * X_{s,t} + \epsilon_{s,t} \ , \tag{4}$$

where Y measures the incremental change in the growth of credit received at a two-digit SIC sector s at time t. To analyze the real effects, we also use as a dependent variable the incremental changes (growth) in the investment, total debt, size of the industry, employment and sales. The $Exposure_{s,t-1}$ variable is the bank's specialization exposure at the industry-level and is defined as a weighted sum approach based on the shares that each bank (b) holds within a sector (s). $X_{s,t}$ is a vector of time-varying sector-level control variables and $\epsilon_{s,t}$ is a stochastic disturbance at the industry-semester level. We double cluster our standard errors at the industry and time level.

3 Data and Measurement

This section defines the main variables used in the empirical analysis, their data sources, and descriptive statistics.

3.1 Measuring Granular Non-Financial Shocks

An essential step in the analysis is to identify periods when industries experience negative shocks. In this section, we describe the process for constructing two industry-level biannual shocks.

First, we follow Opler and Titman (1994), Carvalho (2015) and Giannetti and Saidi (2019) and classify a negative shock of industry downturns according to the industry stock returns.[11] We define a distress episode, denoted by $Distress_{s,t}$, as a dummy variable that takes the value one if the semi-annual returns in a two-digit SIC industry code s and semester t were lower than -10%, and zero otherwise.

$$Distress_{s,t} = \begin{cases} \mathbb{1} & \text{if semi-annual returns in } s \text{ at } t < -10\% \\ 0 & \text{Otherwise} \end{cases} \tag{5}$$

Periods of distress are intended to capture unpredictable non-financial shocks that can constraint a firm's ability to raise external funds (Carvalho, 2015). We set the stock return threshold at -10% similar to the one used by Giannetti and Saidi (2019) to allow for a broader variation in distress episodes.[12] In our bank-firm sample about 40% of the sectors in our sample are associated with distress episodes.

A potential concern with the stock returns approach for identifying downturns is that industries' financial health may influence the likelihood of identifying a distress episode. In other words, investor reaction can be correlated with an industry's prospects and thus downturns can be endogenous to (among other things) banks' lending intensity. To alleviate this concern, we use a second definition based on unexpected oil price movements to measure negative shocks. We define the oil price shock as a dummy variable that takes the value one if the oil price change is higher than the expected price in oil-dependent sectors.

[11] In the remaining sections, we use the words downturn and distress interchangeably to refer to the shock.

[12] Also, in unreported results, we refine our distress definition by employing a -5% and -15% threshold for industry stock returns.

$$Oil\ shock_t = \begin{cases} \mathbb{1} & \text{if } P_t > E(P_t) \text{ in oil-dependent sectors} \\ 0 & \text{Otherwise} \end{cases} \tag{6}$$

For the construction of oil price expectations, we use two alternative measures. Initially, we rely on Kilian and Murphy (2014) for the "economist" expectations and secondly on Hamilton and Wu (2014) for the "financial market" expectations.[13] To characterize if a sector is oil-dependent or not, we rely on the harmonized SIC-BEA linkage and measure for each industry the fraction of oil or refined products that have been used as inputs. We assume that a sector is oil-dependent if the inputs are above the sample mean and zero otherwise.

3.2 Measuring Bank Specialization and Market Shares

We construct the main variables of interest at the bank-sector level. Bank sector specialization is defined as the ratio of total credit granted by bank b to sector s at time t relative to bank's total credit granted:

$$Specialization_{b,s,t} = \frac{\sum_{f=1}^{F} Loan_{b,f,s,t}}{\sum_{s=1}^{S}\sum_{f=1}^{F} Loan_{b,f,s,t}}\ , \tag{7}$$

where $Loan_{b,f,s,t}$ is the credit granted (in millions of dollars) by bank b to firm f in sector s at time t.[14] The F and S capture the total number of firms and sectors, respectively. Bank sectoral specialization captures the importance of a sector for a bank and ranges from zero (no lending to a sector) to one (perfect specialization in a sector). To measure the degree to which a bank is exposed to industries that are in a distress situation, or negatively affected by an unanticipated increase in oil prices, we use the size of the shock in $t-1$ and the relative exposure of the bank's portfolio to the sector t. Specifically, we use the following formula:

[13] Kilian and Murphy (2014) employ a VAR model specification that includes the real price of oil, global crude oil production, global real economic activity, and changes in global crude oil stocks. Using a different set-up, Hamilton and Wu (2014) document that there is a time-varying risk premium in the oil future market. So, the price expectation is to subtract the risk premium from the oil future prices for a given horizon.

[14] We face some data limitations with respect to the availability of the shares that each arranger retains within a loan. However, we follow a common practice in the literature and equally weigh the missing shares per loan (for instance, Chodorow-Reich, 2014; Giannetti and Saidi, 2019, among others).

$$
Exposure_{b,t} \equiv \begin{cases} Exposure^{Dist}_{b,t-1} = \sum^{n}_{s \in Distress_t} Specialization_{b,s,t-1} \\ Exposure^{Oil}_{b,t-1} = \sum^{n}_{s \in Oil\ shock_t} Specialization_{b,s,t-1} \end{cases} \tag{8}
$$

where the superscript in the exposure variable is used to separate between the distress ($Dist$) and oil prices shock (Oil).

Bank specialization captures the lending amount that a bank has invested in a given sector and hence proxies for the information advantage that the bank has gained in that sector. However, if a bank has a dominant position in a sector, then there are structural advantages concerning the information collection within a given market. To disentangle information advantages between specialization and market presence, we also construct the market shares. We define the market shares as the ratio of total credit granted by bank b to sector s at time t relative to all credit granted by all banks to sector s:

$$
Market\ shares_{b,s,t} = \frac{\sum^{F}_{f=1} Loan_{b,f,s,t}}{\sum^{B}_{b=1}\sum^{F}_{f=1} Loan_{b,f,s,t}}. \tag{9}
$$

A bank's market share reveals the importance of a bank for a sector and lies between zero and one, with higher values indicating a higher lending concentration. As above, to measure the market share exposure, for each bank, we use the size of the shock in t and the bank's shares in $t-1$ as follows:

$$
\begin{aligned} Market\ shares^{Dist}_{b,t-1} &= \sum^{n}_{s \in Distress_t} Market\ shares_{b,s,t-1} \\ Market\ shares^{Oil}_{b,t-1} &= \sum^{n}_{s \in Oil\ shock_t} Market\ shares_{b,s,t-1} \end{aligned} \tag{10}
$$

3.3 Data sources

To test our hypothesis, we need loan-level data for firms in a wide range of industries as well as comprehensive information for banks' credit exposure. Our analysis is based on a matched bank-firm dataset containing corporate loans that were originated in the U.S.. We construct a unique dataset by combining different sources on syndicated loan data, bank balance sheets and M&A activities, firm balance sheets and their SIC codes, and industry-level information on stock returns, oil dependency, product complexity, and supply chains from the Bureau of Economic Analysis (BEA henceforth).

We begin with a brief description of the syndicated market, as several studies have extensively analyzed this market (for instance, Sufi, 2007; Chodorow-Reich, 2014; Delis, Kokas and Ongena, 2017, among others). The main advantage of studying syndicated loans is that a group of banks co-finance a single borrower, and banks' overlapping portfolio feature allows us to exploit different levels of sectoral exposure by syndicate members. In the past two decades, syndicated lending is about half of total commercial and industrial (C&I) lending volumes, and therefore it is often used to assess bank lending policies (Ivashina and Scharfstein, 2010).

We obtain data on syndicated loans at origination from the Thomson Reuters Dealscan database. This database provides detailed information on loan's characteristics (like amount, borrowing spread, maturity, collateral, performance pricing, covenants, etc.), as well as more limited information for the members of the syndicate, the lead bank, the share of each bank in the syndicate and the firm receiving the loan. We apply the following selection rules to avoid including bias in our sample and to provide a realistic insight into the structure of the syndicates. First, we drop loans that are granted to utilities (public services) and financial firms. Second, we follow Roberts (2015) and drop loans that are more likely to be amendments to existing loans, because these are misreported in Dealscan as new loans, but they do not necessarily involve new money. Third, we remove loans with missing industry SIC codes. Finally, we categorize loans as credit lines, term A, and term B, and exclude term loans B because banks usually hold none of these loans after the syndication. Term loans B are structured specifically for institutional investors and almost entirely sold off in the secondary market (Irani, Iyer, Meisenzahl and Peydró, 2020).[15]

To obtain information for the financial statements of banks, we match these data with the Call Reports of the Federal Reserve Board of Governors (FRB). We hand-match Dealscan with Call Reports, because there is no common identifier between these datasets. The matching is initially done by a fuzzy merge algorithm based on names and locations, and we manually review all matching results. This process links the Dealscan's lender ID

[15] Also, we apply a selection rule to avoid bias in our sample. This is an essential part of the sample-selection process that is absent from most empirical studies using the Dealscan database (for a similar strategy see Lim, Minton and Weisbach, 2014; Irani, Iyer, Meisenzahl and Peydró, 2020). We disentangle banks from non-banks. We consider a loan facility to have a non-bank institutional investor if at least one institutional investor that is neither a commercial nor an investment bank is involved in the lending syndicate. Non-bank institutions include hedge funds, private equity funds, mutual funds, pension funds and endowments, insurance companies, and finance companies. To identify commercial bank lenders, we start from lenders whose type in Dealscan is *US Bank*, *African Bank*, *Asian-Pacific Bank*, *Foreign Bank*, *Eastern Europe/Russian Bank*, *Middle Eastern Bank*, *Western European Bank*, or *Thrift/S&L*. We manually exclude the observations that are classified as a bank by Dealscan but are not, such as the General Motors Acceptance Corporation (GMAC) Commercial Finance. We went through all the syndicated loans manually, one-by-one. Second, we exclude loans granted to utilities or to financial companies.

with the bank's ID (RSSD9001) and provides a unique linkage for each lender. With this linkage, we can also match information from the FRB for the Banks' M&As. Because these reports are available every quarter, we match the origination date of the loan deal with the relevant quarter. For example, we match all syndicated loans that were originated from April 1st to June 30th with the second quarter of that year of the Call Reports.

We use the Compustat-Dealscan link provided by Chava and Roberts (2008) to merge Dealscan with the firm's quarterly information on their financial statements, SIC codes and their monthly stock returns. Dealscan provides data on the SIC codes for each borrower during the loan origination. However, for different reasons, a firm can change its industry classification, and thus we rely on Compustat to identify the sector of each firm. As we describe in section 2, this is an essential step for our aggregation at the bank-industry and industry level. Finally, we harmonize the SIC codes with BEA codes to use the input-output linkages to measure the connectedness between sectors.

One of our main objectives is to analyze whether, after a negative economic shock, bank sector specialization can have an effect on loan supply to firms in sectors not directly affected by the economic shock. Therefore, we need to enrich our sample with information at the industry level to control for alternative hypotheses that might affect the results. First, to control for aggregate credit conditions, we use the Gilchrist and Zakrajšek (2012) Excess Bond Premium (EBP) to capture financial frictions during our sample period.[16] Second, we use Baumeister and Kilian (2016) to link different oil price shocks to oil-dependent industries. Finally, to control for product information complexity that might affect the lending decision, we exploit the Rauch (1999) data on the categories of product differentiation. To construct this measure, we harmonize the trade classification with industry classification using OECD information and the Muendler (2009) link.[17]

To control for outliers, we exclude observations in the one per cent from the upper and lower tails of the distribution of the regression variables. The matching process yields a maximum of 26,010 loans originated by 373 banks involving 4,417 non-financial firms spanning from the first semester of 1987 to the first semester of 2016. In our sample, a

[16] Gilchrist and Zakrajšek (2012) use bond-level data and construct the EBP by decomposing a firm's credit spread into on a firm-specific measure of expected default, a vector of bond-specific characteristics and a residual spread component. Then the residuals are averaged across all firms, and they obtain the EBP as a measure that is unrelated to default.

[17] Rauch (1999) sorts products into two broad categories: products traded on international exchanges and differentiated products for which branding information precludes them from being traded on exchanges or reference priced.

median bank has 29 firm connections in a given year. From these connections, 7 (6) firms operate in a distressed sector (oil shock), suggesting that common lenders can potentially substitute credit among firms.

3.4 Descriptive statistics

Figure 1 shows the evolution of bank specialization to distressed sectors, the growth of credit to non-distressed sectors and the market shares during our sample period. We observe that the variation in market shares is relatively small, while specialization to distressed sectors has a substantial variation. Importantly, for different periods like the GFC, we observe a negative correlation between the specialization and growth in credit for non-distressed sectors that have lenders exposed to distressed sectors.

Panel A of table 1 describes the summary statistics for the loan (bank-firm) level sample. The all-in-spread drawn (AISD) is defined as the sum of the spread over LIBOR plus the facility fee (bps) and is on average 155 bps, while the standard deviation indicates sizeable variation (113 bps). When we calculate the distress definition using the input and output linkage-table, then we observe that 39.6% of our sectors are in distress. Panel B reports descriptive statistics for the main variables of interest at the firm level. On average, the firm-level exposure for unaffected industries is 20.1%, and on average half of the observations are categorized in periods with financial frictions. In panel C, we report statistics when we aggregate at the bank-industry level. The average credit growth to an industry is 5.8%. The banks' average specialization in a distressed industry is 17.4%, while their average market shares in a given industry is 29.6%. Panel D aggregates the data at the industry level. The average industry increases external debt and the number of employees by 1.5% and 2.9%, respectively. Table A1 in the appendix defines all variables.

Table A2, in the appendix, contains the unique number of observations across our sample period. Columns I-III report the number of banks, firms and sectors, respectively. Columns IV to V show statistics for the industry returns, and columns VI to VII contain statistics for the proportion of industries in distress (returns less than negative ten per cent). There are several important takeaways from this table. First, the number of unique banks per semester ranges from a minimum of 97 (1987h1) to a maximum of 268 (1995h1). Secondly, there is a downward trend in the number of banks participating in our sample after the GFC. Third, the number of unique sectors at the 2-digit SIC code is relatively stable and ranges from 39 (1987h1) to 68 (1995h2) and remains unaffected after the GFC.

Forth, there is a large degree of heterogeneity across the industry returns and our definition of distress. Importantly, the returns coincide with the NBER recession dates (-41.32% in the second half of 2008, for example) and the highest proportion of industries in distress is 98% in the second half of 2008, while the lowest proportion is zero during normal times.

Table 2 provides raw normalized differences when we split the loan-level dataset between non-distressed and distressed sectors (Imbens and Wooldridge, 2009). The normalized differences for all variables are all less than one-tenth of a standard deviation as a rule of thumb for a linear regression method (Imbens and Lemieux, 2008). We observe that distressed sectors pay on average a higher AISD than non-distressed sectors. The normalized difference is 7% of a standard deviation. Similarly, the distressed sectors pay a higher premium of 5% of a standard deviation when considering only the spread instead of the AISD. Moreover, in distressed sectors banks are slightly more specialized, with higher market presence and have a marginally lower capitalization.

4 Empirical Results

In the presence of adverse industry-specific shocks, we investigate how banks' lending specialization affects credit supply and cost of lending not only to affected sectors that banks specialize in but also crucially to unrelated and unaffected sectors in section 4.1. In section 4.2, we aggregate the loan-level data at the firm level and investigate potential spillover effects and firm real economic consequences. In section 2.3, we ask whether banks that serve as common lenders can create indirect linkages among sectors. In section 2.4, we examine aggregate real economic affects at the industry level.

4.1 Loan-level outcomes

Bank specialization. Table 3 reports results on whether banks specialising in affected sectors are more inclined to provide credit during distress to the affected sectors. In all Table 3 specifications, the dependent variable is the natural logarithm for the loan amount held by each bank at origination, and we use fixed effects at the bank and firm*time level to absorb any time-varying changes in firm demand and also allow variation from the supply side. So, the effect of bank specialization on lending is therefore identified across banks with different exposure to the same firm.

In column I, we use the $Exposure^{Dist}$ variable to capture the bank's lending exposure in $t-1$ to sectors that are in distress in t. The coefficient on bank exposure is positive and statistically significant. This suggests that banks exposed to affected sectors increase their lending to affected firms compared to non-exposed banks during distress. Lending specialization arises due to monitoring and screening, thereby allowing specialized banks to better evaluate borrowers' investment opportunities and smooth fluctuations in credit during turmoils. The effect is quantitatively significant. The coefficient suggests that a one standard deviation increase in the exposure to distressed sectors increases lending to affected firms by approximately 5% (calculated from the product 0.174 * 0.293). This is equivalent to 4.7 percentage points of sample deviation.

In column II, we use the $Market\ shares^{Dist}$ variable to capture the importance of a bank to sectors that are in distress. The coefficient is positive and statistically significant. This evidence is consistent with Giannetti and Saidi (2019) that banks with a significant market share in affected sectors provide liquidity to internalize these externalities (for example from fire sales). For parsimonious reasons, in column III, we add both the bank specialization and market shares in affected sectors. Interestingly, the estimate on the $Market\ shares^{Dist}$ is statistically insignificant, while the $Exposure^{Dist}$ remains similar to the one in column I. So, the increased credit provision to affected sectors does seem to be driven by the lending amount that a bank has invested in a given sector that experiences unexpected difficulties (Carey, Post and Sharpe, 1998).

Loan performance. Having shown in the previous table that banks increase the supply of credit to affected firms when banks have large outstanding lending exposures to these sectors (skin in the game), we next investigate the borrowers' loan performance.

Table 4 analyzes whether banks originate loans to zombie firms or whether banks pick the more profitable firms within affected sectors. In Table 4, Panel A, we regress bank lending on the interaction between the variable of interest ($Exposure^{Dist}$), differences in firm's performance after and before the loan origination (ROA), loan and bank controls, firm*time fixed effects and bank fixed effects. In column I of Panel A, we calculate the difference between the firm's ROA_{t+1} (one year after the loan origination) minus the ROA_t (at the time of the loan). If the difference is positive (negative), then profitability increases (decreases) in the year following the loan. The coefficient of $Exposure^{Dist}$ is significant and similar in magnitude with column I of Table 3. The coefficient of the interaction is also positive and significant at 10%. This result suggests that exposed banks increase credit within affected firms, and this credit supply is even stronger for firms with better profitability outcomes.

We replicate the same analysis in columns II and III, but we expand our rolling window to calculate the post-performance at two and three years, respectively. We restrict our rolling window up to three years because the average loan maturity in our sample is 40 months. The results in column II and III show that exposed banks pick the most profitable firms within the affected sectors. In column IV, we find that banks do not increase lending to affected firms that are relatively poorly performing before the loan origination. Thus, the results provide evidence that the increase in lending to the affected sector is not an artifact of zombie lending but in line with specialized banks lending to profitable firms (consistent with better screening and monitoring, Diamond, 1984) in the negatively affected sector.[18]

While the coefficient on bank exposure positively affects loan supply for affected firms, bank capitalization that acts as a buffer could have a differential marginal effect during unexpected shocks. In other words, banks with low capital might have an even stronger incentive than banks with high capital to lend to firms in affected sectors with potentially good future investment opportunities (Jiménez, Ongena, Peydró and Saurina, 2017; Rehbein and Ongena, 2021). In Panel B, we compare lending by low versus high capitalization banks with different lending exposure to affected sectors. We define a bank with low capital as an indicator that equals one if the bank's Tier 2 is below the sample mean.[19] We want to highlight that Panel B is similar in structure to Panel A, but in addition, we add the triple interaction involving capital ratios. In columns I-III, the coefficient of interest is positive and significant at 10%. Our results suggest that a bank with a lower Tier 2 ratio that is exposed to distressed sectors will increase the supply of credit to borrowers that will perform better up to three years after the loan origination. In column IV, the estimated coefficient for the triple interaction is positive and significant at 5%, suggesting that low capitalized banks will provide credit to firms with a higher profitability a year before the loan origination.

Borrowing costs. So far, our evidence suggests that banks with higher specialization in distressed sectors smooth out credit fluctuations to firms operating in these sectors. Why is this effect happening? On the one hand, bank specialization alleviates sector-specific asymmetric information and fosters comparative advantages in screening and monitoring

[18] In Table A3 of the appendix section, we use alternative indicators for the firm's performance before the loan origination. Specifically, we use the firm's *Investement* and *Tangibility*. The $exposure^{Dist}$ variable remains significant and positive, while the interaction term for each performance variable is insignificant.

[19] The sample mean is equal to 9.1% and 97 banks are characterized with low capital.

(Carey, Post and Sharpe, 1998). On the other hand, especially during distress, specialization not only allows the lender to select the appropriate borrower but also to extract rents on their privilege information (Sharpe, 1990; Stein, 2013).

In Table 5, we examine whether a bank will charge borrowers a higher interest rate if they operate in a sector in which the bank has a higher exposure. In columns I-III, the dependent variable is the all-in-spread drawn ($AISD$) and is defined as the sum of the spread over LIBOR plus the facility fee (bps), while in columns IV-VI, we only include the spread. In column I, the coefficient of $Distress$ is positive and significant, indicating that firms in distressed sectors pay, on average, a higher $AISD$ by 12.16 bps. The coefficient on the interaction term ($Specialization * Distress$) is significant and negative. Thus, banks with a higher specialization to these sectors are decreasing the $AISD$ by 6.5 bps during distress episodes. The total effect of exposure is still positive and significant at around 5.66 bps on average. So, the total positive effect shows that exposed banks get a higher return from lending to affected sectors compared to unaffected sectors (Stein, 2013).

In columns II and III, we add different time-varying fixed effects to alleviate concerns with supply-driven (bank*time fixed effects) and demand-driven omitted factors (firm*time fixed effects). In column III, using firm*time fixed effects, the coefficient of the interaction term remains negative but turns to be very marginally insignificant (P-value equals 0.101). In columns I-III of Panel B, we replicate the analysis in columns I-III of Panel A but we add the triple interaction of $low\ capital * Specialization * Distress$. The coefficient on the triple interaction is positive and significant in all specifications. That is, under-capitalized banks with exposure to distressed sectors increase further the premium that they charge affected firms (Jiménez, Ongena, Peydró and Saurina, 2017; Rehbein and Ongena, 2021).

Thus far, our estimates in Table 5 rely on a relatively comprehensive definition for the cost of borrowing that incorporates the spread plus the facility fee. In the remainder of the table, we test more restrictive definitions on the cost of lending. In particular, In columns IV-VI, we use the spread (without the facility fee) as the dependent variable to disentangle the effects of the fees on the spread (Berg, Saunders and Steffen, 2016). The results in columns IV-VI are slightly more significant than columns I-III, especially when we add the firm*time fixed effects to take variation within a firm. Moreover, the results in columns IV-VI of Panel B on the marginal effects of bank capital are almost identical compared to the findings of columns I-III of Panel B. Overall, Table 5 presents evidence that banks with exposure to affected sectors provide more credit than other lenders because these banks get higher return from lending to affected sectors compared to unaffected sectors, and the effects tend to be stronger for under-capitalized banks. This suggests that an increase in credit supply to firms in the affected sector is not purely an artifact of more credit demand by firms borrowing from specialized banks.

Industry spillovers. Overall, all previous results support the conclusion that sector-specific negative shocks directly impact loan supply in affected firms. Does the higher credit from specialized banks to the affected sectors change lending conditions to the unaffected sector (see equation (1))? To make progress in addressing this question, Table 6 presents industry spillovers for unaffected (and unrelated) sectors using as a dependent variable the natural logarithm of the loan amount that a bank lends to a firm operating in non-affected industries . We capture industry spillovers focusing on the $Exposure^{Dist}$ variable coefficient.

Column I of Panel A in Table 6, reports the baseline specification without any time-varying fixed effects. The negative point estimate indicates that a negative shock in the sectors that a bank is specialized in is related to a decrease in lending for the non-affected firms relative to the pre-shock period. Economically, the baseline estimate of column I indicates that one standard deviation increase (0.293) in the bank's lending specialization in an exposed sector decreases lending in a non-affected firm by 2.3%. In column II, we replace specialization with bank's market shares in the distress sectors. The coefficient is negative but close to zero, even though significant at the 10% level. In column III, we add both the bank specialization and market shares in affected sectors. As in Table 3, the estimate on the $Market\ shares^{Dist}$ is statistically insignificant, while the $Exposure^{Dist}$ coefficient remains similar to the one in column I. These results, therefore, suggest that information advantages stemming from specialization are more likely to create industry spillovers rather than the market shares variable. This can arise from specialized banks being better informed about their borrowers and more capable of assessing the recovery values in case of default.

In columns IV, V, VI and VII of Panel A, we add time-varying fixed effects to alleviate concerns with demand, supply, and bank-firm matching omitted factors. Despite the additional fixed effects, the point estimate is negative, close to the baseline column I, and significant at the 1% level. This evidence shows that the credit supply is perfectly synchronized with the opposite effect observed in affected firms (as presented in the previous tables). That is, at exact same time that exposed banks are increasing lending to affected sectors, these banks are decreasing lending to unaffected sectors. To elaborate on this, in

Table A4, we test whether exposed banks to affected sectors have different lending patterns prior to the downturn to the unaffected sectors. The $exposure^{Dist}$ variable is insignificant. This suggests that there is no difference in the lending behavior concerning the unaffected sectors before the downturn to the industries that banks specialize in.

As discussed extensively in section 2.1, a related concern is that negative shocks to an industry can spread over the supply chain as firms in distress can affect their related suppliers or clients (see for instance Acemoglu, Akcigit and Kerr, 2016; Costello, 2020). To address this potential confound, we identify supplier and customer relationships at the two-digit SIC level using input-output tables from the U.S. Bureau of Economic Analysis (BEA). We harmonize the SIC codes with BEA industry codes to use the input-output linkages to measure unrelated sectors. This constrains our sample in the supply-chain tests by 27%. In columns, VIII, IX and X, we include only unrelated sectors to avoid instances where the initial shock coincide with changes in the firm's demand for credit. In these columns, the estimated coefficients are almost identical to the baseline results, confirming that the observed credit reduction in unaffected and unrelated firms is not confounded by changing demand conditions unique to treated banks.

An additional concern is related to the stock returns approach to measure distress because investor reactions to stock returns for different sectors can be correlated with the industry's prospects, and thus distress situations can be anticipated by bank lending. To alleviate this concern, we use a second definition for the status of the sector based on unexpected oil price movements to measure negative shocks. As highlighted in section 2.1, the oil price shock is defined when the price of oil is higher than the expected price in oil-dependent sectors. Over the years, the oil-dependent sectors have increased their reliance on external financing substantially; as Domanski, Kearns, Lombardi and Shin (2015) point out, external debt increased substantially from roughly one trillion ($) in 2006 to around two and a half trillion ($) in 2014.

In Panel B of Table 6, we use oil shocks instead of stock returns to define shocks and repeat the analysis of Panel A. The only difference compared to Panel A, is that we redefine the bank exposure by using the size of the oil shock to oil-dependent sectors in t and the relative exposure of the bank's portfolio to these sectors in $t-1$. In columns I-V and VI-X, we use the "economist" approach (Kilian and Murphy, 2014) and the "financial market" approach (Hamilton and Wu, 2014) to construct oil price expectations.[20] The

[20] More details in section 3.

interpretation of the results will be based on the "economist" approach for brevity and because the results are similar to the "financial market" approach. In columns I-IV, the coefficient of interest is negative and significant indicating that a negative oil shock in the sectors that a bank is specialized in is related to a decrease in lending to non-oil affected firms relative to the pre-oil shock period.[21] In column V, we exclude related sectors based on the BEA input-output tables, and the coefficient is negative and significant at 1% but with higher magnitude. Therefore, even though our main proxy for industry distress has desirable features that we primarily rely on in our empirical set-up, our results are not dependent on the particular method of identifying distressed economic situations.

Pass-through of industry spillovers. The results so far make an explicit assumption on how banks cut lending to firms in unaffected sectors to support lending towards firms in affected sectors with a higher specialization. Importantly, the identifying assumption of our empirical strategy rests on the following joint condition: the industry shock must be of a sufficiently high magnitude, and the bank must have high specialization in the affected sectors to allow for pass-through of industry spillovers via common lenders linkages.

In Table 7, we relax the condition by using the whole spectrum of negative returns (instead of a *Distress* dummy threshold at -10%) and constructing the $exposure^{Dist}$ variable as the product of the bank specialization times the negative returns. In column I, we use a within sector analysis. The *Specialization* variable varies at the bank-sector-time level, while the *negative returns* variable varies at the sector-time level. The negative and significant coefficient on the interaction variable (-0.005) confirms that banks increase lending to specialized sectors during turmoils. Importantly, higher negative returns increase further the credit supply. Economically, the baseline estimate of column I indicates that one standard deviation increase (9.52%) in the negative returns increase lending in an affected firm by 1%.

In the remaining columns of Table 7, we consider the role of negative returns in industry spillovers using unaffected and unrelated sectors. To do so, we redefine the $Exposure^{Dist}$ variable as the bank's specialization times the negative returns of the sector. In column II, the positive and highly significant coefficient of 0.018 confirms that banks respond to industry shocks by reducing credit supply to unaffected sectors to support the affected

[21] Economically, the baseline estimate of column I indicates that one standard deviation increase (0.161) in the bank's lending specialization in an exposed sector decreases lending in a non-affected firm by almost 2%.

sectors. Overall, this result supports the conclusion of a symmetric treatment effect based on the stock returns and bank's exposure. In column III, we interact the coefficient of interest with the GFC dummy to consider the role of financial frictions. Interestingly, during financial turmoil, the cut in lending for the unaffected sectors is higher. Finally, columns IV and V categorize the bank's specialization for affected and non-affected sectors, and then we interact these indicators, respectively. In column IV, the coefficient on the *specialization in nondistress* show that bank specialized in the unaffected sectors matter and can offset the negative spillovers. In column V, the interaction variable is economically insignificant.

4.2 Firm-level outcomes

The preceding analysis lays the groundwork for asking whether the observed reallocation of credit impacts real economic activity. If it does, the resulting decrease in lending may impact real economic outcomes like investment, total debt, size, employment and sales. Such a finding would demonstrate that sector-specific shocks can spill over and generate externalities to other unaffected and unrelated sectors. Alternatively, it may be the case that an unaffected firm can compensate for the loss of credit with other banks or nonbanks. To investigate this intuition, we aggregate the loan-level data at the firm level to examine whether a substitution effect will tend to average out the spillovers to non-affected firms, leaving firm fundamentals unchanged. Table 8 shows results for regression equation (2). In this table, the idea is to test the substitution hypothesis conditional on periods with higher financial frictions that are likely to amplify the initial shock. To do so, we interact the exposure variable with different proxies for the aggregate credit conditions.

In column I, the positive but insignificant coefficient on $Exposure^{Dist}$ shows that the average effect of total bank credit to firms in unaffected sectors does not have any significant effects. During good times, there are fewer binding credit frictions, and as a result an unaffected firm can compensate the loss of credit from other banks, or alternative funding sources. However, in periods with binding credit frictions like the GFC (Panel A), firms in unaffected sectors witness an overall reduction in their bank credit, since the coefficient of the interaction variable is negative and significant ($Exposure^{Dist}*GFC$). For instance, one standard deviation increase (0.291) in the exposure variable during the GFC decreases lending to an unaffected firm by 46%. During bad economic times, financial frictions can be especially binding for firms with fewer funding options because debt becomes more scarce and information sensitive (Iyer, Peydró, da Rocha-Lopes and Schoar, 2014). In other words, transaction and information costs could make it difficult to change the banking partner during crisis periods.

In the remaining columns (II-VI), we repeat the same exercise but with different firm-level outcomes as the left-hand-side variables. Specifically, we use total investments (column II), external debt excluding the syndicated loan market (column III), size (column IV), the number of employees (column V) and sales (column VI). In all specifications, we use firm and time fixed effects and control for the firm's return on assets and cash flow volatility. We consistently find that firms in unaffected sectors that borrow from exposed banks experience a deterioration in their fundamentals during crises, with the exception of the investment variable. Economically, the estimates suggest that one standard deviation increase in firm exposure to banks that experience shocks to their specialized sectors during bad times leads to a sizeable lower debt (23%), size (34%), employment (17%) and sales (24%).

In Panel B of Table 8, we use a different definition capturing aggregate financial frictions. Specifically, we use the Gilchrist and Zakrajšek (2012) Excess Bond Premium (EBP) to proxy for financial frictions during our sample period. The EBP is the unexplained credit spread component in the corporate bond market, which is unrelated to the borrower's creditworthiness. Higher (positive) values of EBP indicate large and persistent contractions in economic activity. The EBP data are monthly, but the time-frequency in our analysis is semi-annual. To synchronize the frequencies, we aggregate the monthly data at a semi-annual level and create the $financial\ frictions$ dummy variable whether the EBP is positive for more than 3 months within a 6-month rolling window. Compared to Panel A, the only difference is that we use this variable to define the aggregate financial conditions. Our results show that the coefficients of interest are qualitatively similar to Panel A, but the economic significance is lower, as expected because, by construction, the $financial\ frictions$ variable is "smoother" compared to the GFC. For example, column I of Panel B reveals that higher exposure to affected sectors during financial turmoils reduces the credit supply of non-affected but differentiated firms by about 11%. A potential threat to the firm outcomes analysis is that the coefficient of the spillovers is plausibly driven by the fact that during the GFC many sectors were in distressed. For instance, as shown in Table A3, in 2008h1 and 2008h2 the industries in distress were 73% and 98%, respectively. To alleviate this concern, in Table A5 we do a robustness exercise where we exclude the GFC period. Results remain unchanged.

Finally, in Panel C of Table 8, we replicate the analysis in Panel B, but we exploit data on the informational complexity of the products that each sector produces. We measure the degree of product information complexity using international trade classification (SITC) data from Rauch (1999).[22] In short, a firm's product is considered "heterogeneous" if the product is neither sold on an exchange nor does it have reference pricing. In turn, we follow Giannetti, Burkart and Ellingsen (2011) and Campello and Gao (2017) and assign a firm to a given level of differentiated inputs usage according to the industry in which it operates. In our sample, 18% of firms are associated with "differentiated" products, a figure in line with Campello and Gao (2017). We highlight that a firm with higher shares of heterogeneous products (*specificity*) is more likely to be subject to informational frictions because of higher export risk. In Panel C, we keep only firms whose outputs are considered "differentiated". Thus, we expect that these firms will be further credit-constrained during financial frictions compared to Panel B. Indeed, the estimates confirm that the effect of banks' exposure is similar but more economically significant compared to Panel B.

The firm-level findings during good times show that unaffected firms associated with banks exposed to affected sectors can substitute declines in lending from other (non-affected) banks or with other forms of funding. However, during bad times when credit frictions are more likely to be binding, transaction and information costs could make it difficult to change the banking partner, or raise funding from other markets. In sum, Table 8 shows that changes in credit supply arising from the common lender spillovers can have quantitatively important economic consequences during bad times.

4.3 Bank-industry-level evidence: The mechanism

This section provides evidence that common lenders' linkages between sectors can serve as the transmission channel for these shocks' propagation. To shed light on this, we aggregate the loan-level data at the bank-industry-time level. In Table 9, we examine whether there is a decrease in lending for unaffected sectors that share a common lender experiencing

[22]The firm-level sample has information on Standard Industrial Classification (SIC). To link the two data sets, we use information from OECD, and Muendler (2009) to harmonize SITC and SIC. The objective is to create a many-to-one mapping (from SITC to SIC); hence, in some cases, we manually review the efficiency of the mapping to avoid duplicates. Rauch (1999) provide detailed information on industries' use of differentiated inputs by capturing the share of SITC products that are neither sold on an organized exchange nor reference priced (i.e., heterogeneous products). Rauch (1999) classifies a good as homogeneous if it is sold in organized exchanges or if there is a reference price for it. A heterogeneous product, on the other hand, requires building a trading relationship.

distress episodes in the sector that the lender is specialized in (equation (3)).

In column I of Panel A, we find that the coefficient on the exposure variable for common lenders is negative, indicating that unaffected sectors that have an outstanding loan with a bank that has a higher exposure to sectors hit by negative shocks experience a reduction in credit. In column II, we replace the specialization variable with bank's market shares in the distress sectors but the coefficient is insignificant. In column III we add both the exposure and market shares variables. The inclusion of market shares on the right-hand side leaves the estimated coefficient on the exposure variable negative and unaltered compared to the respective coefficient in column I. In columns IV-VI, we validate that the common lender's mechanism holds also when we include more demanding and time-varying fixed effects to capture different levels of omitted factors as highlighted in sub-section 2.3. Last, in columns VII and VIII, we use industry*time fixed effects and include only unrelated sectors concerning the BEA output-input linkages to avoid instances where the initial shock does coincide with changes in the firm's demand for credit. In these columns, we investigate whether our results could be driven by sectors that are identified as "non-distressed", but that are linked to the distressed sectors through the supply chain (for instance, Carvalho, 2014; Acemoglu, Akcigit and Kerr, 2016). The estimated coefficients are negative and almost identical compared to column I.

In Panel B of Table 9, we rely on oil shocks instead of stock returns to define a sector in distress and repeat the Panel A analysis. We redefine the bank exposure by using the size of the oil shock to oil-dependent sectors in t and the relative exposure of the bank's portfolio to these sectors in $t-1$. In columns I-IV and V-VIII, we use the "economist" approach (Kilian and Murphy, 2014) and the "financial market" approach (Hamilton and Wu, 2014) to construct oil price expectations. Interestingly, the coefficient of interest is negative and significant in all specifications, indicating that a negative oil shock in the sectors that a bank is specialized in is related to a decrease in lending to non-oil affected firms relative to the pre-oil shock period.[23]

The above results provide evidence for the common lender mechanism.[24] One con-

[23] In Table A11, we show results for the common lender's mechanism when we use a weighted least square regression to avoid bias towards industries with more observations. For weights, we use the inverse of the probability that an observation is in the sample. Overall, the estimated coefficients are very similar to the baseline results, and we do not suffer from a potential sample selection bias.

[24] In Table A12, we provide some further robustness tests for the common lender's mechanism concerning the syndicate structure (lead lenders) and the GFC period. In columns I-III, we run the baseline specification only for the lead arrangers. In columns IV-VI and VII-IX, we analyse if the estimated coefficient is driven from specific variation when excluding the GFC or during the GFC, respectively.

cern, however, is that the $Exposure^{Dist}$ might be determined simultaneously with syndicated lending practices. To address this potential source of endogeneity, we adopt an instrumental-variables (IV) methodology. To yield exogenous variation in the exposure variable, we follow Favara and Giannetti (2017) and exploit mergers between banks that are active in the syndicated loan market. To do so, we collect data on M&A from the Fed and identify the banks in Dealscan. We then construct an instrument for the $Exposure^{Dist}$ variable using only the historical exposure variables of the target bank (acquired). We restrict attention to mergers occurring within a year preceding the origination of the syndicated loan. We also include bank, industry-time and bank-industry fixed effects. In our set-up, we effectively exploit variations in our exposure variable that is due to a recent merger. Our instrument satisfies the relevance criterion because a merger constitutes a relevant shock to the acquirer's bank portfolios. When a bank acquires another bank, its portfolio of loans subsequently incorporates the acquired bank's previously extended loans, thus exogenously broadening the acquiring bank's experience. In addition, it seems unlikely that the target's exposure affects the acquirer's bank lending decision due to the nature and size of these mergers.

Table A6 in the appendix shows the results from the two-stages least square estimation. In Panel A, we report the estimated coefficients of the first stage, which are positive and highly significant and in line with the literature (Giannetti and Saidi, 2019). The under-identification test shows no concerns regarding the instrument validity. Panel B shows that the second stage estimates are qualitatively and quantitatively similar to the baseline estimates. In Table A7 we replicate the IV analysis of Table A6, but we alter the definition of distress and rely on oil shocks instead of stock returns. Results are similar and comparable and thus are fully robust to this IV strategy.

In Table A8, we analyse any possible differences in loan pricing for different sectors that share the same bank. To do so, we use loan prices as our left-hand-side variable and analyze the average industry pricing. The estimated coefficients remain similar compared to the loan-level sample (Table 5). Finally, we explore the role of capital in the common lender mechanism. We split the bank-industry sample into $Distressed$ and $Non-distressed$ sectors and add the interaction on the $Specialization$*$Low\ capital$ dummy. If the search for extra yield drives the less capitalized banks to increase lending to affected sectors and at the same time decrease lending to non-affected sectors, we should find the results on the $Specialization$ and $Exposure^{Dist}$*$Low\ capital$ to be negative (positive) when sectors are in a non-distressed (distressed) situation. This is exactly what we find in Table A9. This result is in line with the risk-taking capacity of less capitalized banks, which is higher for banks with less capital (Jiménez, Ongena, Peydró and Saurina, 2017). Therefore, lower bank capitalization can enhance the common lender externality.[25]

4.4 Industry-level outcomes: Aggregate real effects

Given that banks are common lenders that can create indirect linkages among sectors, it is important to understand whether sector-specific shocks can spill over and impose negative aggregate externalities from affected to unaffected sectors. In this sub-section, we analyze the aggregate patterns of credit supply and industry fundamentals across unaffected industries with different degrees of exposure to banks that are specialized in affected industries. To do so, we aggregate the data at the industry level. Table 10 reports the estimated coefficients of equation (4) for unrelated and unaffected sectors. In this table, we interact the industry-level exposure variable with different proxies of financial turmoil like the GFC (Panel A) and $financial\ frictions$ (Panel B). The dependent variable is noted in the first row. Specifically, we use the credit supply from the syndicated market (Column I), investments (column II), total debt (column III), size (column IV), the number of employees (column V) and sales (column VI) all in log differences to measure the incremental changes after the shock. We use industry and time fixed effects and control for the industry's return on asset and cash flow volatility in all specifications.

Column I of Panel A shows that on average, the estimated coefficient of $Exposure^{Dist}$ is insignificant. However, the interaction term is negative and significant. The negative sign means, for example, that during the GFC exposed banks reallocate lending towards affected sectors and thus, the unaffected sectors cannot substitute the loss of credit from other sources (Iyer, Peydró, da Rocha-Lopes and Schoar, 2014). In the following columns (II-VI), we use different industry outcomes as left-hand-side variables to analyze aggregate real effects. We find that during good times unaffected sectors that borrow from exposed banks do not observe, on average, a drop in their credit supply, or a deterioration in their fundamentals. Uncorrelated sector-specific shocks diversify away as we aggregate the economy because there are fewer binding credit frictions during good times, and as a result, an unaffected sector can potentially compensate credit from alternative sources. However, we consistently find that during crises, unaffected sectors that borrow from exposed banks

[25] In Table A10, we further strengthen the argument for the role of capital using alternative thresholds (quartiles) and definitions like $Tier\ 1/TA$ to identify the less capitalized banks.

observe a deterioration in their fundamentals (coefficient from the interaction variable). Economically, the estimates suggest that one standard deviation increase in firms exposure to banks that experience shocks to their specialized sectors during bad times leads to a sizeable lower investment (9.6%), debt (8.9%), size (1%), employment (40%) and sales (20%).

In Panel B of Table 10, we follow the structure of Table 8 and use the Gilchrist and Zakrajšek (2012)'s EBP. In line with expectations, the coefficients of interest are qualitatively similar compared to Panel A, but the economic significance is lower, as expected because the $financial\ frictions$ variable is "smoother" compared to the GFC. Finally, in Panel C we replicate the analysis in Panel B, but we exploit data on the informational complexity of the products that each sector produces. Specifically, we keep only firms whose outputs are considered "differentiated". We expect that these firms will be further credit-constrained during financial frictions compared to Panel B. Indeed, the estimates confirm that the effect of banks' exposure is similar but more economically significant compared to Panel B. The above findings demonstrate that during good times non-financial shocks will average out as we aggregate across sectors. But during periods with more intense financial frictions, lending and industry fundamentals for unaffected sectors will be affected by their exposure to common lenders and their lending opportunities.

5 Conclusion

This paper analyses whether banks' lending specialization affects the propagation of sector-specific shocks to the economy. Specifically, in the presence of adverse sector-specific shocks, we investigate how bank lending specialization affects credit supply not only to sectors that banks specialize in but also crucially to unrelated (and unaffected) sectors.

We find that if a sector experiences a negative shock, banks specialising in lending to the sector increase their flow of credit to firms in the affected sector relative to non-specialized banks. We provide evidence that the increased lending to the affected sector is primarily focused on firms with better profitability outcomes up to three years after the loan origination. Thus, the results suggest that an increase in lending to the affected sector is not an artifact of zombie lending but in line with specialized banks lending to profitable firms (consistent with better screening and monitoring) in the negatively affected sector. In addition, we provide evidence that the loan interest rate charged by specialized banks for lending to the affected sectors is higher than that to the other unaffected sectors, and the effects tend to be stronger for under-capitalized banks. Importantly, we find that firms in unaffected sectors that have an outstanding loan with a bank that has a higher exposure to sectors hit by negative shocks experience a reduction in credit. That is, at the same time that specialized banks are increasing lending to affected sectors, these banks are decreasing lending to non-affected sectors.

To understand whether firms in unaffected sectors can compensate for the loss in credit from other banks/sources, we examine firm outcomes like bank credit, investment, total debt, size, employment and sales. We find that on average the firm outcomes in unaffected sectors do not witness any significant change. However, during periods of financial turmoil like the global financial crisis or when aggregate financing frictions are high, firms in unaffected sectors witness an overall reduction in their bank credit, size, employment and sales. Finally, we analyse the aggregate patterns of credit supply and industry fundamentals across unaffected industries with different degrees of exposure to banks that are specialized in affected industries. We find that sector-specific shocks will average out during good times as we aggregate across sectors. But during periods with more intense financial frictions, unaffected sectors that borrow from exposed banks observe a deterioration in their fundamentals.

References

Acemoglu, D., Akcigit, U. and Kerr, W.: 2016, Networks and the macroeconomy: An empirical exploration, *Nber macroeconomics annual* **30**(1), 273–335.

Acemoglu, D., Carvalho, V. M., Ozdaglar, A. and Tahbaz-Salehi, A.: 2012, The network origins of aggregate fluctuations, *Econometrica* **80**(5), 1977–2016.

Acharya, V. V., Hasan, I. and Saunders, A.: 2006, Should banks be diversified? evidence from individual bank loan portfolios, *The Journal of Business* **79**(3), 1355–1412.

Allen, F. and Gale, D.: 2000, Financial contagion, *Journal of Political Economy* **108**(1), 1–33.

Baumeister, C. and Kilian, L.: 2016, Forty years of oil price fluctuations: Why the price of oil may still surprise us, *Journal of Economic Perspectives* **30**(1), 139–60.

Berg, T., Saunders, A. and Steffen, S.: 2016, The total cost of corporate borrowing in the loan market: Don't ignore the fees, *The Journal of Finance* **71**(3), 1357–1392.

Caballero, R. J., Hoshi, T. and Kashyap, A. K.: 2008, Zombie lending and depressed restructuring in japan, *American Economic Review* **98**(5), 1943–77.

Campello, M. and Gao, J.: 2017, Customer concentration and loan contract terms, *Journal of Financial Economics* **123**(1), 108–136.

Carey, M., Post, M. and Sharpe, S. A.: 1998, Does corporate lending by banks and finance companies differ? evidence on specialization in private debt contracting, *The Journal of Finance* **53**(3), 845–878.

Carvalho, D.: 2015, Financing constraints and the amplification of aggregate downturns, *The Review of Financial Studies* **28**(9), 2463–2501.

Carvalho, V. M.: 2014, From micro to macro via production networks, *Journal of Economic Perspectives* **28**(4), 23–48.

Chakraborty, I., Goldstein, I. and MacKinlay, A.: 2020, Monetary stimulus and bank lending, *Journal of Financial Economics* **136**(1), 189–218.

Chava, S. and Roberts, M. R.: 2008, How does financing impact investment? the role of debt covenants, *The Journal of Finance* **63**(5), 2085–2121.

Chodorow-Reich, G.: 2014, The employment effects of credit market disruptions: Firm-level evidence from the 2008–9 financial crisis, *The Quarterly Journal of Economics* **129**(1), 1–59.

Cortés, K. R. and Strahan, P. E.: 2017, Tracing out capital flows: How financially integrated banks respond to natural disasters, *Journal of Financial Economics* **125**(1), 182–199.

Costello, A. M.: 2020, Credit market disruptions and liquidity spillover effects in the supply chain, *Journal of Political Economy* **128**(9), 3434–3468.

Delis, M. D., Kokas, S. and Ongena, S.: 2017, Bank market power and firm performance, *Review of Finance* **21**(1), 299–326.

Diamond, D. W.: 1984, Financial intermediation and delegated monitoring, *The Review of Economic Studies* **51**(3), 393–414.

Domanski, D., Kearns, J., Lombardi, M. J. and Shin, H. S.: 2015, Oil and debt, *BIS Quarterly Review March* .

Fama, E. F.: 1980, Agency problems and the theory of the firm, *Journal of Political Economy* **88**(2), 288–307.

Favara, G. and Giannetti, M.: 2017, Forced asset sales and the concentration of outstanding debt: evidence from the mortgage market, *The Journal of Finance* **72**(3), 1081–1118.

Federico, S., Hassan, F. and Rappoport, V.: 2020, Trade shocks and credit reallocation, *Bank of Italy Temi di Discussione (Working Paper) No* **1289**.

Freixas, X. and Rochet, J.-C.: 2008, *Microeconomics of Banking*, MIT press.

Gabaix, X.: 2011, The granular origins of aggregate fluctuations, *Econometrica* **79**(3), 733–772.

Gabaix, X. and Koijen, R. S.: 2021, In search of the origins of financial fluctuations: The inelastic markets hypothesis, *Technical report*, National Bureau of Economic Research.

Galaasen, S., Jamilov, R., Juelsrud, R. and Rey, H.: 2020, Granular credit risk, *Technical report*, National Bureau of Economic Research.

Giannetti, M., Burkart, M. and Ellingsen, T.: 2011, What you sell is what you lend? explaining trade credit contracts, *The Review of Financial Studies* **24**(4), 1261–1298.

Giannetti, M. and Saidi, F.: 2019, Shock propagation and banking structure, *The Review of Financial Studies* **32**(7), 2499–2540.

Gilchrist, S. and Zakrajšek, E.: 2012, Credit spreads and business cycle fluctuations, *American Economic Review* **102**(4), 1692–1720.

Hamilton, J. D. and Wu, J. C.: 2014, Risk premia in crude oil futures prices, *Journal of International Money and Finance* **42**, 9–37.

Imbens, G. W. and Lemieux, T.: 2008, Regression discontinuity designs: A guide to practice, *Journal of econometrics* **142**(2), 615–635.

Imbens, G. W. and Wooldridge, J. M.: 2009, Recent developments in the econometrics of program evaluation, *Journal of economic literature* **47**(1), 5–86.

Irani, R. M., Iyer, R., Meisenzahl, R. R. and Peydró, J.-L.: 2020, The Rise of Shadow Banking: Evidence from Capital Regulation, *The Review of Financial Studies* . Forthcoming.

Ivashina, V. and Scharfstein, D.: 2010, Bank lending during the financial crisis of 2008, *Journal of Financial Economics* **97**(3), 319–338.

Iyer, R., Peydró, J.-L., da Rocha-Lopes, S. and Schoar, A.: 2014, Interbank liquidity crunch and the firm credit crunch: Evidence from the 2007–2009 crisis, *The Review of Financial Studies* **27**(1), 347–372.

Jiménez, G., Ongena, S., Peydró, J.-L. and Saurina, J.: 2012, Credit supply and monetary policy: Identifying the bank balance-sheet channel with loan applications, *American Economic Review* **102**(5), 2301–26.

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

Jiménez, G., Ongena, S., Peydró, J.-L. and Saurina, J.: 2017, Macroprudential policy, countercyclical bank capital buffers, and credit supply: Evidence from the spanish dynamic provisioning experiments, *Journal of Political Economy* **125**(6), 2126–2177.

Khwaja, A. I. and Mian, A.: 2008, Tracing the impact of bank liquidity shocks: Evidence from an emerging market, *American Economic Review* **98**(4), 1413–42.

Kilian, L. and Murphy, D. P.: 2014, The role of inventories and speculative trading in the global market for crude oil, *Journal of Applied Econometrics* **29**(3), 454–478.

Kilian, L. and Vigfusson, R. J.: 2017, The role of oil price shocks in causing us recessions, *Journal of Money, Credit and Banking* **49**(8), 1747–1776.

Levine, R.: 2005, Finance and growth: theory and evidence, *Handbook of Economic Growth* **1**, 865–934.

Lim, J., Minton, B. A. and Weisbach, M. S.: 2014, Syndicated loan spreads and the composition of the syndicate, *Journal of Financial Economics* **111**(1), 45–69.

Muendler, M.-A.: 2009, Converter from sitc to isic, *University of California-San Diego, unpublished mimeo* .

Opler, T. C. and Titman, S.: 1994, Financial distress and corporate performance, *The Journal of Finance* **49**(3), 1015–1040.

Paravisini, D., Rappoport, V. and Schnabl, P.: 2015, Specialization in bank lending: Evidence from exporting firms, *Technical report*, National Bureau of Economic Research.

Rauch, J. E.: 1999, Networks versus markets in international trade, *Journal of International Economics* **48**(1), 7–35.

Rehbein, O. and Ongena, S.: 2021, Flooded through the back door: The role of bank capital in local shock spillovers, *Journal of Financial and Quantitative Analysis* . Forthcoming.

Roberts, M. R.: 2015, The role of dynamic renegotiation and asymmetric information in financial contracting, *Journal of Financial Economics* **116**(1), 61–81.

Sharpe, S. A.: 1990, Asymmetric information, bank lending, and implicit contracts: A stylized model of customer relationships, *The Journal of Finance* **45**(4), 1069–1087.

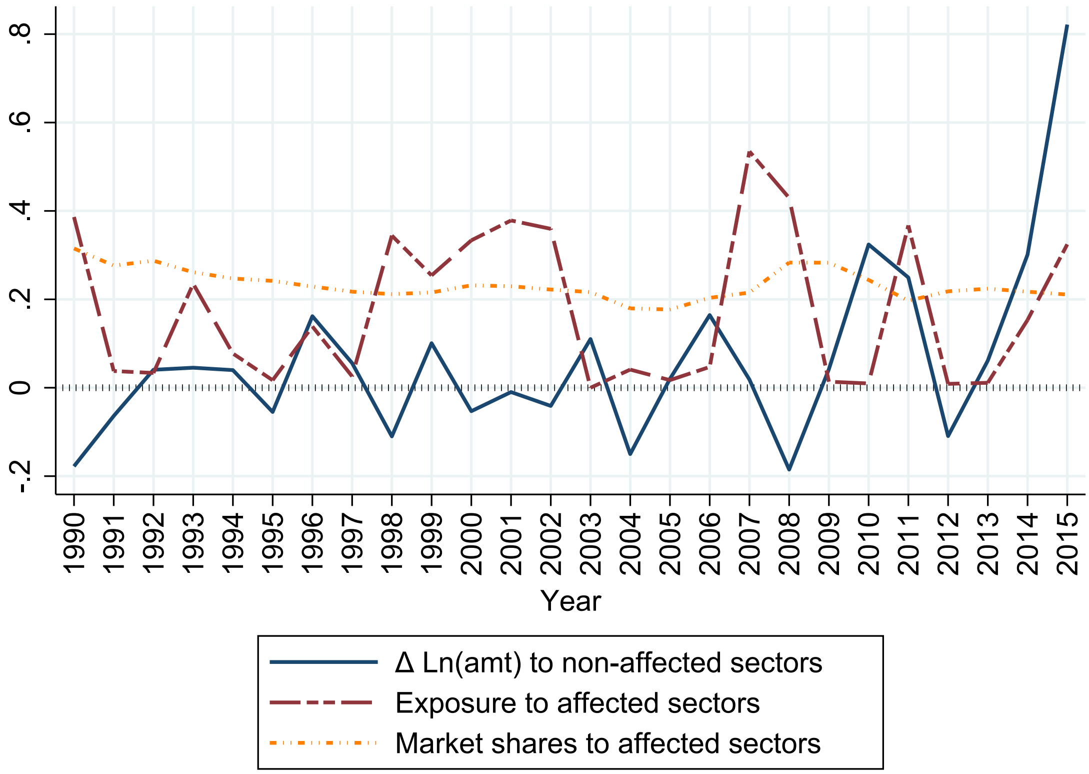
Smolyansky, M.: 2019, Policy externalities and banking integration, *Journal of Financial Economics* **132**(3), 118–139.

Stein, J.: 2013, The fire-sales problem and securities financing transactions, *Speech by Governor Jeremy C. Stein at the Federal Reserve Bank of New York during the Workshop on Fire Sales as a Driver of Systemic Risk in Triparty Repo and other Secured Funding Markets, New York.*

Sufi, A.: 2007, Information asymmetry and financing arrangements: Evidence from syndicated loans, *The Journal of Finance* **62**(2), 629–668.

Figures

Figure 1: Bank lending and industry downturns



Note: This figure aggregates our data at the year level and plots the time series. The blue line shows the changes in the credit amount for non-affected sectors that did not experience negative abnormal returns (lower than -10%). The maroon line shows the degree to which a bank is specialized and exposed to affected sectors and the orange line shows the market shares to affected sectors.

Table 1: Summary statistics

	Obs	Mean	SD	Min	Median	Max
Panel A: Loan-level sample						
Ln(amount)	101,333	3.215	1.071	-4.714	3.239	10.222
AISD (bps)	102,069	155.003	112.985	0.700	137.500	1,275
Margin (bps)	101,724	142.362	108.808	0.01	125.000	1,275
Specialization	102,066	0.107	0.163	0.000	0.053	1.000
Market shares	102,062	0.082	0.091	0.000	0.051	1.000
$Exposure^{Dist}$	102,069	0.204	0.293	0.000	0.025	1.000
$Market\ shares^{Dist}$	102,067	0.052	0.120	0.000	0.005	1.000
Distress	102,069	0.396	0.489	0.000	0.000	1.000
Bank size	102,069	18.130	2.031	8.277	18.185	21.389
Tier 2/TA	102,069	0.091	0.037	0.042	0.083	0.300
C&I Loan/TA	102,069	0.177	0.092	0.000	0.166	0.466
Deposits/TA	102,069	0.666	0.135	0.011	0.681	0.909
ROA (bank)	102,069	0.010	0.006	-0.022	0.011	0.032
Ln(size)	102,069	7.457	1.756	-0.713	7.476	14.608
ROA (firm)	102,069	0.035	0.119	-8.273	0.042	2.528
Tobins' q	102,069	0.539	0.410	-0.903	0.485	5.318
Panel B: Firm-level sample						
Ln(amount)	34,821	4.872	1.715	0.000	4.932	9.808
Ln(investment)	28,522	0.178	0.328	-0.051	0.125	39.000
Ln(debt)	28,405	-1.656	1.336	-11.567	-1.309	2.061
Ln(size)	30,354	6.676	2.075	-6.215	6.691	14.706
Ln(employment)	29,184	1.169	1.923	-6.908	1.229	7.741
Ln(sales)	30,275	6.563	2.004	-6.215	6.627	13.089
$Exposure^{Dist}$	34,669	0.201	0.291	0.000	0.035	1.000
Distress	34,753	0.386	0.469	0.000	0.386	1.000
GFC	35,039	0.068	0.252	0.000	0.000	1.000
Frictions	35,039	0.524	0.499	0.000	1.000	1.000
Firm specificity	35,039	0.180	0.384	0.000	0.000	1.000
Panel C: Bank-industry-level sample						
ΔLn(amount)	69,661	0.058	2.291	-9.284	0.000	9.056
$Exposure^{Dist}$	69,656	0.174	0.268	0.000	0.020	1.000
$Market\ shares^{Dist}$	69,661	0.028	0.089	0.000	0.002	1.000
$Exposure^{Oil}$	69,661	0.091	0.166	0.000	0.000	1.000
Distress	69,520	0.137	0.344	0.000	0.000	1.000
Oil-dependent sectors	67,273	0.199	0.399	0.000	0.000	1.000
$Merger\ implied\ Exposure^{Dist}$	69,624	0.182	0.288	0.000	0.004	1.000
$Merger\ implied\ Exposure^{Oil}$	69,661	0.102	0.179	0.000	0.000	1.406
Panel D: Industry-level sample						
ΔLn(amount)	3,832	-0.004	1.229	-6.344	0.000	5.381
ΔLn(investment)	3,877	-0.004	0.295	-1.124	-0.000	0.898
ΔLn(debt)	3,876	-0.015	0.088	-0.880	-0.013	0.673
ΔLn(size)	3,877	0.003	0.019	-0.369	0.003	0.275
ΔLn(employment)	3,159	0.029	1.393	-9.496	0.075	6.915
ΔLn(sales)	3,877	0.007	0.034	-0.583	0.006	0.358
$Exposure^{Dist}$	3,475	0.012	0.045	0.000	0.001	1.000
Distress (supply chain)	3,826	0.292	0.424	0.000	0.000	1.000
GFC	3,911	0.101	0.301	0.000	0.000	1.000
Frictions	3,911	0.593	0.491	0.000	1.000	1.000
Industry specificity	3,911	0.142	0.349	0.000	0.000	1.000

Panel A reports summary statistics for a sample of syndicated loans that were originated in the U.S. from 1987h1 until 2016h1. Panel B shows summary statistics for the variables of interest when we aggregate loans at the firm-time level. Panel C shows summary statistics when we aggregate loans at the bank-industry-time level. Panel C shows shows summary statistics when we aggregate loans at the industry-time level. Table A1 in appendix defines all variables.

Table 2: Normalized differences in univariate analysis

	I	II	III	IV	V
	Non-Distressed		Distressed		Difference
	(A)		(B)		(B)-(A)
	Mean	SD	Mean	SD	Mean
$AISD$ (bps)	153.414	111.03	161.235	120.13	0.068
$Margin$ (bps)	141.191	107.27	146.951	114.51	0.052
Specialization	0.108	0.162	0.106	0.167	0.009
$Market\ shares$	0.082	0.092	0.08	0.091	0.027
$Tier\ 2/TA$	0.091	0.037	0.09	0.036	-0.051

The table reports normalized differences for a sample of syndicated loans that were originated in the U.S. from 1987h1 until 2016h1. The difference is defined as $\Delta_X = \frac{\overline{X}_1 - \overline{X}_0}{\sqrt{S_0^2 + S_1^2}}$, where the $\overline{X}$ and S^2 is the sample mean and variance in each subsample, respectively. The all-in-spread drawn ($AISD$) is defined as the sum of the spread over LIBOR plus the facility fee (bps), while the $Margin$ includes only the spread. *Specialization* is defined as the ratio of total credit granted by a bank to a specific sector relative to bank's total credit granted. $Market\ shares$ measures the ratio of total credit granted by a bank to a specific sector relative to all credit granted by all banks to the specific sector. $Tier\ 2/TA$ is the ratio of banks capital relative to it's total assets.

Table 3: Do banks lend more to firms in affected sectors: Loan level

Dependent variable:	Ln(amount)		
	I	II	III
$Exposure^{Dist}_{t-1}$	0.174***		0.158***
	(3.517)		(3.146)
$Market\ shares^{Dist}_{t-1}$		0.009**	0.005
		(2.542)	(1.288)
Observations	26,987	26,987	26,987
Adjusted R-squared	0.718	0.719	0.718
Bank and loan controls	Y	Y	Y
Bank FE	Y	Y	Y
Firm*Time FE	Y	Y	Y
Clustered standard errors	Bank,Firm	Bank,Firm	Bank,Firm

The table reports coefficients and t-statistics (in parenthesis) for the bank lending only to firms that operate in distressed industries. The unit of our analysis is at the loan level. The sample consists of syndicated loans that were originated in the U.S. from 1987h1 until 2016h1. The dependent variable is the loan amount held by each lender at origination. $Exposure^{Dist}_{t-1}$ and $Market\ shares^{Dist}_{t-1}$ are the bank specialization and market shares to industries that are in distress, respectively. We define sectors in distress (affected) as a dummy variable that takes the value one if the semi-annual returns of the sector that the firm operates are higher than -10% and zero otherwise. In all specifications we include different levels of fixed effects as noted in the lower part of the table and the following bank and loan control variables: *Bank size*, *Tier 2/TA*, *C&I Loans/TA*, *Deposits/TA*, *ROA (bank)*, *Revolver*, *Maturity (Months)*, *Rel. Lending*. Table A1 in appendix defines all remaining variables. *p <.1; **p <.05; ***p <.01.

Table 4: Do banks lend to better-performing firms in affected sectors: Loan level

Dependent variable:	Ln(amount)			
	I	II	III	IV
Time window:	Post: 1 year	Post: 2 years	Post: 3 years	Pre: 1 year
Panel A: Firm profitability				
$Exposure^{Dist}_{t-1}$	0.143***	0.143***	0.143***	0.124***
	(3.391)	(3.418)	(3.458)	(2.639)
$Exposure^{Dist}_{t-1}$ * $\Delta(ROA_{t+1} - ROA_t)$	0.377*			
	(1.866)			
$Exposure^{Dist}_{t-1}$ * $\Delta(ROA_{t+2} - ROA_t)$		0.720***		
		(2.795)		
$Exposure^{Dist}_{t-1}$ * $\Delta(ROA_{t+3} - ROA_t)$			0.572***	
			(3.350)	
$Exposure^{Dist}_{t-1}$ * ROA_{t-1}				0.446
				(1.054)
Observations	20,976	20,950	21,001	20,029
Adjusted R-squared	0.720	0.721	0.720	0.720
Panel B: The role of capital				
$Low\ capital_t$ * $Exposure^{Dist}_{t-1}$ * $\Delta(ROA_{t+1} - ROA_t)$	0.426*			
	(1.788)			
$Low\ capital_t$ * $Exposure^{Dist}_{t-1}$ * $\Delta(ROA_{t+2} - ROA_t)$		0.634**		
		(2.234)		
$Low\ capital_t$ * $Exposure^{Dist}_{t-1}$ * $\Delta(ROA_{t+3} - ROA_t)$			0.563***	
			(3.550)	
$Low\ capital_t$ * $Exposure^{Dist}_{t-1}$ * ROA_{t-1}				0.970**
				(2.463)
Observations	17,849	17,823	17,874	17,160
Adjusted R-squared	0.721	0.722	0.721	0.721
Bank and loan controls	Y	Y	Y	Y
Bank FE	Y	Y	Y	Y
Firm*Time FE	Y	Y	Y	Y
Clustered standard errors	Bank,Firm	Bank,Firm	Bank,Firm	Bank,Firm

The table reports coefficients and t-statistics (in parenthesis) for the bank lending only to firms that operate in distressed industries. The unit of our analysis is at the loan level. The sample consists of syndicated loans that were originated in the U.S. from 1987h1 until 2016h1. The dependent variable is the loan amount held by each lender at origination. $Exposure^{Dist}_{t-1}$ is the bank specialization to industries that are in distress. We define sectors in distress (affected) as a dummy variable that takes the value one if the semi-annual returns of the sector that the firm operates are higher than -10% and zero otherwise. Panel A shows changes in the firm's ROA. In columns I-III, we calculate the difference between the firm's ROA from the first year until the third year after the loan origination minus the ROA at the time of the loan (post). In column IV, we use the firm's ROA one year before the loan origination (pre). Panel B shows the role of capital. The *Low capital* dummy is equal to one whether the bank's Tier 2 capital is below the sample mean. In all specifications we include different levels of fixed effects as noted in the lower part of the table and the following bank and loan control variables: $Bank\ size$, $Tier\ 2/TA$ (only in Panel A), $C\&I\ Loans/TA$, $Deposits/TA$, ROA $(bank)$, $Revolver$, $Maturity$ $(Months)$, $Rel.\ Lending$. Table A1 in appendix defines all remaining variables. *p <.1; **p <.05; ***p <.01.

Table 5: Is the cost of lending more expensive to firms in affected sectors: Loan level

Dependent variable:	AISD (bps)			Margin (bps)		
	I	II	III	IV	V	VI
Panel A: Cost of lending						
$Distress_t$	12.161***	10.792***	23.433***	12.021***	11.500***	25.392***
	(8.178)	(6.858)	(7.646)	(7.252)	(6.721)	(8.345)
$Specialization_{t-1}$ * $Distress_t$	-6.551***	-4.902*	-4.573	-5.141**	-4.687*	-6.888**
	(-2.669)	(-1.908)	(-1.641)	(-1.964)	(-1.728)	(-2.138)
Observations	102,069	101,580	98,866	102,557	102,075	99,351
Adjusted R-squared	0.701	0.706	0.919	0.625	0.630	0.832
Panel B: The role of capital						
$Low\ capital_t$ * $Specialization_{t-1}$ * $Distress_t$	5.245**	6.004***	7.681**	5.782***	6.572***	7.242**
	(2.540)	(2.849)	(2.329)	(2.645)	(2.929)	(1.997)
Observations	84,565	84,306	82,518	84,883	84,627	82,840
Adjusted R-squared	0.713	0.716	0.916	0.646	0.649	0.836
Bank controls	Y		Y	Y		Y
Firm controls	Y	Y		Y	Y	
Loan controls	Y	Y	Y	Y	Y	Y
Time FE	Y			Y		
Bank FE	Y		Y	Y		Y
Firm FE	Y	Y		Y	Y	
Bank*Time FE		Y			Y	
Firm*Time FE			Y			Y
Clustered standard errors	Bank,Firm	Bank,Firm	Bank,Firm	Bank,Firm	Bank,Firm	Bank,Firm

The table reports coefficients and t-statistics (in parenthesis) for the bank lending to firms that operate in affected and non affected industries. The unit of our analysis is at the loan level. The sample consists of syndicated loans that were originated in the U.S. from 1987h1 until 2016h1. The dependent variables are indicated on the top of each column. In columns I-III, the dependent variable is the all-in-spread drawn (AISD) and is defined as the sum of the spread over LIBOR plus the facility fee (bps), while in columns IV-VI, we only include the spread. $Specialization_{t-1}$ is the bank specialization and is defined as the share of total credit granted by a bank to a specific sector relative to bank's total credit. *Distress* is a dummy variable that takes the value one if the semi-annual returns of the sector that the firm operates are higher than -10% and zero otherwise. Panel A shows the cost of lending for affected and non affected firms, while Panel B shows the role of capital. The *Low capital* dummy is equal to one whether the bank's Tier 2 capital is below the sample mean. In all specifications, we include different levels of fixed effects as noted in the lower part of the table. Bank controls include: $Bank\ size$, $Tier\ 2/TA$ (only in Panel A), $C\&I\ Loans/TA$, $Deposits/TA$, and $ROA\ (bank)$. Firm controls include: $Ln(size)$, $ROA\ (firm)$, and $Tobin's\ q$. Loan controls include: $Revolver$, $Maturity\ (Months)$, and $Rel.\ Lending$. Table A1 in appendix defines all remaining variables. *p <.1; **p <.05; ***p <.01.

Table 6: Do banks reduce lending to firms in non-affected industries: loan level

	I	II	III	IV	V	VI	VII	VIII	IX	X
Panel A: Industry downturns										
Supply chain: BEA Input-Output								Unrelated sectors		
$Exposure^{Dist}_{t-1}$	-0.079***		-0.072***	-0.099***	-0.085***	-0.147***	-0.111***	-0.078**	-0.072**	-0.140**
	(-3.594)		(-3.118)	(-3.816)	(-2.953)	(-2.875)	(-3.749)	(-2.418)	(-2.205)	(-2.021)
$Market\ shares^{Dist}_{t-1}$		-0.006*	-0.002						-0.004	0.007
		(-1.653)	(-0.638)						(-1.502)	(0.620)
Observations	85,560	85,558	85,558	85,064	83,229	82,719	74,926	62,402	62,399	61,894
Adjusted R-squared	0.509	0.509	0.509	0.516	0.679	0.681	0.544	0.674	0.674	0.675
Bank controls	Y	Y	Y		Y					
Firm Controls	Y	Y	Y	Y			Y	Y	Y	
Loan controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y							
Bank FE	Y	Y	Y		Y			Y	Y	
Firm FE	Y	Y	Y	Y						
Bank*Time FE				Y		Y	Y			Y
Firm*Time FE					Y	Y		Y	Y	Y
Bank*Firm FE							Y			
Panel B: Oil shocks										
	I	II	III	IV	V	VI	VII	VIII	IX	X
Oil shock group:	"Economist" approach					"Financial market" approach				
Supply chain: BEA Input-Output					Unrelated					Unrelated
$Exposure^{Oil}_{t-1}$	-0.113***	-0.082**	-0.136***	-0.096*	-0.174***	-0.144***	-0.144***	-0.124***	-0.102**	-0.127***
	(-3.447)	(-2.014)	(-3.883)	(-1.737)	(-3.861)	(-4.727)	(-3.768)	(-3.980)	(-2.086)	(-3.345)
Observations	81,138	80,555	78,759	78,189	48,803	81,138	80,555	78,759	78,189	48,803
Adjusted R-squared	0.525	0.531	0.687	0.689	0.679	0.525	0.531	0.687	0.689	0.679
Bank controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Loan controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	Y					Y				
Bank FE	Y		Y		Y	Y		Y		Y
Firm FE	Y	Y				Y	Y			
Bank*Time FE		Y		Y			Y		Y	
Firm*Time FE			Y	Y	Y			Y	Y	Y
Clustered standard errors	Bank,Firm	Bank,Firm	Bank,Firm	Bank,Firm	Bank,Firm	Bank,Firm	Bank,Firm	Bank,Firm	Bank,Firm	Bank,Firm

The table reports coefficients and t-statistics (in parenthesis) for the bank lending to firms that operate in non-affected industries. The sample consists of syndicated loans that were originated in the U.S. from 1987h1 until 2016h1. The dependent variable is the loan amount that a bank lends to a firm operating in non-affected industries. In Panel A, $Exposure^{Dist}_{t-1}$ and $Market\ shares^{Dist}_{t-1}$ are the bank specialization and market shares to industries that are in distress, respectively. We define sectors in distress as a dummy variable that takes the value one if the semi-annual returns of the sector that the firm operates are higher than -10% and zero otherwise. In columns VIII, IX and X, we use the BEA Input-Output table and exclude related sectors from the regression analysis. In Panel B, we refine the bank exposure ($Exposure^{Oil}_{t-1}$) to measure an unanticipated increase in oil prices by aggregating for each bank the share of the specialization in $t-1$ to industries that are oil affected in t. In columns I-V and VI-X, we use the "economist" approach (Kilian and Murphy, 2014) and the "financial market" approach (Hamilton and Wu, 2014) to construct oil price expectations, respectively. In all specifications, we include different levels of fixed effects, as noted in the lower part of the table. Bank controls include: $Bank\ size$, $Tier\ 2/TA$, $C\&I\ Loans/TA$, $Deposits/TA$, and $ROA\ (bank)$. Firm controls include: $Ln(size)$, $ROA\ (firm)$, and $Tobin's\ q$. Loan controls include: $Revolver$, $Maturity\ (Months)$, and $Rel.\ Lending$. Table A1 in appendix defines all remaining variables. *$p<.1$; **$p<.05$; ***$p<.01$.

Table 7: When do we observe spillovers: Loan level

Dependent variable:	Ln(amount)				
	I	II	III	IV	V
Group:	Within sectors	Only unaffected and unrelated sectors			
$Specialization_{t-1}$	0.334***				
	(6.098)				
$Negative\ returns_t$	-0.001*				
	(-1.727)				
$Specialization_{t-1}$ * $negative\ returns_t$	-0.005**				
	(-1.961)				
$Exposure^{dist}_{t-1}$		0.018***	0.011***	0.015***	0.021***
		(10.672)	(3.332)	(9.280)	(10.223)
$Exposure^{dist}_{t-1}$ * GFC_t			0.009**	0.015***	0.021***
			(2.364)	(9.280)	(10.223)
$Specialization\ in\ nondistress_{t-1}$				0.021***	0.022***
				(54.437)	(54.227)
$Exposure^{dist}_{t-1}$ * $Specialization\ in\ nondistress_{t-1}$					-0.000***
					(-4.243)
Observations	99,323	86,234	86,234	86,234	86,234
Adjusted R-squared	0.499	0.516	0.517	0.572	0.573
Bank controls	Y	Y	Y	Y	Y
Firm controls	Y	Y	Y	Y	Y
Loan controls	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y
Bank FE	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y
Clustered standard errors	Bank,Firm	Bank,Firm	Bank,Firm	Bank,Firm	Bank,Firm

The table reports coefficients and t-statistics (in parenthesis). The unit of our analysis is at the loan level for a sample consisting of syndicated loans that originated in the U.S. from 1987h1 until 2016h1. The dependent variable is the loan amount held by each lender. The variable *Specialization* is the ratio of total credit granted by a bank to individual sectors relative to the bank's total credit. The negative returns variable captures the negative semi-annual returns in a two-digit SIC industry code and zero otherwise. $Exposure^{dist}$ is for each bank the share of their specialization times the negative returns (we replace the -10% threshold dummy with the negative returns). *Specialization in nondistress* is the specialization of the bank to the non distress sectors and GFC is a dummy variable that takes the value of one during the great recession. Columns I reveals a within-sector variation while columns II-V is for only unaffected and unrelated sectors. In all specifications, we include different fixed effects, as noted in the lower part of the table. Bank controls include: $Bank\ size$, $Tier\ 2/TA$, $C\&I\ Loans/TA$, $Deposits/TA$, and $ROA\ (bank)$. Firm controls include: $Ln(size)$, $ROA\ (firm)$, and $Tobin's\ q$. Loan controls include: $Revolver$, $Maturity\ (Months)$, and $Rel.\ Lending$. Table A1 in appendix defines all remaining variables. *p <.1; **p <.05; ***p <.01.

Table 8: Do industry spillovers impact real economic outcomes: Firm level

Dependent variable	Ln(amount)	Ln(investment)	Ln(debt)	Ln(size)	Ln(employment)	Ln(sales)
	I	II	III	IV	V	VI
Panel A: Global Financial Crisis						
$Exposure^{Dist}_{t-1}$	0.081	-0.115***	0.128	-0.057**	0.124	-0.078**
	(1.385)	(-9.917)	(0.945)	(-2.030)	(1.508)	(-2.412)
$Exposure^{Dist}_{t-1}$ * GFC_t	-1.600**	0.116	-0.803*	-1.221***	-0.665**	-0.846***
	(-2.296)	(1.151)	(-1.796)	(-3.413)	(-2.704)	(-3.005)
Observations	19,916	18,888	18,812	19,916	19,366	19,913
Adjusted R-squared	0.660	0.209	0.517	0.931	0.927	0.926
Panel B: Financial Frictions						
$Exposure^{Dist}_{t-1}$	-0.249	-0.072***	0.076	-0.179***	0.008	0.055
	(-1.585)	(-3.426)	(0.692)	(-2.618)	(0.303)	(0.987)
$Exposure^{Dist}_{t-1}$ * $Frictions_t$	-0.389**	-0.059***	-0.201*	-0.124*	-0.082**	-0.082**
	(-2.321)	(-2.603)	(-1.670)	(-1.673)	(-2.403)	(-2.355)
Observations	19,916	18,888	18,812	19,916	19,150	19,689
Adjusted R-squared	0.660	0.209	0.517	0.931	0.926	0.925
Panel C: Firm Specificity						
$Exposure^{Dist}_{t-1}$	-0.721**	-0.042	-0.143	-0.566***	-0.107	-0.063
	(-2.202)	(-1.305)	(-0.566)	(-3.604)	(-1.615)	(-0.857)
$Exposure^{Dist}_{t-1}$ * $Frictions_t$	-0.847**	-0.109***	0.134	-0.461**	-0.292***	-0.366***
	(-2.221)	(-2.806)	(0.448)	(-2.515)	(-3.211)	(-3.671)
Observations	3,847	3,783	3,654	3,847	3,723	3,813
Adjusted R-squared	0.575	0.458	0.479	0.918	0.940	0.922
Firm controls	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Clustered standard errors	Firm,Time	Firm,Time	Firm,Time	Firm,Time	Firm,Time	Firm,Time

The table reports coefficients and t-statistics (in parenthesis) for non-affected firms. We aggregate a sample of U.S. syndicated loans for firms covered in Dealscan at the firm-semester level from 1987h1 until 2016h1. The dependent variables are reported in the second line. In column I, we measure the total syndicated amount held by each firm, column II captures the value of investments, column III captures external debt excluding the syndicated market, column IV the total assets, column V the total number of employees, and in column VI we use the sales. $Exposure^{Dist}$ is the firm-level exposure for bank's specialization to industries that are in distress and is defined as a weighted sum approach. In Panel A, the variables GFC is a dummy equal to one during the Great Recession. In Panel B, the variable $financial\ frictions$ is a dummy equals one if the Excess Bond Premium (EBP) is positive. The EBP is the unexplained component of the credit spread in the corporate bond market, which is not related to borrower' creditworthiness (Gilchrist and Zakrajšek, 2012). In Panel C, following Rauch (1999), we keep only firms whose outputs are considered "differentiated" if neither sold on an exchange nor reference pricing. To do so, for each firm, we capture the share of SITC heterogeneous products. In all specifications, we include firm and time fixed effects as noted in the lower part of the table, and also we control for the firm's return on assets and cash flow volatility. Table A1 in appendix defines all remaining variables. *p <.1; **p <.05; ***p <.01.

Table 9: Common lenders mechanism: bank-industry level

	I	II	III	IV	V	VI	VII	VIII
Panel A: Industry downturns								
Supply chain: BEA Input-Output							Unrelated sectors	
$Exposure^{Dist}_{t-1}$	-0.228***		-0.233***	-0.347***	-0.281***	-0.365***	-0.210**	-0.218**
	(-2.736)		(-2.768)	(-4.518)	(-3.401)	(-4.197)	(-2.340)	(-2.410)
$Market\ shares^{Dist}_{t-1}$		-0.001	0.004					0.009
		(-0.039)	(0.338)					(0.666)
Observations	69,655	69,661	69,655	69,653	69,595	69,268	59,857	59,857
Adjusted R-squared	0.0139	0.0138	0.0139	0.165	0.168	0.185	0.177	0.177
Time FE	Y	Y	Y					
Industry FE	Y	Y	Y					
Bank FE	Y	Y	Y		Y		Y	Y
Industry*Time FE				Y	Y	Y	Y	Y
Bank*Industry FE						Y		
Panel B: Oil shocks								
	I	II	III	IV	V	VI	VII	VIII
Oil shock group:	"Economist" approach				"Financial market" approach			
Supply chain: BEA Input-Output				Unrelated				Unrelated
$Exposure^{Oil}_{t-1}$	-0.548***	-0.535***	-0.543***	-0.490***	-0.592***	-0.572***	-0.590***	-0.477***
	(-7.583)	(-7.359)	(-7.269)	(-5.462)	(-9.181)	(-8.660)	(-8.631)	(-5.998)
Observations	67,996	67,954	67,755	47,148	67,996	67,954	67,755	47,148
Adjusted R-squared	0.0140	0.155	0.161	0.165	0.0143	0.155	0.162	0.165
Bank controls	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	Y				Y			
Industry FE	Y				Y			
Bank FE	Y	Y		Y	Y	Y		Y
Industry*Time FE		Y	Y	Y		Y	Y	Y
Bank*Industry FE			Y				Y	
Clustered standard errors	Bank,Industry	Bank,Industry	Bank,Industry	Bank,Industry	Bank,Industry	Bank,Industry	Bank,Industry	Bank,Industry

The table reports coefficients and t-statistics (in parenthesis) for non-affected sectors. We aggregate a sample of U.S. syndicated loans at the bank-industry-semester level from 1987h1 until 2016h1. The dependent variable is the growth in lending that a bank lends to non-affected industries. In Panel A, $Exposure^{Dist}$ and $Market\ shares^{Dist}$ are the bank specialization and market shares to industries that are in distress, respectively. We define sectors in distress as a dummy variable that takes the value one if the semi-annual returns of the sector that the firm operates are higher than -10% and zero otherwise. In columns VII and VIII, we use the BEA Input-Output table and exclude related sectors from the regression analysis. In Panel B, we refine the bank exposure ($Exposure^{Oil}$) to measure an unanticipated increase in oil prices by aggregating for each bank the share of the specialization in $t-1$ to industries that are oil affected in t. In columns I-IV and V-VIII, we use the "economist" approach (Kilian and Murphy, 2014) and the "financial market" approach (Hamilton and Wu, 2014) to construct oil price expectations, respectively. In all specifications, we include different levels of fixed effects, as noted in the lower part of the table. Bank controls include: *Bank size*, *Tier* $2/TA$, *C&I Loans*$/TA$, *Deposits*$/TA$, and *ROA* (*bank*). Table A1 in appendix defines all remaining variables. *$p<.1$; **$p<.05$; ***$p<.01$.

Table 10: Do industry spillovers impact aggregate real economic outcomes: Industry level

Dependent variable	ΔLn(amount)	Δ Ln(Investment)	ΔLn(Debt)	ΔLn(size)	ΔLn(employment)	ΔLn(sales)
	I	II	III	IV	V	VI
	Panel A: Global Financial Crisis					
$Exposure_{t-1}^{Dist}$	1.294	0.133***	-0.033	-0.018	0.080	0.456
	(0.470)	(2.720)	(-0.261)	(-0.952)	(0.150)	(0.853)
$Exposure_{t-1}^{Dist}$ * GFC_t	-18.210***	-2.147**	-1.987***	-0.109**	-9.590***	-5.417**
	(-5.831)	(-2.492)	(-12.805)	(-2.116)	(-3.193)	(-2.094)
Observations	2,524	2,549	2,549	2,549	2,063	2,549
Adjusted R-squared	0.081	0.779	0.061	0.116	0.885	0.931
	Panel B: Financial Frictions					
$Exposure_{t-1}^{Dist}$	8.799	2.046**	-0.873*	0.046	5.092*	-0.137
	(1.015)	(2.113)	(-1.724)	(0.285)	(1.855)	(-0.629)
$Exposure_{t-1}^{Dist}$ * $Frictions_t$	-13.462**	-2.320**	0.912*	-0.058	-7.259*	0.072
	(-2.024)	(-2.037)	(1.787)	(-0.339)	(-1.705)	(0.240)
Observations	2,524	2,549	2,549	2,549	2,063	2,549
Adjusted R-squared	0.082	0.779	0.061	0.116	0.884	0.120
	Panel C: Industry Specificity					
$Exposure_{t-1}^{Dist}$	-4.951	-1.546	4.169	0.364**	-7.777*	1.080***
	(-1.257)	(-0.697)	(1.653)	(2.365)	(-2.227)	(4.542)
$Exposure_{t-1}^{Dist}$ * $Frictions_t$	-25.093*	0.607	-5.569**	-0.437**	6.061	-0.504**
	(-1.974)	(0.182)	(-2.345)	(-3.028)	(1.081)	(-2.392)
Observations	381	382	382	382	382	382
Adjusted R-squared	0.175	0.779	0.044	0.098	0.899	0.220
Bank controls (weighted)	Y	Y	Y	Y	Y	Y
Industry controls	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y
Clustered standard errors	Industry,Time	Industry,Time	Industry,Time	Industry,Time	Industry,Time	Industry,Time

The table reports coefficients and t-statistics (in parenthesis) for non-affected industries. The unit of our analysis is at the industry-semester level from 1987h1 until 2016h1. The dependent variables are reported in the second line. In column I, we measure the total syndicated amount held by each sector, column II presents the total volume of investments, column III captures external debt excluding the syndicated market, column IV the total assets, column V the total number of employees, and in column VI we use the sales. $Exposure^{Dist}$ is the industry-level exposure for bank's specialization to industries that are in distress and is defined with a weighted sum approach. In Panel A, the variables GFC is a dummy variable equal to one during the Great Recession. In Panel B, the variable $financial\ frictions$ is a dummy equals one if the Excess Bond Premium (EBP) is positive. The EBP is the unexplained component of the credit spread in the corporate bond market, which is not related to borrower' creditworthiness (Gilchrist and Zakrajšek, 2012). In Panel C, following Rauch (1999), we keep only firms whose outputs are considered "differentiated" if neither sold on an exchange nor reference pricing. To do so, for each firm, we capture the share of SITC heterogeneous products. In all specifications, we include industry and time fixed effects as noted in the lower part of the table, and also we use weighted bank and industry controls like bank's size, capitalization, profitability and industry's return on assets and cash flow volatility. Table A1 in appendix defines all remaining variables. *p <.1; **p <.05; ***p <.01.

Appendices - Further tests

Variable definition

Table A1: Variable definitions and sources

Name	Description	Source
Ln(amount)	The natural logarithm of the loan amount that a bank lends to firm at the semi-annual level.	Dealscan
AISD (bps)	The all-in-spread drawn variable is defined as the sum of the spread over LIBOR plus the facility fee (bps).	Dealscan
Margin (bps)	Spread over LIBOR paid on drawn amounts.	Dealscan
Maturity	The loan maturity in months.	DealScan
Revolver	Dummy variable equal to one if the loan type is a credit line.	Dealscan
Specialization	The amount ($M) that a bank lends to a firm classified on a two-digit SIC sector over the total amount of lending ($M) from bank to the total number of sectors. This index ranges from zero to one, with higher values reflecting higher specialization in the sector in which the firm operates.	Own calculations
Market shares	The amount ($M) that a bank lends to a firm classified on a two-digit SIC sector over the total credit of the sector. This index ranges from zero to one, with higher values reflecting higher concentration.	Own calculations
Distress	Dummy variable equal to one if the semi-annual returns in a two-digit SIC industry code and semester were lower than -10%, and zero otherwise.	Own calculations
Oil-price shock	Dummy variable equal to one if the oil price change is higher than the expected price in oil-dependent sectors. For the construction of oil price expectations, we use two alternative measures. Initially, we rely on Kilian and Murphy (2014) for "economist" expectations and secondly on Hamilton and Wu (2014) for "financial market" expectations.	Own calculations
Oil-dependent sectors	Dummy variable equal to one if the fraction of oil or refined products that have been used as inputs in a sector are above the sample mean and zero otherwise.	Own calculations
Unrelated sectors	Dummy variable equal to one if a sector i and its customers or suppliers sectors are not in the BEA output-input linkages.	BEA linkages

Continued on next page

Table A1 – continued from previous page

Name	Description	Source
$Exposure$	The degree to which a bank is exposed to industries that are in a distress situation ($Exposure^{Dist}$) or oil affected ($Exposure^{Oil}$). Specifically, we aggregate for each bank the shares of their specialization in $t-1$ to industries that are in distress or oil affected in t. For the firm-level analysis, we construct a firm-level exposure variable and is defined as a weighted sum approach based on the shares that each bank holds for a firm. Similarly, for the industry-level exposure, we use a weighted sum approach based on the shares that each bank holds within a sector.	Own calculations
$Market\ shares$	The degree to which a bank is exposed to industries in distress ($Market\ shares^{Dist}$) or oil-affected sectors ($Market\ shares^{Oil}$) due to their market presence. For each bank, we sum the bank's shares in $t-1$ for industries that are in distress or oil affected in t.	Own calculations
Merger implied $Exposure$	An instrument for the $Exposure$ variable using only the historical exposure variables of the target bank (acquired). We restrict attention to mergers occurring within a year preceding the origination of the loan.	Own calculations
Merger implied $Market\ shares$	An instrument for the $Market\ shares$ variable using only the historical exposure variables of the target bank (acquired). We restrict attention to mergers occurring within a year preceding the origination of the loan.	Own calculations
Bank size	The natural logarithm of bank's total assets.	Call reports
Tier 2/TA	Bank's tier 2 capital over total assets.	Call reports
Low capital	Dummy variable equal to one if the bank's Tier 2 capital is below the sample mean.	Call reports
C&I Loans/TA	Bank's total consumer and industrial loans over total assets.	Call reports
Deposits/TA	Bank's total deposits over total assets.	Call reports
ROA (bank)	Bank's return on assets.	Call reports
Ln(investment)	The natural logarithm for the firm's fixed tangible assets.	Compustat
Ln(debt)	The natural logarithm of firm's total external debt excluding the syndicated market.	Call reports

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Table A1 – continued from previous page

Name	Description	Source
Ln(size)	The natural logarithm of firm's total assets.	Compustat
Ln(employment)	The natural logarithm of firm's total number of employees.	Compustat
Ln(sales)	The natural logarithm of firm's total sales.	
ROA (firm)	Firm's return on assets.	Compustat
Tobin's q	The natural logarithm of firm's market-to-book value.	Compustat
GFC	Dummy variable equal to one for the Great Recession.	Own calculations
Frictions	Dummy variable equal to one if the Excess Bond Premium (EBP) is positive for more than 3 months within a 6-month rolling window.	Gilchrist and Zakrajšek (2012)
Firm specificity	Dummy variable equal to one if a firm produces heterogeneous goods. We use Rauch (1999) data on the categories of product differentiation: those traded on international exchanges, those with reference prices, or those with differentiated goods for which branding information precludes them from being traded on exchanges or reference priced. For the industry specificity, we use the industry outputs.	Rauch (1999)

Loan-level evidence

Table A2: Sample distribution

	I	II	III	IV	V	VI	VII
				Industry Returns (%)		Industry in Distress (%)	
Period	# of Banks	# of Firms	# of Sectors	Mean	STD	Mean	STD
1987h1	97	87	39	19.34	9.00	0.00	0.00
1987h2	158	285	57	-28.34	8.73	0.98	0.12
1988h1	174	342	60	18.87	6.75	0.01	0.09
1988h2	186	366	62	-3.31	6.35	0.12	0.33
1989h1	218	343	63	10.40	7.03	0.01	0.08
1989h2	223	365	63	-3.00	7.80	0.20	0.40
1990h1	231	369	64	-3.71	4.94	0.13	0.34
1990h2	218	374	64	-22.96	10.36	0.91	0.29
1991h1	234	375	65	22.37	12.00	0.00	0.05
1991h2	231	388	67	3.13	9.88	0.04	0.19
1992h1	227	452	66	1.10	7.68	0.08	0.27
1992h2	256	536	67	7.33	9.12	0.00	0.00
1993h1	260	538	67	5.51	12.96	0.07	0.26
1993h2	271	670	67	6.51	7.40	0.04	0.20
1994h1	263	674	67	-8.90	5.63	0.45	0.50
1994h2	262	759	66	-2.97	7.22	0.19	0.40
1995h1	268	696	67	8.87	7.40	0.02	0.14
1995h2	266	741	68	1.05	8.31	0.07	0.25
1996h1	273	849	67	11.58	7.77	0.00	0.00
1996h2	267	953	67	-4.85	9.85	0.30	0.46
1997h1	260	944	67	7.18	6.69	0.00	0.07
1997h2	255	1,073	67	2.99	8.43	0.02	0.14
1998h1	252	916	67	4.39	8.89	0.04	0.19
1998h2	238	791	67	-18.41	8.89	0.86	0.35
1999h1	256	789	68	5.83	9.18	0.02	0.15
1999h2	261	819	68	-8.57	12.69	0.54	0.50
2000h1	249	797	67	-2.11	11.23	0.18	0.38
2000h2	256	819	66	-19.12	20.29	0.64	0.48
2001h1	246	787	66	7.29	10.38	0.03	0.17
2001h2	251	771	66	-8.20	9.18	0.44	0.50
2002h1	254	813	66	-0.86	12.68	0.23	0.42

Continued on next page

Table A2 – continued from previous page

	I	II	III	IV	V	VI	VII
				Industry Returns (%)		Industry in Distress (%)	
Period	# of Banks	# of Firms	# of Sectors	Mean	STD	Mean	STD
2002h2	243	736	66	-17.87	7.64	0.85	0.36
2003h1	246	740	66	10.60	7.84	0.00	0.06
2003h2	229	794	66	18.55	9.64	0.00	0.00
2004h1	214	719	67	3.49	5.34	0.00	0.06
2004h2	210	753	67	5.59	9.41	0.00	0.00
2005h1	207	737	67	-0.09	6.82	0.08	0.27
2005h2	208	729	67	1.74	6.15	0.01	0.08
2006h1	211	673	67	3.93	6.48	0.02	0.15
2006h2	201	678	67	3.09	6.54	0.05	0.22
2007h1	194	671	67	6.80	8.46	0.02	0.14
2007h2	198	596	67	-14.30	8.97	0.64	0.48
2008h1	199	482	66	-11.31	15.44	0.73	0.44
2008h2	179	385	66	-41.32	12.62	0.98	0.15
2009h1	177	271	66	11.25	10.01	0.00	0.00
2009h2	178	337	66	15.39	10.27	0.01	0.09
2010h1	181	404	65	-2.10	5.11	0.07	0.25
2010h2	176	506	65	16.10	9.50	0.00	0.00
2011h1	169	627	65	2.00	5.07	0.04	0.20
2011h2	166	654	65	-13.71	9.75	0.68	0.47
2012h1	179	515	65	2.77	9.06	0.07	0.25
2012h2	175	529	65	3.83	7.32	0.01	0.12
2013h1	170	500	66	9.82	9.19	0.02	0.14
2013h2	162	487	65	11.75	6.59	0.01	0.12
2014h1	156	418	64	2.79	6.42	0.04	0.20
2014h2	160	472	64	-5.08	12.65	0.23	0.42
2015h1	154	414	63	-0.92	6.12	0.10	0.30
2015h2	140	374	59	-13.76	9.56	0.69	0.46
2016h1	109	278	50	1.78	7.12	0.08	0.27

This table describes the observations used in the paper. Columns I, II and III contain the number of unique banks, firms and sectors in the sample for each semester. In columns IV-V, we present the mean and standard deviation on the average industry returns, respectively, while in columns VI-VII, we show the fraction of observations corresponding to distressed industries in each period.

In Table A3, we test whether banks with higher specialization in distressed sectors are engaged with poorly-performing firms. We use different indicators for the firm's past performance like $Investement$ and $Tangibility$. The $exposure^{Dist}$ variable remains significant and positive, while the interaction term for each performance variable is insignificant. This suggests that an exposed bank is less likely to match and provide credit to affected firms with lower performance one year before the loan.

Table A3: Bank lending to distressed industries: Ex-ante firm performance

	II	III
$Exposure_{t-1}^{Dist}$	0.150***	0.114*
	(2.741)	(1.729)
$Exposure_{t-1}^{Dist} * Investment_{t-1}$	-0.024	
	(-0.160)	
$Exposure_{t-1}^{Dist} * Tangibility_{t-1}$		0.051
		(0.528)
Observations	20,237	20,497
Adjusted R-squared	0.721	0.722
Bank controls	Y	Y
Loan controls	Y	Y
Bank FE	Y	Y
Firm*Time FE	Y	Y
Clustered standard errors	Bank,Firm	Bank,Firm

The table reports coefficients and t-statistics (in parenthesis) for the bank lending only to firms that operate in distressed industries. The unit of our analysis is at the loan level. The sample consists of syndicated loans that were originated in the U.S. from 1987h1 until 2016h1. The dependent variable is the loan amount held by each lender at origination. $Exposure^{Dist}$ is the bank specialization to industries that are in distress. We define sectors in distress (affected) as a dummy variable that takes the value one if the semi-annual returns of the sector that the firm operates are higher than -10% and zero otherwise. $Investment$ and $Tangibility$, are calculated one year before the loan origination (pre-loan). In all specifications we include different levels of fixed effects as noted in the lower part of the table and the following bank and loan control variables: $Bank\ size$, $Tier\ 2/TA$, $C\&I\ Loans/TA$, $Deposits/TA$, ROA ($bank$), $Revolver$, $Maturity$ ($Months$), $Rel.\ Lending$. Table A1 in appendix defines all remaining variables. *p <.1; **p <.05; ***p <.01.

In Table A4, we test whether exposed banks to affected sectors have different lending patterns prior to the downturn to the unaffected sectors. The dependent variables are each lender's loan amount and spread in columns I and II, respectively. The $exposure^{Dist}$ variable is insignificant. This suggests that there is no difference in the lending behavior concerning the unaffected sectors before the downturn to the industries that banks specialize in.

Table A4: Bank lending prior to the downturn

	I	II
Dependent variable:	Ln(amount)	AISD (bps)
$exposure^{Dist}_{t-1}$	-0.038	0.261
	(-0.940)	(0.141)
Observations	62,063	58,758
Adjusted R-squared	0.673	0.927
Bank controls	Y	Y
Loan controls	Y	Y
Bank FE	Y	Y
Firm*Time FE	Y	Y
Clustered standard errors	Bank,Firm	Bank,Firm

The table reports coefficients and t-statistics (in parenthesis) for the bank lending to unaffected sectors prior to the downturn. The unit of our analysis is at the loan level. The sample consists of syndicated loans that were originated in the U.S. from 1987h1 until 2016h1. The dependent variable is resported in the second line. In all specifications we include different levels of fixed effects as noted in the lower part of the table and the following bank and loan control variables: *Bank size*, *Tier 2/TA*, *C&I Loans/TA*, *Deposits/TA*, *ROA* (*bank*), *Revolver*, *Maturity* (*Months*), *Rel. Lending*. Table A1 in appendix defines all remaining variables. *p <.1; **p <.05; ***p <.01.

Firm-level evidence

A potential threat to the firm outcomes analysis is that the coefficient of the spillovers is plausibly driven by the fact that during the GFC many sectors were in distressed. For instance, as shown in Table A3, in 2008h1 and 2008h2 the industries in distress were 73% and 98%, respectively. To alleviate this concern, in Table A5 we do a robustness exercise where we exclude the GFC period. Results remain unchanged.

Table A5: Do industry spillovers impact real economic outcomes: Firm level

	I	II	III	IV	V	VI
Dependent variable	Ln(amount)	Ln(investment)	Ln(debt)	Ln(size)	Ln(employment)	Ln(sales)
$Exposure^{Dist}_{t-1}$	-0.240	-0.075***	0.077	-0.175**	0.010	0.058**
	(-1.534)	(-3.578)	(0.695)	(-2.549)	(0.392)	(2.129)
$Exposure^{Dist}_{t-1}$ * $Frictions_t$	-0.365**	-0.056**	-0.195	-0.126*	-0.077**	-0.076**
	(-2.195)	(-2.467)	(-1.608)	(-1.693)	(-2.240)	(-2.171)
Observations	19,322	18,297	18,255	19,322	18,592	19,096
Adjusted R-squared	0.667	0.206	0.516	0.931	0.926	0.925
Time FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y
Clustered standard errors	Industry,Time	Industry,Time	Industry,Time	Industry,Time	Industry,Time	Industry,Time

The table reports coefficients and t-statistics (in parenthesis) for non-affected firms. We aggregate a sample of U.S. syndicated loans for firms covered in Dealscan at the firm-semester level from 1987h1 until 2016h1. The dependent variables are reported in the second line. In column I, we measure the total syndicated amount held by each firm, column II captures the value of investments, column III captures total debt, column IV the total assets, column V the total number of employees, and in column VI we use the sales. $Exposure^{Dist}$ is the firm-level exposure for bank's specialization to industries that are in distress and is defined as a weighted sum approach. The variable $financial\ frictions$ is a dummy equals one if the Excess Bond Premium (EBP) is positive. The EBP is the unexplained component of the credit spread in the corporate bond market, which is not related to borrower' creditworthiness (Gilchrist and Zakrajšek, 2012). In all specifications, we include firm and time fixed effects as noted in the lower part of the table, and also we control for the firm's return on assets and cash flow volatility. Table A1 in appendix defines all remaining variables. *p <.1; **p <.05; ***p <.01.

Bank-industry-level evidence

Table A6 shows the results from the two-stages least square estimation exploiting exogenous variation from mergers between banks that are active in the syndicated loan market. To do so, we collect data on M&A from the Fed and identify the banks in Dealscan. Then we construct an instrument for $Exposure^{Dist}$ variable using only the historical exposure variables of the target bank (acquired). We restrict attention to mergers occurring within a year preceding the origination of the syndicated loan. In Panel A, we report the estimated coefficients of the first stage. Importantly, the coefficients are positive and highly significant and in line with the literature. In addition, the under-identification test shows no concerns regarding the instrument validity. Panel B shows that the second stage estimates are qualitatively and quantitatively similar to the baseline estimates.

Table A6: Common lenders mechanism: IV estimates (distress)

	I	II	III	IV
Supply chain: Input-Output				Unrelated
Panel A: First Stage				
Merger implied $Exposure^{Dist}_{t-1}$	0.316***	0.314***	0.314***	0.311***
	(38.851)	(38.930)	(38.057)	(32.967)
Adjusted R-squared	0.841	0.840	0.846	0.800
F-stat	21.04	20.44	26.08	10.94
Panel B: Second Stage				
$Exposure^{Dist}_{t-1}$	-2.376***	-2.271***	-2.368***	-1.860***
	(-10.115)	(-9.613)	(-9.571)	(-7.014)
Observations	69,665	69,609	69,260	60,008
P-value for under identification	0.000	0.000	0.000	0.000
Bank controls	Y	Y	Y	Y
Time FE	Y			
Industry FE	Y			
Bank FE	Y	Y		Y
Industry*Time FE		Y	Y	Y
Bank*Industry FE			Y	
Clustered standard errors	Bank,Industry	Bank,Industry	Bank,Industry	Bank,Industry

The table reports coefficients and t-statistics (in parenthesis) for non-affected sectors. We aggregate a sample of U.S. syndicated loans at the bank-industry-semester level from 1987h1 until 2016h1. The dependent variable is the growth in lending that a bank lends to non-affected industries. $Exposure^{Dist}$ and $Market\ shares^{Dist}$ are the bank specialization and market shares to industries that are in distress, respectively. We define sectors in distress as a dummy variable that takes the value one if the semi-annual returns of the sector that the firm operates are higher than -10% and zero otherwise. In column IV, we use the BEA Input-Output table and exclude related sectors from the regression analysis. In all specifications, we include different levels of fixed effects, as noted in the lower part of the table. Bank controls include: $Bank\ size$, $Tier\ 2/TA$, $C\&I\ Loans/TA$, $Deposits/TA$, and $ROA\ (bank)$. Table A1 in appendix defines all remaining variables. *p <.1; **p <.05; ***p <.01.

Table A7 shows the results from the two-stages least square estimation exploiting exogenous variation from mergers between banks that are active in the syndicated loan market. In this table, we alter the definition of distress and rely on oil shocks instead of stock returns. To do so, we collect data on M&A from the Fed and identify the banks in Dealscan. Then we construct an instrument for $Exposure^{Oil}$ variable using only the historical exposure variables of the target bank (acquired). We restrict attention to mergers occurring within a year preceding the origination of the syndicated loan. In Panel A, we report the estimated coefficients of the first stage. Importantly, the coefficients are positive and highly significant and in line with the literature. In addition, the under-identification test shows no concerns regarding the instrument validity. Panel B shows that the second stage estimates are qualitatively and quantitatively similar to the baseline estimates.

Table A7: Common lenders mechanism: IV estimates (oil shocks)

	I	II	III	IV	V	VI	VII	VIII
Oil shock group:	"Economist" approach				"Financial market" approach			
Supply chain: Input-Output				Unrelated				Unrelated
Panel A: First Stage								
Merger implied $Exposure^{Oil}_{t-1}$	0.326***	0.325***	0.317***	0.350***	0.264***	0.263***	0.250***	0.254***
	(34.010)	(33.612)	(31.874)	(31.501)	(32.729)	(32.314)	(30.118)	(29.628)
Adjusted R-squared	0.741	0.739	0.737	0.743	0.746	0.743	0.746	0.743
F-stat	12.11	13.95	19.43	5.002	18.30	19.57	24.59	10.07
Panel B: Second Stage								
$Exposure^{Oil}_{t-1}$	-1.439***	-1.516***	-1.536***	-1.100***	-2.217***	-2.226***	-2.307***	-2.048***
	[-6.687]	[-6.982]	[-6.814]	[-4.335]	[-8.906]	[-8.956]	[-8.673]	[-6.937]
Observations	67,996	67,954	67,755	47,148	67,996	67,954	67,755	47,148
P-value for under identification	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Bank controls	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	Y				Y			
Industry FE	Y				Y			
Bank FE	Y	Y		Y	Y	Y		Y
Industry*Time FE		Y	Y	Y		Y	Y	Y
Bank*Industry FE			Y				Y	
Clustered standard errors	Bank,Industry	Bank,Industry	Bank,Industry	Bank,Industry	Bank,Industry	Bank,Industry	Bank,Industry	Bank,Industry

The table reports coefficients and t-statistics (in parenthesis) for non-affected sectors. We aggregate a sample of U.S. syndicated loans at the bank-industry-semester level from 1987h1 until 2016h1. The dependent variable is the growth in lending that a bank lends to non-oil affected industries. $Exposure^{Oil}$ measures the unanticipated increase in oil prices by aggregating for each bank the share of the specialization in $t-1$ to industries that are oil affected in t. We assume that a sector is oil-dependent if the fractions of oil or refined product used as inputs are above the sample mean. In columns I-IV and V-VIII, we use the "economist" approach (Kilian and Murphy, 2014) and the "financial market" approach (Hamilton and Wu, 2014) to construct oil price expectations, respectively. In columns IV and VIII, we use the BEA Input-Output table and exclude related sectors from the regression analysis. In all specifications, we include different levels of fixed effects, as noted in the lower part of the table. Bank controls include: *Bank size*, *Tier 2/TA*, *C&I Loans/TA*, *Deposits/TA*, and *ROA* (*bank*). Table A1 in appendix defines all remaining variables. *$p<.1$; **$p<.05$; ***$p<.01$.

In Table A8, we analyse any possible differences in loan pricing at the bank-industry level. In columns I-III, the dependent variable corresponds to the all-in-spread drawn amount ($AISD$), while in columns IV-VI, we only include the *spread*. The average of $AISD$ in our bank-industry sample is 160 bps, while the standard deviation indicates sizeable variation (95 bps). In column I, the coefficient on $Distress$ is positive and significant. The coefficient on the interaction term ($Specialization * Distress$) is significant and negative. So, banks with a higher specialization in these sectors are decreasing the $AISD$ by 1.48 bps during distress episodes. Importantly, the total effect is still positive and significant at around 2 bps. In columns II and III, we add different fixed effects to alleviate concerns with industry-level loan demand and bank-industry relationships, respectively. The estimated coefficients remain similar compared to column I. Similar interpretation for columns IV-VI.

Table A8: Do common lenders charge the affected sectors with a higher cost: bank-industry level

Dependent variable:	AISD (bps)			Margin (bps)		
	I	II	III	IV	V	VI
$Distress_t$	3.403***			3.341***		
	(3.659)			(3.501)		
$Specialization_{t-1}$*$Distress_t$	-1.479***	-0.800*	-1.381***	-1.747***	-1.041**	-1.677***
	(-3.032)	(-1.724)	(-3.001)	(-3.606)	(-2.231)	(-3.625)
Observations	92,795	92,726	91,059	92,783	92,714	91,047
Adjusted R-squared	0.397	0.437	0.462	0.400	0.434	0.456
Bank controls	Y	Y	Y	Y	Y	Y
Time FE	Y			Y		
Industry FE	Y			Y		
Bank FE	Y	Y		Y	Y	
Industry*Time FE		Y	Y		Y	Y
Bank*Industry FE			Y			Y
Clustered standard errors	Bank,Industry	Bank,Industry	Bank,Industry	Bank,Industry	Bank,Industry	Bank,Industry

The table reports coefficients and t-statistics (in parenthesis) for affected and unaffected sectors. The unit of our analysis is at the bank-sector-semester level from 1987h1 until 2016h1. The dependent variables are different proxies for the cost of lending and are indicated in the second row. In columns I-III, we use the all-in-spread-drawn (*AISD*) defined as the sum of the spread over LIBOR plus the facility fee (bps) and in columns IV-VI, we use the *spread* defined as the margin (bps). The variable *Specialization* is defined as the ratio of total credit granted by a bank to individual sectors relative to bank's total credit. We define sectors in distress as a dummy variable that takes the value one if the semi-annual returns of the sector that the firm operates are higher than -10% and zero otherwise. In all specifications, we include different levels of fixed effects, as noted in the lower part of the table. Bank controls include: *Bank size*, *Tier* $2/TA$, *C&I Loans*$/TA$, *Deposits*$/TA$, and *ROA* (*bank*). Table A1 in appendix defines all remaining variables. *p <.1; **p <.05; ***p <.01.

In Table A9 we explore the role of capital in the common lenders mechanism. To do so, we split the bank-industry sample into *Distressed* and $Non-distressed$ sectors and add the interaction on the *Specialization***Low capital* dummy. If the search for extra yield drives the less capitalized banks to increase lending to affected sectors and at the same time decrease lending to non-affected sectors, we should find the results on the *Specialization* and $Exposure^{Dist}$**Low capital* to be negative (positive) when sectors are in a non-distressed (distressed) situation. This is exactly what we find in Table A9. The coefficients of the *Specialization* and *Specialization***Low capital* are significant and negative for the non-distressed sectors, while they are significant and positive for the distressed sectors. Our finding suggests that specialized banks with less capital search for higher yields in sectors that suffer from negative shocks.

Table A9: Cross-sectional differences for the capitalization of common lenders: Bank-industry level

	I	II	III	IV
Sector:	*Distressed*	$Non-distressed$	*Distressed*	$Non-distressed$
$Specialization_{t-1}$	0.403**	-0.280***	0.439**	-0.306***
	(2.499)	(-3.589)	(2.371)	(-3.791)
$Low\ capital_t$ * $Specialization_{t-1}$	0.268	-0.188***	0.376*	-0.203***
	(1.581)	(-2.800)	(1.941)	(-2.885)
Observations	13,827	49,532	13,040	49,189
Adjusted R-squared	0.130	0.129	0.077	0.078
Bank controls	Y	Y	Y	Y
Bank FE	Y	Y		
Industry*Time FE	Y	Y	Y	Y
Bank*Industry FE			Y	Y
Clustered standard errors	Bank,Industry	Bank,Industry	Bank,Industry	Bank,Industry

The table reports coefficients and t-statistics (in parenthesis). The unit of our analysis is at the bank-sector-semester level from 1987h1 until 2016h1. The dependent variable is the growth in bank lending to industries. *Specialization* is the bank's specialization and is defined as the share of total credit granted by a bank to a specific sector relative to the bank's total credit. We split the bank-industry sample into *Distressed* (columns I and III) and $Non-distressed$ (columns II and IV) sectors based on their semi-annual returns. A sector is in a distress situation if the stock returns are higher than -10% and in non-distress otherwise. The *Low capital* dummy is equal to one whether the bank's Tier 2 capital is below the sample mean. In all specifications, we include different levels of fixed effects, as noted in the lower part of the table. Bank controls include: *Bank size*, *C&I Loans*/TA, *Deposits*/TA, and *ROA* (*bank*). Table A1 in appendix defines all remaining variables. **p* <.1; ***p* <.05; ****p* <.01.

In Table A10 we explore the role of capital in the common lender's mechanism. To do so, we split the bank-industry sample into $Distressed$ and $Non-distressed$ sectors and add the interaction on the *Specialization*Low capital* dummy. The results suggest that lower bank capitalization can enhance the common lender externality.

Table A10: The capitalization of common lenders: Alternative definitions

	I	II	III	IV
Group:	Low: ($\mathbb{1} < 25^{th}$)		Low: ($\mathbb{1} < 25^{th}$)	
Sector:	Distressed	Non-distressed	Distressed	Non-distressed
$Specialization_{t-1}$	0.619***	-0.346***	0.438**	-0.302***
	(3.715)	(-4.538)	(2.106)	(-3.100)
$Low\ capital_t$ * $Specialization_{t-1}$	0.135	-0.249***		
	(0.649)	(-2.776)		
$Low\ capital\ (Tier1)_t$ * $Specialization_{t-1}$			0.298	-0.137*
			(1.423)	(-1.713)
Observations	13,040	49,189	13,040	49,189
Adjusted R-squared	0.076	0.078	0.076	0.078
Bank controls	Y	Y	Y	Y
Industry*Time FE	Y	Y	Y	Y
Bank*Industry FE	Y	Y	Y	Y
Clustered standard errors	Bank,Industry	Bank,Industry	Bank,Industry	Bank,Industry

The table reports coefficients and t-statistics (in parenthesis). The unit of our analysis is at the bank-sector-semester level from 1987h1 until 2016h1. The dependent variable is the growth in bank lending to industries. *Specialization* is the bank's specialization and is defined as the share of total credit granted by a bank to a specific sector relative to the bank's total credit. We split the bank-industry sample into $Distressed$ (columns I and III) and $Non-distressed$ (columns II and IV) sectors based on their semi-annual returns. A sector is distressed if the stock returns are higher than -10% and in non-distress otherwise. In columns I and II, the *Low capital* dummy equals one whether the bank's Tier 2 capital is in the first quartile (up to the 25^{th}) of the sample distribution. In columns III and IV, we identify lees capitalized banks by comparing the Tier 1capital ratio. In all specifications, we include different levels of fixed effects, as noted in the lower part of the table. Bank controls include: *Bank size*, $C\&I\ Loans/TA$, $Deposits/TA$, and *ROA* (*bank*). Table A1 in appendix defines all remaining variables. *p <.1; **p <.05; ***p <.01.

In Table A11 we show results for the common lender mechanism when we use a weighted least square regression to avoid bias towards industries with more observations. Due to sector heterogeneity, some sectors have more firms from the middle and higher end of the distribution. In contrast, some other sectors have firms from the lower end of the distribution. When there are no weights concerning the sector's size, the regression results on the pass-through of externalities at the bank-industry level might be biased towards sectors from the lower end of the distribution. To alleviate this potential concern, we use weights that are the inverse of the probability that an observation is in the sample. Overall, the estimated coefficients are very similar to the baseline results, and we do not suffer from a potential sample selection bias.

Table A11: Common lenders mechanism: Weighted least square regression

			Panel A: Industry downturns			
	I	II	III	IV	V	VI
$Exposure^{Dist}_{t-1}$	-0.235***		-0.241***	-0.345***	-0.288***	-0.373***
	(-2.835)		(-2.867)	(-4.494)	(-3.492)	(-4.292)
$Market\ shares^{Dist}_{t-1}$		-0.002	0.005			
		(-0.141)	(0.354)			
Observations	69,655	69,661	69,655	69,653	69,595	69,268
Adjusted R-squared	0.008	0.008	0.008	0.131	0.130	0.087
Time FE	Y	Y	Y			
Industry FE	Y	Y	Y			
Bank FE	Y	Y	Y		Y	
Industry*Time FE				Y	Y	Y
Bank*Idustry FE						Y
			Panel B: Oil shocks			
	I	II	III	IV	V	VI
Oil shock group:		"Economist" approach			"Financial market" approach	
$Exposure^{Oil}_{t-1}$	-0.518***	-0.515***	-0.527***	-0.566***	-0.557***	-0.577***
	(-7.013)	(-7.009)	(-6.994)	(-8.684)	(-8.406)	(-8.420)
Observations	67,996	67,954	67,755	67,996	67,954	67,755
Adjusted R-squared	0.008	0.118	0.075	0.008	0.119	0.076
Bank controls	Y	Y	Y	Y	Y	Y
Time FE	Y			Y		
Industry FE	Y			Y		
Bank FE	Y	Y		Y	Y	
Industry*Time FE		Y	Y		Y	Y
Bank*Industry FE			Y			Y
Clustered standard errors	Bank,Industry	Bank,Industry	Bank,Industry	Bank,Industry	Bank,Industry	Bank,Industry

The table reports coefficients and t-statistics (in parenthesis) for non-affected sectors. We aggregate a sample of U.S. syndicated loans at the bank-industry-semester level from 1987h1 until 2016h1. The dependent variable is the growth in lending that a bank lends to non-affected industries. In Panel A, $Exposure^{Dist}$ and $Market\ shares^{Dist}$ are the bank specialization and market shares to industries that are in distress, respectively. We define sectors in distress as a dummy variable that takes the value one if the semi-annual returns of the sector that the firm operates are higher than -10% and zero otherwise. In Panel B, we refine the bank exposure ($Exposure^{Oil}$) to measure an unanticipated increase in oil prices by aggregating for each bank the share of the specialization in $t-1$ to industries that are oil affected in t. In columns I-IV and V-VIII, we use the "economist" approach (Kilian and Murphy, 2014) and the "financial market" approach (Hamilton and Wu, 2014) to construct oil price expectations, respectively. In all specifications, we include different levels of fixed effects, as noted in the lower part of the table. Bank controls include: *Bank size*, *Tier 2/TA*, *C&I Loans/TA*, *Deposits/TA*, and *ROA* (*bank*). Table A1 in appendix defines all remaining variables. *p <.1; **p <.05; ***p <.01.

Table A12 provides some further robustness tests for the baseline result concerning the syndicate structure (lead lenders) and the GFC. In columns I-III, we run the baseline specification only for the lead arrangers. In columns IV-VI and VII-IX, we analyse if the estimated coefficient is driven from specific variation when excluding the GFC or during the GFC, respectively.

Table A12: Bank lending to non-distressed industries: Sensitivity tests

	I	II	III	IV	V	VI	VII	VIII	IX
Sample:		Only Lead lenders			Exclude GFC			Only GFC	
$Exposure_{t-1}^{Dist}$	-0.651***	-0.805***	-0.733***	-0.184**	-0.251***	-0.337***	-1.386***	-0.987*	-1.029*
	(-3.899)	(-4.487)	(-3.706)	(-2.147)	(-2.964)	(-3.780)	(-2.606)	(-1.846)	(-1.675)
Observations	15,973	15,553	14,601	62,914	62,854	62,499	6,730	6,730	6,618
Adjusted R-squared	0.059	0.169	0.126	0.007	0.131	0.086	0.009	0.121	-0.080
Bank controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	Y			Y			Y		
Idustry FE	Y			Y			Y		
Bank FE	Y	Y		Y	Y		Y	Y	
Industry*Time FE		Y	Y		Y	Y		Y	Y
Bank*Industry FE			Y			Y			Y
Clustered standard errors	Bank,Industry	Bank,Industry	Bank,Industry	Bank,Industry	Bank,Industry	Bank,Industry	Bank,Industry	Bank,Industry	Bank,Industry

The table reports coefficients and t-statistics (in parenthesis) for non-affected sectors. We aggregate a sample of U.S. syndicated loans at the bank-industry-semester level from 1987h1 until 2016h1. The dependent variable is the growth in lending that a bank lends to non-affected industries. In Panel A, $Exposure^{Dist}$ is the bank specialization and market shares to industries that are in distress, respectively. We define sectors in distress as a dummy variable that takes the value one if the semi-annual returns of the sector that the firm operates are higher than -10% and zero otherwise. In columns I-III, the sample includes only lead lenders. We exclude the GFC period in columns IV-VI, while in columns VII-IX, we include only the GFC period. Bank controls include: *Bank size*, *Tier 2/TA*, *C&I Loans/TA*, *Deposits/TA*, and *ROA* (*bank*). Table A1 in appendix defines all remaining variables. *p <.1; **p <.05; ***p <.01.