Shock Absorbers and Transmitters: The Dual Facets 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

November 15, 2022

Abstract

This paper highlights the dual facets of bank specialization. After negative industry-specific shocks, banks specializing in an affected-sector act as shock absorbers, by increasing their lending to firms in that sector at lower interest rates than non-specialized banks. This lending is to firms with ex-post higher profitability, thus not consistent with zombie lending. However, when there are funding constraints, increased lending to the affected sector by specialized banks is accompanied by a simultaneous cut in lending to unrelated sectors, thereby transmitting the shock. These firms compensate by raising funds externally, however, in overall tight financing conditions, there are negative aggregate real effects.

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

JEL Classification: G20, G21, E51

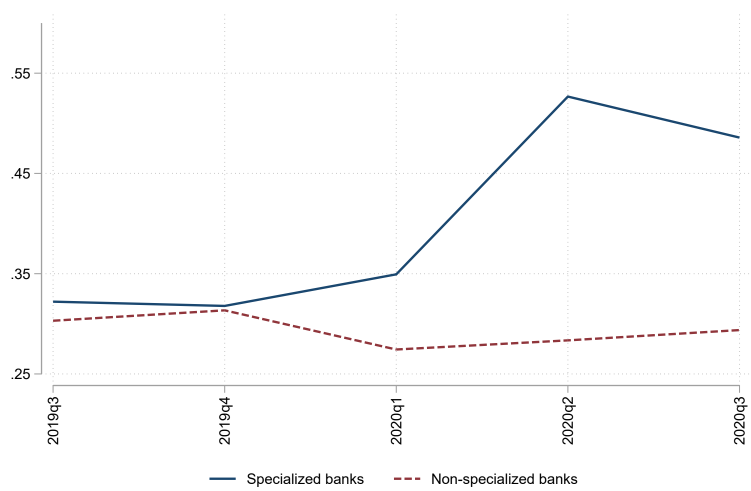
*We thank for their helpful comments Fadi Hassan, Jean Helwege, Emiel Jerphanion, Ying Liu, Glenn Schepens and participants at AEA 2022, Bank of Greece, FDIC Bank Research Conference, FINEST 2021, 2nd FINPRO (EBRD-IWH), FMARC 2022, FMCG 2022, Ghent University, 7th SDU and University of Essex. Peydró acknowledges financial support from the Spanish Ministry of Science, Innovation and Universities grant PGC2018-102133-B-I00 (MCIU/AEI/FEDER, UE) and the Severo Ochoa Programme for Centres of Excellence in RD (CEX2019-000915-S). All errors are our responsibility. Emails: r.iyer@imperial.ac.uk; skokas@essex.ac.uk; a.michaelides@imperial.ac.uk; and j.peydro-alcalde@imperial.ac.uk.

1 Introduction

A key role of banks is to provide credit to firms to help smooth liquidity shocks (see e.g., Holmström and Tirole, 1998; Freixas and Rochet, 2008). Banks provide liquidity to firms not only by monitoring and screening (see e.g., Diamond, 1984; Fama, 1985), but also via lending specialization in specific sectors, as this behavior allows banks to gather information about many different firms within a sector (Paravisini, Rappoport and Schnabl, 2022).

In this paper, we show the importance of banks' lending specialization, in providing liquidity to firms in their specialized sectors, when the sector experiences a negative shock. For instance, during COVID-19, banks that specialized in hospitality and aviation increased their lending to these sectors compared to banks that did not specialize in these sectors (see Figure 1). More generally, after negative industry-specific shocks, banks specializing in an affected sector increase their lending to firms in that sector and lend at a lower interest rate than other banks. However, while banks with lending-specialization to affected sectors help with absorbing negative shocks, this function does not come without costs. When there are funding constraints at the bank, the increase in lending in response to sector-specific shocks leads to a reduction in credit to other unrelated sectors. Thus, lending specialization helps banks perform the role of liquidity providers to sectors affected by a shock, thereby acting as shock absorbers. However, banks also simultaneously act as transmitters of shocks to other unaffected sectors in the presence of funding constraints.

Figure 1: Credit Shares in Hospitality and Aviation



Conceptually, in the presence of negative industry-specific shocks, the effect of lending specialization by banks on credit supply to sectors that they specialize in and to unrelated (unaffected) sectors is not clear-cut. On the one hand, if there is a negative shock to an industry, specialized banks with higher exposure to that industry will have lower profits (hence lower capital), thereby they may reduce 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, unrelated sectors (Stein, 2013). In this scenario, specialized banks may reallocate credit supply towards the negatively affected sector. However, in the presence of bank funding constraints, this reallocation could curtail lending to unaffected sectors due to credit supply constraints.

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 between 1987 and 2016.[1] We define a negative economic shock at the industry level by using episodes in which the industry median stock return is lower than -10%. 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 (Blickle, Parlatore and Saunders, 2021). 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 when a sector experiences a negative shock, banks that specialize in lending to that sector increase their flow of credit to firms in the affected sector relative to non-specialized banks. In terms of magnitude, a one standard deviation increase in the bank's exposure to the affected sector increases total credit to the firms in the (negatively) affected sector by approximately 5% ($23.8 million). Prior to the negative shock, there is no difference in the lending behavior of specialized banks between affected and unaffected sectors. Finally, specialized banks sustain a higher loan supply in absolute terms (not only relative to non-specialized banks) to affected sectors.

[1] 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).

To further understand the reason for the increase in lending to the affected sector by specialized banks, we investigate the interest rate on new loans. 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 other unaffected sectors. After a negative shock, specialized banks get higher ex-ante yields (6-19 bps) from lending to affected sectors, as compared to unaffected sectors. When we compare the loan interest rates charged by non-specialized banks for lending within the affected sectors, we find that post the negative shock, 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 to firms in the affected sector. These results suggest that these loan outcomes are beneficial to both firms in the affected sector and banks specializing in the sector: specialized banks receive higher ex-ante yields from lending to the affected sector, and firms in the affected sector are able to secure credit at a lower price than borrowing from non-specialized banks.

Could the results be driven by zombie lending? One could be concerned that banks lend to the firms in the negatively affected sector not to obtain higher profits but to delay loan defaults (Caballero, Hoshi and Kashyap, 2008). 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. Thus, the results suggest that increasing lending to the affected sector is not an artifact of zombie lending.

Does the higher credit from specialized banks to the affected sectors after a negative shock change lending conditions to unaffected sectors? We find that firms in unaffected sectors with an outstanding loan by a bank that has a higher exposure to sectors hit by negative shocks, experience a reduction in credit. Economically, one standard deviation increase in the bank's lending specialization in an exposed sector decreases lending to 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, as compared to non-specialized banks.[2]

We use several approaches to address the concern that the increase in lending to the affected sector and the cut back in credit to the unrelated sectors could be driven by credit

[2]The results are robust to excluding periods where there are large aggregate shocks which simultaneously affect many industries (like the Global Financial Crisis).

demand. We saturate the loan level specifications with granular bank-time, firm-time, and bank-firm fixed effects to control for a range of unobserved factors (Khwaja and Mian, 2008; Jiménez, Ongena, Peydró and Saurina, 2012, 2014).[3] Furthermore, without loan prices, it is difficult to rule out a demand channel as firms in the affected sector might just prefer borrowing from the specialized banks. However, the decrease in loan interest rates to firms in the affected sector by specialized banks, as compared to non-specialized banks, provides evidence in favor of a credit supply mechanism. Moreover, we use unexpected oil price movements for oil-dependent sectors to get exogenous variation in negative industry-specific shocks and find similar results.[4] Finally, we also control for coincident fluctuations between sectors in a supply chain because a negative shock to a sector can spread over the production network and affect related suppliers or customers.[5]

A key question that remains unaddressed is whether firms in unaffected sectors can compensate for the loss in credit with borrowing from other banks and nonbanks. To examine this question, as well as to analyze the associated real effects (if any), we aggregate the loan-level data first 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 sectors 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 (Gilchrist and Zakrajšek, 2012), higher credit supply by specialized banks to the affected sector has an effect on total debt availability to firms in unrelated sectors. As a consequence, these firms witness an overall reduction in their bank credit, total debt, and also employment, sales and size.[6] The results reported

[3]These fixed effects control for a wide range of unobserved factors such as a bank's time-varying unobserved overall (credit supply) conditions, a firm's time-varying overall unobserved conditions (fundamentals, including overall firm-level demand for credit), and bank-firm matching (Paravisini et al., 2022).

[4]In effect, we use oil price movements to identify industry specific negative episodes as oil-price trends can be orthogonal to industries' financial health (Hamilton and Wu, 2014; Kilian and Murphy, 2014; Kilian and Vigfusson, 2017).

[5]Specifically, we use the input-output table from the U.S. Bureau of Economic Analysis (BEA) and include only unrelated sectors (Costello, 2020).

[6]In addition, at the firm level, we use an IV approach to control for the potential endogeneity that unobservable borrower characteristics may be determined simultaneously with the syndicated lending amount and firm outcomes. We exploit exogenous changes in a bank's exposure to affected sectors that stem from bank mergers (Favara and Giannetti, 2017). Results from the IV strategy are similar.

above at the firm level also hold at the aggregate industry level.

Our paper contributes to the literature on lending specialization by banks. Existing studies find that specialized banks concentrate their lending in certain industries and invest more in information collection (Diamond and Rajan, 2011; Blickle et al., 2021). Furthermore, firms take into account bank specialization when selecting their banking partner, and bank credit supply shocks disproportionately affect a firm's exports to markets where the lender specializes in Paravisini et al. (2022). Our paper adds to this literature by showing that specialized banks increase the allocation of resources to the affected sector when there are negative industry specific shocks. In addition, our findings suggest that specialized banks get higher ex-ante loan yields in the affected industries and therefore increase credit supply to the affected sectors while cutting credit supply to other unrelated sectors. Thus, increased credit provision to specialized sectors -in search for higher yields- can cause negative externalities to other unrelated sectors Diamond and Rajan (2011), Stein (2013) and Abbassi, Iyer, Peydró and Tous (2016) . More broadly, our findings suggest that banks act as shock absorbers in sectors that they specialize in, and simultaneously also transmitters of shocks to unrelated sectors.

Our paper also contributes to the literature that relates to transmission of negative shocks by banks. Many researchers have analyzed the role of banks in the propagation of negative shocks.[7] The main focus of papers in this literature is to show that negative shocks to banks emanating from the asset side of their balance sheet, or negative shocks directly to the liability side, lead to funding constraints for banks, causing a contraction in credit supply to firms, thus further propagating the shock.[8] A novel contribution of our paper relative to this literature is documenting that, when there are negative shocks to the sectors that banks specialize in, banks increase lending to these sectors (and this is not zombie lending). When the magnitude of the shock to the affected sectors is large, the increase in lending to affected sectors is accompanied by a credit contraction to other unrelated sectors in the banks' portfolio. Thus, different from the other papers, we highlight a novel mechanism that can explain credit supply reduction to unrelated sectors in a bank's

[7] A non-exhaustive list is the following: Carey, Post and Sharpe (1998); Paravisini (2008); Ivashina and Scharfstein (2010); Schnabl (2012); Chodorow-Reich (2014); Iyer, Peydró, da Rocha-Lopes and Schoar (2014); Cortés and Strahan (2017); Chakraborty, Goldstein and MacKinlay (2018); Costello (2020); Galaasen, Jamilov, Juelsrud and Rey (2020); Paravisini et al. (2022).

[8] Relatedly, there is a set of papers which documents whether and how negative shocks propagate by firms, including firms' leverage Giroud and Mueller (2017) and firms' internal networks of establishments Giroud and Mueller (2019).

portfolio post a negative industry-specific shock; the reduction arises due to increased lending to sectors that banks specialize in.

Our paper also relates to two different strands of literature that find a similar increase in lending by banks to a sector that experiences a negative shock (the underlying mechanism is different). One literature is on the internalization of negative spillovers by banks. Consistent with this literature, Giannetti and Saidi (2019) 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). The other related literature is on zombie lending (Caballero et al., 2008; Bruche and Llobet, 2014; Acharya, Eisert, Eufinger and Hirsch, 2019; Acharya, Lenzu and Wang, 2021). In line with this literature, Agarwal, Correa, Morais, Roldán and Ruiz Ortega (2020) find that banks increase lending to riskier firms where they have high debt concentration post a negative shock. In contrast to these results, our findings highlight that banks increase their lending especially to profitable firms in the sectors they specialize in, post negative shocks (even after controlling for measures of concentration). We find that banks obtain higher yields from lending to the affected sector, consistent with the idea that banks benefit from specialization. Furthermore, we find that negative externalities arise for firms in unaffected sectors due to banks' specialization when there are funding constraints.

Finally, the paper also contributes to the literature that highlights those economic shocks at the individual firm level may lead to aggregate fluctuations through real and financial channels (Allen and Gale, 2000; Gabaix, 2011; Acemoglu, Carvalho, Ozdaglar and Tahbaz-Salehi, 2012; Chodorow-Reich, 2014; Iyer et al., 2014; Costello, 2020; Gabaix and Koijen, 2021).[9] Our paper highlights banks might play a much more important role in the transmission of negative sector-specific shocks - beyond the mechanical effect of financial linkages.[10] We find that banks lend more to the sectors they specialize in, post a negative shock and, as a consequence, when there are funding constraints, they cut back on credit to unrelated sectors in their portfolio. Thus our paper highights a less mechanical way of transmission of shocks in which bank specialization helps in absorbing negative shocks but at the cost of transmission of shocks to other unrelated sectors. Our paper

[9]On the real side, idiosyncratic shocks to large firms can generate aggregate shocks, and also lead to spillovers via input-output production linkages. On the financial side, micro shocks can propagate between firms through, for instance, a financial network arising from trade credit linkages; or due to linkages via banking intermediaries leading to aggregate fluctuations.

[10]See also Acharya, Hasan and Saunders (2006), Federico, Hassan and Rappoport (2020), and Paravisini et al. (2022).

also provides evidence that negative sector-specific shocks transmitted through financial intermediary linkages do not have real effects, unless financing conditions are tight. Thus, the paper provides evidence on conditions under which transmission of shocks through intermediaries has an important effect on real economic activity.

The rest of the paper is structured as follows. Section 2 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 3. Section 4 concludes.

2 Data and Measurement

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

2.1 Measuring Granular Non-Financial Shocks

An essential step in the analysis is to identify periods when industries experience negative shocks. Below, 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-also referred to as affected sector-according to the industry stock returns. We define a downturn episode, $Downturn_{s,t}$, as a dummy variable that takes the value one if the cumulative (semi-annual) median stock returns in a two-digit SIC industry s and time t is lower than -10%, and zero otherwise.[11]

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

Periods of downturn are intended to capture unpredictable non-financial shocks that can constrain 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 downturn episodes.[12] In our sample about 40% of the sector-time observations are associated with downturn episodes.

[11] We aggregate the stock returns data at the biannual frequency in order to capture time-varying industry conditions.

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

A potential concern with the stock returns approach for identifying downturns is that investor reaction can be correlated with an industry's prospects, and thus downturns can be endogenous to 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.

$$Oil\ shock_{s,t} = \begin{cases} 1 & \text{if } P_t > E(P_t) \text{ in oil-dependent sectors} \\ 0 & \text{Otherwise} \end{cases} \tag{2}$$

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.

2.2 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:

$$Specialization_{b,s,t} = \frac{\sum_{f=1}^{F} Loan_{b,f,s,t}}{\sum_{s=1}^{S} \sum_{f=1}^{F} Loan_{b,f,s,t}} , \tag{3}$$

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] F and S capture the total number of firms and sectors, respectively. Bank specialization captures the importance of a sector for a bank and ranges from zero (no

[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).

lending to a sector) to one (perfect specialization in a sector). To measure the degree to which a bank is exposed to industries negatively affected by a downturn or an unanticipated increase in oil prices, we sum the bank's lending exposure in $t-1$ to sectors that are affected in t. Specifically, we use the following definition:

$$Exposure_{b,t-1} \equiv \begin{cases} Exposure^{Down}_{b,t-1} = \sum^{n}_{s \in Downturn_{s,t}} Specialization_{b,s,t-1} \\ Exposure^{Oil}_{b,t-1} = \sum^{n}_{s \in Oil\ shock_{s,t}} Specialization_{b,s,t-1} \end{cases} \tag{4}$$

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

We also construct a measure of market shares of banks within an industry to use as a control variable in the analysis.[15] 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:

$$Market\ shares_{b,s,t} = \frac{\sum^{F}_{f=1} Loan_{b,f,s,t}}{\sum^{B}_{b=1} \sum^{F}_{f=1} Loan_{b,f,s,t}}. \tag{5}$$

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 sum the bank's market shares in $t-1$ to sectors that are affected in t as follows:

$$Market\ shares_{b,t-1} \equiv \begin{cases} Market\ shares^{Down}_{b,t-1} = \sum^{n}_{s \in Downturn_{s,t}} Market\ shares_{b,s,t-1} \\ Market\ shares^{Oil}_{b,t-1} = \sum^{n}_{s \in Oil\ shock_{s,t}} Market\ shares_{b,s,t-1} \end{cases} \tag{6}$$

2.3 Data sources

For the analysis, we use 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 con-

[15] Banks with high market shares in a sector might have different incentives in terms of lending to that sector and might be differently affected by downturn in that sector (see Giannetti and Saidi, 2019).

struct 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, 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 provisions, covenants, among others. DealScan does not contain complete information on lenders' shares for all loans. For the loans with a full breakdown of shares, we allocate the exact loan portions to the individual lenders. For the remaining loans, we follow Chodorow-Reich (2014) and Giannetti and Saidi (2019) and divide the loan volumes among the missing syndicate members on a pro-rata basis. Importantly, we also use alternative rules like keeping only a subsample of loans with complete information or estimating a model in which the loan shares of individual lenders is the dependent variable and obtain predictions (De Haas and Van Horen, 2013).

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 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 et al., 2020).[16]

[16] 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

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 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. 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. However, to examine differential effects when aggregate credit conditions are tight, we use the Gilchrist and Zakrajšek (2012) Excess Bond Premium (EBP) to capture financial frictions during our sample period.[17] In addition, we use Baumeister and Kilian (2016) to link different oil price shocks to oil-dependent industries.

To control for outliers, we exclude observations in the one per cent from the upper and

strategy see Lim, Minton and Weisbach, 2014; Irani et al., 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.

[17] 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.

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 median bank has 29 firm connections in a given year. From these connections, 7 firms operate in an affected sector, suggesting that banks acting as common lenders can potentially substitute credit among firms.

2.4 Descriptive statistics

Panel A of Table 1 describes the summary statistics for the loan (bank-firm) level sample. The average loan amount arranged and retained by a lender is \$49 million. 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). The average bank has 10% of its loans invested in an industry, although there is a significant variation (16.3%). The relative exposure of the bank's portfolio to all affected sectors amounts to 20%. Notably, about 21% of the observations in our sample are associated with industry downturns.[18] The remaining variables in panel A correspond to different characteristics of the banks' and firms' balance sheets.

Panel B of Table 1 reports statistics for the main variables of interest at the firm level. The exposure variable is aggregated at the firm level using as weights the share of credit that the firm receives from affected banks relative to toal firm credit. The average exposure is 20.1%, and about 52% of the firm-time observations in our sample are associated with periods that aggregate financing conditions are high (following Gilchrist and Zakrajšek, 2012, shocks). In panel C, we report statistics when we aggregate at the industry level. Table A1, in the appendix, defines all remaining variables.

In Table 2 we follow the approach of Imbens and Wooldridge (2009) and provide normalized differences when we split the loan-level dataset between affected and non-affected sectors. The normalized difference for all variables is 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 affected sectors pay on average a higher AISD than non-affected sectors. The balance is 7% of a standard deviation. Similarly, the affected sectors pay a higher premium of 5% of a standard deviation when considering only the spread instead of the AISD. Moreover, in affected sectors banks are slightly more specialized and have a lower

[18] About 79% of industry downturns in our sample are not preceded or followed by another downturn.

capitalization.

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 downturn. There are several important takeaways from this table. First, the number of unique banks per period 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.

3 Empirical Results

In the presence of adverse industry-specific shocks, we first explore whether specialized banks increase their flow of credit to firms in the affected sector relative to non-specialized banks. Then, we will examine whether firms in unaffected and unrelated sectors that have a credit relationship with a bank lending to an affected sector face a credit reduction.

3.1 Loan-level outcomes

Bank specialization. To test whether banks specialising in affected sectors are more inclined to provide credit during downturns to the affected sectors, we estimate the following specification:

$$\begin{aligned} Ln(amount)_{b,f,t} = \alpha_{f,t} + \alpha_{b,t} + \alpha_{f,b} + \beta_1 \times Specialization_{b,s,t-1} + \beta_2 \times Downturn_{s,t} + \\ + \beta_3 \times Specialization_{b,s,t-1} \times Downturn_{s,t} + \gamma_1 \times X + \epsilon_{b,f,t} \ . \end{aligned} \tag{7}$$

The dependent variable is the natural logarithm of the loan amount that bank b lends to firm f at time t. $Specialization_{b,s,t-1}$ measures bank's specialization and $Downturn_{s,t}$ is a dummy variable that takes the value one if the cumulative returns of the sector that the firm operates are higher than -10% and zero otherwise. X is a vector of control variables. We saturate the loan-level specification with granular firm-time ($\alpha_{f,t}$), bank-time ($\alpha_{b,t}$), and bank-firm ($\alpha_{f,b}$) fixed effects to control for a broad range of unobserved factors. $\epsilon_{b,f,t}$

is a stochastic disturbance. Finally, we double cluster our standard errors at the bank and firm level to account for serial correlation within firm and bank across time.

Table 3 reports results of estimating equation (7). In column I of Table 3, the coefficient on bank specialization is positive and statistically significant. This is consistent with the notion that banks' in general lend more to sectors in which they specialize. The coefficient on downturn is insignificant. However, the interaction of downturn and specialization is positive and significant. This suggests that, during downturn episodes, banks lend more to sectors in which they specialize. Economically, the baseline estimate of column I indicates that banks specialized in sectors that are affected increase their lending by \$23.8 million. In columns II, III and IV 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). The coefficient on the interaction term is also very stable across different specifications (column 2 to column 4), when we introduce fixed effects (adj R-squared increases). This suggests that results are not driven by selection on unobservables and hence by omitted variables problems (Altonji, Elder and Taber, 2005; Oster, 2019).

The evidence reported above suggests that when there is an advsere shock, banks with higher specialization in the affected sector smooth out credit fluctuations to firms operating in these sectors. To further understand the underlying driver behind these results, we examine the interest rate charged by banks for lending to firms in the affected sectors. In Table 4 we report these results. In columns I-IV, 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 V-VIII, we only include the spread. In column I, the coefficient of downturn is positive and significant, indicating that firms in affected sectors pay, on average, a higher $AISD$ by 12.16 bps. The coefficient on the interaction term ($Specialization * Downturn$) is significant and negative. That is, banks with a higher specialization to affected sectors are decreasing the $AISD$ by 6.5 bps during downturn episodes. The total effect of exposure is still positive and significant at around 5.66 bps on average. Thus, specialized banks get a higher return from lending to affected sectors compared to unaffected sectors (Stein, 2013). The results above highlight that banks which do not have specialization in lending to a sector, charge higher rates for lending to firms in the affected sector as compared to specialized banks. Thus, specialized lenders obtain higher returns from lending to firms in the affected sectors and at the same the firms in the affected sector can avail credit at lower rates relative to borrowing from non-specialized lenders.

In columns II, III and IV 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 Panel B, we replicate the analysis in of Panel A but we add the triple interaction of $low\ capital * Specialization * Distress$. 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] The coefficient on the triple interaction is positive and significant in all specifications. That is, under-capitalized banks with exposure to affected sectors increase further the premium that they charge for lending to affected firms (Jiménez, Ongena, Peydró and Saurina, 2017; Rehbein and Ongena, 2021).

Thus far, our estimates in Table 4 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. We find similar results to those presented earlier. Overall, the results so far provide evidence that banks lend more to the sectors that they specialize in, post an adverse shock, as compared to other lenders. These banks also get higher return from lending to affected sectors compared to unaffected sectors, and the effects tend to be stronger for under-capitalized banks. The change in the rates charged for lending to firms in the affected sector, also helps address the concern that credit supply to firms in the affected sector is purely an artifact of more credit demand by firms borrowing from specialized banks.

The results above highlight the benefit of lending specialization of banks in terms of credit provision and the price of credit, for firms in the affected sector post an adverse shock. However, one could be concerned that the specialization measure could also be picking up concentration of lending in a particular sector. More, precisely, if the market share of the bank in a particular sector was high (as compared to the total credit outstanding in that sector), the bank lend more to that sector as it internalizes the risk of negative spillovers. To do so, in column I of Table 5, we use the *Exposure* variable to capture the total bank's lending exposure in $t-1$ to all sectors that are in downturn in t exploiting variation only within affected firms. The coefficient on bank exposure is positive and statistically significant. In line with the results in Table 3, during downturn episodes, banks specializing in affected sectors increase their lending to affected firms compared to non-specialized

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

banks. In column II, we use the *Market shares* variable to capture the importance of a bank to sectors that are in downturn. 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. In column III, we add both the bank specialization and market shares in affected sectors. Interestingly, the estimate on the *Market shares* is statistically insignificant, while the *Exposure* remains similar to the one in column I.

Table 6 analyzes whether banks originate loans to zombie firms or whether banks pick the more profitable firms within affected sectors. In Table 6, Panel A, we regress bank lending on the interaction between the variable of interest (*Exposure*), 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* is significant and similar in magnitude with column I of Table 5. 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 columns 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.[20]

While the results above suggest that zombie lending is less of a concern, we further examine if banks with lower levels of capital are more likely to engage in lending more to worse firms in affected sectors after an adverse shock.[21] In Panel B of Table 6, we compare

[20]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* variable remains significant and positive, while the interaction term for each performance variable is insignificant.

[21]The literature on zombie lending (Caballero et al., 2008; Acharya et al., 2019) highlights that the incentive to lend to worse firms after an adverse shock is higher for banks that have lower capital.

lending by low versus high capitalization banks with different lending exposures to affected sectors. Panel B is similar in structure to Panel A, but in addition, we add the triple interaction involving capital ratios. In columns I-III of Panel B, the coefficient of interest is positive and significant at 10%. Our results suggest that even banks with a lower Tier 2 ratio that are exposed to affected sectors increase the supply of credit to borrowers that 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 credit to firms with ex-ante higher profitability.

Industry spillovers. Overall, the previous results suggest that specialized banks act as shock absorbers in the face of negative industry specific shocks by providing credit to firms in the affected sector. This raises the question whether higher credit from specialized banks to the affected sectors change lending conditions to the unaffected sector? To make progress in addressing this question, we estimate the following loan specification:

$$Ln(amount)_{b,f,t} = \alpha_{f,t} + \alpha_{b,t} + \alpha_{f,b} + \beta \times Exposure_{b,t-1} + \gamma_1 * X + \epsilon_{b,f,t}\ . \qquad (8)$$

The dependent variable is the natural logarithm of the loan amount that bank b lends to firm f operating in a non-affected industry at time t. $Exposure_{b,t-1}$ measures the total bank's specialization in all affected industries. X is a vector of loan controls. $\alpha_{f,t}$, $\alpha_{b,t}$, and $\alpha_{f,b}$ are firm-time, bank-time, and firm-bank fixed effects, and $\epsilon_{b,f,t}$ 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.

Column I of Panel A in Table 7, 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. Economically, the baseline estimate of column I indicates that one standard deviation increase (0.293) in the bank's lending specialization in an affected sector decreases lending in a non-affected firm by 2.3%. In column II, we control for market shares in affected sectors. As in Table 5, the estimate on the *Market shares* is statistically insignificant, while the *Exposure* coefficient remains similar to the one in column I.

In columns III, IV, V and VI of Panel A, we add time-varying fixed effects to alleviate concerns with demand, supply, and bank-firm matching unobserved 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 synchronized with the opposite effect observed in affected firms (as presented in the previous tables).[22] That is, at the same time that specialized 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 specialized banks have different lending patterns prior to the downturn to the unaffected sectors. The *exposure* 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.

A related concern is that negative shocks to an industry can spread over the supply chain as firms in affected sectors 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, VII, VIII and IX, we report these results. The estimated coefficients are almost identical to the baseline results, confirming that the observed credit reduction in unaffected and unrelated firms is not driven by supply chain linkages.

An additional concern is related to the stock returns approach to measure downturn. Investor reactions to stock returns for different sectors can be correlated with the industry's prospects, potentially making the interpretation of results difficult. 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 Table A5, we use oil shocks instead of stock returns to define shocks and repeat the analysis of Panel A. The only difference compared to Table 7, is that we redefine the bank

[22] In Table A6, we use the whole spectrum of negative returns (instead of a threshold at -10%). In column I, the negative and significant coefficient on the interaction variable (0.005) confirms that banks increase lending to specialized sectors that are affected. Importantly, higher negative returns further increase the credit supply. In column 2, the negative 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 sectors.

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.[23] The 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.[24] 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. These results suggest that the findings are robust to different definitions of negative industry specific shocks.

3.2 Firm-level outcomes

The preceding analysis lays the groundwork for asking whether the observed reallocation of credit impacts real economic activity. If unaffected firms can compensate for the loss of credit with other banks or bond markets there would be no real effects. However, if firms cannot compensate for loss in credit, this could impact real economic outcomes like investment, size, employment and sales. To investigate this, we aggregate the loan-level data at the firm level using the share of credit in each bank-firm relationship as weights and estimate the following specification only for non-affected firms:

$$\begin{aligned} Ln(Y)_{f,t} = \alpha_t + \alpha_f + \beta_1 \times AvgExposure_{f,t-1} + \\ + \beta_2 \times AvgExposure_{f,t-1} \times Frictions_t + \gamma_1 \times X_{f,t} + \epsilon_{f,t} \ . \end{aligned} \quad (9)$$

In the baseline regression of equation (9), the dependent variable is the natural logarithm of the total loan amount that a non-affected firm f at time t receives. In addition, to analyze the real effects, we also use as a dependent variable the investment, external

[23] 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. More details in section 2.

[24] 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%.

debt, size, employment and sales. $AvgExposure_{f,t-1}$ measures the average firm exposure to affected banks using as weights the share of credit that a firm receives from these banks relative to total firm credit. To examine whether the effects are larger in periods with higher financial frictions, we interact the exposure variable with different proxies for aggregate credit conditions. Controls ($X_{f,t}$) include the firm's return on assets and cash flow volatility measured as the standard deviation of the firm's cash flow divided by the absolute value of the mean cash flow, and fixed effects at the firm (α_f) and year (α_t) levels. Finally, $\epsilon_{f,t}$ is a stochastic disturbance and we cluster our standard errors at the firm and time level.

Table 8 shows the results only for non-affected firms. In column I, the positive but insignificant coefficient on the $AvgExposure$ 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 ($AvgExposure$*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 et al., 2014). In other words, transaction and information costs could make it difficult to change the banking partner during crisis periods.[25]

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). 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. Economi-

[25] $AvgExposure$ might be determined simultaneously with syndicated lending amounts and firm outcomes. To address this potential source of endogeneity, we adopt an instrumental-variables (IV) methodology. We collect data on M&A from the Fed and identify the banks in Dealscan. We then construct an instrument for the $AvgExposure$ variable using only the historical exposure variables of the target bank (acquired). 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. Table A8 reports the results. The results are similar to that reported above.

cally, 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 substantially 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 turmoil reduces the credit supply of non-affected 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 distress. For instance, as shown in Table A3, in 2008h1 and 2008h2 the share of industries in distress were 73% and 98%, respectively. To alleviate this concern, in Table A7 we do a robustness exercise where we exclude the GFC period. Results remain unchanged.

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.

3.3 Industry-level outcomes

Given the real effects at the firm level, especially in times when financing frictions are high, it is important to understand whether these results also hold at the industry level. 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 using the share of credit in each bank-industry relationship as weights. We employ a specification similar to the firm level analysis and run the following regression only for non-affected sectors:

$$\Delta Ln(Y)_{s,t} = \alpha_t + \alpha_s + \beta_1 \times AvgIndExposure_{s,t-1} \\ + \beta_2 \times AvgIndExposure_{s,t-1} \times Frictions_t + \gamma_1 \times X_{s,t} + \epsilon_{s,t} \ , \quad (10)$$

where Y is in log differences to measure the incremental changes after the shock and corresponds to one of the following variables: credit supply from the syndicated market, investments, total debt, size, the number of employees and sales. $AvgIndExposure_{s,t-1}$ measures the average sector exposure to affected banks using as weights the share of credit that a sector receives from these banks relative to total credit. As in the firm-level analysis (section 3.2) we interact the weighted industry-level exposure variable with different proxies of financial turmoil like the GFC (Panel A) and $financial\ frictions$ (Panel B). $X_{s,t}$ includes the industry's return on asset and cash flow volatility measured as the standard deviation of the industry's cash flow divided by the absolute value of the mean cash flow. α_t and α_s are fixed effects at the sector and year levels, respectively. Finally, $\epsilon_{s,t}$ is a stochastic disturbance and we cluster our standard errors at the industry and time level.

Column I of Panel A (Table 9) shows that on average, the estimated coefficient of $AvgIndExposure$ 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. 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 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 substantially lower investment (9.6%), debt (8.9%), size (1%), employment (40%) and sales (20%).

In Panel B of Table 9, we follow the structure of Table 8 and use the Gilchrist and Zakrajšek (2012)'s EBP to proxy for financial frictions during our sample period. 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. Comparison of the results at the industry level with firm level results (Table 8) point to important differences. While the effect being concentrated in times of financial frictions shows up in both the tables, the effect during normal times is more mixed when looking at firm level real effects. The effects for investment, size and sales for firms in unaffected sectors were negatively related to higher exposure to banks with specialization in affected sectors. However, at the industry level the effect of exposure to banks with specialization in affected sectors has no negative effect on real outcomes in normal times. Thus, on a broader these findings suggest that spillover effects to unaffected sectors mainly arise during times when there are aggregate financing frictions, and not during normal times.

4 Conclusion

This paper analyses banks' lending specialization and the effects on credit supply in the presence 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 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. 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 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. We also 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 to obtain higher yields, these banks are decreasing lending to non-affected sectors.

Examining the real effects, we find that on average the firm outcomes in unrelated 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. Thus, our results suggest that while firms in unrelated sectors are able to avail credit from other sources to make up for the reduction in credit in normal times, this does hold in times of financial turmoil. Overall, our findings highlight that bank specialization helps in absorbing negative industry specific shocks but at the cost of transmission of shocks to other unrelated sectors when financing frictions are high.

References

Abbassi, P., Iyer, R., Peydró, J.-L. and Tous, F. R.: 2016, Securities trading by banks and credit supply: Micro-evidence from the crisis, *Journal of Financial Economics* **121**(3), 569–594.

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., Eisert, T., Eufinger, C. and Hirsch, C.: 2019, Whatever it takes: The real effects of unconventional monetary policy, *The Review of Financial Studies* **32**(9), 3366–3411.

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.

Acharya, V. V., Lenzu, S. and Wang, O.: 2021, Zombie lending and policy traps, *Technical report*, National Bureau of Economic Research.

Agarwal, S., Correa, R., Morais, B., Roldán, J. and Ruiz Ortega, C.: 2020, Owe a bank millions, the bank has a problem: Credit concentration in bad times, *FRB International Finance Discussion Paper* (1288).

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

Altonji, J. G., Elder, T. E. and Taber, C. R.: 2005, Selection on observed and unobserved variables: Assessing the effectiveness of Catholic schools, *Journal of Political Economy* **113**, 151–184.

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.

Blickle, K., Parlatore, C. and Saunders, A.: 2021, Specialization in banking, *FRB of New York Staff Report* (967).

Bruche, M. and Llobet, G.: 2014, Preventing zombie lending, *The Review of Financial Studies* **27**(3), 923–956.

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

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.

Chakraborty, I., Goldstein, I. and MacKinlay, A.: 2018, Housing price booms and crowding-out effects in bank lending, *The Review of Financial Studies* **31**(7), 2806–2853.

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.

De Haas, R. and Van Horen, N.: 2013, Running for the exit? international bank lending during a financial crisis, *The Review of Financial Studies* **26**(1), 244–285.

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.

Diamond, D. W. and Rajan, R. G.: 2011, Fear of fire sales, illiquidity seeking, and credit freezes, *The Quarterly Journal of Economics* **126**(2), 557–591.

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

Fama, E. F.: 1985, What's different about banks?, *Journal of Monetary Economics* **15**(1), 29–39.

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. 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.

Giroud, X. and Mueller, H. M.: 2017, Firm leverage, consumer demand, and employment losses during the great recession, *The Quarterly Journal of Economics* **132**(1), 271–316.

Giroud, X. and Mueller, H. M.: 2019, Firms' internal networks and local economic shocks, *American Economic Review* **109**(10), 3617–49.

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

Holmström, B. and Tirole, J.: 1998, Private and public supply of liquidity, *Journal of political Economy* **106**(1), 1–40.

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.

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.

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

Oster, E.: 2019, Unobservable selection and coefficient stability: Theory and evidence, *Journal of Business & Economic Statistics* **37**(2), 187–204.

Paravisini, D.: 2008, Local bank financial constraints and firm access to external finance, *The Journal of Finance* **63**(5), 2161–2193.

Paravisini, D., Rappoport, V. and Schnabl, P.: 2022, Specialization in bank lending: Evidence from exporting firms, *The Journal of Finance* . Forthcoming.

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.

Schnabl, P.: 2012, The international transmission of bank liquidity shocks: Evidence from an emerging market, *The Journal of Finance* **67**(3), 897–932.

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.

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
Exposure	102,069	0.204	0.293	0.000	0.025	1.000
Downturn	102,069	0.203	0.402	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
AvgExposure	34,669	0.201	0.291	0.000	0.035	1.000
GFC	35,039	0.068	0.252	0.000	0.000	1.000
Financial frictions	35,039	0.524	0.499	0.000	1.000	1.000
Panel C: 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
AvgIndExposure	3,475	0.012	0.045	0.000	0.001	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 industry-time level. Table A1 in appendix defines all variables.

Table 2: Normalized differences in univariate analysis

	I	II	III	IV	V
	$Non-Affected$		$Affected$		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
$Tier\ 2/TA$	0.091	0.037	0.09	0.036	-0.051

The table reports normalized differences for a sample of syndicated loans that 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. $Affected$ is a sector if the semi-annual returns of the sector that the firm operates are higher than -10%. 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 the ratio of total credit granted by a bank to a specific sector relative to the bank's total credit granted. $Tier\ 2/TA$ is the ratio of the bank's capital relative to its total assets.

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

Dependent variable:	Ln(amount)			
	I	II	III	IV
$Specialization_{b,s,t-1}$	0.260***	0.436***	0.149***	0.331***
	(4.721)	(6.968)	(3.193)	(6.689)
$Downturn_{s,t}$	0.017	0.013	0.011	0.004
	(1.531)	(1.159)	(0.358)	(0.119)
$Specialization_{b,s,t-1}$ * $Downturn_{s,t}$	0.236***	0.317***	0.214***	0.221***
	(3.070)	(3.617)	(3.340)	(2.848)
Observations	99,254	98,845	96,325	95,894
Adjusted R-squared	0.501	0.508	0.677	0.680
Bank controls	Y		Y	
Firm controls	Y	Y		
Loan controls	Y	Y	Y	Y
Time FE	Y			
Bank FE	Y		Y	
Firm FE	Y	Y		
Bank*Time FE		Y		Y
Firm*Time FE			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 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 originated in the U.S. from 1987h1 until 2016h1. The dependent variable is the loan amount held by each lender at origination. $Specialization_{b,s,t-1}$ is the bank specialization and is defined as the share of total credit granted by a bank b to a specific sector s relative to the bank's total credit. $Downturn_{s,t}$ 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. 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 4: Is the cost of lending more expensive to firms in affected sectors: Loan level

	I	II	III	IV	V	VI	VII	VIII
Dependent variable:	AISD (bps)				Margin (bps)			
	Panel A: Cost of lending							
$Specialization_{b,s,t-1}$	-9.558***	-11.862***	-6.272***	-8.137***	-10.629***	-11.900***	-5.097***	-7.170***
	(-6.879)	(-7.440)	(-5.276)	(-5.149)	(-7.160)	(-7.029)	(-3.969)	(-4.327)
$Downturn_{s,t}$	12.161***	10.792***	23.433***	16.982***	12.021***	11.500***	25.392***	15.350***
	(8.178)	(6.858)	(7.646)	(6.467)	(7.253)	(6.721)	(8.346)	(5.835)
$Specialization_{b,s,t-1}$ * $Downturn_{s,t}$	-6.551***	-4.902*	-4.571	-5.519**	-5.142**	-4.687*	-6.888**	-4.491*
	(-2.669)	(-1.908)	(-1.640)	(-2.242)	(-1.965)	(-1.728)	(-2.138)	(-1.716)
Observations	102,069	101,580	98,866	98,363	102,557	102,075	99,351	98,849
Adjusted R-squared	0.701	0.706	0.919	0.918	0.625	0.630	0.832	0.830
	Panel B: The role of capital							
$Low\ capital_{b,t}$ * $Specialization_{b,s,t-1}$ * $Downturn_t$	5.245**	6.004***	7.681**	9.117**	5.782***	6.572***	7.242**	10.295**
	(2.540)	(2.849)	(2.329)	(2.376)	(2.645)	(2.929)	(1.997)	(2.527)
Observations	84,565	84,306	82,518	82,257	84,883	84,627	82,840	82,578
Adjusted R-squared	0.713	0.716	0.916	0.915	0.646	0.649	0.836	0.834
Bank controls	Y		Y		Y		Y	
Firm controls	Y	Y			Y	Y		
Loan controls	Y	Y	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		Y		Y
Firm*Time FE			Y	Y			Y	Y
Clustered standard errors	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 affected and non-affected industries. The unit of our analysis is at the loan level. The sample consists of syndicated loans originated in the U.S. from 1987h1 until 2016h1. The dependent variables are indicated at the top of each column. In columns I-IV, 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 V-VIII, we only include the spread. $Specialization_{b,s,t-1}$ is the bank specialization and is defined as the share of total credit granted by a bank b to a specific sector s relative to the bank's total credit. $Downturn_{s,t}$ 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, while Panel B shows the role of capital. The $Low\ capital_{b,t}$ 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 5: Do exposed banks lend more to firms in affected sectors: Loan level

Dependent variable:	Ln(amount)		
	I	II	III
$Exposure_{b,t-1}$	0.174***		0.158***
	(3.517)		(3.146)
$Market\ shares_{b,t-1}$		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 affected industries. The unit of our analysis is at the loan level. The sample consists of syndicated loans originated in the U.S. from 1987h1 until 2016h1. The dependent variable is the loan amount held by each lender at origination. $Exposure_{b,t-1}$ and $Market\ shares_{b,t-1}$ are the bank specialization and market shares to industries that are in downturns, respectively. We define affected sectors (downturn) 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 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 6: Do exposed 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				
$Exposure_{b,t-1}$	0.143***	0.143***	0.143***	0.124***
	(3.391)	(3.418)	(3.458)	(2.639)
$Exposure_{b,t-1}$ * $\Delta(ROA_{f,t+1} - ROA_{f,t})$	0.377*			
	(1.866)			
$Exposure_{b,t-1}$ * $\Delta(ROA_{f,t+2} - ROA_{f,t})$		0.720***		
		(2.795)		
$Exposure_{b,t-1}$ * $\Delta(ROA_{f,t+3} - ROA_{f,t})$			0.572***	
			(3.350)	
$Exposure_{b,t-1}$ * $ROA_{f,t-1}$				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				
$Low\ capital_{b,t}$ * $Exposure_{b,t-1}$ * $\Delta(ROA_{t+1} - ROA_t)$	0.426*			
	(1.788)			
$Low\ capital_{b,t}$ * $Exposure_{b,t-1}$ * $\Delta(ROA_{t+2} - ROA_t)$		0.634**		
		(2.234)		
$Low\ capital_{b,t}$ * $Exposure_{b,t-1}$ * $\Delta(ROA_{t+3} - ROA_t)$			0.563***	
			(3.550)	
$Low\ capital_{b,t}$ * $Exposure_{b,t-1}$ * 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 affected industries. The unit of our analysis is at the loan level. The sample consists of syndicated loans originated in the U.S. from 1987h1 until 2016h1. The dependent variable is the loan amount held by each lender at origination. $Exposure_{b,t-1}$ is the bank specialization to industries that are in downturns. We define affected sectors (downturns) 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 $(t + 1)$ until the third year $(t + 3)$ after the loan origination minus the ROA at the time of the loan (t). In column IV, we use the firm's ROA one year before the loan origination $(t - 1)$. 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 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 7: Do banks reduce lending to firms in non-affected industries: loan level

	I	II	III	IV	V	VI	VII	VIII	IX
Supply chain: BEA Input-Output							Unrelated sectors		
$Exposure_{b,t-1}$	-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)
$Market\ shares_{b,t-1}$		-0.002						-0.004	0.007
		(-0.638)						(-1.502)	(0.620)
Observations	85,560	85,558	85,064	83,229	82,719	74,926	62,402	62,399	61,894
Adjusted R-squared	0.509	0.509	0.516	0.679	0.681	0.544	0.674	0.674	0.675
Bank controls	Y	Y		Y					
Firm Controls	Y	Y	Y			Y	Y	Y	
Loan controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	Y	Y							
Bank FE	Y	Y		Y			Y	Y	
Firm FE	Y	Y	Y						
Bank*Time FE			Y		Y	Y			Y
Firm*Time FE				Y	Y		Y	Y	Y
Bank*Firm FE						Y			
Clustered standard errors	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 unit of our analysis is at the loan level. The sample consists of syndicated loans originated in the U.S. from 1987h1 until 2016h1. The dependent variable is the loan amount that a bank lends to a firm in non-affected industries. $Exposure_{b,t-1}$ and $Market\ shares_{b,t-1}$ are the bank specialization and market shares to industries that are affected, respectively. We define affected sectors (downturn) 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, VIII and IX , 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 $ROA\ (bank)$. 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						
$AvgExposure_{f,t-1}$	0.081	-0.115***	0.128	-0.057**	0.124	-0.078**
	(1.385)	(-9.917)	(0.945)	(-2.030)	(1.508)	(-2.412)
$AvgExposure_{f,t-1}$ * 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						
$AvgExposure_{f,t-1}$	-0.249	-0.072***	0.076	-0.179***	0.008	0.055
	(-1.585)	(-3.426)	(0.692)	(-2.618)	(0.303)	(0.987)
$AvgExposure_{f,t-1}$ * $Frictions_t$	-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
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-time 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. $AvgExposure_{f,t-1}$ is the bank's exposure to industries that are affected at the firm-time level using the share of credit in each bank-firm relationship as weights. In Panel A, the variable 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 the borrower's creditworthiness (Gilchrist and Zakrajšek, 2012).In all specifications, we include firm and time fixed effects, as noted in the table's lower part, and 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: 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					
$AvgIndExposure_{s,t-1}$	1.294	0.133***	-0.033	-0.018	0.080	0.456
	(0.470)	(2.720)	(-0.261)	(-0.952)	(0.150)	(0.853)
$AvgIndExposure_{s,t-1}$ * 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					
$AvgIndExposure_{s,t-1}$	8.799	2.046**	-0.873*	0.046	5.092*	-0.137
	(1.015)	(2.113)	(-1.724)	(0.285)	(1.855)	(-0.629)
$AvgIndExposure_{s,t-1}$ * $Frictions_t$	-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
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. We aggregate a sample of U.S. syndicated loans for firms covered in DealScan at the industry-time 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. $AvgIndExposure_{s,t-1}$ is the bank's exposure to industries that are affected at the industry-time level using the share of credit in each bank-industry relationship as weights. In Panel A, the variable 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 the borrower's creditworthiness (Gilchrist and Zakrajšek, 2012).In all specifications, we include industry and time fixed effects as noted in the table's lower part. We also 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.	DealScan
AISD (bps)	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 ($M) that a bank lends to a firm classified on a two-digit SIC sector over bank's total lending ($M). This index ranges from zero to one, with higher values reflecting higher specialization.	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
Downturn	Dummy variable equal to one if the semi-annual returns in a two-digit SIC sector were lower than -10%, and zero otherwise.	Own calculations
Oil-price shock	Dummy variable equal to one if the oil price is higher than the expected price. 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.	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 downturn (or oil affected). Specifically, we aggregate for each bank the shares of their specialization in $t-1$ to industries that are in downturn (or oil affected) in t. For the firm-level analysis, we aggregate the exposure variable at the firm level ($AvgExposure$) using as weights the share of credit that a firm receives from affected banks over total firm credit. Similarly, for the industry-level exposure ($AvgIndExposure$) but we use as weights the share of credit that a sector receives from affected banks over total credit.	Own calculations
Bank size	The natural logarithm of the bank's total assets.	Call reports
Tier 2/TA	Bank's tier 2 capital over total assets.	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
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)

Loan-level evidence

Table A2: Sample distribution

	I	II	III	IV	V	VI	VII
				Industry Returns (%)		Industry Downturns (%)	
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 Downturns (%)	
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 industries in downturn (stock returns less than -10%) in each period.

In Table A3, we test whether banks with higher exposure to affected sectors are engaged with poorly-performing firms. We use different indicators for the firm's past performance like *Investement* and *Tangibility*. The $exposure_{b,t-1}$ 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 affecteded industries: Firm performance

	II	III
$Exposure_{b,t-1}$	0.150***	0.114*
	(2.741)	(1.729)
$Exposure_{b,t-1}$ * $Investment_{f,t-1}$	-0.024	
	(-0.160)	
$Exposure_{b,t-1}$ * $Tangibility_{f,t-1}$		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 affected industries. The unit of our analysis is at the loan level. The sample consists of syndicated loans originated in the U.S. from 1987h1 until 2016h1. The dependent variable is the loan amount held by each lender at origination. $Exposure_{b,t-1}$ is the bank specialization to industries that are affected. We define affected sectors (downturn) 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. $Investment_{f,t-1}$ and $Tangibilityf, t-1$, are calculated one year before the loan origination (pre-loan). In all specifications we include 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 change their credit supply to the unaffected sectors before the downturn. The dependent variables are each lender's loan amount and spread in columns I and II, respectively. The $exposure^{b,t-1}$ 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)
$Exposure_{b,t-1}$	-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 originated in the U.S. from 1987h1 until 2016h1. The dependent variable is reported in the second line. In all specifications we include 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 A5, we use oil shocks instead of stock returns to define shocks and repeat the analysis of Table 7. The only difference compared to Table 7, 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*.

Table A5: Do banks reduce lending to firms in non-oil affected industries: loan level

	I	II	III	IV	V	VI	VII	VIII	IX
Oil shock group:	"Economist" approach				"Financial market" approach				
Supply chain: BEA Input-Output				Unrelated					Unrelated
$Exposure_{b,t-1}$	-0.113***	-0.136***	-0.096*	-0.174***	-0.144***	-0.144***	-0.124***	-0.102**	-0.127***
	(-3.447)	(-3.883)	(-1.737)	(-3.861)	(-4.727)	(-3.768)	(-3.980)	(-2.086)	(-3.345)
Observations	81,138	78,759	78,189	48,803	81,138	80,555	78,759	78,189	48,803
Adjusted R-squared	0.525	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
Firm Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Loan controls	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			
Bank*Time FE			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

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 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. $Exposure_{b,t-1}$ 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. In columns I-IV and V-IX, 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.

In Table A6, we relax the condition by using the whole spectrum of negative returns (instead of a *downturn* dummy threshold at -10%). In column I, the negative and significant coefficient on the interaction variable (0.005) confirms that banks increase lending to specialized sectors that are affected. Importantly, higher negative returns further increase the credit supply. Economically, the baseline estimate of column I indicates that one standard deviation increase in the negative returns increases lending in an affected firm by 1%. In column 2, the negative 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 sectors. Overall, this result supports the conclusion of a symmetric treatment effect based on the stock returns and banks' exposures.

Table A6: Bank lending and negative returns : Loan level

Dependent variable:	Ln(amount)	
	I	II
Group:	All sectors	Only unaffected and unrelated sectors
$Specialization_{b,t-1}$	0.334***	
	(6.098)	
$Negative\ returns_{s,t}$	-0.001*	
	(-1.727)	
$Specialization_{b,t-1}$ * $negative\ returns_{s,t}$	0.005**	
	(1.961)	
$Exposure\ returns_{b,t-1}$		-0.018***
		(-10.672)
Observations	99,323	86,234
Adjusted R-squared	0.499	0.516
Bank controls	Y	Y
Firm controls	Y	Y
Loan controls	Y	Y
Time FE	Y	Y
Bank FE	Y	Y
Firm FE	Y	Y
Clustered standard errors	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 originated in the U.S. from 1987h1 until 2016h1. The dependent variable is the loan amount held by each lender. The variable $Specialization_{b,s,t-1}$ 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 absolute value of negative semi-annual returns in a two-digit SIC industry code and zero otherwise. $Exposure\ returns_{b,t-1}$ is for each bank the share of their specialization times the absolute value of negative returns (we replace the -10% threshold dummy with the negative returns). In all specifications, we include 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. *$p<.1$; **$p<.05$; ***$p<.01$.

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 share of industries in distress were 73% and 98%, respectively. To alleviate this concern, in Table A7 we do a robustness exercise where we exclude the GFC period. Results remain unchanged.

Table A7: Do industry spillovers impact real economic outcomes excluding the GFC period: Firm level

	I	II	III	IV	V	VI
Dependent variable	Ln(amount)	Ln(investment)	Ln(debt)	Ln(size)	Ln(employment)	Ln(sales)
$AvgExposure_{b,t-1}$	-0.240	-0.075***	0.077	-0.175**	0.010	0.058**
	(-1.534)	(-3.578)	(0.695)	(-2.549)	(0.392)	(2.129)
$AvgExposure_{b,t-1}$ * $Frictions_t$	-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 at the firm-time 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. $AvgExposure_{f,t-1}$ is the bank's exposure to affected industries at the firm-time level using the shares of credit in each bank-firm relationship as weights. 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.

Table A8 shows the results from the two-stages least square estimation exploiting exogenous variation from mergers between active banks 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 the $AvgExposure_{f,t-1}$ 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.

Table A8: Do industry spillovers impact real economic outcomes: IV estimates

Panel A: Glofal Financial Crisis						
Dependent variable	Ln(amount)	Ln(Investment)	Ln(Debt)	Ln(size)	Ln(employment)	Ln(sales)
	I	II	III	IV	V	VI
Fitted AvgExposure	-0.177	-0.179***	-0.014	0.007	0.068	-0.014
	(-1.463)	(-6.065)	(-0.177)	(0.142)	(1.431)	(-0.293)
Fitted AvgExposure * GFC	-2.930***	0.296***	0.300	-0.535**	-0.337*	-0.543***
	(-8.770)	(7.283)	(0.878)	(-2.485)	(-1.857)	(-2.930)
Observations	18,342	17,341	17,345	18,342	17,837	18,339
Adjusted R-squared	0.696	0.201	0.528	0.930	0.928	0.925
Panel B: Financial Frictions						
Fitted AvgExposure	0.304*	-0.045	0.165	-0.040	0.047	-0.054
	(1.916)	(-1.518)	(1.410)	(-0.613)	(0.713)	(-0.846)
Fitted AvgExposure * Frictions	-0.955***	-0.200***	-0.246*	0.028	0.006	0.018
	(-6.258)	(-5.336)	(-1.829)	(0.359)	(0.075)	(0.232)
Observations	18,342	17,341	17,345	18,342	17,837	18,339
Adjusted R-squared	0.695	0.202	0.528	0.930	0.928	0.925
Controls (weighted)	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-time 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. Fitted $AvgExposure_{f,t-1}$ measures the average firm exposure to affected banks (instrument for the $AvgExposure_{f,t-1}$ variable using only the historical exposure variables of the target bank (acquired)) using as weights the share of credit that a firm receives from these banks relative to total firm credit. In Panel A, the variable 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 the borrower's creditworthiness (Gilchrist and Zakrajšek, 2012).