IWH Halle Institute for Economic Research
Member of the Leibniz Association

Discussion Papers

No. 10

May 2023

Long-run Competitive Spillovers of the Credit Crunch

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IWH Discussion Papers are indexed in RePEc-EconPapers and in ECONIS.

Editor

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ISSN 2194-2188

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Abstract

Competition in the U.S. appears to have declined. One contributing factor may have been heterogeneity in the availability of credit during the financial crisis. I examine the impact of product market peer credit constraints on long-run competitive outcomes and behavior among non-financial firms. I use measures of lender exposure to the financial crisis to create a plausibly exogenous instrument for product market credit availability. I find that credit constraints of product market peers positively predict growth in sales, market share, profitability, and markups. This is consistent with the notion that firms gained at the expense of their credit constrained peers. The relationship is robust to accounting for other sources of inter-firm spillovers, namely credit access of technology network and supply chain peers. Further, I find evidence of strategic investment, i.e. the idea that firms increase investment in response to peer credit constraints to commit to deter entry mobility. This behavior may explain why temporary heterogeneity in the availability of credit appears to have resulted in a persistent redistribution of output across firms.

Keywords: financial crisis, instrumental variables, long-run effects, spillovers, strategic behavior

JEL classification: G01, G21, G30, L11

1 Introduction

Across a wide spectrum of measures, competition in the United States appears to have declined. Profit shares (Barkai, 2020), markups (De Loecker, Eeckhout, and Unger, 2020), and industry concentration (Autor et al., 2020; Grullon, Larkin, and Michaely, 2019) have all risen in recent decades. Starting sometime in the 2000s, increasing price competition and growing productivity of industry leaders appears unable to explain this trend (Covarrubias, Gutiérrez, and Philippon, 2020).

In this paper, I introduce a novel explanation for the increase in industrial concentration seen in recent years: the credit crunch. The financial crisis resulted in a shock to firms' ability to finance their activities. However, there was substantial variation in the availability of credit across borrowers (Huber, 2018) - with smaller firms being the most harmed by the credit crunch (Chodorow-Reich, 2014). Differences in access to credit during the crisis appears to explain firms' growth path years after the crisis subsided (Wix, 2017). As financial constraints have been shown theoretically and empirically to drive competitive outcomes and behavior (Benoit, 1984; Bolton and Scharfstein, 1990; Chevalier and Scharfstein, 1995; Frésard, 2010), the credit crunch may have had an important impact on firms' long-run product market outcomes.

To trace the product market spillovers of credit constraints across firms, I create an index of peer credit constraints. I find that changes in product market *peers'* access to credit is a first-order determinant of sales, market share, and profitability of the focal firm. This is the case regardless of whether or not I control for equivalent measures of the focal firm's own access to credit. Depending on the specification, a one standard deviation decline in the lending of a firm's peers' banks results in a 5.9 to 7.8 percentage point increase in sales of the focal firm. This indicates that compared to firms whose peers had stronger lenders over the financial crisis, firms whose peers borrowed from weak lenders observed greater changes in sales over the post-crisis period relative to the pre-crisis period. This redistribution in output is persistent. The effect of the peers' lender shock is observable into 2016-Q4, the last quarter of the sample period.

On its own, a random distribution of credit supply shocks could be thought to have an ambiguous impact on the concentration of aggregate output and profit. However, credit constraints are not random. In reality, small, young and private firms are far more likely to become financially constrained in the event of a credit crunch (Chodorow-Reich, 2014). It then should follow that if large scale credit contractions do result in a redistribution of output and rents within product markets, in aggregate this should serve to increase concentration.

Consistent with the idea that peer credit constraints weaken competition, I find evidence that firms whose peers had weaker lenders observed a greater increase in markups. Hence, it appears that not only did the credit crunch redistribute market share, it also weakened the competition faced by benefiting firms.

The main contribution of this paper is to establish the importance of a credit crunch for long-run competitive outcomes. Starting as early as Tesler (1966), the theoretical literature has examined how financial constraints drive cross-firm strategic interaction. Benoit (1984) and Bolton and Scharfstein (1990) posit that financially unconstrained incumbents engage in price wars to deter the entry of financially constrained potential entrants. However, to the best of my knowledge, no research has connected the more recent credit crunch to wider developments in competition.

Following Chodorow-Reich (2014), I proxy for firm credit constraints using changes in the loan issuance of the firm's relationship lender over the financial crisis. I combine this proxy with the text-based network industry classification (TNIC) provided by Hoberg and Phillips (2016) to create a sales-weighted index of changes in the loan issuance of the lender of each firm's product market peers over the financial crisis. The idea is that I have a measure of the mean credit supply shock experienced by each firm's product market peers.

Lenders may specialize in lending to particular product markets. Accordingly, to ensure my results are driven by spillovers and not, for example, common lenders, I control for changes in loan issuance of the focal firm's lead lender.

To avoid endogeneity possibly related to lender-product market assortative matching, as in Chodorow-Reich (2014), I instrument for changes in loan issuance using three measures that shock bank's liquidity during the credit crunch. Namely, lender exposure to Lehman

Brother's, lender exposure to the mortgage-backed securities (MBS) market, and net trading revenue. Banks' pre-crisis MBS exposure predict the volume of lenders' corporate loans during the financial crisis, but should be orthogonal to pre-crisis borrower characteristics. I instrument both at the firm and sales-weighted TNIC product market level. As firms are unlikely to influence their peers' choice of lender, the exposure of a peer's lender to the mortgage-backed securities market should only impact the focal firm via the credit availability of its peers.

The persistence of this redistribution of output and profit suggests a puzzle. Firms that lost market share should face little entry barriers and switching costs to retake their market share once credit conditions improve. As one potential explanation for this persistence, I look to the theoretical literature on entry deterrence and investigate whether peer lender exposure drives firms' strategic behavior. Dixit (1980) and Spence (1977) suggest that firms may preemptively invest in production capacity to deter entry and mobility. The central idea is that by lowering the marginal cost of production, investment credibly commits the incumbent firm to a more aggressive strategy in the event of entry, thereby deterring prospective entrants.

According to Etro (2006), when entry is endogenous to the capital decision of the firm, the leader will always find it optimal to pursue an aggressive investment strategy, regardless of whether or not the market is characterized by strategic substitutes or strategic complements. Hence, similar to Simintzi (2021), I focus on investment as an empirical measure of competitive actions as opposed to pricing or output strategies which are difficult to observe empirically and depend on whether competition is Cournot or Bertrand. While the theoretical context of entrants versus incumbents may not perfectly describe my empirical setting, the process of defending recently captured product market space from reentry of unseated peers should reasonably be approximated by a theory of entry behavior.

Consistent with the theory that firms invest to deter entry, product market peers' credit constraints appear to be associated with greater growth in investment of the focal firm during the crisis. My preferred estimate suggests that a one standard deviation in peer exposure to the credit crunch is associated with roughly a 0.86 percentage point change in investment ratios. This is equivalent to approximately 35% of the average decline in investment observed in this sample over the credit crunch. Hence, a credit crunch may offer a "first-mover" advantage to firms with credit constrained peers who then strategically invest to deter entry and capacity expansion.[1] This may then explain the persistence of the redistribution of market share and profit that I identify.

However, empirically distinguishing between strategic versus non-strategic investment is a challenge. Peer constraints may also increase the firm's expectations about its marginal productivity of capital by decreasing competition and thereby increase expected future profits (Nickell, 1996). This would predict that peer constraints would increase investment absent any strategic considerations of the firm.

Following Frésard and Valta (2016), I seek to distinguish empirically between strategic and non-strategic investment by controlling for variables which capture growth opportunities. If investment is entirely driven by non-strategic considerations, including variables such as various proxies for Tobin's q and the ex-post change in sales and profitability should result in a much smaller coefficient on peer credit crunch exposure. While I do find that measures of growth opportunities predict investment, the coefficient on peer credit crunch exposure remains statistically significant and does not decline in magnitude. This provides at least suggestive evidence that firms indeed strategically invest to deter entry.

Additionally, my results contribute to the growing empirical literature examining spillovers of financial constraints across firms. Direct estimation of spillovers from large scale shocks can inform macroeconomic models as to which general equilibrium effect should be included (Huber, 2021).

An important question for understanding the aggregate impact of a credit crunch is whether or not the product market peers of credit constrained firms pick up the slack or are afflicted by agglomeration spillovers. Chevalier and Scharfstein (1995) and Frésard (2010) find that firms with more liquidity relative to industry peers gain market share, suggesting that financially unconstrained firms pursue aggressive product market strategies to capture market share. Using a sample of German firms, Sonderhaus (2019) finds a reduction in employment

[1] As in Tirole (1988), I define "strategic" behavior as actions taken with consideration to its impact on product market peers.

and investment among firms whose county-industry peers' lenders benefited more from unconventional monetary policy, suggesting competitive spillovers. Huber (2018) and Berg, Reisinger, and Streitz (2021) find that firms operating in the same county as borrowers facing a lending cut saw a decline in employment and sales. They interpret this as evidence of agglomeration spillovers related to reduced local demand.

These differing set of results suggests that whether competitive or agglomeration effects will dominate following a credit shock depends on which relevant peers are examined. My sample consists of large, publicly-listed U.S. firms. Understanding how spillovers propagate across publicly-listed firms is of particular importance given their large role in the US economy: Publicly-listed firms' value-added represents roughly one quarter of GDP and their share in total employment is nearly one third as of 2019 (Schlingemann and Stulz, 2022). As publicly-listed firms compete on a national, if not global level, it is intuitive that competitive spillovers dominate any possible agglomeration spillovers in this sample.

This paper also contributes to the empirical literature examining the impact of the financial crisis and the great recession on *long-run* firm outcomes. It is now well established that bank finance during the crisis mattered in the short-run for firm employment and output (Cingano, Manaresi, and Sette, 2016; Huber, 2018), there is growing evidence that heterogeneity in the supply of credit can have persistent effects on output and employment. Chodorow-Reich (2014) documents that employment losses from financial frictions had not dissipated at all after two years and concludes that future research should seek to explain this persistence.

One notable paper in this area is Wix (2017), who observes that firms exposed to rollover risk during the credit crunch end up on persistently lower output trajectories and points to wage rigidities as a reinforcing factor. Joseph, Kneer, and van Horen (2021) find that SMEs with greater pre-crisis cash holdings relative to industry peers are considerably more profitable and have greater market share than cash-poor industry peers years after the crisis. This provides suggestive evidence that financially unconstrained firms enjoy long-run gains at the expense of their constrained peers.

I propose that the reallocation of market share and strategic behavior along credit constraints may explain some of the persistence in output and employment losses at the microeconomic level. Intuitively, if a credit constrained firm loses market share to a product market peer, it is unclear whether or not that firm will be able regain their market share once they are no longer constrained. I provide evidence that this reallocation of market share is persistent.

Consequently, this papers suggests that there is a trade off to the reallocation of output associated with the recovery of a credit crunch. However, absent the reallocation of market share from credit constrained firms, aggregate economic recovery would hinge solely on the ability of constrained firms to resume operations to pre-recession levels. The reallocation of market share should accelerate the recovery by circumventing many of the frictions associated with being credit constrained.

Hence, at the macroeconomic level, the welfare impacts of this reallocation is ambiguous. Policy makers should thus be cautious to interpret the increase in profitability and market share along peer credit constraints as warranting antitrust action.

In the following section, I describe the data and empirical setting. Section 3 provides descriptive statistics and empirical results. Section 4 includes a battery of robustness test. Section 5 provides a brief discussion and conclusion.

2 Data and Empirical Specification

I use the Text-Based Network Industry Classifications (TNIC) (Hoberg and Phillips, 2010, 2016) to identify firms' product market peers. This database is based on text-based analysis of product descriptions available in annual 10-K reports of publicly-listed firms and assigns similarity scores of product descriptions ranging from 0 to 1 to firm-by-firm pairs for each year. Specifically, I use the TNIC-3 product market classification which defines product markets to be as granular as the SIC 3-digit industry classification such that only firms with a minimum similarity score threshold are considered to be in the same product market.

Compared to traditional classifications of product markets such as NAICS and SIC classifications, this classification has the advantages that it is updated annually. This means that firms are assigned product markets each year rather than at the inception of the firm or the classification system. Most importantly for my purposes, it is non-transitive, meaning that if a firm shares product market space with firm A and firm B, this does not imply that firm A and B share product market space. Accordingly, each firm has its own unique set of product market peers. This is especially useful for capturing the relevant product market peers of conglomerates. Hoberg and Phillips (2016) show that the TNIC better explain product market characteristics such as profitability, sales growth, and risk relative to the NAICS and SIC.

I proxy for firms' credit availability using changes in their relationship lender's percent change in loan issuance over the financial crisis, specifically over October 2005 to June 2007 relative to October 2008 to June 2009. Insofar as the cost of switching lenders is high (Sharpe, 1990), firms with relationships with liquidity constrained lenders should face an increase in borrowing costs. My sample of lenders consists of Chodorow-Reich's (2014) data-set of the most active lead lenders in the syndicated loan market.[2] I infer a firm's relationship lender as the lead arranger of the firm's last syndicated loan in Thomson Reuter's LPC Dealscan

[2]Chodorow-Reich and Falato (2022) show that this sample of 43 lenders captures over 90% of the loan volume of covenant-specified loans in the Shared National Credit Program dataset (the universe of syndicated loans) and that the sample of loans provided by these lenders are almost identical along observables to those of the whole dataset.

database prior September 2008.[3] Hence, each firm receives a single value for the change in lending of their relationship lender which serves as a proxy for the credit availability of the firm. I refer to this measure as "lender health."

Using the lender to infer a borrower's credit constraints, as opposed to firm balance sheet data, has two advantages. First, compared to a peer's lender choice, the balance sheet health of a firm's peer is plausibly endogenous to the product market outcomes of the firm. Balance sheet measures such as profitability and cash reserves have been repeatedly demonstrated in the literature to cluster along product markets (Bates, Kahle, and Stulz, 2009; Hoberg and Phillips, 2016). Moreover, an aggressive competitor may impact the sales and profitability of its product market peers (Benoit, 1984), but it is less obvious how it would drive a peer's choice of lender. Second, balance sheet outcomes may reflect an endogenous response to credit constraints. Both Kahle and Stulz (2013) and Kim (2021) find that firms raise liquidity in response to negative lender shocks. Kim (2021) provides evidence that this is the outcome of fire sales to increase cash flow in response to credit constraints.

I obtain balance sheet data on public US firms from Compustat. I link Compustat with Dealscan using the gvkey link provided by Chava and Roberts (2008). I then combine the index of peer groups and lender health. I measure product market credit constraints as the sales-weighted mean lender health of product market peers. Product market peers are defined using the aforementioned TNIC-3 product market classification as of 2007. The idea is that I have a proxy for the average credit availability of the focal firm's product market peers. Moreover, I exclude the focal firm from its own measure of product market health, i.e. the measure is a 'leave-out mean.'

Firms presumably have little influence over which lender their product market peers borrow from. Hence, the availability of credit to a firm's peers over the financial crisis is arguably exogenous to the focal firm.

The most important identification problem here is omitted-variable bias from the correla-

[3] In some instances, syndicated loans involve multiple lead arrangers. In order to bring lender characteristics, e.g. changes in total loan issuance, to the firm-level, I weigh the lender characteristics by the credit share of each lead arranger. Similar to Chodorow-Reich's (2014), in cases where credit shares are missing, I impute credit shares based on loans with the same arranger-participant lender structures.

tion between changes in lending of the product market's lenders and other product market characteristics, such as the unobservable risk of firms in the product market. For example, a bank may reduce its corporate lending if its lending was concentrated in product markets that were particularly susceptible to an economic downturn. However, group-level risk should be positively correlated with firm-level risk. This implies that measures correlated with negative group-level outcomes should predict worse outcomes for each member of the group in the absence of competitive spillovers. Hence, estimates of the impact of changes in lending of product market peers' lenders is most plausibly biased against finding competitive spillovers.

Still, to ensure that my results are not driven by assortative matching along lender-product market characteristics, I use three measures of lender exposure to the financial crisis from Chodorow-Reich (2014) to instrument for changes in loan issuance. The first indicator of lender health measures the bank's exposure to Lehman Brothers as the share of the lender's syndicated loans in which Lehman Brothers was the lead lender. Ivashina and Scharfstein (2010) argue that banks with loans co-syndicated with Lehman lost liquidity following the collapse of Lehman as these banks had to meet commitments that would have been met by Lehman when firms drew down their already existing credit lines. The second indicator measures exposure to mortgage-backed securities inferred by the correlation of the bank's daily stock return with the return of the ABX AAA 2006-H1 index over Q4-2007. This index tracks the price of AAA rated mortgage-backed securities issued over the last two quarters of 2005. This correlation should indicate the degree to which the market perceives the bank as exposed to toxic mortgage-backed securities. The third measure captures asset write downs using the 2007-08 trading revenue as a share of total assets, following from the fact that most write down occurred in trading accounts. Arguably, all three measures of lender exposure to the crisis are unrelated to the lender's corporate loan portfolio and should therefore be exogenous to firm characteristics.

Following Chodorow-Reich and Falato (2022), I extract the first principal component of all three measures to create a rank-normalized lender exposure indicator in which the first principal component rank is divided by the total number of lenders. Hence, the worst exposed lender has a value of 1 and the least exposed lender has a value of 0. Chodorow-Reich and

Falato (2022) confirm that this measure is unrelated to pre-crisis borrower observables such as borrower leverage, size, and risk rating, but do explain cross-sectional variation in firms' access to credit during the crisis.

In Figure 1, I plot percent changes in the annualized number of new loans over October 2005 to June 2007 relative to October 2008 to June 2009 along the rank-normalized change in lending of each bank. Intuitively, one observes a negative relationship between the ranked measure of bank exposure to the mortgage-backed securities market and a decline in new lending over the crisis period relative to the pre-crisis period.

This proxy for lender MBS market exposure is then weighted by product market peers' sales and used to instrument changes in the sales-weighted lending of product market peers' banks. Should banks specialize in lending to particular product markets, any instrument for product market lender health will be correlated with the lender health of the focal firm if they share common lenders or if changes in lending cluster along product markets. I address this potential violation of the exclusion restriction by also treating the focal firm's lender health as endogenous and including the exposure to the MBS market of the lender to the focal firm as an instrument for the focal firm's lender health.

My approach of instrumenting for both the direct effect and peer effect follows that outlined by Huber (2021). Using simulations, he demonstrates that this approach resolves bias related to multiple spill over types and measurement error as long as the individual-level instrument predicts individual treatment, but not group-level treatment. I confirm in the next section that the instrument for the loan issuance of the focal firm's lender is indeed uncorrelated with variation in the instrument of the the loan issuance of the lenders to the focal firm's peers.

Figure 2 compares the evolution in the mean log change in firm investment ratios relative to 2008-Q2 at the lowest and highest quartiles of lender loan issuance. I observe that firms which borrowed from lenders that saw a greater decline in loan issuance had a lower investment growth over the credit crunch relative to firms which borrowed from lenders which reduced lending less. These differences in investment ease potential concerns that variation in lender health may be irrelevant for the competitive strength of the large, publicly-listed firms that populate the Dealscan-Compustat universe.

Corroborating this interpretation, in a sample of publicly-listed firms borrowing in the US syndicated loans market, Wix (2017) finds that firms which had to refinance during the credit crunch saw a temporary gap in investment ratios compared to firms who did not need to refinance. He finds that this temporary gap in investment appears to have resulted in a persistent gap in growth trajectories.

My final data set consists of the combination of the Thomson Reuter's LPC Dealscan database, quarterly data on firms' balance sheets and income statements from Compustat's North America Fundamentals Quarterly database, Chodorow-Reich's database on lender health, and the TNIC-3 product market definition database. Depending on the specification used, the sample consists of 1,217 to 1,491 firms. I define each variable in Table 1 and winsorize continuous variables at the 1% level.

The main regression specification is as follows:

$$\Delta Y_i = \beta_0 + \beta_1 \ \Delta Market\bar{L}_i + \beta_2 \Delta L_i + \boldsymbol{\beta X_i} + \sigma_i + \epsilon_i \tag{1}$$

where ΔY_i is defined as the log change in dependent variables of post-crisis (2010-Q2:2016-Q4) over pre-crisis (2006-Q4:2008-Q2) period means. ΔL_i is the percentage change in the annualized number of loans made by firm i's lender between the periods October 2005 to June 2007 and October 2008 to June 2009. ΔMarket $\bar{L}_i$, the central variable of interest, is firm i's TNIC-3 product market peers' sales-weighted leave-out mean of the equivalent measure. For interpretability, in all regressions, I standardize ΔL_i and ΔMarket $\bar{L}_i$ to have a mean of zero and a standard deviation of one.

Additionally, $\boldsymbol{X_i}$ is a battery of controls which consists of the log of total assets of firm i, the net leverage of firm i, the sales-weighted mean of net leverage of firm i's competitors, and the natural log of the total number of product market peers. I provide precise variable definitions in Table 1. All control variables are as of the last quarter of the pre-crisis period (2008-Q2).

I also control for whether or not the firm is bank dependent,' which I define as not having access to bond markets. Similar to Schwert (2018), I infer firms as having access to bond markets if they have any rated debt in the S&P Credit Rating database prior June 2008.

The variable σ_i captures SIC single-digit sector fixed effects. While the independent variable of interest is essentially a product market effect, ideally one would compare firms in similar product markets that differ only with respect to their peer's exposure to the credit crunch. Hence, in a number of specifications, I control for the overall sector to capture the variation related to product offerings without subsuming all variation in my more granular TNIC 3-digit product market measure.

By controlling for the firm's own lender health and for the balance sheet characteristics of firm i and its competitors, I seek to address any possible cluster of bank health along variation in firm financials or product markets. Hence, I am interested not in firms' financial constraints, but rather spillovers from plausibly exogenous variation in the degree of constraints of its product market peers. The main coefficient of interest is thereby β_1.

$\Delta Lending_i$ is instrumented by the previously described index of lender exposure to the MBS market. ΔMarket $\bar{L}_i$ is then instrumented by the sales-weighted leave-out mean of the same index across TNIC-3 product market peers of firm i.

Table 2 Panel A provides summary statistics with all control and outcome variables as of the last pre-crisis observation, 2008-Q2. The average firm in my sample is large, with roughly \$1.28 billion in sales and \$5.69 billion in assets. However, size is highly right-skewed: the mean of sales and assets is above the 75th percentile. As of 2008-Q2, the average firm is profitable in my sample. The mean ROA, measured as operating income before depreciation and amortization over the previous quarter's assets is 4%.

Net leverage, i.e. debt minus cash scaled by assets, is positive for the majority of firms in my sample, with a mean of 0.15. This indicates that most firms would not be able to use to repay total debt with liquid assets. This observation is in line with Kahle and Stulz (2017) who observe that net leverage ratios were unusually high in 2008 and that large firms tend to have positive net leverage ratios.

Note that, similar to Frésard (2010), market share is defined as sales relative to the mean sales of the firm's 2007 product market peers. I use this definition for three reasons. First, fixing the set of relevant peers to a given year reduces measurement error. The TNIC defines product market proximity as a continuous variable ranging from 0 to 1. To define a set of relevant peers, the TNIC-3 applies a cut off to the proximity score such that each firm-firm pair is as likely to be product market peers as in the SIC 3-digit classification. Hence, for firm pairs close to the cut off, small changes in the product space proximity of a pair can introduce entrance into or exit from a product market. If a product market is small and a peer is large, this can result in large measured changes in market shares. Second, including the focal firm's sales in the denominator would introduce attenuation bias. Third, taking the peer average avoids a scenario where most of the variation in market share is driven by the number of peers that leave the sample - e.g. due to acquisitions or delistings. So while the level of market share of a firm may exceed one by this measure, the relevant development is how a firm's sales develop relative to its product market peers.

I observe that the median firm has 14 competitors and sales equivalent to 38% that of the sum of their TNIC 3-digit peers, although there is a long right tail with respect to sales and thereby market share.

I recover firm markups by estimating production functions as in De Loecker, Eeckhout, and Unger (2020) using standard assumptions of the proxy variable literature. Similar to the markup estimation procedure of De Loecker and Warzynski (2012), this procedure has the advantage that it does not rely on assumptions about the nature of competition nor firm-level price data to capture market power. This procedure is described in more detail in Appendix A2.

I find that the average firm in my sample has a mark up of 1.71 as of 2008-Q2, which is higher than that of the mean found by De Loecker, Eeckhout, and Unger (2020) for the same year using the entire Compustat sample. This is perhaps driven by the fact that all firms in my sample are active borrowers in the syndicated loan market and hence larger than the average Compustat firm. However, for my purposes and that of De Loecker, Eeckhout, and Unger (2020), changes in mark ups are of more interest than the level. I find that the average markup declines by 0.21. This need not contradict the thesis put forth by De Loecker, Eeckhout, and Unger (2020) that market power has increased, who find that the within firm change in existing firms only plays a small role in the rise in markups, with most of the change attributable to high markup firms capturing market share.

I observe that the median firm's bank saw a decline in lending volume between the periods October 2005 to June 2007 and October 2008 to June 2009 of approximately 54%. Intuitively, lender health variable of the focal firm shows more dispersion than the sales-weighted mean of product market lender health, as the latter is averaged out along product markets.

3 Results

3.1 First Stage

I begin by testing the relevance of my proxy of bank's exposure to the financial crisis for bank lending. The proxy is the first principal component of three measures: (1) lender exposure to Lehman Brother's, (2) lender exposure to the MBS market, and (3) net trading revenue as a share of total assets. To instrument for sales-weighted changes in lender to the firm's product market peers, I take the sales-weighted MBS market exposure proxy of the peers. Importantly, a firm's peers' lenders exposure to the financial crisis should be even further removed from any endogenous characteristics of the focal firm.

In Column 1 of Table 3, I find that the MBS exposure of the firm's peers is a stronger predictor of changes in the lending of the peers' lenders. The corresponding F-statistic is 428.97. Including controls in column 2, the corresponding F-statistic on MBS exposure remains significant at 374.17. Column 2 demonstrates that the relationship between changes in lending to the product market peers and the exposure of the focal firm's lender is small and statistically indistinguishable from zero.

Finally, I instrument for changes in loan issuance of the focal firm's lender. The F-statistic is again significant with a value of 175.54. The MBS exposure of the peers' lenders is statistically unrelated to changes in loan issuance of the focal firm's lender. Together, the first stage results are intuitive and speak strongly to the relevance of the instruments for the regressors of interest.

It is reassuring that the instrument of lender MBS predicts lending of the firm's lender, but does not predict that of its product market peers. Similarly the sales-weighted mean of the product market's lenders MBS exposure does not predict lending of the focal firm's lender. In simulations performed by Huber (2021), assuming relevance and exogeneity of the instruments, as long as the instrument predicts individual treatment, but not that of the group, and vice-versa, then the coefficient on the spillover should not be confounded by bias related to multiple spillover sources and measurement error.

3.2 Outcomes: Sales, Market Share, and Profitability

A glance at the evolution of firm sales along upper and bottom quartiles of loan issuance of product market peers' lenders provides evidence in favor of the hypothesis that firms gained in the long-run from having credit constrained peers. Figure 3 presents the unadjusted mean log changes in sales relative to 2008-Q2 over time for firms with values of ΔMarket $\bar{L}$ below the bottom quartile and above the bottom quartile. One sees visibly different long-run developments in firms' sales growth based on the credit crunch exposure of their peers alone. Even through 2018, there is no sign of this difference abating.

Moving into the empirical results for sales and market share, Table 4 presents results for log percentage changes over the post-(2010-Q2:2016-Q4) to pre-crisis (2006Q1:2008-Q2) periods in sales. The first column presents simple bivariate OLS results of changes in sales regressed on the sales-weighted average change in loan issuance of a firm's product market peers' lenders. The coefficient indicates that firms with more credit constrained peers observe greater long-term sales growth. As ΔMarket $\bar{L}$ is standardized, the coefficient can be interpreted as indicating that a one standard deviation difference in ΔMarket $\bar{L}$ is associated with a 3.27 percentage point change in sales over the post-crisis relative to the pre-crisis period. Column 2 demonstrates that adding control variables, such as changes in the focal in the loan issuance of the focal firm's lender, serves to increase the estimated magnitude of the coefficient on ΔMarket $\bar{L}$.

Columns 3 to 5 of Table 4 present second stage results from two-stage least squares (2SLS) specifications. All three columns instrument for changes in ΔMarket $\bar{L}$ using the sales-weighted mean of the product market's lenders MBS exposure. Columns 4 and 5 additionally instrument for ΔL, the direct effect of credit constraints, using lender MBS exposure. Finally, Column 5 also controls for SIC-1 digit sector effects. Depending on covariates included in the model, Columns 3 through 5 indicate that a one standard deviation change in the availability of credit to a firm's peers drives a 11.1% to 14.7% of a standard deviation change in sales.

I find that the coefficient on credit constraints spillovers is greater in the 2SLS least squares setting relative to equivalent OLS estimates. This could be interpreted as suggesting that OLS estimates are downward biased by negative assortative matching of peer lender health and the focal firm characteristics. However, given that the R^2 of the OLS regression in Column 1 is higher than the R^2 of the equivalent 2SLS regression in Column 3, it seems at least as plausible that OLS may simply be using more variation in ΔMarket $\bar{L}$, which results in estimating a lower coefficient.

Table 5 presents the results of our model regressed on percentage change in market share, the level of which is measured as firm sales divided by mean sales of the firm's TNIC-3 product market peers. The OLS (Columns 1 through 2) and 2SLS (Columns 3 through 5) results indicate that changes in the availability of credit to a firm's product market peers positively predict growth in the focal firm's market share.

The coefficients on ΔMarket $\bar{L}$ across the specifications in Table 4 conform to a similar pattern as that of Table 5. The coefficient is greater in magnitude with covariates than without. Also, the 2SLS results are greater in magnitude than the OLS results.

The coefficient of the spillover effect in these models is economically significant. For example, in the most saturated 2SLS version of the model (Column 5), one standard deviation change in peer credit availability is associated with a 4.74 percentage point change in market share over the post- to pre-crisis period. This is equivalent to 32.46% of a standard deviation of the variable.

Moving to ROA as a proxy for profitability in Table 6, I find that larger declines in the availability of credit to a firm's product market peers is positively associated with changes in the focal firm's ROA. This spillover effect is statistically significant at the 1% level in every specification. The most saturated 2SLS model indicates that a one standard deviation decline in peers' credit availability induces a 0.59 percentage point greater change in ROA. This is equivalent to 19.5% of a standard deviation in the change in ROA over the pre- to post-crisis period.

Together, the results observed in tables 4 through 6 lend strong support for the hypothesis that firms benefited from the credit constraints of their product market peers. These results speak against the credit crunch as primarily being a negative inter-regional product market shock due to agglomeration effects such as, for example, up-stream supply chain shocks and

R&D spillovers.

That I find that firms appear to benefit from their peers' being constrained eases concerns that unobserved factors which drive systematic variation in product market exposure to weak lenders also drive firm outcomes. If weaker banks are more likely to lend to product markets with low growth potential then that should generate a positive correlation between measures of peers' health and focal firm outcomes.

One potential concern is related to estimates of the direct effect of credit constraints compared to that of the spillover effect of credit constraints of the firm's peers. Intuitively, I consistently find greater declines in the loan issuance of the focal firm's lender is associated with lower sales, market share, and profitability growth. However, this direct effect of credit constraints is statistically insignificant in most specifications and in all but one specification, the implied importance of the direct effect for explaining variation in the dependent variable is smaller than that of the spillover effect.

What may seem like a contradiction at first glance is likely the result of attenuation bias driven by measurement error. As discussed by Angrist (2014), results in which empirical estimates of peer effects exceed direct effects are commonplace in the peer effects literature. In this setting, changes in the total lending of a bank with which a firm has a borrowing-relationship does not perfectly measure the extent to which firms are credit constrained, in particular among the publicly-listed firms that populate this sample. This measurement error biases the coefficient toward zero.

When aggregating this measure at the product market level, much of this measurement error is averaged-out, converging to its mean value of zero the more firms are in the product market. This mitigates attenuation bias in the spillover effect, which may explain why the spillover effect is statistically significant, while that of the direct effect is not.

These results should not be taken to imply that there is no direct impact of a credit shock on measures of firm performance. To the contrary, my results are consistent with that of (Chodorow-Reich, 2014), who finds that large publicly-listed firms were less impacted by the credit contraction. However, the contribution of this paper is to document the presence of product market spillovers of a credit contraction.

Note that the measurement error in the product market effect could bias the spillover estimate if there is a common component for members of the same TNIC-3 product market that determines each firm's respective ΔL. Such a common component is plausible, as banks are likely to specialize in lending to specific product markets. The reason ΔMarket $\bar{L}$ may be biased by this common component is that by containing less measurement error than ΔL, it has a higher loading of the common component in relative terms.

However, as argued by Huber (2021), the direction of the spillover estimate's bias should follow the coefficient of the direct effect. The coefficients on ΔL and ΔMarket $\bar{L}$ have the opposite sign. Firms with peers subject to a greater credit shock do better and firms subject to a greater credit shock do worse. Hence, should measurement error induce a bias in estimates of the product market spillover, it would be biased toward zero relative to the estimates presented in this paper.

3.3 Outcome: Markups

That firms with credit constrained peers enjoy greater increases in sales, market share, and profitability suggests a redistribution of activity within product markets following a credit shock. This redistribution should serve to dampen the immediate economic harm of a credit crunch in aggregate. At first glance, this appears unambiguously welfare enhancing.

Still, credit shock spillovers could increase product market concentration and thereby weaken competition. Considering that large incumbents are less susceptible to becoming credit constrained than small entrants, one would expect the existence of credit shock spillovers through product markets to increase concentration on aggregate.

Still, on their own, these results do not demonstrate that credit constrained peers reduce competition. To assess the impact on competition faced by the focal firm, I examine changes in markups in Table 7.

The sample size is moderately reduced relative to previous specifications due to reduced coverage of the variables needed to estimate markups. The coefficient on ΔMarket $\bar{L}$ is consistently positive across the OLS and 2SLS specifications. However, it is only statistically significant at the 10% level or above with the inclusion of control variables and is insignificant on its own. The magnitude of the coefficient in the most saturated model appears however economically significant. A one standard deviation increase in ΔMarket $\bar{L}$ drives a change in markups equivalent to 7.69% of a standard deviation.

This provides at least some evidence that firms with credit constrained peers face reduced competition. Hence, it seems that not only did the credit crunch result in a redistribution of output and profitability, its spillovers may have also allowed some firms to extract rents.

Moreover, I find evidence that firms with better access to credit saw greater increases in markups. Specifically, the coefficient on ΔL is positive and statistically significant at the 10% level or 5% level across specifications in which it is included. Its economic magnitude also exceeds that of ΔMarket $\bar{L}$. Column 5 of Table 7 suggests that firms with a one standard deviation better access to credit saw an increase of markups equivalent to 14.8% of a standard deviation.

This result is consistent with that of Kim (2021), who, using an identification strategy similar to that of this paper, finds that firms subject to a credit shock reduced prices to liquidate inventory and generate more cash flow. It is also reassuring for the validity of the markup estimation strategy that markup estimates and credit constraints appear to follow a dynamic similar to that of prices and credit constraints.

3.4 Outcome: Investment

One could expect firms to return to their previous market shares following the credit crunch. However, my results suggest a persistent reallocation of output and rents related to peer credit constraints. Why does this impact appear to result in a persistent redistribution of output?

One potential explanation is labor market rigidities. Wix (2017) finds that firms facing more rigid wages during the Great Recession grew more slowly. Presumably the cost of firing and then rehiring would encumber firms' capacity to recapture market share once demand resumes. Similarly, switching costs among customer bases may result in a more persistent redistribution of output.

In this paper, I focus on one potential explanation for the persistence reallocation. Namely that firms which benefited from this redistribution engaged in behaviors which disincentived aggressive competition from their potential peers. I posit that firms facing credit constrained peers gained an incumbency or first-mover advantage: a temporary state in which their peers had little ability to compete on prices (Chevalier and Scharfstein, 1995), output, or other costly strategies due to financial constraints. I investigate whether firms faced with this scenario invested in capital to deter future entry mobility from existing peers or potential entrants. By investing in capital, firms credibly commit to compete aggressively should a firm choose to enter their market (Dixit, 1980; Spence, 1977). Capital investment as a measure of competitive aggression is empirically interesting in that, unlike prices and output, incumbents should invest to deter entry regardless of whether they compete in Cournot or Bertrand competition (Etro, 2006).

Using the same regression OLS and 2SLS specifications as in the previous section, Table 8 presents results for changes in investment from the pre-crisis period (2006Q1 to 2008Q2) mean over the crisis period (2008Q3 to 2010Q1) mean. This earlier time period would be point the point where any investment differential driven by peer credit constraints should be visible. I define investment as the rolling four quarter expenditure on capital and R&D scaled by lagged assets. I replace missing R&D values with zero.

I observe that peer credit constraints positively predict changes in investment over the crisis. Depending on the specification used, I observe that a standard deviation difference in peer credit constraints induces a change in investment equivalent to 6.8% to 19.8% of a standard deviation. This appears consistent with the notion that firms invest strategically to protect market share from constrained peers.

Intuitively, I also find that access to credit as proxied by ΔL positively predicts changes in investment. Moreover, in the most saturated specification, Column 5 of Table 8, the magnitude of the coefficient on ΔL exceeds that of Δ Market $\bar{L}$.

An alternative and not mutually exclusive interpretation of the relationship between peer credit constraints and firm investment is that peer credit constraints may drive investment by increasing growth opportunities. In other words, the marginal product of capital is likely to be higher if a firm is more likely to grow and be more profitable in the future. Hence, the competitive outcomes in market share and rents that I show are associated with peer credit constraints may be driving firm investment behavior by expanding investment opportunities, rather than the other way around. As such the above results with respect to investment behavior do not distinguish between strategic and non-strategic investment.

Similar to the approach of Frésard and Valta (2016), I contend that if the association between peer credit constraints and investment behavior is driven by non-strategic considerations as opposed to strategic considerations, then I should observe a significant reduction in the magnitude of the coefficient of peer constraints on investment once I include measures of growth opportunities. To plausibly capture growth opportunities, I include a battery of controls which proxy for expectations of firm growth.

First, I include changes in various empirical measures of Tobin's Q. The first is the standard measure of Q, which is the market value of the firm to total book assets as used in Chung and Pruitt (1994) and Gutiérrez and Philippon (2016), among others. The second measure, Q_{Total}, includes estimates of intangible capital from Peters and Taylor (2017) in the denominator, to address measurement error related to intangible assets. Finally, I include $Q_{Alt.}$, which is as the ratio of market value of productive assets to gross PP&E plus intangibles. All three measures suffer from acounting and economic issues in capturing Tobin's Q, but by using a three-pronged approach as in Gutiérrez and Philippon (2016), I hope to ease measurement concerns.

Similar to the approach of Frésard and Valta (2016), I contend that if the association between peer credit constraints and investment behavior is driven by non-strategic considerations as opposed to strategic considerations, i.e. the impact of investment on peers' entry choice, then I should observe a significant reduction in the magnitude of the coefficient of peer constraints on investment once I include measures of growth opportunities. To plausibly capture growth opportunities, I include a battery of controls which proxy for expectations of firm growth.

Second, I include the ex-post realized change in profitability from the pre-crisis over the post-crisis periods. Insofar as firms' ex-ante growth expectations are correlated with realized future growth in profitability, this should capture growth expectations of the firm. The management earnings forecast literature has consistently found a correlation between management forecasts and future earnings (Hassell and Jennings (1986); Lee, Matsunaga, and Park (2012)). Hence, in choosing the firm's investment level, management should in most instances already have a reasonable approximation of the firm's growth, which can thereby be roughly approximated by the ex-post growth of the firm's profitability.

Table 9 presents 2SLS results with both changes in the loan issuance of the focal firm's and sales-weighted product average lenders instrumented by equivalent MBS exposure of the lenders. The specifications in Table 9 are the same as in Table 8 Column 5 with firm controls, product market controls, and SIC sector effects, except various combinations of the aforementioned proxies for non-strategic motives to invest are also included. Columns 1 through 5 of Table 9 include each aforementioned proxy and column 6 includes all the proxies together.

I find that changes in the standard measure of Tobin's Q is the strongest predictors of future investment, while changes in ROA and Q_{Total} also predict investment. Changes in $Q_{Alt.}$ does not appear to positively predict changes in investment.

Most importantly however, the coefficient on Δ Market $\bar{L}$ is essentially unchanged with the inclusion of these proxies. Its value ranges from 0.722 to 0.866, which is approximate to its value of 0.864 in the same specification without growth proxies.

This lends support to the notion that the association between product market peer constraints and investment is not driven by differences in growth opportunities alone, but rather, there appears to be a strategic element to this difference in investment ratio growth. Firms with constrained peers appear to invest more in order to deter future entry mobility of potential peers.

4 Robustness

4.1 Omitted Spillovers

Product market proximity may be correlated with proximity across firms along other channels, in particular through supply chains and technology networks. Firms with similar products likely rely on similar technology inputs and supply chains. One possible concern could be that results presented in this paper are driven not by product market spillovers, but spillovers from alternative firm networks that cluster along product markets.
However, it is difficult to argue that my results are likely driven by these alternative channels. This is because presumably the most likely outcome is that firms' are harmed by negative shocks to their technological and supply-chain peers. Product market spillovers should induce competitive effects, whereas technology and supply chain spillovers are more likely characterized by agglomeration effects (Huber, 2021).

For example, Bloom, Schankerman, and Van Reenen (2013) find that firms benefit from R&D tax-subsidies to their technological peers, but are harmed by R&D tax-subsidies to their product market rivals. Similarly, it is unclear why firms should benefit from negative shocks to firms along their supply chain. Insofar as product market proximity coincides with proximity along these alternative networks, one would expect that my results underestimate the positive spillovers of a negative credit shock to one's product market peers.

Still, if the TNIC measure captures both horizontal and vertical relationships between firms, then it is possible to argue that my results could be driven by credit supply shocks to the focal firm's upstream suppliers or downstream customers. If suppliers are forced to liquidate inventories in the event of credit constraints and such suppliers are erroneously categorized as competitors to the focal firm due to textually similar product offerings, downstream customers could conceivably benefit from reduced input prices. To some extent the concern that product markets maybe overlapping with supply chain relationships should be mitigated by the fact that Hoberg and Phillips (2016) remove TNIC pairs that are in traditional industries classified as shipping to each other using BEA Input - Output tables.

To investigate the possibility that my results are driven by vertical, rather than horizontal, relationships across firms, I create a measure of changes in lending of the firm's vertically related peers' lenders. The variable's construction is the same as ΔMarket $\bar{L}$, except that rather than defining the relevant peers as TNIC product market pairs, I use the Vertical TNIC of Frésard, Hoberg, and Phillips (2020). The Vertical TNIC captures the vertical relatedness of firm-pairs by relating textual descriptions of commodities and sub-commodities in the BEA Input-Output Tables to firms' 10-K product descriptions. I refer to the measure as ΔVTNIC $\bar{L}$.

Another aforementioned possibility is that the peer effects captured in this paper are driven not by product markets, but by technology networks. Firms overlapping in product market space are also likely to overlap in technological space. It would appear plausible that firms could benefit from their technological competitors being subject to a negative credit supply shock. However, the empirical literature indicates that agglomeration spillovers of R&D investment of firms' peers are likely to dominate any competitive effects (Bloom, Schankerman, and Van Reenen, 2013).

In order to address this potential source of endogeneity directly, I follow Bloom, Schankerman, and Van Reenen (2013) in creating a measure of technological proximity of firms by measuring the extent to which their patenting activities overlap along technology classes. More specifically, I merge Compustat with PATSTAT using the DISCERN linking table provided by Arora, Belenzon, and Sheer (2021). I then measure the share of each firm's patents from 2003 to 2007 in each 3-digit IPC technology class to create the firm-specific technology vector $T_i = (T_{i1}, T_{i2}, ..., T_{i,126})$, where $T_{i,\tau}$ is the share of patents of firm i in technology class τ. Technological proximity is then defined as in the uncentered correlation for all firm pairs i and j as:

$$PROX_{i,j} = \frac{T_i T_j}{\sqrt{T_i T_i^{\top}} \sqrt{T_j T_j^{\top}}} \tag{2}$$

In order to gauge the relative potential for spillovers of each technology peer, I measure each firm's R&D stock using the perpetual inventory method described by Hall, Jaffe, and Trajtenberg (2005), in which past R&D spending is iterated forward with an annual depreciation rate of 0.15. The R&D stock is then defined as $G_t = R_t + (1-\delta)G_{t-1}$, where δ is the depreciation rate and R_t is the R&D spending at time t. I then combine the two measures to create a measure of potential technology spill-ins for each focal firm, $SPILL_i = \sum_{j \neq i} PROX_{ij} G_j$, which I use to weigh the mean change in loan issues of the lenders to the focal firm's technology peers, which are defined as those firms with non-zero technological proximity to the focal firm. This measure provides a proxy for the credit access of the firm's technological peers that is weighted by an index of the potential magnitude and relevance of their research to the focal firm. I refer to the measure as ΔTEC $\bar{L}$.

Table C1 of Appendix C presents summary statistics with respect to ΔTNIC $\bar{L}$ and ΔTEC $\bar{L}$. Given that a majority of the sample either does not issue patents or have no measured technological proximity with R&D spending firms in the sample, the sample of firms with non-missing ΔTEC $\bar{L}$ is limited to 497.

In Table C2 of Appendix C, I examine the pairwise correlations of my three measures of changes in lending to firm networks, namely ΔMarket $\bar{L}$, ΔTNIC $\bar{L}$, and ΔTEC $\bar{L}$. I also include the instrument for the sales-weighted mean of the product market lenders' exposure to the MBS, my instrumental variable for ΔMarket $\bar{L}$. Excepting a weak correlation between ΔMarket $\bar{L}$ and ΔTEC $\bar{L}$, all cross-correlations between the three measures of changes in loan issuance to given firm networks are statistically indistinguishable from zero. I take this as evidence that, at least with respect to changes in lending, these networks are distinct from one another with little overlap.

Interestingly, the correlation between ΔTEC $\bar{L}$ and ΔMarket $\bar{L}$ is negative, albeit only statistically-significant at the 10%. This suggests that firms whose product market peers saw a greater contraction in credit access also had technological peers which saw a smaller contraction in credit access. Theoretically, if the agglomeration spillovers of technology peers dominate the competitive spillovers of technology peers, this could result in overestimating the importance of ΔMarket $\bar{L}$ for the focal firm when ΔTEC $\bar{L}$ is omitted. However, as shown in Table C2, the variation in ΔMarket $\bar{L}$ explained by the instrument should be unbiased given that the correlation between ΔTEC $\bar{L}$ is equal to zero.

Panels A of Table 10 presents the results of the 2SLS model for the main dependent variables with the measure of changes in loan issuance of the lender to the focal firm's vertical peers, labeled ΔVTNIC $\bar{L}$. All estimates include the same control variables as in previous specifications in addition to SIC-1 digit sector fixed effects. Under all specifications, changes in lending to the firms' vertically related peers fails to predict changes in the focal firm's lending. This suggests that credit shocks to the focal firms' vertical peers is unlikely to be a first-order driver of firm outcomes. Importantly, the coefficient on Δ Market $\bar{L}$ remains qualitatively and quantitatively similar to the baseline specifications for all dependent variables.

Table 10 Panel B presents the baseline 2SLS for the main dependent variables with the inclusion of ΔTEC $\bar{L}$. Despite the substantial decline in observations and inclusion of ΔTEC $\bar{L}$, the results remain qualitatively similar. The coefficients on Δ Market $\bar{L}$ in explaining changes in investment, markups, ROA, and market share are of similar magnitude to previous specifications absent ΔTEC $\bar{L}$, albeit with higher standard errors presumably due to the reduced sample size.

The coefficient on ΔMarket $\bar{L}$ is however roughly halved with respect to sales. It appears unlikely that this is due to a reduction in omitted variable bias given that ΔTEC $\bar{L}$ has no explanatory power for changes in sales. Sample characteristics, such as heterogeneity in the impact of ΔMarket $\bar{L}$ among patenting versus non-patenting firms or simply sample size seems like more plausible candidate explanations. To investigate this possibility, in Table C3 I present the same sample of firms with non-missing values for ΔTEC $\bar{L}$, but remove ΔTEC $\bar{L}$ from the specification. I find that the coefficient on ΔMarket $\bar{L}$ with respect to sales is essentially unchanged in this sample irrespective of whether or not ΔTEC $\bar{L}$ is included.

Finally, I also find some evidence of the importance of technological peers in explaining the focal firm's ROA. Firms whose technological peers were less subject to the credit contraction appear to observe greater growth in ROA, as suggested by Column 3 of Panel B in Table 10. This suggests the presence of agglomeration spillovers across technology peers and is consistent with the results of Bloom, Schankerman, and Van Reenen (2013), who find that firms benefit from the R&D spending of their technological peers.

4.2 Timing of Lender-Borrower Matching

One potential concern with the results presented in this paper is that firms may observe the extent to which potential lenders are exposed to the financial crisis, resulting in assortative matching. This is more likely to be the case the closer the period used for defining borrower-lender pairs is to the credit crunch. While I follow Chodorow-Reich (2014), Chodorow-Reich and Falato (2022), and Kim (2021) in matching borrower-lender pairs using the borrower's last syndicated loan before September 30, 2008, one could argue that lenders' exposure to the financial crisis was observable by borrowers by this point in time. If this results in higher quality firms switching to higher quality lenders, the 2SLS results could be biased due to assortative matching. For example, Lehman Brother's stock price lost over 83% of its value between June 2007 and August 2008. The potential for collapse of Lehman Brother's over this period may have already raised fears of risk among borrowers for those banks highly connected to Lehman Brother's through co-syndication.

However, assuming lender exposure was observable to firms, it is not clear in which direction this would bias the results in this paper. It sounds plausible that better firms would borrow from better banks. However, more financially robust firms and firms with better access to alternative sources of finance should be less concerned with the health of their lender. For instance, Schwert (2018) finds that firms with access to bond markets borrowed from less capitalized banks on average.

To ease concerns of possible assortative matching, as a robustness test, I infer the firm's relationship lender using its last syndicated loan prior June 2007. This is five quarters earlier than the main specification.

This approach may introduce measurement error by assigning firms to lenders that have less salience to the firm going into the crisis period. Borrowers who began new lending-relationships with a different bank between June 2007 and September 2008 will be treated as though their most recent lender is of no importance.

Using the most saturated versions of my main 2SLS specifications from Column 5 of Tables 4 through 8, I present results for changes in sales, market share, ROA, markups, and investment in Table 11 using the earlier matched borrower-lender sample. The coefficients on instrumented variation in changes in loan issuance of peers' lenders are generally of equivalent or larger magnitude to those of the baseline specifications, but with greater standard errors. I interpret the manitude of the coefficients as suggesting that the previously presented estimates in Table 4 through 8 are not upward biased by assortative matching. This should ease concerns that temporal proximity to the credit crunch of the formation of lender-borrower relationships could be resulting in assortative matching that may bias results. Additionally, the greater standard errors is consistent with a weaker quality matching between relationship lenders and borrowers.

5 Conclusion

This paper documents evidence of large, positive spillovers of credit contractions across firms within product markets. The empirical literature has previously documented negative intra-regional spillovers of the credit crunch and negative direct effects on firms. To the best of my knowledge, this paper is the first to document inter-regional product market spillovers from a credit crunch. These results suggest an important aspect of a credit crunch is the redistribution of output and profitability within product markets.

As firms whose product market peers are hit by credit shocks grow faster, this redistributional spillover should serve to dampen the negative impact of credit crunches on aggregate output. This is in contrast to other credit spillovers previously identified in the literature, in particular regional spillovers (Huber, 2018), which exasperate the aggregate impact of direct credit shocks.

However, the results in this paper may also raise issues related to competition. Because small firms are particularly sensitive to credit contractions, this redistribution should serve to increase product market concentration and may have played a meaningful role in the increase in concentration. I find that credit shock spillovers may have increased markups, which is in line with the hypothesis that this redistribution lowered competition. Hence, from a welfare perspective, the impact of this redistribution is ambiguous. A fruitful direction for future research may be to document the macroeconomic impact of banking crises on concentration and economic rents.

Moreover, I find that peer credit constraints are positively associated with investment growth during the credit crunch and that this relationship is unmitigated by proxies for growth opportunities. This is consistent with theories of strategic investment, which suppose that firms may invest to deter entry mobility by credibly committing to a more aggressive output strategy in the event of entry. This behavior may in part explain why the losses in output and employment documented by Wix (2017) and Chodorow-Reich (2014) are persistent: Once market share is lost, rivals invest strategically to ensure the new equilibrium persists.

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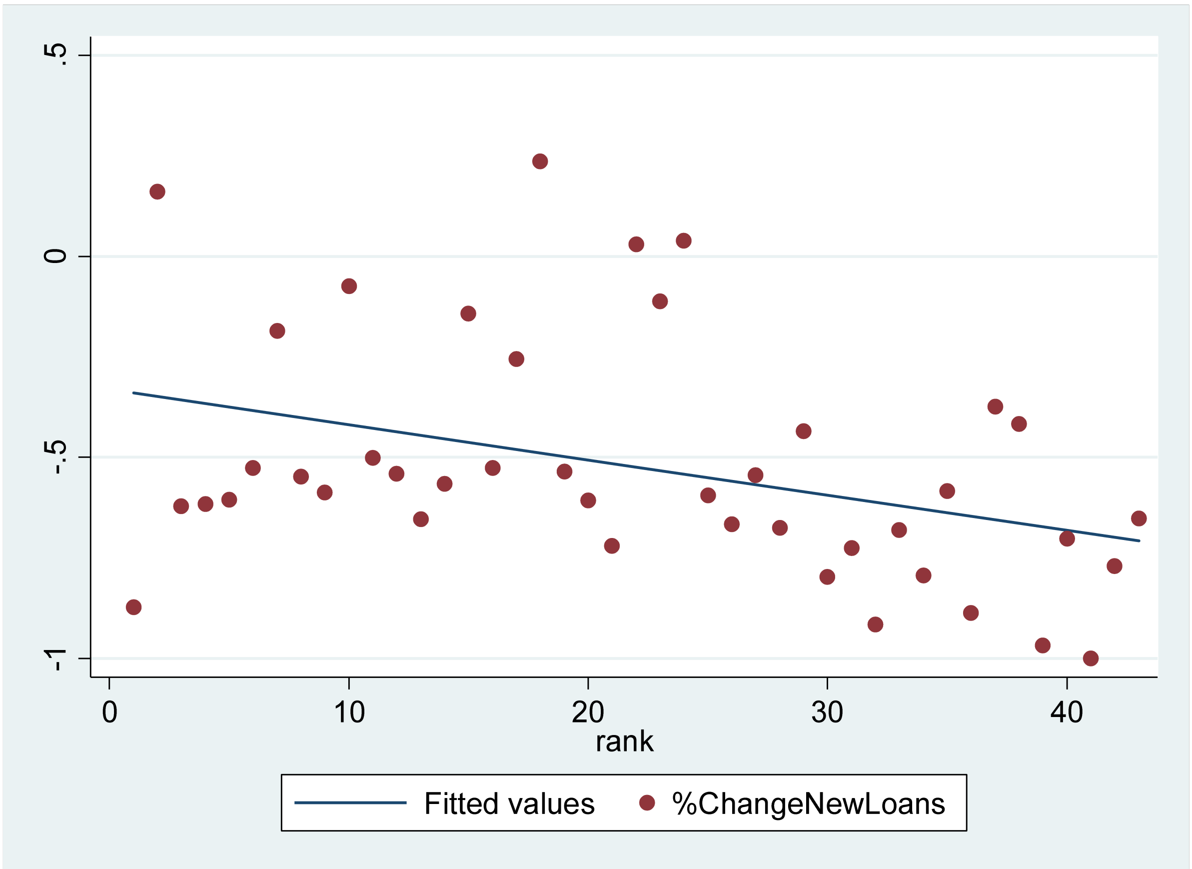
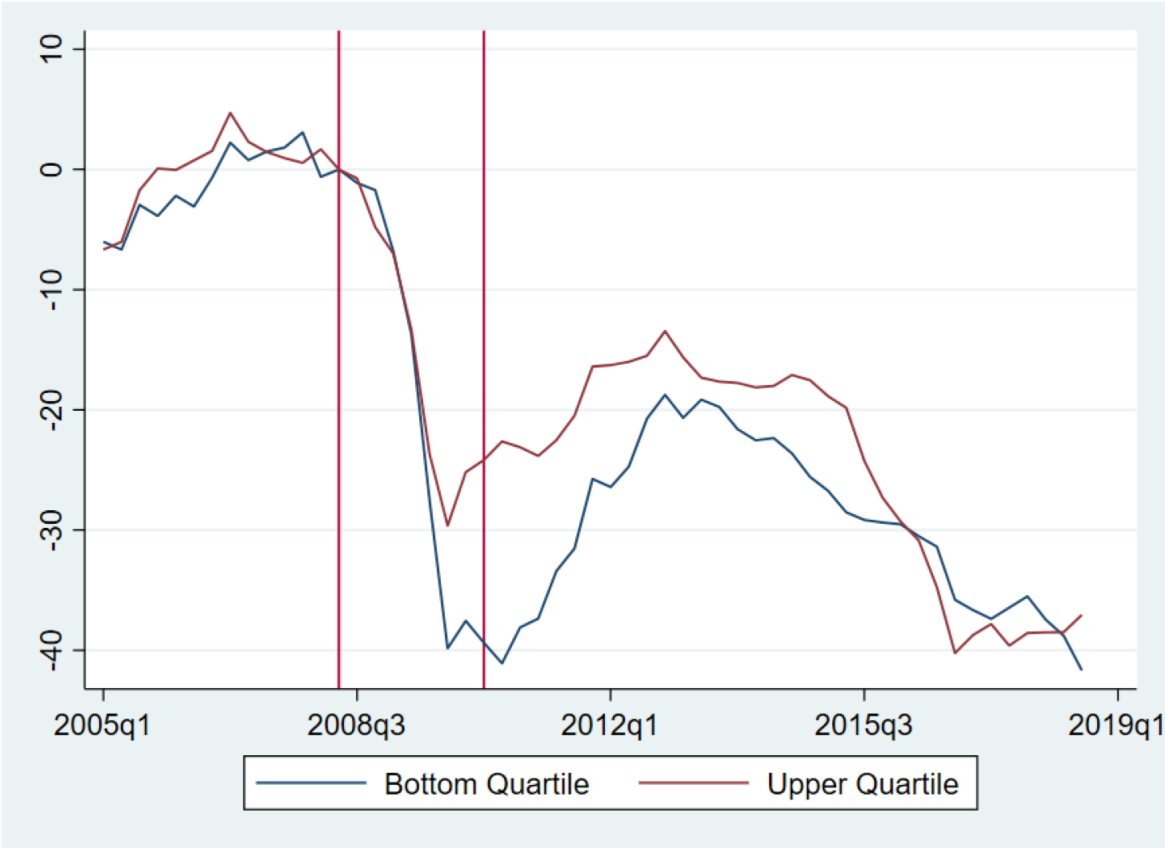
Figures

Figure 1: Rank of First Principle Component Value and Percent Change New Loans



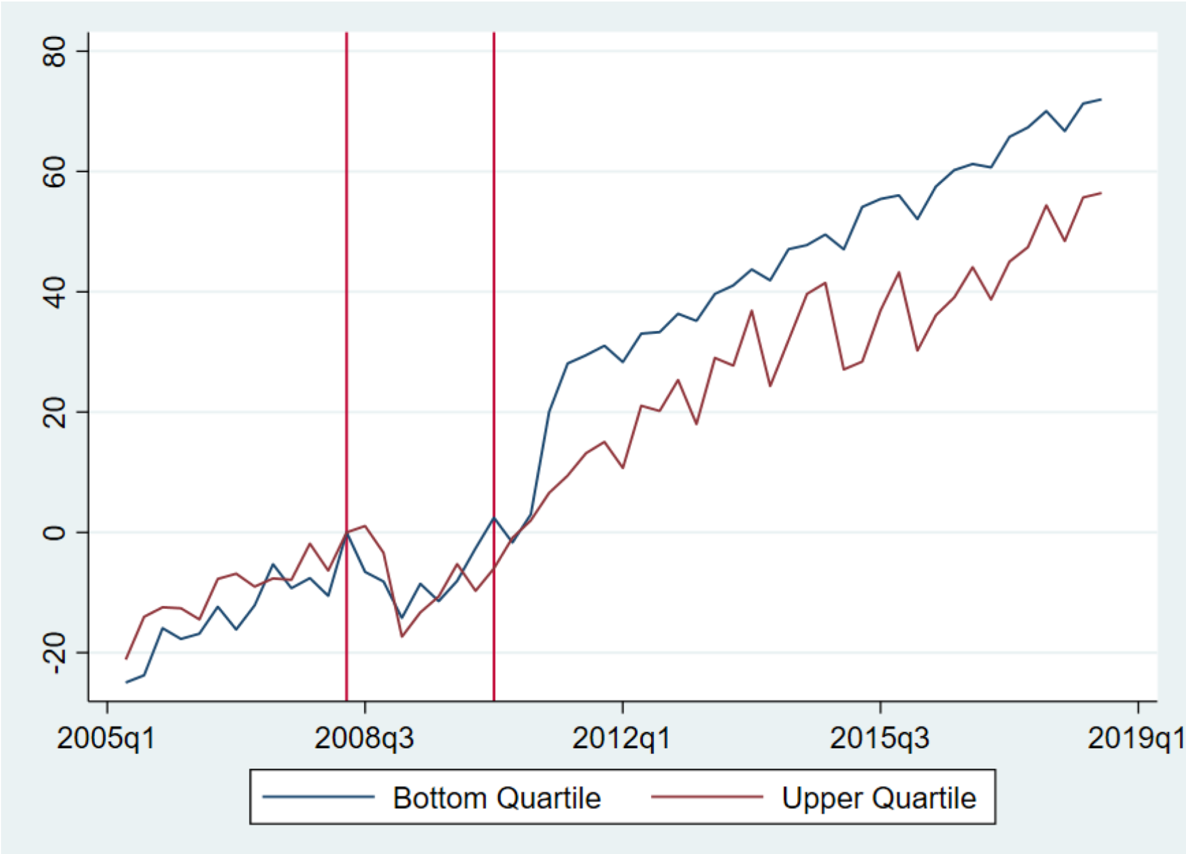
Percent change (annualized number of new loans), Oct-05 to Jun 07, to Oct-08 to Jun-09. The first principle component captures the banks exposure to the mortgage-backed securities market as measured by its share of syndicated loans where Lehman Brothers was the lead lender, the banks's stock price correlation with the ABX AAA 2006-H1 index over Q4-2007, and the share of revenue from trading in 2007-2008 over total assets. All data provided by Chodorow-Reich as from Chodorow-Reich (2014) https://scholar.harvard.edu/chodorow-reich/publications/loan-covenant-channel-how-bank-health-transmits-real-economy

Figure 2: Firm Investment Growth along Upper and Lower Quartile of Changes in Lender Loan Issuance



This figure shows the evolution of the mean log percentage growth in investment ratios relative to 2008-Q2 over time for firms with borrowing relationships with lead lenders in the bottom and top quartile of the distribution of lender health.

Figure 3: Mean log percentage growth of firms sales along changes in loan issuance of product market peers' lenders



This figure shows the evolution of the mean change in firms sales relative to 2008-Q2 over time of the lower and upper quartile of the distribution of changes in loan issuance of TNIC peers' lenders.

Tables

Table 1: Variable Descriptions

This table shows the definitions of all variables. The definitions provide the Compustat Quarterly mnenomics when applicable. Firm financial data is sourced from Compustat. Changes in bank lending is sourced from Chodorow-Reich (2014). Lead lenders are connected to firms via pre-2008Q2 syndicated lending relationship.

Variable	Definition
Dependent Variables	
ΔSales	$ln(\overline{SALEQ}_{(2010Q2:2016Q4)} + 1) - ln(\overline{SALEQ}_{(2006Q1:2008Q2)} + 1)$
ΔMarket Share	ΔSales minus mean ΔSales of TNIC product market
ΔROA	$\ln(\overline{ROA}_{(2010Q2:2016Q4)} + 1 - ln(\overline{ROA}_{(2006Q1:2008Q2)} + 1)$
ΔInvestment	$ln(\overline{Investment}_{(2010Q2:2016Q4)} + 1) - ln(\overline{Investment}_{(2006Q1:2008Q2)} + 1)$
ΔL	Change in bank's lending: Oct/2005 - Jun/2007 over Oct/2008 - Jun/2009
ΔMarket $\bar{L}$	Sales-weighted leave-out mean of TNIC3 product market peers' ΔL
Size	$\ln(ATQ)$
Net Leverage	$\frac{DLLTQ-CHEQ}{ATQ}$
Market Net Leverage	Sales-weighted mean of peers' net leverage
No. of peers	ln(No. of peers in TNIC3 Product Market)
Investment	$\frac{(CAPXY_t+XRDY_t+CAPXY_{t-1}+XRDY_{t-1}+CAPXY_{t-2}+XRDY_{t-2}+CAPXY_{t-3}+XRDY_{t-3})}{ATQt-4}$
Sales	$SALEQ$
ROA	$\frac{OIBDPQ_t}{ATQ_{t-1}}$
Q	$\frac{ATQ-CEQQ+(CSHOQ*PRCCQ)}{ATQ}$
Alt. Q	$\frac{MKVALTQ+DLTTQ+DLCQ-ACTQ}{PPEGTQ}$
Total Q	Market value to tangible + intangible capital (see Peters and Taylor (2017))

Table 2: Summary Statistics

This table shows summary statistics for the 1,491 firms used in the sample. Variable definitions as reported in Table 1. ΔL refers to the percent change in loan issuance of the focal firm's lender over Oct. 2005 to Jun. 2007 relative to Oct. 2008 to June 2009. ΔMarket $\bar{L}$ refers to the sales-weighted leave-out mean of the same index aggregated along the focal firm's product market peers. All other variables in Panel A defined as of the last pre-crisis quarter (2008-Q2) and are winsorized at the 1st and 99th percentile. Panel B reports percentage log changes in dependent variables. Changes in dependent variables are over the pre-crisis period (2006-Q1 to 2008-Q2) to the post-crisis period (2010-Q2 to 2016-Q4), except for ΔInvestment (Crisis), where the latter period is set as the crisis period (2008-Q3 to 2010-Q1).

Panel A	Mean	Std.Dev.	p25	Med.	p75
Sales (Million USD)	1283.61	3225.84	114.01	319.70	979.18
Assets (Million USD)	5694.23	15894.15	439.20	1305.44	3892.01
ΔL	-51.80	16.26	-60.34	-53.97	-47.00
ΔMarket $\bar{L}$	-55.95	5.57	-58.55	-56.26	-52.81
Investment	14.61	14.89	4.81	10.04	19.20
Market Share	1.12	2.71	0.13	0.38	1.01
Net Leverage	0.15	0.26	-0.01	0.15	0.30
Market Net Leverage	0.15	0.15	0.05	0.16	0.26
No. Competitors	29.44	38.90	5.00	14.00	38.00
ROA	0.03	0.03	0.02	0.03	0.05
Mark Up	1.71	1.54	1.14	1.35	1.75
Bank Dependent	0.46	0.50	0.00	0.00	1.00
Panel B					
Δ Sales	8.15	53.38	-17.69	9.23	35.97
Δ Market Share	-6.82	21.23	-13.90	-2.38	2.48
Δ ROA	-1.16	3.03	-2.04	-0.61	0.30
Δ Investment (Crisis)	-2.45	7.38	-4.24	-0.95	0.92
Δ Markup	-2.21	11.48	-3.76	-0.40	2.20

Table 3: First-Stage Results

This table reports the first-stage results of the two-stage least squares regressions. Lender Exposure refers to the rank-normalized first principal component of the focal firm's lender's exposure to three measures of the financial crisis. Market Lender Exposure refers to the sales-weighted leave-out mean of the same index aggregated along the focal firm's product market peers. Firm-level controls consist of log assets, net leverage, market net leverage, a dummy indicating whether or not the firm is bank dependent, and the log number of TNIC product market peers. The sample consists of the intersection of firms in the Compustat, Thomson Reuter's Dealscan, and the Hoberg and Phillips (2016) TNIC databases.

	ΔMarket $\bar{L}$		ΔL
	(1)	(2)	(3)
Market Lender Exposure	0.439***	0.421***	0.051
	(0.022)	(0.022)	(0.051)
Lender Exposure		-0.002	0.423***
		(0.007)	(0.032)
Constant	-35.432***		
	(2.213)		
F-test of Instrument	428.97	374.17	175.54
Firm-level Controls	No	Yes	Yes
SIC-1 FEs	No	Yes	Yes
Observations	1422	1409	1409

* $p < .10$, ** $p < .05$, *** $p < .01$. Heteroskedasticity-robust standard errors reported in parentheses.

Table 4: Sales

The table reports cross-sectional OLS and 2SLS regressions. Variables defined as in Table 1. Changes in sales defined over the pre-credit crunch period (2006Q1 to 2008Q2) to the post-credit crunch period (2010Q2 to 2016Q4). All control variables as of 2008Q2. ΔL refers to the percent change in loan issuance of the focal firm's lender over Oct. 2005 to Jun. 2007 relative to Oct. 2008 to June 2009. ΔMarket $\bar{L}$ refers to the sales-weighted leave-out mean of the same index aggregated along the focal firm's product market peers. Both ΔL and ΔMarket $\bar{L}$ are standardized. Columns 1 and 2 present OLS regressions results. Columns 3 to 5 present 2SLS results.

	OLS		2SLS		
	ΔSales: 2006Q1-2008Q2 to 2010Q2-2016Q4				
	(1)	(2)	(3)	(4)	(5)
-(Δ Market $\bar{L}$)	3.277**	4.939***	5.914**	7.862***	6.045**
	(1.418)	(1.479)	(2.394)	(2.616)	(2.850)
Δ L		1.964		3.390	3.469
		(1.729)		(4.075)	(4.120)
Log Assets		-0.922		-0.926	-0.769
		(1.125)		(1.192)	(1.222)
Net Leverage		16.576**		17.642**	15.143**
		(6.650)		(7.151)	(7.332)
Market Net Leverage		-40.303***		-44.492***	-39.047***
		(10.594)		(10.581)	(11.101)
Log No. Competitors		2.180**		1.909*	2.744**
		(1.059)		(1.080)	(1.277)
Bank Dependent		11.206***		10.995***	10.554***
		(3.862)		(3.877)	(3.902)
Constant	8.188***	8.393	8.216***	9.739	
	(1.414)	(9.740)	(1.415)	(10.232)	
Observations	1422	1409	1422	1409	1409
Adjusted R^2	0.003	0.029	0.001	0.026	0.017
SIC 1-dig. FEs	No	No	No	No	Yes

* $p < .10$, ** $p < .05$, *** $p < .01$.Heteroskedasticity-robust standard errors are reported in parentheses.

Table 5: Market Share

The table reports cross-sectional OLS and 2SLS regressions. Variables defined as in Table 1. Changes in market share are defined over the pre-credit crunch period (2006-Q1 to 2008-Q2) to the post-credit crunch period (2010-Q2 to 2016-Q4). All control variables as of 2008-Q2. ΔL refers to the percent change in loan issuance of the focal firm's lender over Oct. 2005 to Jun. 2007 relative to Oct. 2008 to June 2009. ΔMarket $\bar{L}$ refers to the sales-weighted leave-out mean of the same index aggregated along the focal firm's product market peers. Both ΔL and ΔMarket $\bar{L}$ are standardized. Columns 1 and 2 present OLS regressions results. Columns 3 to 5 present 2SLS results.

	OLS		2SLS		
	ΔMarket Share: 2006Q1-2008Q2 to 2010Q2-2016Q4				
	(1)	(2)	(3)	(4)	(5)
-(Δ Market $\bar{L}$)	1.115	1.555**	3.100***	4.111***	4.746***
	(0.737)	(0.734)	(1.148)	(1.195)	(1.330)
Δ L		0.206		0.951	0.465
		(0.478)		(1.362)	(1.384)
Log Assets		-3.722***		-3.740***	-3.936***
		(0.481)		(0.495)	(0.513)
Net Leverage		7.141***		8.010***	8.060***
		(2.456)		(2.683)	(2.696)
Market Net Leverage		2.337		-1.161	-2.961
		(5.005)		(5.212)	(5.610)
Log No. Competitors		1.569***		1.406***	1.123**
		(0.454)		(0.453)	(0.530)
Bank Dependent		-0.194		-0.331	0.050
		(1.345)		(1.377)	(1.380)
Constant	-6.841***	14.973***	-6.878***	15.977***	
	(0.580)	(3.682)	(0.582)	(3.740)	
Observations	1348	1337	1348	1337	1337
Adjusted R^2	0.002	0.077	-0.006	0.063	0.060
SIC 1-dig. FEs	No	No	No	No	Yes

* $p < .10$, ** $p < .05$, *** $p < .01$. Heteroskedasticity-robust standard errors reported in parentheses.

Table 6: ROA

The table reports cross-sectional OLS and 2SLS regressions. Variables defined as in Table 1. Changes in ROA defined over the pre-credit crunch period (2006-Q1 to 2008-Q2) to the post-credit crunch period (2010-Q2 to 2016-Q4). All control variables as of 2008-Q2. ΔL refers to the percent change in loan issuance of the focal firm's lender over Oct. 2005 to Jun. 2007 relative to Oct. 2008 to June 2009. ΔMarket $\bar{L}$ refers to the sales-weighted leave-out mean of the same index aggregated along the focal firm's product market peers. Both ΔL and ΔMarket $\bar{L}$ are standardized. Columns 1 and 2 present OLS regressions results. Columns 3 to 5 present 2SLS results.

	OLS		2SLS		
	ΔROA: 2006Q1-2008Q2 to 2010Q2-2016Q4				
	(1)	(2)	(3)	(4)	(5)
-(Δ Market $\bar{L}$)	0.350***	0.404***	0.578***	0.691***	0.591***
	(0.083)	(0.085)	(0.125)	(0.132)	(0.135)
Δ L		0.089		0.249	0.133
		(0.116)		(0.222)	(0.221)
Log Assets		-0.046		-0.044	-0.072
		(0.062)		(0.068)	(0.067)
Net Leverage		1.312***		1.443***	1.282***
		(0.377)		(0.416)	(0.422)
Market Net Leverage		-0.437		-0.854	-0.234
		(0.618)		(0.616)	(0.623)
Log No. Competitors		-0.298***		-0.326***	-0.198***
		(0.064)		(0.066)	(0.072)
Bank Dependent		-0.380*		-0.404*	-0.319
		(0.210)		(0.209)	(0.204)
Constant	-1.157***	-0.023	-1.155***	0.092	
	(0.080)	(0.548)	(0.080)	(0.577)	
Observations	1416	1403	1416	1403	1403
Adjusted R^2	0.013	0.041	0.007	0.031	0.014
SIC 1-dig. FEs	No	No	No	No	Yes

* $p < .10$, ** $p < .05$, *** $p < .01$. Heteroskedasticity-robust standard errors reported in parentheses.

Table 7: Markups

The table reports cross-sectional OLS and 2SLS regressions. Variables defined as in Table 1. Changes in mark ups defined over the pre-credit crunch period (2006-Q1 to 2008-Q2) to the post-credit crunch period (2010-Q2 to 2016-Q4). All control variables as of 2008-Q2. ΔL refers to the percent change in loan issuance of the focal firm's lender over Oct. 2005 to Jun. 2007 relative to Oct. 2008 to June 2009. ΔMarket $\bar{L}$ refers to the sales-weighted leave-out mean of the same index aggregated along the focal firm's product market peers. Both ΔL and ΔMarket $\bar{L}$ are standardized. Columns 1 and 2 present OLS regressions results. Columns 3 to 5 present 2SLS results.

	OLS		2SLS		
	ΔMarkup: 2006Q1-2008Q2 to 2010Q2-2016Q4				
	(1)	(2)	(3)	(4)	(5)
-(Δ Market $\bar{L}$)	0.187	0.592**	0.233	0.870*	0.883*
	(0.279)	(0.296)	(0.447)	(0.506)	(0.518)
Δ L		0.828**		2.297**	1.705*
		(0.401)		(0.992)	(1.007)
Log Assets		0.019		0.195	0.170
		(0.293)		(0.312)	(0.312)
Net Leverage		2.824*		4.018**	4.244**
		(1.695)		(1.861)	(1.890)
Market Net Leverage		-7.724***		-8.568***	-4.147*
		(2.480)		(2.500)	(2.417)
Log No. Competitors		-1.644***		-1.707***	-0.819***
		(0.302)		(0.307)	(0.297)
Bank Dependent		-1.106		-1.327	-1.021
		(0.844)		(0.874)	(0.862)
Constant	-2.201***	2.839	-2.199***	1.780	
	(0.329)	(2.445)	(0.330)	(2.589)	
Observations	1230	1217	1230	1217	1217
Adjusted R^2	-0.001	0.042	-0.001	0.029	0.000
SIC 1-dig. FEs	No	No	No	No	Yes

* $p < .10$, ** $p < .05$, *** $p < .01$. Heteroskedasticity-robust standard errors reported in parentheses.

Table 8: Investment Over the Crisis

The table reports cross-sectional OLS and 2SLS regressions. Variables defined as in Table 1. Changes in investment defined over the pre-credit crunch period (2006-Q1 to 2008-Q2) to the credit crunch period (2008-Q3 to 2010-Q1). All control variables as of 2008-Q2. ΔL refers to the percent change in loan issuance of the focal firm's lender over Oct. 2005 to June 2007 relative to Oct. 2008 to June 2009. ΔMarket L refers to the sales-weighted leave-out mean of the same index aggregated along the focal firm's product market peers. Both ΔL and ΔMarket $\bar{L}$ are standardized. Columns 1 and 2 present OLS regressions results. Columns 3 to 5 present 2SLS results.

	OLS		2SLS		
	ΔInvestment: 2006Q1-2008Q2 to 2008Q3-2010Q1				
	(1)	(2)	(3)	(4)	(5)
-(Δ Market $\bar{L}$)	0.509***	0.740***	1.078***	1.499***	0.864***
	(0.183)	(0.186)	(0.285)	(0.306)	(0.303)
Δ L		0.255		1.130**	1.066**
		(0.233)		(0.545)	(0.525)
Log Assets		0.077		0.132	0.112
		(0.133)		(0.146)	(0.143)
Net Leverage		-1.757**		-1.006	-1.809**
		(0.838)		(0.894)	(0.898)
Market Net Leverage		-4.501***		-5.777***	-4.793***
		(1.388)		(1.468)	(1.461)
Log No. Competitors		-0.760***		-0.840***	-0.650***
		(0.160)		(0.166)	(0.161)
Bank Dependent		-2.230***		-2.363***	-2.185***
		(0.514)		(0.533)	(0.518)
Constant	-2.453***	0.879	-2.453***	0.841	
	(0.191)	(1.107)	(0.191)	(1.159)	
Observations	1491	1480	1491	1480	1480
Adjusted R^2	0.004	0.048	-0.002	0.028	0.009
SIC 1-dig. FEs	No	No	No	No	Yes

* $p < .10$, ** $p < .05$, *** $p < .01$. Heteroskedasticity-robust standard errors reported in parentheses.

Table 9: Changes in Investment over the Crisis with Growth Expectations

The table reports cross-sectional 2SLS regressions. Variables defined as in Table 1. Changes in investment defined over the pre-credit crunch period (2006-Q1 to 2008-Q2) to the credit crunch period (2008-Q3 to 2010-Q1). All control variables as of 2008-Q2. ΔL refers to the percent change in loan issuance of the focal firm's lender over Oct. 2005 to Jun. 2007 relative to Oct. 2008 to June 2009. ΔMarket L refers to the sales-weighted leave-out mean of the same index aggregated along the focal firm's product market peers. Both ΔL and ΔMarket $\bar{L}$ are standardized. Columns 1 and 2 present OLS regressions results. Columns 3 to 5 present 2SLS results.

	ΔInvestment: 2006Q1-2008Q2 to 2008Q3-2010Q1				
	(1)	(2)	(3)	(4)	(5)
-(Δ Market $\bar{L}$)	0.722**	0.815**	0.823***	0.886***	0.754**
	(0.295)	(0.321)	(0.301)	(0.321)	(0.328)
Δ L	0.902*	1.299**	1.013*	0.956*	1.028*
	(0.506)	(0.595)	(0.529)	(0.559)	(0.596)
Δ Q	6.853***				7.587***
	(1.828)				(2.377)
Δ Q Alt.		-0.299			-1.445***
		(0.368)			(0.410)
Δ Q Total			1.537**		0.364
			(0.605)		(0.758)
Δ ROA				0.127	0.045
				(0.086)	(0.093)
Observations	1480	1402	1464	1356	1285
Adjusted R^2	0.035	0.002	0.012	0.014	0.030
Controls	Yes	Yes	Yes	Yes	Yes

* $p < .10$, ** $p < .05$, *** $p < .01$. Heteroskedasticity-robust standard errors reported in parentheses.

Table 10: Robustness: Vertical and Technological Spillovers

The table reports second-stage results of 2SLS regressions. Changes in dependent variables in columns 1 through 3 defined over the pre-credit crunch period (2006-Q1 to 2008-Q2) to the post-credit crunch period (2010-Q2 to 2016-Q4). In column 4, changes in investment defined over the pre-credit crunch period (2006-Q1 to 2008-Q2) to the credit crunch period (2008-Q3 to 2010-Q1). ΔL refers to the percent change in loan issuance of the focal firm's lender over Oct. 2005 to Jun. 2007 relative to Oct. 2008 to June 2009. ΔMarket $\bar{L}$ refers to the leave-out mean of the same index aggregated along the focal firm's product market peers. Both ΔL and ΔMarket $\bar{L}$ are instrumented by the respective lenders' exposure to the MBS market. ΔVTNIC $\bar{L}$ is the same as ΔMarket $\bar{L}$, but defined along the firm's vertical counterparts. ΔTec $\bar{L}$ is the same, but defined along the firm's technology peers. Variables otherwise defined as in Table 1. Control variables from baseline regressions included, but not shown.

	(1)	(2)	(3)	(4)	(5)
	Δ Sales	Δ Market Share	Δ ROA	Δ Markup	Δ Investment
		Panel A: Vertical Spillovers			
-(Δ Market $\bar{L}$)	5.920**	3.286**	0.653***	0.997*	1.483***
	(2.957)	(1.354)	(0.143)	(0.540)	(0.341)
Δ L	1.456	0.762	0.180	2.165**	1.182*
	(4.702)	(1.599)	(0.253)	(0.942)	(0.636)
Δ VTNIC $\bar{L}$	173.217	-29.425	3.839	-11.051	-15.295
	(114.337)	(55.343)	(5.375)	(23.600)	(13.469)
Observations	1204	1142	1197	1036	1269
Adjusted R^2	0.019	0.068	0.029	0.035	0.023
Controls	Yes	Yes	Yes	Yes	Yes
		Panel B: Technology Spillovers			
-(Δ Market $\bar{L}$)	2.774	3.380	0.784***	1.102	0.641
	(5.112)	(2.867)	(0.192)	(0.879)	(0.422)
Δ L	-2.602	0.339	0.088	4.213**	1.489**
	(6.861)	(2.304)	(0.302)	(1.657)	(0.746)
Δ TEC $\bar{L}$	17.572	-83.629	20.484***	23.362	-10.395
	(138.605)	(62.278)	(7.191)	(31.300)	(16.716)
Observations	456	423	450	443	478
Adjusted R^2	0.010	0.041	0.060	-0.009	0.024
Controls	Yes	Yes	Yes	Yes	Yes

* $p < .10$, ** $p < .05$, *** $p < .01$. Heteroskedasticity-robust standard errors reported in parentheses.

Table 11: Robustness: Adjusted Lender-Borrower Matching Timing

The table reports cross-sectional 2SLS regressions. Borrowers are matched to lenders over 2003-Q1 to 2007-Q2, one year earlier compared to previous specifications. Changes in dependent variables in columns 1 through 4 defined over the pre-credit crunch period (2005-Q1 to 2007-Q2), one year earlier than in other specifications, to the post-credit crunch period (2010-Q2 to 2016-Q4). In column 5, changes in investment defined over the pre-credit crunch period (2005-Q1 to 2007-Q2) to the credit crunch period (2008-Q3 to 2010-Q1). All control variables as of 2008-Q2. ΔL refers to the percent change in loan issuance of the focal firm's lender over Oct. 2005 to Jun. 2007 relative to Oct. 2008 to June 2009 and is standardized. ΔMarket L refers to the standardized sales-weighted leave-out mean of the same index aggregated along the focal firm's product market peers. Both ΔL and ΔMarket $\bar{L}$ are instrumented by the respective lenders' exposure to the MBS market. Variables defined as in Table 1.

	(1)	(2)	(3)	(4)	(5)
	Δ Sales	Δ Market Share	Δ ROA	Δ Markup	Δ Investment
-(Δ Market $\bar{L}$)	11.840*	4.731*	0.547*	1.417*	1.049*
	(6.495)	(2.777)	(0.281)	(0.837)	(0.543)
Δ L	6.576*	0.244	0.172	0.280	0.835*
	(3.990)	(1.384)	(0.238)	(0.841)	(0.484)
Log Assets	0.397	-3.927***	-0.114	-0.218	0.232
	(1.244)	(0.584)	(0.074)	(0.285)	(0.156)
Net Leverage	19.588**	6.796**	1.199***	1.799	-2.383**
	(7.925)	(2.780)	(0.447)	(1.786)	(0.931)
Market Net Leverage	-38.463***	-3.275	-0.306	-2.063	-5.655***
	(13.373)	(7.575)	(0.707)	(2.365)	(1.696)
Log No. Competitors	2.078	0.874	-0.263***	-0.630**	-0.684***
	(1.583)	(0.673)	(0.088)	(0.281)	(0.181)
Bank Dependent	7.453*	0.526	-0.454**	-0.052	-1.689***
	(4.002)	(1.437)	(0.217)	(0.821)	(0.516)
Observations	1300	1233	1287	1099	1383
Adjusted R^2	-0.013	0.069	0.000	0.000	0.001
SIC 1-dig. FEs	Yes	Yes	Yes	Yes	Yes

* $p < .10$, ** $p < .05$, *** $p < .01$. Heteroskedasticity-robust standard errors reported in parentheses.

Appendices

A Principal Component Analysis and Lender Health

For a sample of the 43 largest syndicated lenders, I estimate the first principal component along three measures of bank exposure to the financial crisis: the correlation of the bank's stock return with an index of AAA mortgage-backed securities, the share of syndicated loans the bank participated in where Lehman Brother's had a lead role, and the share of trading revenue relative to the lender's total assets.

The first principal component (eigenvalue 1.539) captures 51.33% of the variation in the three variables. It has a correlation coefficient of 0.88 with the share of syndicated loans the bank participated in which Lehman Brother's had a lead role, 0.73 with the correlation of the bank's stock return with an index of AAA mortgage-backed securities, and 0.48 with the share of trading revenue relative to the lender's total assets.[4]

Following Chodorow-Reich and Falato (2022), I then rank the banks according along the first principal component score. This ranking is able to explain variation in the change of lending across banks from the pre-crisis to the crisis period. Below is a scatter plot and univariate regression slope for the percent change in the annualized number of new loans from the period of October 2005 to June 2007 and October 2008 to June 2009 regressed on the banks PCA ranking, with the most exposed bank being ranked last.

[4]Chodorow-Reich's dataset on bank exposure to the financial crisis has four missing cells. With respect to the share of syndicated loans the bank participated in which Lehman Brother's had a lead role, there is no obvious value besides absent or 1. Additionally, Cobank, Utrecht-America, and WestLB are not publicly-listed, so it was not possible to calculate the correlation of the bank's stock return with an index of AAA mortgage-backed securities. Technically, this poses a problem to PCA, which requires that all variables be non-missing for each observation. While Chodorow-Reich and Falato (2018) also extract the first principal component for these variables with the same sample of banks, they do not allude to how they address the missing cells. I use the iterative imputation approach of Husson and Josse (2016), which essentially replaces the missing cell with its sample mean and adjusts it depending on values of the available variables for the given row, its sample correlation with the other variables, and the standard deviation of the missing variable.

B Mark Up Estimation Procedure

Here I briefly outline the markup estimation procedure. The notation and procedure closely follows that of De Loecker, Eeckhout, and Unger (2020), who consider the following production function:

$$Q_{it} = F(\Omega_{it}, \mathbf{V}_{it}, K_{it}), \tag{1}$$

where $F(.)$ is the production technology which transforms inputs into outputs, Ω_{it} is a Hicks-neutral productivity term, $\mathbf{V}_{it}$ a vector of variable inputs, and K_{it} is the capital stock.

Using standard first-order conditions and defining the markup, μ_{it}, as the price over marginal cost, it can be shown that:

$$\mu = \theta_{it}^{v} \frac{P_{it} Q_{it}}{P_{it}^{V} V_{it}} \tag{2}$$

where θ_{it}^{v} is the output elasticity of the variable input, $P_{it} Q_{it}$ are firm revenues, and $P_{it}^{v} V_{it}$ are total variable cost expenditures. While the latter two variables are available in Compustat, θ_{it}^{v} must be estimated. Here, annual, industry-specific (NAICS 2-digit) Cobb-Douglas production functions are estimated:

$$q_{it} = \theta_{st}^{V} v_{it} + \theta_{st}^{K} k_{it} + \omega_{it} + \epsilon_{it} \tag{3}$$

where lower cases denote logs and ϵ_{it} is unanticipated shock to output or measurement error.[5] In estimating θ_{st}^{V} and θ_{st}^{K} we are faced with the endogeneity problem that the unobservable

[5]The industry-specific out elasticities from 1980 to 2016 as estimated in De Loecker, Eeckhout, and Unger (2020) are available at: https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/5GH8XO

productivity shock term, ω_{it}, may be correlated with the firm's input choice. Note that k_{it} is fixed and dynamic (a state variable) at time t and is chosen before productivity at time t is known by the firm, whereas v_{it} is chosen at time t. The productivity process is given by a first order Markov process:

$$\omega_{it} = g(\omega_{it-1} + \chi_{it}) \tag{4}$$

where productivity shocks, $\chi_i t$ are uncorrelated with input decisions chosen before period t. This gives rise to the moment condition:

$$\mathbb{E}[\chi_t | k_t, v_{t-1}, k_{t-1}, ...] = 0 \tag{5}$$

Intuitively, variable input demand can be written as a function of productivity and capital, e.g. $v_{it} = v(\omega_{it}, kit)$ where v is strictly increasing in ω_{it}. This gives rise to the "proxy structure" - where productivity can be modeled as the inverse of the input demand function and thereby estimated using observables: $v^{-1}(v_{it}, k_{it}) = a(v_{it}, k_{it})$. "Guesses" of the variable output elasticity (θ^v) and capital elasticity (θ^k) are then chosen to yield estimates $\hat{\omega}_{it}$ and $\hat{\epsilon}_{it}$ which satisfy (5) and (3). Finally, the estimated industry-specific output elasticities are used to obtain firm-level markup estimates as in equation 2.

C Supply Chain and Technology Network Spillovers

Table C1: Summary Statistics

	Mean	Std.Dev.	p25	Med.	p75	n
Δ TEC $\bar{L}$	-0.50	0.02	-0.51	-0.50	-0.49	497
Δ VTNIC $\bar{L}$	-0.56	0.01	-0.57	-0.57	-0.56	1316

Table C2: Pairwise Correlations

	Δ TEC $\bar{L}$	Δ VTNIC $\bar{L}$	Δ Market $\bar{L}$	Market Lender Exposure
Δ TEC $\bar{L}$	1			
Δ VTNIC $\bar{L}$	0.00842	1		
Δ Market $\bar{L}$	-0.0786*	0.0359	1	
Market Lender Exposure	-0.0405	-0.0140	.5940***	1

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C3: Robustness: Technology Spillovers Sample Without Technology Spillovers

The table reports second-stage results of 2SLS regressions. Specifications and the sample are the same as in Table 10 Panel B except ΔTec $\bar{L}$ is excluded. Changes in dependent variables in columns 1 through 5 defined over the pre-credit crunch period (2006-Q1 to 2008-Q2) to the post-credit crunch period (2008-Q3 to 2010-Q1). In column 4, changes in investment defined over the pre-credit crunch period (2006-Q1 to 2008-Q2) to the credit crunch period (2008-Q3 to 2010-Q1). ΔL refers to the percent change in loan issuance of the focal firm's lender over Oct. 2005 to Jun. 2007 relative to Oct. 2008 to June 2009. ΔMarket $\bar{L}$ refers to the leave-out mean of the same index aggregated along the focal firm's product market peers. Both ΔL and ΔMarket $\bar{L}$ are instrumented by the respective lenders' exposure to the MBS market. ΔTec $\bar{L}$ is change in lending to the firm's technology peers. Variables otherwise defined as in Table 1. Control variables from baseline regressions included.

	(1)	(2)	(3)	(4)	(5)
	Δ Sales	Δ Market Share	Δ ROA	Δ Markup	Δ Investment
-(Δ Market $\bar{L}$)	2.790	3.263	0.802***	1.129	0.636
	(5.076)	(2.855)	(0.195)	(0.880)	(0.423)
Δ L	-2.542	0.089	0.166	4.297***	1.447**
	(6.732)	(2.258)	(0.301)	(1.643)	(0.725)
Observations	456	423	450	443	478
Adjusted R^2	0.012	0.040	0.038	-0.011	0.026
Controls	Yes	Yes	Yes	Yes	Yes

* $p < .10$, ** $p < .05$, *** $p < .01$. Heteroskedasticity-robust standard errors reported in parentheses.

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ISSN 2194-2188