Bank Concentration and Product Market Competition*

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Abstract

This paper documents a link from bank concentration to markups in non-financial sectors. Exploiting concentration-increasing bank mergers and variation in banks' market shares across industries, we show that higher credit concentration is associated with higher markups, and high-market-share lenders charge lower loan rates. We argue that this is due to the greater incidence of competing firms sharing common lenders that induce less aggressive product market behavior among their borrowers, thereby internalizing potential adverse effects of higher rates. Consistent with our conjecture, the effect is stronger in industries with competition in strategic substitutes where negative product market externalities would be greatest.

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1 Introduction

Recent evidence documents that U.S. industries are becoming increasingly concentrated (Autor, Dorn, Katz, Patterson, and Reenen, 2017; Head and Spencer, 2017; Grullon, Larkin, and Michaely, 2019) and due to higher average market power, economic profits and markups are on the rise (De Loecker, Eeckhout, and Unger, 2020; Hall, 2018). At the same time, banking-sector concentration is increasing as well (Janicki and Prescott, 2006; Laeven, Ratnovski, and Tong, 2016; Fernholz and Koch, 2016), giving rise to the emergence of dominant banks in credit markets (Ross, 2010). Clearly, both trends could be driven by common factors, i.e., the relation could be spurious. Alternatively, however, the competitive behavior of bank-dependent firms may be affected by higher concentration in the credit market. That is, bank concentration and product market competition could in fact be linked (Cetorelli and Gambera, 2001).

In this paper, we scrutinize whether this is true, and how concentration in the banking sector affects an industry's ability to commit to less competitive product market behavior, thereby increasing profit margins. Our analysis proceeds in two steps. First, we document that credit concentration is associated with higher industry markup. Second, we shed light on the mechanism underlying the relationship between bank concentration and product market competition.

Banks with market power may be reluctant to lend to entrants as this would harm existing borrowers, i.e., incumbents (Cestone and White, 2003). That is, bank finance constitutes a potential barrier to entry (Cetorelli and Strahan, 2006). However, we show empirically that higher credit concentration translates to higher markups even after accounting for the level of competition and the number of firms in an industry.

Motivated by this observation, we put forward, and provide evidence for, an alternative, non-mutually exclusive mechanism based on the idea that banks with market power internalize potential externalities of their lending decisions, as has been argued by Petersen and Rajan (1995) and documented more recently by Giannetti and Saidi (2019). We show that when firms competing in strategic substitutes share a common lender, which is more likely to be the case when bank concentration in a given industry is high, they can sustain less competitive outcomes. In particular, even in existing lending relationships, banks may soften credit conditions to avoid aggressive product market behavior among their competing borrowers (Poitevin, 1989).

We start out by analyzing the link between credit concentration and industry markup. In particular, we use transaction-level data on syndicated lending in the U.S. to compute banks' shares in the market for credit of a given industry. We use these market shares to yield a credit-concentration measure at the industry level, which we show to be positively correlated with average firm-level markups in an industry. This relationship proves robust to including a host of control variables, such as industry size, degree of indebtedness, or the pre-existing level of competition in an industry.

A less competitive outcome is associated with both higher industry markup and lower industry output. We focus on industry markup as granular information on sales quantities is not available (firms only report total revenue, i.e., quantity $\times$ price). For robustness, we test for output effects using annual chain-type quantity indices, and find that higher concentration in the credit market is not only associated with higher industry markup, but also with lower industry output.

To ascertain whether the relationship between industry-level credit concentration and markup can be interpreted causally, we exploit bank mergers that lead to a rise in industry-level credit concentration, following Garmaise and Moskowitz (2006), Favara and Giannetti (2017), and Benmelech, Bergman, and Kim (2019). In particular, we differentiate between mergers of banks that both have non-zero market shares in the same industry, implying an increase in credit concentration, and mergers involving only one bank with a non-zero market share in a given industry, which are not associated with an increase in credit concentration.

We find that the positive relationship between industry-level credit concentration and markup is robust to instrumenting for the former by concentration-increasing merger activity. Using a difference-in-differences strategy, we further demonstrate that while industries that are previously covered by both merging banks, rather than just one of them, are equally profitable prior to any bank merger, only concentration-increasing bank mergers are subsequently associated with higher industry markups.

We then test the conjecture that credit concentration affects product market competition because of competing firms sharing common lenders. We start from the premise that debt finance serves as a strategic commitment to a product market strategy. As argued in the seminal paper by Brander and Lewis (1986), higher leverage or interest rates lead to more aggressive product market strategies (the limited-liability effect of debt), ultimately leaving all firms worse off.[1] As common lenders maximize the aggregate debt value, and effectively treat their borrowers as a multi-plant firm, they internalize potential externalities among their borrowers stemming from higher loan rates (Poitevin, 1989).

As argued by, among others, Showalter (1995), if firms compete in strategic complements, these externalities depend on the type of uncertainty in the product market, so there exists no unambiguous need for internalization by a common lender. However, if firms compete in strategic substitutes, a common lender charges lower loan rates so as to internalize any adverse effect of aggressive product market strategies of its borrowers. The resulting aggregate industry output will be lower and profit will be higher than it would be for separate lenders. Therefore, common lenders serve as a commitment device for firms' product market decisions in the same industry, and centralized financing helps firms to implement less competitive outcomes.

We test this hypothesis empirically at the bank-industry-time level. Lenders with larger market shares imply a more frequent occurrence of common lenders within industries. Our evidence is consistent with the idea that lenders that have issued a large share of the loans outstanding in an industry internalize potential externalities among their borrowers stemming from more aggressive product market behavior induced by higher loan rates, and subsequently charge lower cost of debt. Importantly, high-market-share lenders lower the cost

[1] The empirical evidence is mixed. This may be because it depends on the mode of industry competition, and may not hold for strategic complements (Showalter, 1995). In addition, leverage is typically an endogenous firm-level variable, and finding plausibly exogenous variation in the latter is difficult.

of debt primarily for firms that compete in strategic substitutes. By including industry-time and bank-time fixed effects, our empirical analysis of lower cost of debt charged by high-market-share lenders takes into account time-varying unobserved heterogeneity both at the industry level – e.g., fluctuations in industry-level loan demand – and at the bank level – including but not limited to bank-level credit supply.

Balanced against the benefit of lower cost of debt, Asker and Ljungqvist (2010) point out a potential downside by considering firms' decision to share underwriting investment banks, namely the possibility of commercially sensitive information leaking to competitors, which firms may actively try to avoid. Additionally, changes in market shares could reflect a bank's industry expertise and, thus, the cost of monitoring borrowers. By showing that our result is stronger for firms competing in strategic substitutes, rather than complements, we can rule out that such informational effects drive our estimates, as the value of information should be independent of the mode of competition. We further address endogeneity concerns by using variation in banks' industry market shares stemming from bank mergers (following Giannetti and Saidi, 2019). Focusing on recent and gradual increases in market shares due to mergers, we identify a treatment effect that is unlikely to be due to any pre-merger private information held by the merging banks.

Our findings suggest that, on average, high-market-share lenders charge lower loan rates, which is consistent with our conjecture that high-market-share (common) lenders minimize internal cannibalization among firms in their loan portfolios by setting loan terms that induce less aggressive product market behavior. To the extent that banks with higher market shares also have greater market power, allowing them to charge higher loan spreads, the average effect implied by our estimates may mask this heterogeneity.

We address this by identifying instances in which loan spreads charged by banks with high market shares are more likely to be governed by common lenders' incentives to internalize product market externalities, rather than by their market power. The scope for internalizing externalities is greater, or less ambiguous, when firms compete in strategic substitutes rather than complements. In line with this argument, we show that the effect of banks' higher market shares on lower cost of debt is generally more emphasized for firms competing in strategic substitutes. Furthermore, lenders' incentives to take into account potential adverse effects of higher loan rates on the product market behavior among their competing borrowers should be more emphasized when debt is particularly risky, and subsequently behaves more like equity, which we also show to hold true.

Our paper is related to Cetorelli and Strahan (2006), who also consider the relationship between concentration in the banking sector and industry structure in product markets, in particular the number of firms and the shape of the firm-size distribution. They find that higher bank competition aids smaller non-financial firms in bank-dependent sectors, whereas the largest establishments are unaffected. These findings suggest that bank concentration constitutes a financial barrier to entry in product markets. Cestone and White (2003) formalize this idea, and argue that investors may use equity, rather than debt, to deter the entry of potential competitors by not funding them.

We zoom in on a potential mechanism that can shed light on why concentration in the banking sector is correlated with concentration in product markets, as suggested by Cetorelli (2004). In particular, we show that loan pricing, rather than loan availability (Black and Strahan, 2002; Cetorelli and Strahan, 2006), is an important channel for the transmission from bank concentration to product market competition. By charging lower loan rates, common lenders induce less aggressive product market behavior among their competing borrowers, for whom sharing a common lender serves as a commitment device for product market decisions and, thus, profits. This mechanism complements any effect that bank concentration may have on entry and exit (Cetorelli and Strahan, 2006).

As borrowers that are more likely to share a common lender benefit from lower cost of debt, our findings are consistent with those in Ross (2010). In contrast, however, we put forward an explanation for lower cost of debt that is unrelated to the mitigation of asymmetric information through lender certification. In fact, our identification allows us to control for such time-varying heterogeneity at the bank level. After doing so, we show that high-market-share lenders charge lower loan rates especially when there is greater scope for the internalization of negative externalities. This, in turn, enables competing borrowers to commit to less aggressive product market strategies, leading to higher industry markup.

The main idea of a common agent facilitating a less competitive outcome, without entering into explicit collusive agreements, goes back to Bernheim and Whinston (1985). A common agent can be characterized by financial ties. For instance, Azar, Schmalz, and Tecu (2018) analyze the competitive effects of institutional investors holding shares in multiple firms in the airline industry, which they dub "common ownership." Anton, Ederer, Giné, and Schmalz (2017) document such common-ownership effects across different industries, and Gutiérrez and Philippon (2017) provide evidence that firms under-invest when they operate in industries where common ownership is more prevalent.

Common lenders can affect outcomes in the product market in many ways. Bhattacharya and Chiesa (1995) conjecture that common lenders can facilitate knowledge transfer among competing firms, which would otherwise face the difficulty of legal non-verifiability. More recently, Frattaroli and Herpfer (2019) provide evidence that common lenders enable strategic alliances among their borrower firms. Moreover, Hellwig (1991) argues that monitoring and prevention of too-competitive behavior may be the main purpose of banks with large market shares in certain industries (e.g., the Austrian Kontrollbank in the late 19$^{\text{th}}$/early 20$^{\text{th}}$ century). This is because cartels are subject to the moral-hazard problem of individual firms deviating from the collusive equilibrium and undercutting one another. Lastly, the idea that debt finance can serve as a coordination mechanism for less competitive product market strategies is consistent with recent evidence by Dasgupta and Žaldokas (2019), who find that firms issue more equity and subsequently delever when competition increases.

We stress the identity of lenders, rather than the fact that firms are levered, to investigate the link from debt finance to product market competition. By pointing out the importance of common lenders for the interpretation of the limited-liability effect, our findings offer an alternative explanation for studies rejecting the existence of a limited-liability effect due to a negative correlation between leverage and output (e.g., Phillips, 1995), namely that firms with common lenders are able to coordinate on their product market strategies.

2 Credit Concentration and Industry Markup

In this section, we document the relationship between concentration in the credit market and industry markup. We start by describing the data, and then discuss our empirical tests.

2.1 Data Description

We use industry markup as an empirical measure of the degree of product market competition. Using Compustat data, we follow Bustamante and Donangelo (2017), and define markup as the sum of firms' sales by industry-year (i.e., Compustat annual data item "SALE") minus the sum of firms' cost of goods sold by industry-year (i.e., Compustat annual data item "COGS"), scaled by the sum of firms' sales.[2]

For robustness, we additionally calculate industry-level markup (henceforth labeled as "DLW") following the procedure laid out in De Loecker, Eeckhout, and Unger (2020), which is a modified version of the framework proposed by De Loecker and Warzynski (2012). In particular, De Loecker and Warzynski (2012) derive firm-level markups from a production function framework, without having to rely on price data or specifying any assumptions about market structure. Instead, markups are obtained under the assumption that producers minimize the costs associated with a variable input of production. We assume a Cobb-Douglas production function for this purpose. Similarly to De Loecker, Goldberg, Khandelwal, and Pavcnik (2016), we trim observations with markups that are below the 5$^{\text{th}}$ and above the 95$^{\text{th}}$ percentile within each industry. We provide further details on the estimation procedure in Appendix A (of the Online Appendix).

Our conjecture is that banks' incentives to internalize potential externalities derive from their share of the loans outstanding in an industry. We follow Giannetti and Saidi (2019), and

[2] Using Compustat data allows us to calculate industry-level markups for a broad set of industries over a long time period. The drawback is that Compustat covers only public firms. However, Bustamante and Donangelo (2017) document that the correlation between Compustat-based markup measures and alternative measures based on Census data (comprising both private and public firms) is high. This suggests that Compustat-based average industry-markup measures are not subject to significant sample-selection bias despite their focus on publicly listed firms (in contrast to Compustat-based concentration measures, cf. Ali, Klasa, and Yeung, 2009).

define *Market Share*$_{ijt-1}$ as the proportion of bank j's total loan volume granted to industry i over the aggregate loan volume of industry i in the previous year $(t-1)$. Both the bank's and the industry's loan volumes are measured over the previous five years, which is approximately equal to the average maturity of the loans. We use these market shares to compute a Herfindahl-Hirschman Index (HHI) capturing credit concentration at the industry-year level, *Bank-Industry HHI*$_{it-1}$. In our analysis, we alternatively compute credit concentration based on the number of loans granted, loan volume outstanding, and the number of loans outstanding at the time of measurement.

We obtain transaction-level data on syndicated loans from LPC DealScan. We focus on loans issued to publicly listed or privately held U.S. firms. The sample period is 1990 to 2015.[3] We exclude financial firms (SIC codes 6000-6999) and public-service firms (SIC codes 9000-9999), and identify bank-industry lending relationships by focusing on the lead arrangers of syndicated loans. We aggregate wholly owned bank subsidiaries under the ultimate parent using the link table provided in Schwert (2018). This link includes all lenders that acted as lead arrangers on at least 50 loans or at least $10bn in volume over the 1987–2012 period, as well as their related subsidiaries.[4] This adjustment further takes into account ownership changes arising as a result of bank mergers. In this manner, we yield a total of 488 banks.

In Panel A of Table 1, we present summary statistics for our main variables at the industry-year level, including our different measures of industry markup.

2.2 Results

2.2.1 Baseline Results

We start with graphical evidence for the relationship between bank concentration and product market competition. In Figure 1, we plot coefficients from a regression that relates indus-

[3] DealScan provides comprehensive information about the U.S. syndicated-loan market from the mid-1980s onwards. We start our sample period in 1990 given that we require a five-year lookback window for the computation of banks' market shares.

[4] For about 10% of observations, no parent name can be assigned. For these cases, we use the bank names as given in the DealScan database.

try markup to concentration in the credit market, as measured by a Herfindahl-Hirschman Index over banks' market shares in terms of credit granted to a given industry. Controlling for industry and year fixed effects, we find that starting with the fifth decile, industry markup increases almost monotonically across deciles of the credit-concentration distribution.

We scrutinize this effect further by means of regressions at the industry-year level it. In particular, we estimate the same regression specification as in the figure, but replace the main explanatory variable by a continuous measure of credit concentration:

$$\textit{Industry markup}_{it} = \beta \textit{Bank-Industry HHI}_{it-1} + \gamma^{'} X_{it-1} + \delta_i + \chi_t + \epsilon_{it}, \tag{1}$$

where the outcome variable $\textit{Industry markup}_{it}$ is equal to the sum of firms' sales minus the sum of firms' cost of goods sold in industry i in year t, scaled by the sum of firms' sales. $\textit{Bank-Industry HHI}_{it-1}$ is defined as the sum of the squared bank market shares, where bank market shares are measured over the last five years, i.e., from year $t-1$ to $t-5$. We also include industry-level controls, X_{it-1}, to control for heterogeneity in industry characteristics. δ_i and χ_t denote industry and year fixed effects, respectively. Standard errors are clustered at the industry level. Industries are defined using three-digit SIC codes.

The results are in Table 2. In column 1, we find that higher credit concentration is indeed associated with higher industry markup. Adding industry fixed effects in column 2 halves the coefficient, which is not surprising given that $\textit{Bank-Industry HHI}_{it-1}$ does not vary much over time. The coefficient is robust to including a plethora of industry characteristics in column 3, among which are its lagged size, total loan volume (as a measure of industry-wide credit demand), and leverage.

By including industry leverage, we address the possibility that markups could be systematically overestimated for firms with more debt. While our main argument is about the source, rather than the amount, of debt finance, it is still worthwhile to acknowledge that if firms engage in marginal-cost pricing, and marginal cost entails firms' cost of debt, then prices may be higher for firms with more debt. That is, debt financing may be associated with higher marginal cost and may, therefore, drive up prices. Estimated production cost based on Compustat – using the item COGS – does not include the associated cost of debt. That is, more indebted firms may have higher *estimated* (but not de-facto) markups.

Crucially, we also include industry-level concentration, which does not affect the coefficient either. This lends support to our hypothesis that higher credit concentration is associated with higher markups due to differing levels of common lending, and not because of its potential correlation with industry concentration. In untabulated tests, we yield virtually the same results when we control for the actual number of firms in the industry on the basis of which the markup is calculated. The robustness to both industry-level concentration and the number of firms active in an industry suggests that credit concentration matters for product market competition, above and beyond any potential role for finance as a barrier to entry (Cetorelli and Strahan, 2006). That is, industry markup does not increase solely because competition decreases. Furthermore, our results are robust to the inclusion of the ratio of intangible over total assets. This may be particularly relevant as investment in intangibles, such as innovation, is more likely in highly concentrated industries, with higher markups, as conjectured by Crouzet and Eberly (2018).

In column 4, these findings remain to hold true when we replace our continuous measure of credit concentration with an indicator variable that equals one for observations in the top quartile of the distribution of $\textit{Bank-Industry HHI}_{it-1}$. When moving to the highest quartile of the latter distribution, industry markup increases by 0.009, which corresponds to 6.9% of a standard deviation.

In columns 5 and 6, we re-run the same specifications as in columns 3 and 4, but use as dependent variable the average industry markup based on firm-level estimates following De Loecker and Warzynski (2012) and De Loecker, Eeckhout, and Unger (2020). The estimates for our main effect exhibit roughly similar economic significance when using DLW industry markups. When moving to the highest quartile of the distribution of $\textit{Bank-Industry HHI}_{it-1}$, industry markup increases by 0.022 (column 6), which corresponds to 4.2% of a standard deviation.

In Table C1 of the Online Appendix, we present robustness of our results to the industry definition. For this purpose, we move the analysis to the firm level, and calculate the markup of each firm's peers based on text-based network industry classifications (Hoberg and Phillips, 2016). The positive correlation between credit concentration and markup persists in column 1, and becomes even stronger after including the same peer-group characteristics as we previously did at the industry level (column 2).

Our results are also robust to different definitions of our independent variable, credit concentration. In Table C2 of the Online Appendix, we re-run the same specification as in column 3 of Table 2, but deviate from computing *Bank-Industry* HHI_{it-1} based on loan volumes. Our results are unaltered, or even stronger, when we compute credit concentration based on the number of loans, rather than their volume, granted (column 1), loan volume outstanding (column 2), or the number of loans outstanding at the time of measurement (column 3).

Finally, in column 4, we replace the credit-concentration measure by a "common lending index," *CL* $Index_{it-1}$. For each borrower we calculate the fraction of industry peers with whom the borrower shares at least one lender during the last five years, i.e., $t-1$ to $t-5$, and take the average fraction across all borrowers in industry i. Alternatively, in column 5, we use a weighted version of said common lending index, which is calculated as the average fraction across all borrowers in industry i, weighted by their total borrowing volume during the last five years.

Both variables account for overlapping lending in the past, whereas *Bank-Industry* HHI_{it-1} reflects the ex-ante likelihood of overlapping lending also going forward. As the coefficients on *CL* $Index_{it-1}$ and *CL Index (weighted)*$_{it-1}$ are, as before, positive and significant (at the 6% and 5% level, respectively), we conclude that our results do not depend on this measurement choice. Furthermore, when we move our analysis to the bank-industry-time level in Section 3, the common lending index would be confined to the time-varying industry level, whereas banks' market shares are measured at the more granular bank-industry-time level.

2.2.2 Instrumental-variable and Difference-in-Differences Strategies

Due to the aggregate nature of our explanatory variable, credit concentration at the industry level, one may be concerned that it captures other underlying developments across industries as well. While we control for a host of time-varying factors at the industry level, using plausibly exogenous variation in bank concentration would enable us to take a first step towards a causal interpretation of our findings even at the aggregate industry level.

For this purpose, we employ an instrumental-variable strategy based on bank mergers (similarly to Garmaise and Moskowitz, 2006; Favara and Giannetti, 2017).[5] We use a set of hand-collected bank mergers where both merging parties are active lead arrangers in the syndicated-loan market. To exploit meaningful increases in banks' market shares across industries, we focus on large takeovers after which the target is wholly owned by the acquirer. Furthermore, we require that all acquirers can be linked to Compustat (according to Schwert, 2018) or arrange more than 30 loans during our sample period. In this manner, we yield 79 bank-merger events.

In particular, we use as an instrument for $\textit{Bank-Industry HHI}_{it-1}$ the cumulative number of bank mergers by the previous year-end $t-2$ for which it holds that both the acquirer and the target had non-zero market shares (in terms of syndicated lending) in industry i in the pre-merger year $t-3$.[6] We count only those mergers involving acquirers *and* targets with non-zero market shares in a given industry because otherwise the credit concentration at the industry level would be unaffected by the bank merger (in an application analogous to Benmelech, Bergman, and Kim, 2019). We label the resulting instrument $\textit{Merger-implied Bank-Industry HHI}_{it-2}$, for the construction of which we add any new mergers to the stock of bank mergers that fulfill our criterion to capture the rate of change of concentration-increasing bank mergers after accounting for industry fixed effects.

In Table 3, we run the counterparts to the specifications from columns 2 and 3 in Table 2,

[5] In similar spirit, Benmelech, Bergman, and Kim (2019) use merger activity as an instrument for local labor-market concentration.

[6] As a consequence, the respective sample starts in 1992 rather than 1990.

and show the respective first-stage regressions in the first two columns, and the second-stage regressions in columns 3 and 4. In the last two columns, we show the same second-stage regressions using industry markups based on DLW as dependent variable. All of these estimates point to a positive and significant effect of higher credit concentration on industry markup, in line with our previous findings. While the second-stage estimates are larger than the respective OLS estimates, they are unlikely to reflect a weak-instrument problem as the first stage (see first two columns) is strong, with F-statistics of 18.8 and 11.9. The first stage confirms our conjecture that additional mergers of banks with non-zero market shares in a given industry are associated with increases in industry-level credit concentration.

For the exclusion restriction to hold, bank mergers must affect industry markups only through higher credit concentration. This assumption would be violated if, for example, banks decided to merge so as to increase their market share in particularly profitable industries in which both the acquirer and the target already had clients. However, the average individual industry only accounts for a small fraction of the total syndicated-loan portfolio of a bank, and overall syndicated lending makes only for a fraction of banks' total lending. Therefore, each industry in the syndicated-loan market constitutes a small portion of banks' balance sheets, so mergers are unlikely to occur because of banks' business strategies tailored around syndicated lending to certain industries.

To provide evidence for our assumption, we use a difference-in-differences strategy to estimate the dynamic effects on markups across industries around bank mergers. In particular, we wish to test for any potential pre-trends at the industry level around the subset of bank mergers that we use for our instrumental-variable strategy, i.e., those mergers involving acquirers and targets that both hold non-zero market shares in a given industry prior to their merger ("treatment"). As a comparable control group, we choose industries in which only one bank (either the acquirer or the target) has a non-zero market share prior to a bank merger. As argued above, any such bank merger would not be associated with an increase in credit concentration at the industry level.

Akin to Prager and Schmitt (2019), we use the differential effect of mergers across industries, and create a sample at the merger-industry-year level mit. For each merger m, we keep all industries in which at least one of the two merging banks has a non-zero market share (in terms of syndicated lending) in the last year before the merger. For each merger-industry pair mi, we record up to seven observations representing seven time periods t, from two years before to four years after a given merger m. As we use only bank mergers involving banks that are active lead arrangers in the syndicated-loan market, and after which the target is wholly owned by the acquirer, there is little double-counting of industry-year-level markup observations, which could arise if there were multiple mergers within a short time frame.

For each merger-industry-year mit, we then regress industry i's markup in year t on a dummy variable that equals one if both the acquirer and the target involved in merger m have non-zero market shares in industry i in the last pre-merger year, alongside an interaction with a dummy variable for the post-merger period. In addition, we control for merger-period fixed effects that capture aggregate trends across all industries during the time window (which we vary from five to seven years) of the respective merger m. We also include merger-industry fixed effects that control for all sources of unobserved heterogeneity at the industry level that does not vary during the merger window.

The results are in Table 4. We use a five-year (seven-year) window, from one year (two years) before to three years (four years) after a given merger m, in the first two (last two) columns. In addition, we use industry markups as dependent variable in columns 1 and 3, and those based on DLW in columns 2 and 4. As can be seen across all specifications in Table 4, industry markups increase following concentrating-increasing mergers of banks with non-zero market shares in industry i.

Although not necessarily all bank mergers are associated with a large increase in industry-wide credit concentration, the difference-in-differences estimates in columns 1 and 2, or columns 3 and 4 for the seven-year window, compare favorably with the economic significance implied by our baseline estimates in columns 3 and 5, respectively, of Table 2. For example, the difference-in-differences estimate in column 2 implies that following a concentration-increasing merger, compared to a bank merger involving only one bank with a non-zero market share in the same industry, industry markups increase by 0.007, which is quite similar to our baseline effect of a one-standard-deviation increase in credit concentration, namely $0.057 \times 0.18 = 0.010$ (see column 5 of Table 2 and Panel A of Table 1).

Generally, our results are a bit stronger for the seven-year window in columns 3 and 4, rather than the five-year window in columns 1 and 2, which hints at the idea that the effect is not short-lived. To visualize this, and also to test the crucial assumption of parallel trends, in Figure 2, we plot the year-by-year estimates for the specification with industry markups as dependent variable, from five years before to five years after any bank merger. In each one of the five years leading up to a bank merger, industries that are previously covered by both merging banks, rather than just one of them, are indistinguishable in terms of their markups. Starting in the second year after a bank merger at the latest, markups increase by at least as much as implied by the estimates in columns 1 and 3 of Table 4.

As a robustness check, we use the gradual removal of restrictions on interstate branching in the U.S. as a shock to industry-level bank concentration. As branching deregulation increases bank competition, we would expect industries' exposure to said deregulation to be associated with lower markups. To capture industry-level exposure to branching deregulation, we use firms' state of incorporation, and weight the respective Rice and Strahan (2010) deregulation index by the number of firms in a given state and industry. In Table C3 of the Online Appendix, we show that markups drop in industries that are more exposed to deregulated states. This also chimes with Keil and Müller (2020) insofar as they find that branching deregulation reduced the issuance of syndicated loans, allowing for overlapping lending, in favor of bilateral lending relationships.

In Table C4 of the Online Appendix, we test whether higher markups could be explained by firms' coordinating on lower output. We generally focus on markups to infer output decisions, because granular information on sales quantities is not readily available. Instead, firms (or selected industries) only report total revenue (shipments), i.e., quantity $\times$ price (Kovenock and Phillips, 1997; Maksimovic and Phillips, 2002). For robustness, we can replace industry markups as dependent variable by a proxy for industry output, which is based on annual chain-type quantity indices for each industry's gross output provided by the U.S. Bureau of Economic Analysis (BEA) for our sample period from 1990 to 2015.[7] In particular, we use the one-year growth rate in the BEA's gross-output index as dependent variable, and re-run the same OLS specifications as in columns 2 and 3 of Table 2. The results are in columns 1 and 2 of Table C4, and suggest that a one-standard-deviation increase in credit concentration (see Panel A in Table 1) is associated with an approximately 0.2 percentage point lower output growth.

This correlation holds up to employing our instrumental-variable strategy. The second-stage estimates corresponding to the specifications in columns 3 and 4 of Table 3 are in columns 3 and 4 of Table C4, and are significant at the 9 and 4% levels, respectively. The first-stage F-statistic is strong, at 19 and 28, and the relationship between IV and OLS estimates is quite similar to that for industry markup. Finally, our results are also robust to replacing the dependent variable in the two specifications of our difference-in-differences strategy from Table 4 by our proxy for industry output (see last two columns of Table C4).

2.2.3 Cross-sectional Heterogeneity and Defaults in Industries

In general, our findings should be stronger for firms that actually use bank credit for financing their production. Furthermore, in relating credit concentration to industry markup, we rely on syndicated-loan data from DealScan, which may not be representative for debt financing for all firms in our sample. Therefore, one would expect our findings to hold primarily for firms that rely on syndicated lending. To test this, we re-run the specification from column 3 in Table 2, and include interactions with $Synd.\ Firm_{it-1}$ and $Synd.\ Vol_{it-1}$, which capture the proportion of firms issuing syndicated loans in industry i in year $t-1$ and the total loan volume scaled by total debt in industry i in year $t-1$, respectively.

[7] The BEA industry-level quantity index reflects an inflation-adjusted measure of the quantities of gross output produced by the industry excluding price-change effects. In particular, the index captures changes in the quantities of goods and services provided by an industry over time. The index is constructed relative to the reference year 2012, i.e., the index is equal to 100 in 2012. We translate BEA industry codes (53 non-financial industries) to SIC codes and assign one BEA industry to each SIC-3 code. Note that the match is not always unique, i.e., some BEA codes are assigned to multiple SIC-3 industries. See https://www.bea.gov/industry/industry-economic-accounts-information-guide for details on the index construction.

In columns 1 and 3 of Table 5, the effect of credit concentration on industry markup is more emphasized when many firms in an industry rely on financing from the syndicated-loan market. This remains to hold true in columns 2 and 4 where we replace the respective independent variables by a dummy version (for the top quartile of the respective distributions).

In the last two columns, we test whether the effect of credit concentration on industry markup varies by the mode of product market competition. For this purpose, we include an interaction effect with $TSIMM_{it-1}$ in column 5, which is a text-based measure of product similarity across firms based on Hoberg and Phillips (2016). For large and positive values of $TSIMM_{it-1}$, firms in industry i are more likely to compete in strategic substitutes rather than complements. As such, it is consistent with our conjecture that the interaction of the latter variable with credit concentration bears a positive correlation with industry markup.

In column 6, we furthermore show that the effect is stronger in more concentrated industries. To this end, we use $Industry\ HHI_{it-1}$ as a proxy for industry concentration, with the caveat that industry competition is inherently difficult to measure (Ali, Klasa, and Yeung, 2009). The fact that our results are (i) robust to controlling for the level of industry competition (see Table 2) but (ii) stronger in more concentrated industries reflects the idea that our effect relies on oligopolistic competition in an industry, as otherwise coordination would be infeasible.

We conclude our industry-level analysis by showing that higher credit concentration is not only associated with higher industry markup, but that some of these benefits flow back to the lenders through lower bankruptcy risk. We re-run the first three specifications from Table 2, and replace the dependent variable by the natural logarithm of one plus the number of delistings due to bankruptcy in a given industry-year it.[8] The results are in Table 6, and indeed reflect lower bankruptcy risk in industries with higher credit concentration.

[8] As a proxy for incidences of bankruptcy, we use delisting information from the CRSP database. While these data cover public firms only, they enable us to analyze defaults for all industries in our sample over a long period of time. We use the following CRSP delisting codes to identify bankruptcy: any type of liquidation (400-490); price fell below acceptable level; insufficient capital, surplus, and/or equity; insufficient (or non-compliance with rules of) float or assets; company request, liquidation; bankruptcy, declared insolvent; delinquent in filing; non-payment of fees; does not meet exchange's financial guidelines for continued listing; protection of investors and the public interest; corporate governance violation; and delist required by Securities Exchange Commission (SEC).

In column 3, we also control for industry concentration, which may be motivated by the idea that default risk drops when competition is weaker (Valta, 2012). The fact that doing so leaves the coefficient unaltered in comparison to its counterpart in column 2 speaks to the potential importance of credit concentration for explaining industry-level default risk, above and beyond market structure.

3 Coordination through Common Lenders

We next turn to our conjecture, which we test empirically, for a potential mechanism underlying the relationship between bank concentration and industry markup.

3.1 Hypothesis Development

To explain the relationship between bank concentration and industry markup, we argue that a distinguishing feature of bank concentration is the higher incidence of competing firms sharing common lenders. That is, common lenders enable firms to achieve a less competitive outcome in the product market. This conjecture is based on two observations in the theoretical literature, namely the pro-competitive role of debt and common lenders' incentives to internalize product market externalities among their borrowers. In the following, we lay out these two components and their interplay, and derive testable hypotheses from them.

Brander and Lewis (1986) argue that oligopolistic firms issue debt to commit to more aggressive product market strategies, irrespective of whether their competitors share the same lender. If marginal returns to production are higher in better states of the world, leverage commits a firm to a more aggressive output stance: the limited-liability effect. While closely related to the asset-substitution effect, the limited-liability effect induces firms to choose leverage, taking as given the distribution of earnings (and not the other way around). Its existence may, however, depend crucially on the mode of industry competition. It may not hold for firms competing in strategic complements, as argued by Showalter (1995) and Chevalier and Scharfstein (1996) (see Chevalier, 1995, for empirical evidence).

We base our main conjecture on the general existence of a limited-liability effect, but focus on the identity of lenders. In doing so, we take as given firms' (endogenous) choice of leverage, and consider outcomes associated with loan contracts. In the model of Brander and Lewis (1986), in which the identity of lenders plays no role, debt makes firms "tough," which reduces firms' general ability to collude (Maksimovic, 1988). In contrast, common lenders, rather than separate lenders, moderate the pro-competitive effect of debt.[9]

This point is made more concretely by Poitevin (1989) whose model generates empirical predictions which we test in an empirical setting that allows us to focus on the effect of common lenders, taking as given firms' financial-structure choices and their demand for debt. We focus on the idea that common lenders help competing firms to pre-commit to less competitive product market strategies. In Poitevin (1989), a common lender can better control the incentive effects of debt and, thus, limit the extent of competition in the product market. Similarly, Spagnolo (2004) argues that a concentrated banking sector can control borrowers' choice of managerial incentives, leading to reduced competition in downstream product markets.

In particular, a common lender internalizes any adverse effects of a higher interest rate r_k on the value of debt of borrower k's competitors. As in Brander and Lewis (1986), a crucial assumption is that marginal returns to production are higher in better states of the world. Therefore, higher cost of debt pre-commits the firm to a more aggressive stance in the product market. In the case of a duopoly, this implies that a higher rate r_1 is associated with a higher quantity q_1 but a lower quantity q_2. A common lender takes into account the loans' correlation by maximizing the aggregate debt value of both firms. Therefore, a common lender charges a lower interest rate than separate lenders would, so that $\Delta r_k \equiv r_k^{common} - r_k^{separate} < 0$.

[9] This is similar to considering – instead of pure debt contracts – warrants, convertible debt, and dividend restrictions in Maksimovic (1988) or managerial incentives in Spagnolo (2005), which commit manager-shareholders to a more conservative behavior. See Cestone (1999) for a comprehensive overview and in-depth discussion of this literature.

The strategic effect of debt increases in the extent of competitive interaction within industries (see Lyandres, 2006, for empirical evidence). Holding constant such leverage decisions, the rate reduction offered by a common lender, as opposed to separate lenders, depends on the potential externalities of a higher interest rate and, thus, of firm k's more aggressive product market strategy (as reflected by a higher quantity chosen, q_k).

This explains firms' product market decisions and, thus, markups in an industry. In particular, in Poitevin (1989), lower loan rates charged by common lenders lead to less competitive outcomes. For the sake of simplicity, consider a duopoly. In Brander and Lewis (1986), both firms borrow in equilibrium, produce higher output, and are therefore worse off than under a full-equity solution. In contrast, in Poitevin (1989), a common lender charges a lower loan rate, which pre-commits the firms to produce less output (given the common assumption in both models that marginal returns to production are higher in better states of the world). This is because to maximize the aggregate debt value of both firms, a common lender incorporates potential externalities that firm 1's output has on its rival's expected debt value. Hence, common lenders moderate the pro-competitive effect of debt.

Importantly, there is greater scope for a common lender to internalize the externalities of a higher interest rate if firms compete in strategic substitutes. In this case, a higher interest rate lowers the output by competing firms, which does not maximize debt value. This prediction is more ambiguous if firms compete in strategic complements. As pointed out by Showalter (1995), there is a negative strategic effect of debt, which a common lender could internalize, only if there is cost uncertainty but not if firms face uncertain demand. Thus, we hypothesize that common lenders reduce loan rates in industries in which firms compete in strategic substitutes rather than complements.

This mechanism is consistent with our industry-level evidence. As we have seen in the last two columns of Table 5, the effect of bank concentration, implying a greater incidence of overlapping lending, on industry markup is stronger if firms in a given industry are more likely to compete in strategic substitutes (as measured by their product similarity), and if the industry has oligopolistic competition.

To test whether these insights translate to the corresponding effects of overlapping lending on cost of debt, we approximate the likelihood of firms in the same industry sharing the same lender by means of banks' market shares in terms of lending to a given industry. We summarize our argument about the impact of banks' higher market shares on the cost of debt in an industry in the following testable hypothesis:

Hypothesis: *Common lenders internalize the externalities of charging higher loan rates to other firms' output in the same industry and, thus, do not increase loan rates as much as separate lenders would. If a bank has granted a large fraction of the loans in an industry, firms operating in that industry are more likely to share the same lender. Therefore, banks with higher market shares in an industry charge lower loan rates. This effect should be more emphasized for industries with competition in strategic substitutes.*

3.2 Data and Empirical Strategy

We next devise an empirical strategy for testing our hypothesis. Since our objective is to explore whether lender j's (past) market share in industry i affects the cost of loans to firms in industry i at time t, we aggregate data at the bank-industry-time level ijt, where time refers to the quarterly frequency and industries are defined using three-digit SIC codes. The resulting bank-industry-quarter panel is based on the sample of all syndicated loans from 1990 to 2015 granted to industry i for which bank j served as a lead arranger in quarter t.

Banks' market shares are a proxy for the likelihood that any two firms in an industry share the same lender. A high market share of bank j in industry i indicates a high likelihood of firms in industry i having a common lender. In contrast, a variable recording the de-facto overlap in lender connections across firms in an industry would be confined to the time-varying industry, rather than the more granular bank-industry, level (as is the case in columns 4 and 5 of Table C2 in the Online Appendix). Besides offering the advantage to exploit bank-industry-quarter-level variation, banks' market shares do not only capture existing common lenders, but also reflect the potential for future overlap in common lenders.

For this purpose, we use as our explanatory variable $\textit{Market Share}_{ijt-4}$, which is the proportion of bank j's total loan volume granted to industry i over the aggregate loan volume in industry i, measured over five years, from $t-4$ to $t-23$ (20 quarters). Our baseline regression specification is:

$$y_{ijt} = \beta \textit{Market Share}_{ijt-4} + \theta_{it} + \psi_{jt} + \epsilon_{ijt}, \tag{2}$$

where the outcome variable y_{ijt} is a function of the cost of debt in industry i charged by bank j in quarter t, and θ_{it} and ψ_{jt} denote industry-quarter and bank-quarter fixed effects (where a quarter refers to a specific quarter of a given year), respectively. Standard errors are clustered at the bank level.

In this setting, industry-quarter fixed effects θ_{it} capture all time-varying unobserved heterogeneity at the industry level, in particular industry-level loan demand across all banking relationships. In addition, bank-quarter fixed effects ψ_{jt} control for time-varying unobserved heterogeneity at the bank level, e.g., differences in credit supply or other developments, such as differential treatment by concurrent regulatory changes, across banks.

For robustness, we contrast a bank's market share to the share of an industry in a bank's loan portfolio. The difference between $\textit{Portfolio Share}_{ijt-4}$ and $\textit{Market Share}_{ijt-4}$ is the denominator. We define the former to be equal to the proportion of bank j's total loan volume to industry i over the aggregate loan volume granted by bank j over the previous five years.

In order to test our hypothesis that common lenders are more likely to internalize the externalities of a higher interest rate if firms compete in strategic substitutes, we require a measure that reflects the mode of competition and the degree of competitive interaction among firms in the same industry. We use two different measures. First, we compute the total similarity measure (TSIMM) developed by Hoberg and Phillips (2016), which we have already made use of in column 5 of Table 5.[10] This measure is based on a web-crawling and

[10] The data are available from http://hobergphillips.tuck.dartmouth.edu/. Note that TSIMM is available only from 1996 onwards.

text-parsing algorithm that compares business descriptions by firms as given in their 10-K annual filings. Each firm's product description is compared to the product description of all other firms in the CRSP/Compustat universe to calculate firm-by-firm pairwise similarity scores. Total similarity is then the sum of the pairwise similarities between a given firm and all other firms in the sample. For our analysis, we use the average TSIMM level by industry and quarter (Bayar, Cornett, Erhemjamts, Leverty, and Tehranian, 2018), $TSIMM_{it}$. A higher value indicates that firms in a three-digit SIC-code industry i produce more related products, i.e., they are more likely to compete in strategic substitutes.

An alternative measure of strategic interaction that we use is based on Chod and Lyandres (2011). Assuming that sales proxy for firms' actions, the Competitive Strategy Measure (CSM) is defined as the correlation between the ratio of the change in a firm's profit to the change in its sales and the change in the combined sales of the firm's product market rivals. In particular, for firm k, it is equal to:

$$CSM_k = \text{corr}\left[\frac{\Delta\pi_k}{\Delta S_k}, \Delta S_{-k}\right], \tag{3}$$

where $\Delta\pi_k$ is the change in firm k's profit, ΔS_k is the change in its sales, and ΔS_{-k} is the change in its rivals' combined sales.

The measure is a direct proxy for the cross-partial derivative of a firm's value with respect to its own and its rivals' competitive actions. In particular, a positive (negative) value for CSM_k indicates that firms compete in strategic complements (substitutes). We classify industries accordingly, depending on the average value for CSM_k across firms therein.

We measure CSM_k following Chod and Lyandres (2011). In particular, we use quarterly Compustat data, and define profit as operating profit before depreciation and rivals' sales as combined sales of all other firms operating in the same industry (three-digit SIC code). Next, we calculate CSM_{kt} for each individual firm k and each quarter t using 20-quarter rolling windows. We require at least ten non-missing observations for changes in sales and profits in the estimation window. CSM_{kt} is then averaged across all firms in industry i and quarter t, for which we, in turn, require an industry to comprise at least five firms.

In Panel B of Table 1, we present summary statistics at the industry-quarter level, conditional on the issuance of any syndicated loans. On average, within each industry-quarter, we have over five different firms attaining syndicated loans from five banks (lead arrangers). We also report summary statistics for our two measures of competitive interaction, TSIMM and CSM. For CSM, we distinguish between strategic substitutes and strategic complements by limiting the sample to industry-quarter observations for which CSM_{it} is negative or positive, respectively. Consistent with Sundaram, John, and John (1996), Chod and Lyandres (2011), and Lyandres (2006), we find that, overall, slightly more than half of the industry-quarters have a negative estimated CSM_{it}. To account for the dispersion of firm-level values CSM_{kt} within a given industry-quarter, we add summary statistics for a standardized measure equal to the average value of CSM_{kt} divided by its standard error.

In Panel C of Table 1, we report descriptive statistics at the bank-industry-quarter level. The average bank market share in a given industry is 8%.[11] As such, the market-share distribution is somewhat skewed, with a relatively large set of banks with small market shares (e.g., smaller banks that are only infrequently active in the syndicated-loan market). For comparison, the average portfolio share is only 2%. The correlation between portfolio shares and market shares is low (1%), indicating that if a bank is important for an industry, this does not necessarily imply that the industry also accounts for a large share of a bank's portfolio, and vice versa.

3.3 Results

3.3.1 The Effect of Banks' Market Shares on Cost of Debt

The results from estimating (2) are in Table 7. In column 1, we use as dependent variable the natural logarithm (to account for skewness) of the volume-weighted average all-in-drawn

[11] This value is higher than the one in Giannetti and Saidi (2019) because our sample requires loan prices which are only observed in quarters with positive issue volume.

spread of all loans granted to industry i by bank j in quarter t. In line with our hypothesis, banks' higher market shares are associated with significantly lower cost of debt in an industry. The effect is both statistically and economically significant. A one-standard-deviation increase in a bank's market share of 0.12 (see Panel C in Table 1) is associated with a 6.7% lower loan rate, which corresponds to a drop by 16 basis points relative to the average spread (241 basis points). Furthermore, as suggested by Figure 1, the effect on markups is most pronounced in the tails. If we apply a similar logic to our cost-of-debt result, then a shift from the 5^{th} to the 95^{th} percentile in terms of $\mathit{Market\ Share}_{ijt-4}$ implies a $(0.32–0.00) \times 0.56 = 17.9\%$ reduction in the loan spread, corresponding to a drop by 43 basis points.[12]

We argue that the reduction in cost of debt is due to common lenders' ability to internalize product market externalities. However, banks' market shares may also capture properties of their loan portfolios. In particular, if banks' market shares are a reflection of their specialization, then our results could plausibly be explained by lenders' information advantage (Acharya, Hasan, and Saunders, 2006; Loutskina and Strahan, 2011). To account for this, in column 2, we control for banks' portfolio shares, i.e., the shares of different industries in banks' loan portfolios. The inclusion of portfolio shares on the right-hand side leaves the estimated coefficient on market shares virtually unaltered compared to the respective coefficient in the first column. This result is even more pronounced in column 3 where we replace the (volume-weighted) average all-in-drawn spread as dependent variable by the (volume-weighted) average usage-weighted spread, as defined in Berg, Saunders, Steffen, and Streitz (2017).[13]

In the last two columns of Table 7, we validate that these results hold also at the more ag-

[12] In terms of economic magnitude of this loan-spread reduction, it compares favorably with other important effects documented in the literature. For instance, the benefit of borrowing from a relationship lender has been found to range from 10 to 17 basis points (Bharath, Dahiya, Saunders, and Srinivasan, 2011), the benefits of loan securitization are around 17 basis points (Nadauld and Weisbach, 2012), and the base effect of industry competition on loan spreads is also around 17 basis points (Valta, 2012).

[13] While the all-in-spread-drawn (AISD) is a good measure for the cost of term loans, the pricing of credit lines is more complex (Berg, Saunders, and Steffen, 2016). In particular, the AISD reflects the payment for the used part of a loan commitment. For the unused part borrowers pay the all-in-spread-undrawn (AISU). We follow Berg, Saunders, Steffen, and Streitz (2017), and calculate the usage-weighted spread (UWS) as an alternative loan-pricing proxy. This measure is easily computable for our entire loan sample, and captures the key pricing aspect for lines of credit, i.e., the difference between AISD and AISU. See Berg, Saunders, Steffen, and Streitz (2017) for details.

gregate industry-year level. For this purpose, we replace the dependent variable by the natural logarithm of the (volume-weighted) average all-in-drawn spread (column 4) or the natural logarithm of the (volume-weighted) average usage-weighted spread in a given industry-year (column 5), and use as explanatory variable industry i's credit concentration in the previous year, *Bank-Industry* HHI_{it-1}. In terms of economic magnitude, these industry-level estimates suggest that for a one-standard-deviation increase in *Bank-Industry* HHI_{it-1}, loan spreads decrease by $0.12 \times 0.18 = 2.2\%$. The same one-standard-deviation increase in credit concentration is found to be associated with a $0.029 \times 0.18 = 0.52\%$ (see column 3 of Table 2) higher markup. As such, the impacts of credit concentration on industry-level cost of debt and markup are comparable and, thus, plausible.

A lingering concern may be that banks' market shares are endogenous. For instance, although we control for industry-quarter fixed effects which absorb time-varying unobserved heterogeneity at the industry level, including but not limited to industry-level loan demand, it may still be that industries with particularly low cost of debt, which tend to be safer, have particular demand for loans granted by high-market-share lenders. Further, increasing market shares might be the result of long-term lending relationships. If a bank's market share in an industry increases as a result of repeat borrowing, lower spreads may simply reflect a decrease in bank monitoring costs over the course of the lending relationship that are (partially) passed on to the borrower (Bharath, Dahiya, Saunders, and Srinivasan, 2011). To address such potential sources of endogeneity underlying banks' market shares, we exploit plausibly exogenous variation in market shares stemming from bank mergers, following the procedure in Giannetti and Saidi (2019). For this purpose, we use the same set of hand-collected bank mergers as in Section 2.2.2.

As our analysis is, and the dependent variable is measured, at the bank-industry-quarter level, we exploit bank mergers as a source of variation in banks' market shares across industries over time. In particular, we can use banks' merger-implied market shares directly as an instrument, without any further adjustments. This also allows for the inclusion of industry-time (in this case, industry-quarter) fixed effects, which we were unable to account for in Section 2.2 where the dependent variable was itself measured at the industry-year level. This controls for general time-varying conditions at the industry level, such as loan demand. We can also include bank-quarter fixed effects. As a result, we effectively exploit between-industry variation in market shares within bank mergers, while controlling for the overall effect of the two banks merging itself (which is captured by bank-quarter fixed effects).

In case of a bank merger in the year prior to that associated with quarter $t-4$, we instrument bank j's market share in industry i in $t-4$ by the sum of the two merging banks' historical market shares (if the target's market share is non-zero) in industry i in the last quarter of the pre-merger year.[14] Otherwise, our instrument is equal to zero (before the first merger), or equal to the previous value of the instrument (after the first merger). Thus, we use as our instrument any increases in the merged entity's (surviving bank j's) market share in industry i due to the merger.

The first stage in column 1 of Table 8 is strong. In the second stage, the estimated coefficient on the instrumented market share of banks is negative and significant (column 2). Most importantly, it is very similar in size to the OLS estimate (column 2 of Table 7). While the IV estimate is similar to the OLS estimate, there may still be some limitations of our proposed identification strategy. For the exclusion restriction to hold, we require bank mergers to impact industries' cost of debt solely through changes in banks' market shares in those industries. However, if a merger enables banks to pool their expertise about certain industries, thereby reducing informational asymmetries in lending, then this may explain our estimates. More generally, any bank-industry-quarter-level variation that may be correlated with our bank-merger events poses an alternative mechanism that we cannot rule out.

Having said this, we can – at the very least – rule out the reduction of informational asymmetries as a competing explanation because we focus on (i) recent mergers and (ii) gradual increases in market shares. Therefore, we identify a treatment effect that is unlikely to be due to any private information that the participating banks may hold before or shortly after the merger. Another source of potential omitted-variable bias due to endogenous market

[14] For this reason, as is also the case in Table 3, the sample starts in 1992 rather than 1990.

shares may be that highly specialized lenders, with potentially high market shares, merge to serve the particular needs of industries that exhibit characteristics that are correlated with low cost of debt. While this may be plausible in general, it is less likely to hold true for our sample as we condition on mergers between large financial institutions (that tend to be publicly listed), which are subsequently more diversified across industries.

Our results are consistent with those in Erel (2011), who shows that bank mergers reduce loan spreads on average, which she interprets as evidence of cost savings dominating any market-power effects. Furthermore, she argues that there exists a non-monotonic relationship between loan spreads and the extent of (geographical) market overlap between the merging banks. In contrast to Erel (2011), we examine loan spreads not at the average bank level, but at the level of bank-industry relationships.[15]

3.3.2 Banks' Market Power vs. Internalization of Externalities

Even though we find an overall negative effect of banks' market shares on loan rates, the respective estimates might lump together various sources of heterogeneity. Typically, higher market shares imply greater market power, driving up loan rates. We find the opposite to hold true on average. In the following, we present multiple pieces of evidence that the sign of the coefficient on banks' market shares is indeed driven by the extent to which common lenders internalize product market externalities, rather than extract market power.

We start by testing whether the effect of banks' higher market shares on lower cost of debt is more emphasized in industries where firms compete in strategic substitutes rather than complements, as conjectured in our hypothesis. This is because there is greater scope for internalizing product market externalities when firms compete in strategic substitutes. To distinguish between firms operating out of industries in which they compete in strategic substitutes vs. complements, we use the same text-based measure capturing product similarity across firms (Hoberg and Phillips, 2016) as in column 5 of Table 5. In column 1 of Table 9, we see that high-market-share lenders lower their cost of debt, and especially so for

[15] In this regard, our analysis is similar in spirit to Fraisse, Hombert, and Lé (2018).

industries in which firms are weakly differentiated from their competitors, as reflected by large and positive values of $TSIMM_{it-4}$. A high degree of product similarity, as defined by (Hoberg and Phillips, 2016), suggests that firms compete in strategic substitutes.

To capture the degree of competitive interaction, we also use the competitive strategy measure (CSM) introduced by Chod and Lyandres (2011). Similar to Chod and Lyandres (2011), we split our sample into industries characterized by competition in strategic substitutes vs. strategic complements, and interact $Market\ Share_{ijt-4}$ with a standardized measure of industry-level CSM. To account for the reality that the firm-level values CSM_{kt-4} are dispersed, we compute CSM_{it-4} at the industry level by dividing the average value of CSM_{kt-4} by its standard error in industry i, and use the absolute value thereof ($Absolute\ CSM_{it-4}$). We then classify industry-quarter it observations as strategic substitutes (complements) if $CSM_{it-4} < 0$ ($CSM_{it-4} > 0$).

Comparing the estimates in column 2 vs. 3 of Table 9, we do not only see that the coefficient on $Market\ Share_{ijt-4}$ is somewhat more negative in the strategic-substitutes sample, but its interaction with $Absolute\ CSM_{it-4}$ is negative and significant only in the latter sample as well. This implies that only in the case of strategic substitutes do banks with larger market shares reduce loan rates as a function of competitive interaction within industries. Holding constant banks' market shares, a one-standard-deviation increase in $Absolute\ CSM_{it-4}$ (see summary statistics for strategic substitutes in Panel B of Table 1) is associated with a loan-spread reduction by $0.064 \times 0.72 = 4.6\%$.

These differences become more emphasized when instead of considering the interaction between banks' market shares and the extent of competitive interaction, we focus on the average effect of banks' market shares on loan spreads for strategic substitutes and complements (last two columns of Table 9). By dividing the average value of CSM_{kt-4} by its standard error in industry i, we account for the possibility that our results are driven by noise, e.g., due to outliers in CSM_{kt-4} within an industry i. Alternatively to using this standard-error adjustment, we address this issue by requiring the upper (lower) bound of the 70% confidence interval for CSM_{kt-4} in a given industry-quarter to be negative (positive) for firms in that industry to be labeled as competing in strategic substitutes (complements).

To better control for remaining potentially confounding factors, we translate these tests from the bank-industry-quarter to the facility-bank level fj, i.e., we record one observation for each lead bank j's share of a given facility f. We focus on the facility level within syndicated loans as loan pricing varies across facilities (Berg, Saunders, and Steffen, 2016; Berg, Saunders, Steffen, and Streitz, 2017). The coefficient on *Market Share*$_{ijt-4}$ in column 1 of Table 10 suggests that moving the analysis to a more granular level does not lead to drastically different results. The coefficient on *Market Share*$_{ijt-4}$ is similar to that in column 1 of Table 7. In addition to bank-quarter and industry-quarter fixed effects, we control for (borrowers') state-quarter fixed effects that account for time-varying local economic conditions.

These estimates are robust to the inclusion of loan-purpose and loan-type fixed effects in column 2. After controlling for loan characteristics in column 3, the coefficient on *Market Share*$_{ijt-4}$ drops somewhat, but remains statistically significant in spite of adding relevant controls for general determinants of loan spreads: the loan amount granted by each bank, maturity, collateralization, and the use of financial covenants. In column 4, we also control for borrower fixed effects, which greatly affects the magnitude of the coefficient on *Market Share*$_{ijt-4}$, which remains statistically significant at the 2% level, as we identify the latter effect using firms that are observed to receive a single syndicated loan with two lead arrangers or at least two syndicated loans (even if with only one lead arranger) over time, which applies to only a subset of the firms in our sample.

In the remaining columns, we use the specification from column 2 as our baseline, and show in the same two ways as in Table 9 that the effect of high-market-share lenders on firms' cost of debt holds primarily for firms that compete in strategic substitutes. This holds in column 5 where the effect is stronger for firms with higher product-similarity scores with their peers (Hoberg and Phillips, 2016), and also in columns 6 and 7 where the coefficient on *Market Share*$_{ijt-4}$ is negative and significant only for the subsample of firms competing in strategic substitutes (defined as in columns 4 and 5 of Table 9). In addition, in Table C5 of the Online Appendix, we implement the same instrumental-variable strategy as in Table

8, but apply it to the specifications in columns 3 and 4 of Table 10 at the loan level. The respective results are all similar to the baseline estimates in the latter table.

These findings at the loan level confirm the idea that firms contracting with high-market-share lenders reap the benefit of incurring lower cost of debt. However, for this to incentivize competing firms to commit to a less aggressive product market stance, ultimately leading to higher industry markups, one requires that a sufficiently large number of firms in a given industry share the same lender. This explanatory variable is best measured at the (more aggregate) bank-industry level.

Our evidence thus far suggests that high-market-share lenders charge lower loan rates at the industry level, and that they do so despite their strong presence in the respective market. We argue this is because common lenders internalize potential externalities among their borrowers stemming from product market effects of higher loan rates. As this is a consequence of banks' maximizing the aggregate debt value, lenders should be more inclined to take into account potential adverse effects of higher loan rates on the product market behavior among their competing borrowers when the latter's debt behaves more like equity.

To capture whether an industry's debt is more sensitive to its high-market-share lenders' setting of loan rates, we interact $\textit{Market Share}_{ijt-4}$ with an indicator for whether an industry is in the top quartile in terms of its riskiness, as measured by its firms' ROA volatility. As can be seen in column 1 of Table 11, this is indeed the case, and the effect of banks' market shares on lower loan rates is over (0.243/0.585 =) 42% larger for risky industries.

Similarly, high-market-share lenders should be more prone to internalize product market externalities by setting lower loan rates if higher cost of debt is more likely to lead firms into dire straits. This is more likely to be the case when firms' interest coverage ratio is low. To capture this empirically, we create an indicator variable for whether a given industry's firms' interest coverage ratio is in the bottom quartile of the distribution. The coefficient on the respective interaction with $\textit{Market Share}_{ijt-4}$ is negative and significant, and carries similar economic significance as the coefficient on the interaction with ROA volatility (column 2). This evidence is consistent with our findings at the industry level in Table 6. Overlapping lending is optimal from the bank's perspective, and as bankruptcy risk is reduced, high-market-share lenders can afford to offer cheaper loans.

In Table 9, we show that our results are stronger for firms competing in strategic substitutes, thereby putting more weight on the internalization-of-externalities channel of banks with large market shares. Alternatively, we can also do the reverse, that is, identify instances in which the market power of high-market-share banks outweighs their incentives to internalize externalities through charging lower cost of debt. For this purpose, we use banks' market shares in terms of underwriting corporate debt and equity as a proxy for greater market power without affecting their incentives to internalize product market externalities among their clients. This is because the returns to underwriting services (fees), as opposed to loans (interest), are orthogonal to firm performance.

In this manner, a high market share may indicate that a bank has market power, but not necessarily incentives to internalize externalities. Non-loan products that fit this characterization are underwriting services. As most U.S. banks active in the syndicated-loan market tend to be universal banks, they also serve as underwriters of corporate debt and equity (e.g., Neuhann and Saidi, 2018). Using SDC Platinum data and hand-matching underwriters with lead arrangers in DealScan, we define $\textit{Underwriting Share}_{ijt-4}$ as the proportion of bank j's total number of debt and equity underwriting mandates in industry i over the aggregate number of debt and equity issuances in industry i, measured over the previous five years, similarly to $\textit{Market Share}_{ijt-4}$. Doing so, in Table C6 of the Online Appendix, we find that banks' market shares in terms of lending are associated with higher cost of debt when they are accompanied by higher market shares in terms of underwriting (column 4), thereby weakening common lenders' incentives to internalize externalities rather than to extract market power.

Thus far, we have presented evidence that high-market-share lenders would find it optimal to lend to borrowers that compete in strategic substitutes, thereby minimizing bankruptcy risk (see Table 6). According to Poitevin (1989), this outcome is optimal from both the common lender's and the borrowers' point of view. In Appendix B (of the Online Appendix), we test whether firms find it optimal to switch to high-market-share lenders, thereby increasing the likelihood of sharing common lenders within an industry, when given the chance to do so. As a shock to firms' ability to switch to new lenders, we use the differences in regulatory barriers to interstate branching that were gradually removed in the U.S. over time. We find that firms in deregulated states are more likely to establish new lending relationships with out-of-state banks that have high market shares in the same industry. The effect pertains to firms competing in strategic substitutes rather than complements. This is consistent with the idea that firms deem it optimal to share a common lender when this enables them to commit to less aggressive product market strategies and to simultaneously benefit from cheaper loans.

4 Conclusion

In this paper, we show that credit concentration matters for product market competition of non-financial firms. When firms competing in strategic substitutes are more likely to share common lenders, they are charged lower cost of debt and achieve higher markups. Our evidence suggests that common lenders serve as a commitment or coordination device for firms' product market decisions. We argue that this mechanism complements any effect that bank concentration may have, for example, on entry and exit.

To characterize lending relationships, we use data on syndicated loans, which make for a specific type of debt claim held by banks, besides a whole range of other, non-debt claims. Furthermore, banking (de)regulation is likely to govern bank concentration in a non-trivial way. We point out the importance of only one facet of bank concentration, namely the occurrence of common lenders, for product market competition. It would be instrumental to shed light on how other facets of bank concentration interact with the relationship between common lenders and product market competition, which we leave for future work.

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5 Figures

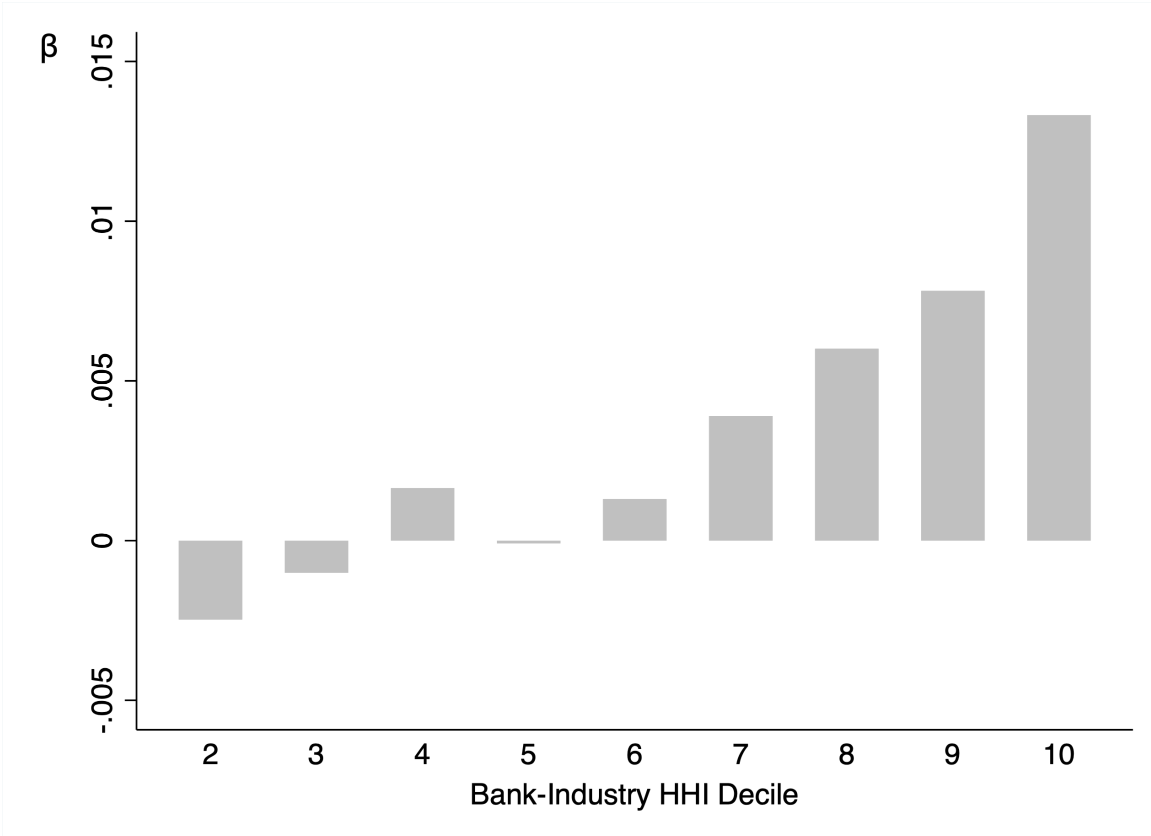

Figure 1: **Bank Concentration and Industry Markup**
This figure plots the impact of bank concentration on industry markup. Specifically, the figure plots estimated coefficients from the following regression specification:

$$\text{Industry Markup}_{it} = \sum_{k=2}^{10} \beta_k \text{ Bank-Industry HHI Decile } k_{it-1} + \delta_i + \chi_t + \epsilon_{it},$$

where *Bank-Industry HHI Decile* k_{it-1} equals one if *Bank-Industry HHI*$_{it-1}$ is in the k^{th} decile of the distribution, and zero otherwise. The first decile is the omitted category. The dependent variable is $Industry\ Markup_{it}$, i.e., the sum of firms' sales by industry-year minus the sum of firms' cost of goods sold by industry-year, scaled by the sum of firms' sales (cf. Bustamante and Donangelo, 2017). δ_i and χ_t denote industry and year fixed effects, respectively.

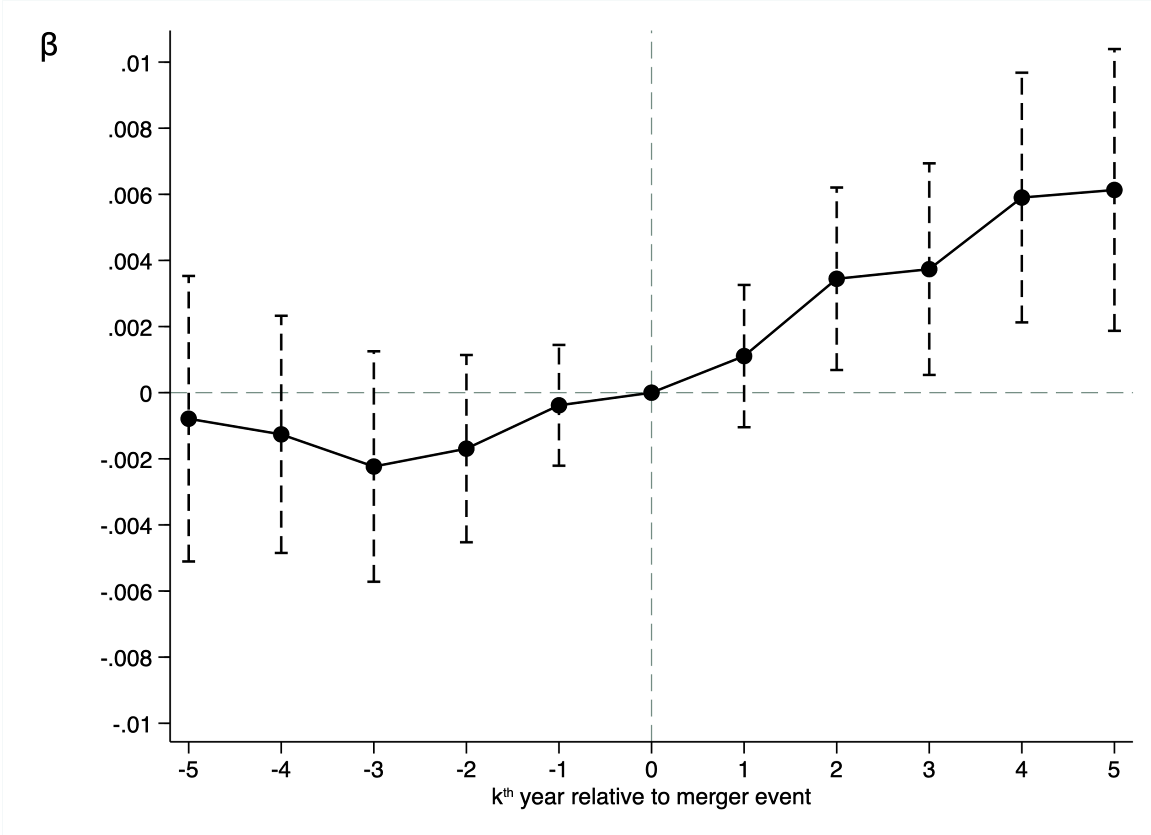

Figure 2: **Difference-in-Differences Estimates at the Industry Level around Bank Mergers**
This figure plots the evolution of industry-level markups around bank-merger events (m). Specifically, the figure plots estimated coefficients from the following difference-in-differences specification:

$$\text{Industry Markup}_{mit} = \sum_{k=-5}^{5} \beta_k \text{Treated}_{mi} \times \ \text{D}_{mt}^{k} + \delta_{mi} + \chi_{mt} + \epsilon_{mit}.$$

For each bank merger m, we consider an eleven-year window around the merger event [-5,+5]. The unit of observation is the merger-industry-year level *mit*. The dependent variable is $Industry\ Markup_{mit}$, i.e., the sum of firms' sales by (merger-)industry-year minus the sum of firms' cost of goods sold by (merger-)industry-year, scaled by the sum of firms' sales (cf. Bustamante and Donangelo, 2017). The treatment indicator, $Treated_{mi}$, equals one if both the acquirer bank *and* the target bank have a non-zero market share in industry i in the last year before merger m. Industries in which only the acquirer bank *or* the target bank has a non-zero market share in the last year before their respective merger form the control group ($Treated_{mi} = 0$). D_{mt}^{k} equals one in the k^{th} year before/after merger event m, and zero otherwise. The year of the merger event, $k = 0$, is the omitted category. δ_{mi} and χ_{mt} denote merger-industry and merger-year fixed effects, respectively. The dashed lines represent 90% confidence intervals, adjusted for industry-level clustering.

6 Tables

Table 1: **Descriptive Statistics**

Panel A reports descriptive statistics at the industry-year level. Panel B reports descriptive statistics at the industry-quarter level. Panel C reports descriptive statistics at the bank-industry-quarter level.

	p05	Median	p95	Mean	Std. Dev	Obs.
Panel A: Industry-year level						
Industry Markup	0.12	0.29	0.56	0.31	0.13	5,252
Industry Markup DLW	-0.12	1.10	1.86	1.04	0.52	5,229
Bank-Industry HHI	0.09	0.20	0.63	0.25	0.18	5,252
High Bank-Industry HHI	0.00	0.00	1.00	0.25	0.43	5,252
Industry Size	5.80	9.14	12.35	9.05	2.03	5,250
Industry HHI	0.08	0.28	1.00	0.36	0.26	5,250
Industry Leverage	0.10	0.30	0.57	0.31	0.15	5,250
ln(1 + Industry Loan Volume)	0.00	7.17	9.83	6.74	2.44	5,250
Industry Intangible Assets	0.00	0.13	0.48	0.17	0.15	5,250
Industry Output	52.24	97.39	136.53	97.91	37.29	5,147
Panel B: Industry-quarter level						
Number of firms	1.00	3.00	15.00	5.17	5.43	11,545
Number of banks	2.00	4.00	13.00	5.08	4.10	11,545
TSIMM	1.05	1.58	6.34	2.41	2.13	8,480
Strategic substitutes:						
CSM	-0.13	-0.04	-0.00	-0.05	0.04	4,671
Standard-error-adjusted CSM	-2.30	-0.78	-0.07	-0.94	0.72	4,671
Strategic complements:						
CSM	0.00	0.04	0.14	0.05	0.04	4,254
Standard-error-adjusted CSM	0.07	0.70	2.38	0.89	0.75	4,254
Panel C: Bank-industry-quarter level						
Spread (in bps)	37.50	225.00	515.96	240.98	150.97	58,694
UWS (in bps)	17.25	127.18	502.24	188.19	165.42	52,371
Market Share	0.00	0.02	0.32	0.08	0.12	58,694
Portfolio Share	0.00	0.00	0.07	0.02	0.05	58,694

Table 2: **Bank Concentration and Industry Markup**

The unit of observation is the industry-year level *it*. The sample period is 1990 to 2015. The dependent variable in columns 1 to 4 is $Industry\ Markup_{it}$, i.e., the sum of firms' sales minus the sum of firms' cost of goods sold in industry i in year t, scaled by the sum of firms' sales (cf. Bustamante and Donangelo, 2017). The dependent variable in columns 5 and 6 is *Industry Markup* DLW_{it}, i.e., the average markup in industry i in year t, estimated following De Loecker and Warzynski (2012) and De Loecker, Eeckhout, and Unger (2020). Industries are defined based on three-digit SIC codes. *Bank-Industry* HHI_{it-1} measures the credit concentration in industry i in year $t-1$, and is defined as the sum of the squared bank market shares. Bank market shares are measured over the last five years, i.e., $t-1$ to $t-5$. *High Bank-Industry* HHI_{it-1} is a dummy variable that equals one for observations in the highest quartile of the *Bank-Industry HHI* distribution, and zero otherwise. Industry characteristics, when included, are as follows. *Industry* $Size_{it-1}$ is the (log of the) sum of firms' assets in industry i in year $t-1$. *Industry* HHI_{it-1} is a proxy for industry concentration (sales-based Herfindahl-Hirschman Index) in industry i in year $t-1$. *Industry* $Leverage_{it-1}$ is the sum of firms' total debt, scaled by the sum of firms' total assets in industry i in year $t-1$. $\ln(1 + Industry\ Loan\ Volume_{it-1})$ is the (log of the) total amount of loans issued in industry i in year $t-1$. *Industry Intangible* $Assets_{it-1}$ is the sum of firms' intangible assets, scaled by the sum of firms' total assets in industry i in year $t-1$. p-values based on robust standard errors, clustered at the industry level, are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Variable:	Industry Markup_{it}	Industry Markup_{it}	Industry Markup_{it}	Industry Markup_{it}	Industry Markup DLW_{it}	Industry Markup DLW_{it}
	(1)	(2)	(3)	(4)	(5)	(6)
Bank-Industry HHI_{it-1}	0.063**	0.028**	0.029**		0.057**	
	(0.044)	(0.048)	(0.035)		(0.024)	
High Bank-Industry HHI_{it-1}				0.009**		0.022**
				(0.033)		(0.016)
Year FE	No	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	Yes	Yes	Yes	Yes
Industry Characteristics	No	No	Yes	Yes	Yes	Yes
Observations	5,253	5,252	5,250	5,250	5,229	5,229
Adj R^2	0.01	0.83	0.84	0.84	0.94	0.94

Table 3: **Bank Concentration and Industry Markup – IV Estimates**

The unit of observation is the industry-year level *it*. The sample period is 1992 to 2015. First-stage regressions are reported in columns 1 and 2. The dependent variable in the second stage (columns 3 and 4) is *Industry* $Markup_{it}$, i.e., the sum of firms' sales minus the sum of firms' cost of goods sold in industry i in year t, scaled by the sum of firms' sales (cf. Bustamante and Donangelo, 2017) or, alternatively (in columns 5 and 6), *Industry Markup* DLW_{it}, i.e., the average markup in industry i in year t, estimated following De Loecker and Warzynski (2012) and De Loecker, Eeckhout, and Unger (2020). The first-stage results for columns 5 and 6 are untabulated but virtually identical to those in columns 1 and 2. Industries are defined based on three-digit SIC codes. *Bank-Industry* HHI_{it-1} measures the credit concentration in industry i in year $t-1$, and is defined as the sum of the squared bank market shares. Bank market shares are measured over the last five years, i.e., $t-1$ to $t-5$. *Bank-Industry* HHI_{it-1} is instrumented by *Merger-implied Bank-Industry* HHI_{it-2}, which is defined as the cumulative number of bank mergers in industry i by the previous year-end $t-2$. For each industry i, only mergers for which both the acquirer bank *and* the target bank have a non-zero market share in the industry in the last pre-merger year ($t-3$) are considered. Industry controls are included when indicated (see Table 2 for details). p-values based on robust standard errors, clustered at the industry level, are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

	First Stage					
Variable:	Bank-Ind. HHI_{it-1}	Bank-Ind. HHI_{it-1}	Ind. $Markup_{it}$	Ind. $Markup_{it}$	Ind. Markup DWL_{it}	Ind. Markup DWL_{it}
	(1)	(2)	(3)	(4)	(5)	(6)
Merger-impl. Bank-Ind. HHI_{it-2}	0.009***	0.010***				
	(0.000)	(0.000)				
Bank-Ind. HHI $(instr.)_{it-1}$			0.194*	0.145*	0.677**	0.616**
			(0.056)	(0.096)	(0.019)	(0.014)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry Characteristics	No	Yes	No	Yes	No	Yes
First-stage F-stat	18.83	11.89				
Observations	4,852	4,851	4,852	4,851	4,831	4,831
Adj R^2	0.52	0.54				

Table 4: **Bank Concentration and Industry Markup – DiD Estimates**

This table analyzes industry markups around bank-merger events. For each bank merger m, we consider a five-year (columns 1 and 2) or seven-year (columns 3 and 4) window around the merger event. The unit of observation is the merger-industry-year level *mit*. The dependent variable in columns 1 and 3 is $Industry$ $Markup_{mit}$, i.e., the sum of firms' sales by (merger-)industry-year minus the sum of firms' cost of goods sold by (merger-)industry-year, scaled by the sum of firms' sales (cf. Bustamante and Donangelo, 2017). The dependent variable in columns 2 and 4 is *Industry Markup* DLW_{mit}, i.e., the average markup in industry i in (merger-)year t, estimated following De Loecker and Warzynski (2012) and De Loecker, Eeckhout, and Unger (2020). The treatment indicator, $Treated_{mi}$, equals one if both the acquirer bank *and* the target bank have a non-zero market share in industry i in the last year before merger m. Industries in which only the acquirer bank *or* the target bank has a non-zero market share in the last year before their respective merger form the control group ($Treated_{mi} = 0$). $Post_{mt}$ equals one in the post-merger window, and zero otherwise. p-values based on robust standard errors, clustered at the industry level, are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Window:	[-1,+3]		[-2,+4]	
Variable:	Industry Markup$_{mit}$	Industry Markup DLW$_{mit}$	Industry Markup$_{mit}$	Industry Markup DLW$_{mit}$
	(1)	(2)	(3)	(4)
Treated$_{mi}$ × Post$_{mt}$	0.003**	0.007*	0.004**	0.008*
	(0.038)	(0.068)	(0.014)	(0.072)
Merger-period FE	Yes	Yes	Yes	Yes
Merger-industry FE	Yes	Yes	Yes	Yes
Observations	29,530	29,469	41,254	41,180
Adj R^2	0.95	0.97	0.94	0.96

Table 5: **Bank Concentration and Industry Markup – Cross-sectional Heterogeneity**

The unit of observation is the industry-year level it. The sample period is 1990 to 2015 (1997 to 2015 in column 5). The dependent variable is $Industry\ Markup_{it}$, i.e., the sum of firms' sales minus the sum of firms' cost of goods sold in industry i in year t, scaled by the sum of firms' sales (cf. Bustamante and Donangelo, 2017). Industries are defined based on three-digit SIC codes. *Bank-Industry* HHI_{it-1} measures the credit concentration in industry i in year $t-1$, and is defined as the sum of the squared bank market shares. Bank market shares are measured over the last five years, i.e., $t-1$ to $t-5$. *Synd.* $Firm_{it-1}$ is defined as the total number of firms in industry i in year $t-1$ that are active borrowers in the syndicated-loan market, scaled by the total number of firms in the industry. The number of active borrowers is measured over the last five years, i.e., $t-1$ to $t-5$. The total number of firms in the industry is measured in year $t-1$. *Synd.* Vol_{it-1} is the total amount of syndicated loans issued in industry i in year $t-1$, scaled by the sum of firms' total debt. *High Synd. Firm (Vol)*$_{it-1}$ equals one if *Synd. Firm* (*Synd. Vol*) is in the top quartile of the respective distribution, and zero otherwise. $TSIMM_{it-1}$ is the total similarity measure of product market competition in industry i in year $t-1$, based on Hoberg and Phillips (2016). *Industry* HHI_{it-1} is a proxy for industry concentration (sales-based Herfindahl-Hirschman Index) in industry i in year $t-1$. Additional industry controls are included (see Table 2 for details). p-values based on robust standard errors, clustered at the industry level, are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Variable:	Industry Markup$_{it}$ (1)	Industry Markup$_{it}$ (2)	Industry Markup$_{it}$ (3)	Industry Markup$_{it}$ (4)	Industry Markup$_{it}$ (5)	Industry Markup$_{it}$ (6)
Bank-Industry HHI × Synd. Firm$_{it-1}$	0.033*					
	(0.069)					
Bank-Industry HHI × High Synd.Firm$_{it-1}$		0.073*				
		(0.053)				
Bank-Industry HHI × Synd. Vol$_{it-1}$			0.002*			
			(0.063)			
Bank-Industry HHI × High Synd. Vol$_{it-1}$				0.043**		
				(0.023)		
Bank-Industry HHI × TSIMM$_{it-1}$					0.005**	
					(0.048)	
Bank-Industry HHI × Industry HHI$_{it-1}$						0.083*
						(0.071)
Bank-Industry HHI$_{it-1}$	0.006	0.022	0.025*	0.020	0.031*	-0.013
	(0.737)	(0.123)	(0.077)	(0.198)	(0.056)	(0.632)
Synd. Firm$_{it-1}$	-0.007					
	(0.260)					
High Synd. Firm$_{it-1}$		-0.015*				
		(0.068)				
Synd. Vol$_{it-1}$			-0.000			
			(0.261)			
High Synd. Vol$_{it-1}$				-0.018***		
				(0.001)		
TSIMM$_{it-1}$					-0.001	
					(0.501)	
Industry HHI$_{it-1}$	0.002	0.004	0.010	0.009	0.012	-0.017
	(0.908)	(0.856)	(0.619)	(0.672)	(0.613)	(0.516)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,250	5,250	5,239	5,239	3,763	5,250
Adj R^2	0.84	0.84	0.84	0.84	0.89	0.84

Table 6: **Bank Concentration and Industry Defaults**

The unit of observation is the industry-year level *it*. The sample period is 1990 to 2015. The dependent variable is $\ln(1 + Defaults_{it})$, i.e., the (log) number of delistings due to bankruptcy in industry i in year t. Industries are defined based on three-digit SIC codes. *Bank-Industry* HHI_{it-1} measures the credit concentration in industry i in year $t-1$, and is defined as the sum of the squared bank market shares. Bank market shares are measured over the last five years, i.e., $t-1$ to $t-5$. Industry controls are included when indicated (see Table 2 for details). p-values based on robust standard errors, clustered at the industry level, are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Variable:	$\ln(1 + \text{Defaults}_{it})$	$\ln(1 + \text{Defaults}_{it})$	$\ln(1 + \text{Defaults}_{it})$
	(1)	(2)	(3)
Bank-Industry HHI_{it-1}	-0.527***	-0.133*	-0.142**
	(0.000)	(0.060)	(0.041)
Year FE	No	Yes	Yes
Industry FE	No	Yes	Yes
Industry Characteristics	No	No	Yes
Observations	5,218	5,217	5,215
Adj R^2	0.03	0.50	0.50

Table 7: **Bank Market Share and Cost of Debt**

In columns 1 to 3, the unit of observation is the bank-industry-quarter level *ijt*, based on the sample of all completed syndicated loans from 1990 to 2015 granted to industry i for which bank j served as a lead arranger in quarter t. Furthermore, the sample is limited to quarters with non-zero loans granted to industry i by bank j. In columns 4 and 5, the unit of observation is the industry-year level *it*, based on the sample of all completed syndicated loans from 1990 to 2015 granted to industry i. The sample is limited to years with non-zero loans granted to industry i. The dependent variable in columns 1, 2, and 4 is the logged (volume-weighted) average all-in-drawn spread of all loans granted to industry i (by bank j) in period t. The dependent variable in columns 3 and 5 is the logged (volume-weighted) average usage-weighted spread (UWS) of all loans granted to industry i (by bank j) in period t. The UWS is defined following Berg, Saunders, Steffen, and Streitz (2017): UWS (PDD) $=$ PDD $\times$ AISD $+ (1 -$ PDD$) \times$ AISU, where PDD is the probability of drawdown, i.e., the probability that a committed loan is actually drawn down. The all-in-drawn spread (AISD) is the spread paid by the borrower on the used part of a loan commitment. The all-in-undrawn spread (AISU) is the spread paid by the borrower on the committed but not used part of the loan commitment. Following Berg, Saunders, Steffen, and Streitz (2017), we assume a PDD of 25% for credit lines. For term loans the USW is equal to the AISD (i.e., PDD = 100%). Special loan types, i.e., loans that cannot be categorized as either term loans or lines of credit, are removed in columns 3 and 5. *Market Share*$_{ijt-4}$ is the proportion of bank j's total loan volume to industry i over the aggregate loan volume in industry i, measured over five years (20 quarters) from $t-4$ to $t-23$. *Portfolio Share*$_{ijt-4}$ is the proportion of bank j's total loan volume to industry i over the aggregate loan volume granted by bank j, measured over five years (20 quarters) from $t-4$ to $t-23$. *Bank-Industry* HHI_{it-1} measures the credit concentration in industry i in year $t-1$, and is defined as the sum of the squared bank market shares. Bank market shares are measured over the last five years, i.e., $t-1$ to $t-5$. p-values based on robust standard errors, clustered at the bank level (columns 1 to 3) or industry level (columns 4 to 5), are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

	Bank-industry-quarter level			Industry-year level	
Variable:	ln(Spread)$_{ijt}$	ln(Spread)$_{ijt}$	ln(UWS(25%))$_{ijt}$	ln(Spread)$_{it}$	ln(UWS(25%)$_{it}$
	(1)	(2)	(3)	(4)	(5)
Market Share$_{ijt-4}$	-0.557***	-0.544***	-0.639***		
	(0.000)	(0.000)	(0.000)		
Portfolio Share$_{ijt-4}$		-0.165**	-0.295**		
		(0.034)	(0.013)		
Bank-Industry HHI$_{it-1}$				-0.120*	-0.207**
				(0.060)	(0.019)
Bank-quarter FE	Yes	Yes	Yes		
Industry-quarter FE	Yes	Yes	Yes		
Year FE				Yes	Yes
Industry FE				Yes	Yes
Observations	58,694	58,694	51,127	6,563	6,282
Adj R^2	0.55	0.55	0.57	0.43	0.41

Table 8: **Bank Market Share and Cost of Debt – IV Estimates**

The unit of observation is the bank-industry-quarter level *ijt*, based on the sample of all completed syndicated loans from 1992 to 2015 granted to industry i for which bank j served as a lead arranger in quarter t. Furthermore, the sample is limited to quarters with non-zero loans granted to industry i by bank j. The first-stage regression is in column 1. The dependent variable in the second stage (column 2) is the logged (volume-weighted) average all-in-drawn spread of all loans granted to industry i by bank j in quarter t. $Market\ Share_{ijt-4}$ is the proportion of bank j's total loan volume to industry i over the aggregate loan volume in industry i, measured over five years (20 quarters) from $t-4$ to $t-23$. In case of a bank merger in the year prior to that associated with quarter $t-4$, $Market\ Share_{ijt-4}$ is instrumented by the sum of the two merging banks' historical market shares (if the target's market share is non-zero) in industry i in the last quarter of the pre-merger year, $Merger\text{-}implied\ Market\ Share_{ijt-4}$. Otherwise, $Merger\text{-}implied\ Market\ Share_{ijt-4}$ is equal to zero (before the first merger), or equal to the previous value of the instrument (after the first merger). As in column 2 of Table 7, $Portfolio\ Share_{ijt-4}$ is controlled for. p-values based on robust standard errors, clustered at the bank level, are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Variable:	Market Share$_{ijt-4}$	ln(Spread)$_{ijt}$
	(1)	(2)
Merger-implied Market Share$_{ijt-4}$	0.400***	
	(0.000)	
Market Share (instrumented)$_{ijt-4}$		-0.647***
		(0.001)
Bank-quarter FE	Yes	Yes
Industry-quarter FE	Yes	Yes
First-stage F-stat	563.96	
Observations	57,473	57,473
Adj R^2	0.59	

Table 9: **Bank Market Share and Cost of Debt – Strategic Substitutes vs. Complements**

The unit of observation is the bank-industry-quarter level *ijt*, based on the sample of all completed syndicated loans from 1990 to 2015 (1997 to 2015 in column 1) granted to industry i for which bank j served as a lead arranger in quarter t. Furthermore, the sample is limited to quarters with non-zero loans granted to industry i by bank j. The dependent variable is the logged (volume-weighted) average all-in-drawn spread of all loans granted to industry i by bank j in quarter t. $Market\ Share_{ijt-4}$ is the proportion of bank j's total loan volume to industry i over the aggregate loan volume in industry i, measured over five years (20 quarters) from $t-4$ to $t-23$. $TSIMM_{it-4}$ is the total similarity measure of product market competition in industry i in $t-4$, based on Hoberg and Phillips (2016). In columns 2 and 4 (3 and 5), the sample is restricted to industries with competition in strategic substitutes (complements). In columns 2 and 3, the strategic substitutes (complements) sample refers to all industry-quarters in which CSM_{it-4} is negative (positive). In columns 4 and 5, the strategic substitutes (complements) sample refers to all industry-quarters in which the upper (lower) bound of the 70% confidence interval for CSM_{it-4} is negative (positive). The Competitive Strategy Measure (CSM) is a measure of the degree of competitive interaction (see Section 3.2 and Chod and Lyandres, 2011, for details). *Absolute* CSM_{it-4} refers to the absolute value of the average of CSM_{kt-4} divided by the standard error of the mean (variation within industry-quarter across firms). p-values based on robust standard errors, clustered at the bank level, are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Variable:	$\ln(\text{Spread})_{ijt}$	$\ln(\text{Spread})_{ijt}$	$\ln(\text{Spread})_{ijt}$	$\ln(\text{Spread})_{ijt}$	$\ln(\text{Spread})_{ijt}$
		Type of competition			
		Strategic Substitutes	Strategic Complements	Strategic Substitutes	Strategic Complements
Specification:		CSM $<$ 0	CSM $>$ 0	70% conf.	70% conf.
	(1)	(2)	(3)	(4)	(5)
$\text{Market Share}_{ijt-4} \times \text{TSIMM}_{it-4}$	-0.092***				
	(0.000)				
$\text{Market Share}_{ijt-4} \times \text{Absolute CSM}_{it-4}$		-0.064*	0.051		
		(0.100)	(0.231)		
$\text{Market Share}_{ijt-4}$	-0.419***	-0.758***	-0.685***	-0.750***	-0.313***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.005)
Bank-quarter FE	Yes	Yes	Yes	Yes	Yes
Industry-quarter FE	Yes	Yes	Yes	Yes	Yes
Observations	46,928	25,087	21,888	8,584	5,872
Adj R^2	0.54	0.53	0.54	0.53	0.56

Table 10: **Bank Market Share and Cost of Debt – Loan Level**

The unit of observation is the facility-bank level *fj*, i.e., one observation for each lead bank *j*'s share of a given facility *f*, based on the sample of all completed syndicated loans from 1990 to 2015 granted to firm *k*. The dependent variable is the logged all-in-drawn spread of facility *f*. $Market\ Share_{ijt-4}$ is the proportion of bank *j*'s total loan volume to industry *i* over the aggregate loan volume in industry *i*, measured over five years (20 quarters) from $t-4$ to $t-23$. $TSIMM_{it-4}$ is the total similarity measure of product market competition in industry *i* in $t-4$, based on Hoberg and Phillips (2016). In column 6 (7), the strategic substitutes (complements) sample refers to all industry-quarters in which the upper (lower) bound of the 70% confidence interval for CSM_{it-4} is negative (positive). The Competitive Strategy Measure (CSM) is a measure of the degree of competitive interaction (see Section 3.2 and Chod and Lyandres, 2011, for details). Loan characteristics [ln(Facility Amount), ln(Facility Maturity), Secured (0/1), ln(1+ Financial Covenants)], as well as loan-purpose and loan-type fixed effects are included when indicated. *p*-values based on robust standard errors, clustered at the bank level, are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Variable:	$\ln(\text{Spread})_f$	$\ln(\text{Spread})_f$	$\ln(\text{Spread})_f$	$\ln(\text{Spread})_f$	$\ln(\text{Spread})_f$	$\ln(\text{Spread})_f$	$\ln(\text{Spread})_f$
						Type of competition	
						Strategic Substitutes	Strategic Complements
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\text{Market Share}_{ijt-4} \times \text{TSIMM}_{it-4}$					-0.044***		
					(0.000)		
$\text{Market Share}_{ijt-4}$	-0.472***	-0.417***	-0.216***	-0.041**	-0.327***	-0.313***	-0.094
	(0.000)	(0.000)	(0.000)	(0.011)	(0.000)	(0.008)	(0.141)
Industry-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan-purpose FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Loan-type FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Loan characteristics	No	No	Yes	Yes	No	No	No
Firm FE	No	No	No	Yes	No	No	No
Observations	140,601	140,601	134,652	130,573	116,307	23,774	17,919
Adj R^2	0.59	0.63	0.74	0.89	0.61	0.72	0.79

Table 11: **Bank Market Share and Cost of Debt – Industry Risk**

The unit of observation is the bank-industry-quarter level *ijt*, based on the sample of all completed syndicated loans from 1990 to 2015 granted to industry i for which bank j served as a lead arranger in quarter t. Furthermore, the sample is limited to quarters with non-zero loans granted to industry i by bank j. The dependent variable is the logged (volume-weighted) average all-in-drawn spread of all loans granted to industry i by bank j in quarter t. $Market\ Share_{ijt-4}$ is the proportion of bank j's total loan volume to industry i over the aggregate loan volume in industry i, measured over five years (20 quarters) from $t-4$ to $t-23$. $High\ ROA\ Vola_{it-4}$ equals one if $ROA\ Vola_{it-4}$ is in the top quartile of the distribution, and zero otherwise. $ROA\ Vola_{it-4}$ is a volatility measure over 8 quarters from $t-4$ to $t-11$, where ROA is defined as operating income over total assets. $Low\ Coverage_{it-4}$ equals one if $Coverage_{it-4}$ is in the bottom quartile of the distribution, and zero otherwise. $Coverage_{it-4}$ is defined as pre-tax income plus interest expenses, all over interest expenses. p-values based on robust standard errors, clustered at the bank level, are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Variable:	ln(Spread)$_{ijt}$	ln(Spread)$_{ijt}$
	(1)	(2)
Market Share$_{ijt-4}$ × High ROA Vola$_{it-4}$	-0.243***	
	(0.000)	
Market Share$_{ijt-4}$ × Low Coverage$_{it-4}$		-0.321***
		(0.000)
Market Share$_{ijt-4}$	-0.585***	-0.578***
	(0.000)	(0.000)
Bank-quarter FE	Yes	Yes
Industry-quarter FE	Yes	Yes
Observations	54,844	54,789
Adj R^2	0.55	0.55

ONLINE APPENDIX

A Markup Estimation

This section briefly outlines the markup estimation methodology proposed by De Loecker and Warzynski (2012), DLW henceforth, and De Loecker, Eeckhout, and Unger (2020). We refer the reader to these papers for an in-depth discussion. The description and notation closely follow De Loecker, Eeckhout, and Unger (2020).

DLW propose to estimate firm-level markups using balance-sheet data without having to make explicit assumptions on the mode of competition. Markups are instead derived from the production function. In particular, DLW consider a setting with heterogeneous firms (i) with access to a common production technology $Q\left(.\right)$ that transforms inputs into output:

$$Q\left(\Omega_{it}, V_{it}, K_{it}\right) = \Omega_{it} F_t\left(V_{it}, K_{it}\right), \tag{A.1}$$

where V is the set of variable production inputs, K is the capital stock, and Ω is the Hicks-neutral firm-specific productivity term. Firms minimize production cost given the production function. DLW derive a simple expression for the markup (defined as price over marginal cost) from the first-order condition with respect to V of the optimization problem:

$$\mu_{it} = \theta_{it}^{V} \frac{P_{it} Q_{it}}{P_{it}^{V_j} V_{it}}, \tag{A.2}$$

where θ_{it}^{V} is the output elasticity of the variable input. The advantage of this approach is that sales, i.e., $S_{it} = P_{it} Q_{it}$, and total variable cost of production, i.e., $C_{it} = \sum_j P_{it}^{V_j} V_{it}^{j}$, can be observed directly in the data.[1] The output elasticity of input has to be estimated. De Loecker, Eeckhout, and Unger (2020) consider an industry-specific Cobb-Douglas production function with variable inputs and capital:

$$q_{it} = \beta_v v_{it} + \beta_k k_{it} + w_{it} + \varepsilon_{it}, \tag{A.3}$$

where lower cases denote logs, $w_{it} = \ln \Omega_{it}$, q_{it} is the log of deflated sales, v_{it} is the log of deflated total production cost, and k_{it} is the log of deflated capital. The unobserved productivity term w_{it} is given by a function of the firm's inputs and a control variable (variable input) such that $w_{it} = h\left(v_{it}, k_{it}\right)$. Estimation proceeds in two stages. In the first stage, measurement error and unanticipated shocks to sales are purged using

$$q_{it} = \phi_{it}\left(v_{it}, k_{it}\right) + \varepsilon_{it}, \tag{A.4}$$

where $\phi = \beta_v v_{it} + \beta_k k_{it} + h\left(v_{it}, k_{it}\right)$. Productivity is assumed to follow an $AR(1)$ process,

[1] A breakdown into the different variable-cost positions is not readily available in Compustat, so the reported total cost of production is used.

$w_{it} = pw_{it-1} + \xi_{it}$, giving rise to the moment condition used to obtain the industry-specific output elasticity:

$$\mathbb{E}\left(\xi_{it}\left(\beta_v\right) v_{it-1}\right) = 0, \tag{A.5}$$

where $\xi_{it}\left(\beta_v\right)$ is obtained, given β_v, by projecting productivity $w_{it}\left(\beta_v\right)$ on its lag $w_{it-1}\left(\beta_v\right)$. Productivity is obtained using $\phi_{it} - \beta_v v_{it} - \beta_k k_{it}$ and the estimate ϕ from the first-stage regression of sales on the variable input, capital, and year dummies. The identification assumptions are that (i) variable input responds to productivity shocks but not the lagged values, and that (ii) lagged variable input is correlated with current input.

The estimated industry-specific output elasticity is used to obtain firm-level markup estimates following (A.2).

B Inferring Optimality of Common Lenders from Firms' Switching Decisions

In this additional section, we test whether firms find it optimal to share common lenders. In particular, we exploit the episode of U.S. branching deregulation as a state-level shock allowing firms to switch to out-of-state banks.

B.1 Empirical Strategy

As a shock to firms' scope for switching lenders, we use the differences in regulatory barriers to interstate branching that were gradually removed over time. Prior to the passage of the Interstate Banking and Branching Efficiency Act (IBBEA) in 1994, which fully came into effect in 1997, banks had only limited abilities to acquire or open out-of-state branches. While formally relaxing geographical restrictions for banks, IBBEA granted states the right to erect/maintain entry barriers for out-of-state banks.

That is, there was still significant variation across states after 1996, and within states across time, in the extent to which a bank j could expand its business to state s. We hypothesize that a firm k, incorporated in state s, is more likely to establish a new lending relationship with an out-of-state lender j if entry barriers are relaxed in state s. Furthermore, given the opportunity to switch, the firm should be more likely to establish a new lending relationship with an out-of-state lender that has a high market share in firm k's industry, and especially so if firm k is in an industry with competition in strategic substitutes.

Note that branching restrictions did not legally prohibit firms from borrowing from out-of-state banks. For instance, a Silicon Valley firm could obtain funding from a New York bank, irrespective of whether the bank was allowed to open a branch in California or not. However, the ability to open/acquire branches closer to (potential) borrowers reduces the physical distance between banks and firms, which lowers banks' cost of information acquisition (see, e.g., Agarwal and Hauswald, 2010).

Thus, the removal of branching restrictions can be viewed as an exogenous reduction in the information advantage of in-state vs. out-of-state banks, which should positively affect the propensity of contracting with out-of-state banks. There is ample evidence that geographic proximity also matters in the market for large syndicated loans. For instance, Hollander and Verriest (2016) provide evidence that the closer a borrower is located to a bank branch, the lower the level of asymmetric information between borrower and lender. See also Bharath, Dahiya, Saunders, and Srinivasan (2011) and Dass and Massa (2011), among others. We conjecture that given a reduction in the cost of switching to out-of-state banks, firms should be particularly likely to establish new relationships with high-market-share banks.

We use the Rice and Strahan (2010) index of interstate branching restrictions to capture the degree to which barriers to interstate branching were erected/removed across states and over time. As in Loutskina and Strahan (2015), we start the sample period in 1994 (the year in which IBBEA was passed), and set the index to 0 at the beginning of the sample period for all states.[2] The index is then increased depending on how a state implements potential means to facilitate entry for out-of-state banks. That is, our index ranges from 0 (highly regulated) to 4 (deregulated). We stop the sample in 2008 as the last regulatory change identified by Rice and Strahan (2010) was implemented in 2005, leaving us with a post-deregulation window of at least three years for each event.

For the period from 1994 to 2008, we build a panel at the bank-firm-year level kjt, and limit the sample to all bank-firm pairs for which a new lending relationship is established at any point during the sample period. The dependent variable of interest is a dummy variable indicating a new lending relationship established between bank j and firm k in year t.

The structure of the panel allows for the inclusion of bank-firm, firm-year, and bank-year fixed effects. The level of identifying variation is a firm-year-level shock to the ability to switch lenders in conjunction with a bank-level characteristic determining the desirability to switch to lender j. The index of interstate banking deregulation reflects switching opportunities, and the desirability to switch to lender j is a function of its market share in firm k's industry. We then estimate the following regression specification:

$$\begin{aligned} \textit{New Rel}_{kjt} &= \beta_1 \textit{Dereg Index}_{kt} \times \textit{Out-of-State}_{kj} \times \textit{Market Share}_{kjt-1} \\ &\quad + \beta_2 \textit{Dereg Index}_{kt} \times \textit{Out-of-State}_{kj} + \beta_3 \textit{Dereg Index}_{kt} \times \textit{Market Share}_{kjt-1} \\ &\quad + \beta_4 \textit{Out-of-State}_{kj} \times \textit{Market Share}_{kjt-1} + \beta_5 \textit{Market Share}_{kjt-1} \\ &\quad + \mu_{kj} + \theta_{kt} + \psi_{jt} + \epsilon_{kjt}, \end{aligned} \tag{B.1}$$

where $\textit{New Rel}_{kjt}$ is equal to one if firm k obtained a loan from bank j (as lead arranger) in year t from which the firm did not borrow in the last ten years, $\textit{Dereg Index}_{kt}$ is the index of interstate banking deregulation of firm k's state of incorporation, $\textit{Out-of-State}_{kj}$ is a dummy variable indicating bank-firm pairs across different states, $\textit{Market Share}_{kjt-1}$ is the market share of bank j in firm k's industry (excluding loans granted by bank j to firm k itself) in year $t-1$; and μ_{kj}, θ_{kt}, and ψ_{jt} denote bank-firm, firm-year, and bank-year fixed effects, respectively. Standard errors are clustered at the firm level.

We hypothesize $\beta_1 > 0$, i.e., firms switch to high-market-share lenders when given the

[2] Rice and Strahan (2010) identify four roadblocks to branch expansion that states can erect: (i) states can impose a minimum age on target institutions of interstate acquirers, (ii) states can restrict de-novo interstate branching, (iii) states can restrict acquisitions of individual branches by out-of-state banks, and (iv) states can impose a deposit cap with respect to interstate bank mergers (i.e., given a cap of x%, an out-of-state bank cannot engage in a merger that would increase its deposit share in the respective state above x%).

opportunity to do so. In this case, the opportunity to switch opens up because bank j is an out-of-state bank that can – thanks to the deregulation – enter firm k's state. The distinction between out-of-state and same-state banks j with a high market share in firm k's industry is crucial insofar as high-market-share lenders may generally be affected in their credit-supply decisions by the state-level deregulation. To the extent that this is not differentially so for out-of-state vs. same-state banks, we control for this possibility by means of bank-year fixed effects and the interaction term between the deregulation index and banks' market shares.

B.2 Results

The results are in Table C7. In column 1, we find that firms are more likely to establish new relationships with out-of-state banks following a deregulatory episode.[3] Firms are more likely to switch to high-market-share lenders when offered this possibility.

In column 2, we estimate the full specification (B.1), and find some indication that the switching effect is indeed more emphasized for out-of-state banks with large market shares in firm k's industry. The effect, however, is only significant at the 22% level. This estimate may mask important heterogeneity at the firm level. For instance, information-leakage concerns may make some firms reluctant to share a common lender with competitors (Asker and Ljungqvist, 2010).

The limited-liability effect of debt (Brander and Lewis, 1986) should hold irrespective of whether firms in an industry share the same lender or not. However, the internalization of externalities by common lenders pertains primarily to strategic substitutes.

To test this, in the last two columns, we split up the sample by firms competing in strategic substitutes (column 3) and complements (column 4). The effect on firms' switching to out-of-state banks with high market shares is positive and statistically significant for strategic substitutes, but negative and insignificant for strategic complements.

While our empirical strategy uses firms' switching behavior to uncover their preferences, we cannot pin down their true motives for switching lenders. For instance, firms' switching to high-market-share banks, even if confined to firms competing in strategic substitutes, is consistent with the idea that they seek to minimize their cost of debt, independently from any output effects. We argue, however, that lower cost of debt is used by common lenders to induce less aggressive product market behavior.

[3] Note that at the firm level, we calculate the market share excluding lending to firm k itself. That is, a high market share indicates that bank j is already an active lender to firm k's competitors.

C Additional Tables

Table C1: **Bank Concentration and Industry Markup − TNIC Industries**

The unit of observation is the firm-year level *kt*. The sample period is 1997 to 2015. The dependent variable is *Peer* $Markup_{kt}$, i.e., the total sales of the peers of firm k (including firm k itself) in year t minus the total cost of goods sold of the peers of firm k (including firm k itself) in year t, scaled by the total sales of the peers of firm k (including firm k itself). Peers are defined using the TNIC industries developed by Hoberg and Phillips (2016). *Bank-Industry* HHI_{kt-1} measures the credit concentration within each peer group in year $t-1$, and is defined as the sum of the squared bank market shares. Bank market shares are measured over the last five years, i.e., $t-1$ to $t-5$. Additional peer controls are included when indicated (see Table 2 for details). Control variables are calculated as weighted averages across all peers of firm k (including firm k itself). p-values based on robust standard errors, clustered at the industry level, are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Variable:	Peer Markup$_{kt}$ (1)	Peer Markup$_{kt}$ (2)
Bank-Industry HHI$_{kt-1}$	0.007*	0.009**
	(0.091)	(0.041)
Year FE	Yes	Yes
Firm FE	Yes	Yes
Peer Group Characteristics	No	Yes
Observations	101,398	101,386
Adj R^2	0.71	0.71

Table C2: **Bank Concentration and Industry Markup – Alternative HHI Definitions**

This table mirrors Table 2, column 3, but uses alternative proxies for the credit concentration in an industry i. In particular, *Bank-Ind. (count)* HHI_{it-1} is calculated the same way as *Bank-Industry* HHI_{it-1}, but using the number of loans instead of loan volume. *Bank-Ind. (outst.)* HHI_{it-1} uses the outstanding amount (approximated based on the loan maturity indicated at origination) instead of a rolling 5-year window approach. *Bank-Ind. (count, outst.)* HHI_{it-1} is calculated the same way, but using the outstanding number of loans instead of loan volume. $CL\ Index_{it-1}$ measures the degree of common lending in industry i in year $t-1$. In particular, for each borrower we calculate the fraction of industry peers with whom the borrower shares at least one lender during the last five years, i.e., $t-1$ to $t-5$. $CL\ Index_{it-1}$ (*CL Index (weighted)*$_{it-1}$) is then calculated as the average fraction across all borrowers in industry i (weighted by their total borrowing volume during the last five years). Industry controls are included (see Table 2 for details). p-values based on robust standard errors, clustered at the industry level, are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Variable:	Industry Markup$_{it}$	Industry Markup$_{it}$	Industry Markup$_{it}$	Industry Markup$_{it}$	Industry Markup$_{it}$
	(1)	(2)	(3)	(4)	(5)
Bank-Ind. (count) HHI$_{it-1}$	0.036*				
	(0.060)				
Bank-Ind. (outst.) HHI$_{it-1}$		0.029*			
		(0.055)			
Bank-Ind. (count, outst.) HHI$_{it-1}$			0.038**		
			(0.047)		
CL Index$_{it-1}$				0.027*	
				(0.055)	
CL Index (weighted)$_{it-1}$					0.024**
					(0.050)
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Industry Characteristics	Yes	Yes	Yes	Yes	Yes
Observations	5,250	5,241	5,241	5,127	5,127
Adj R^2	0.84	0.84	0.84	0.84	0.84

Table C3: **Bank Deregulation and Industry Markup**

The unit of observation is the industry-year level *it*. The sample period is 1990 to 2015. The dependent variable in columns 1 and 2 is *Industry* $Markup_{it}$, i.e., the sum of firms' sales minus the sum of firms' cost of goods sold in industry i in year t, scaled by the sum of firms' sales (cf. Bustamante and Donangelo, 2017). The dependent variable in columns 3 and 4 is *Industry Markup* DLW_{it}, i.e., the average markup in industry i in year t, estimated following De Loecker and Warzynski (2012) and De Loecker, Eeckhout, and Unger (2020). Industries are defined based on three-digit SIC codes. *Deregulation* $Exposure_{it-1}$ captures industry i's exposure to interstate banking deregulation. The measure is based on the (inverted) Rice-Strahan index, *Dereg* $Index_{st-1}$, which ranges from 0 (highly regulated) to 4 (deregulated) based on regulatory changes in state s (Rice and Strahan, 2010). *Deregulation* $Exposure_{it-1}$ is defined at the industry level as the weighted *Dereg* $Index_{st-1}$ based on the fraction of firms in industry i that are incorporated in state s. Industry-level state weights are time-invariant, i.e., fixed for each industry at the time of the Interstate Banking and Branching Efficiency Act (IBBEA) passage in 1994. Industry controls are included when indicated (see Table 2 for details). p-values based on robust standard errors, clustered at the industry level, are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Variable:	Industry Markup_{it}	Industry Markup_{it}	Industry Markup DLW_{it}	Industry Markup DLW_{it}
	(1)	(2)	(3)	(4)
Deregulation Exposure_{it-1}	-0.015**	-0.013*	-0.021*	-0.016
	(0.043)	(0.080)	(0.062)	(0.129)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Industry Characteristics	No	Yes	No	Yes
Observations	6,049	6,049	6,037	6,037
Adj R^2	0.83	0.83	0.95	0.95

Table C4: **Bank Concentration and Industry Output**

In Panel A (columns 1 to 4), the unit of observation is the industry-year level *it*. The dependent variable is *Industry Output Growth*$_{it}$. This variable is based on the BEA chain-type quantity index for gross output by industry (the index is equal to 100 in the reference year 2012). The index captures changes in the quantities of goods and services provided by an industry over time. Data come from the BEA and are based on 53 non-financial BEA industries, converted to three-digit SIC-code industries. *Industry Output Growth*$_{it}$ is defined as the growth rate of the quantity index from year $t-1$ to t. The sample period is 1990 to 2015 (1992 to 2015 in columns 3 and 4). *Bank-Industry* HHI_{it-1} measures the credit concentration in industry i in year $t-1$, and is defined as the sum of the squared bank market shares. Bank market shares are measured over the last five years, i.e., $t-1$ to $t-5$. In columns 3 and 4, *Bank-Industry* HHI_{it-1} is instrumented by *Merger-implied Bank-Industry* HHI_{it-2}, which is defined as the cumulative number of bank mergers in industry i by the previous year-end $t-2$. For each industry i, only mergers for which both the acquirer bank *and* the target bank have a non-zero market share in the industry in the last pre-merger year ($t-3$) are considered. Panel B (columns 5 and 6) analyzes industry output around bank-merger events. For each bank merger m, we consider a five-year (column 5) or seven-year (column 6) window around the merger event. The unit of observation is the merger-industry-year level *mit*. The dependent variable is the same as in Panel A. The treatment indicator, $Treated_{mi}$, equals one if both the acquirer bank *and* the target bank have a non-zero market share in industry i in the last year before merger m. Industries in which only the acquirer bank *or* the target bank has a non-zero market share in the last year before their respective merger form the control group ($Treated_{mi} = 0$). $Post_{mt}$ equals one in the post-merger window, and zero otherwise. Industry controls are included when indicated (see Table 2 for details). p-values based on robust standard errors, clustered at the industry level, are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

	Panel A: OLS and IV Estimates				**Panel B: DiD Estimates**	
Window:					[-1,+3]	[-2,+4]
Variable:	Industry Output Growth$_{it}$	Industry Output Growth$_{it}$	Industry Output Growth$_{it}$	Industry Output Growth$_{it}$	Industry Output Growth$_{mit}$	Industry Output Growth$_{mit}$
	(1)	(2)	(3)	(4)	(5)	(6)
Bank-Industry HHI$_{it-1}$	-0.009*	-0.009*				
	(0.081)	(0.088)				
Bank-Industry HHI (instrumented)$_{it-1}$			-0.080*	-0.084**		
			(0.083)	(0.039)		
Treated$_{mi}$ × Post$_{mt}$					-0.003*	-0.003*
					(0.053)	(0.066)
Year FE	Yes	Yes	Yes	Yes		
Industry FE	Yes	Yes	Yes	Yes		
Industry Characteristics	No	Yes	No	Yes		
Merger-period FE					Yes	Yes
Merger-industry FE					Yes	Yes
First-stage F-stat			19.49	28.22		
Observations	5,132	5,130	4,762	4,761	28,814	40,204
Adj R^2	0.45	0.45			0.50	0.47
Estimation	OLS	OLS	IV	IV		

Table C5: **Bank Market Share and Cost of Debt – Loan Level, IV Estimates**

The unit of observation is the facility-bank level *fj*, i.e., one observation for each lead bank *j*'s share of a given facility *f*, based on the sample of all completed syndicated loans from 1992 to 2015 granted to firm *k*. The first-stage regressions are in columns 1 and 2. The dependent variable in the second stage (columns 3 and 4) is the logged all-in-drawn spread of facility *f*. *Market Share*$_{ijt-4}$ is the proportion of bank *j*'s total loan volume to industry *i* over the aggregate loan volume in industry *i*, measured over five years (20 quarters) from $t-4$ to $t-23$. In case of a bank merger in the year prior to that associated with quarter $t-4$, *Market Share*$_{ijt-4}$ is instrumented by the sum of the two merging banks' historical market shares (if the target's market share is non-zero) in industry *i* in the last quarter of the pre-merger year, *Merger-implied Market Share*$_{ijt-4}$. Otherwise, *Merger-implied Market Share*$_{ijt-4}$ is equal to zero (before the first merger), or equal to the previous value of the instrument (after the first merger). Loan characteristics [ln(Facility Amount), ln(Facility Maturity), Secured (0/1), ln(1+ Financial Covenants)], as well as loan-purpose and loan-type fixed effects are included when indicated. *p*-values based on robust standard errors, clustered at the bank level, are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Variable:	Market Share$_{ijt-4}$	Market Share$_{ijt-4}$	ln(Spread)$_{ijt}$	ln(Spread)$_{ijt}$
	(1)	(2)	(3)	(4)
Merger-implied Market Share$_{ijt-4}$	0.004***	0.003***		
	(0.000)	(0.000)		
Market Share (instrumented)$_{ijt-4}$			-0.316***	-0.049*
			(0.001)	(0.073)
Industry-quarter FE	Yes	Yes	Yes	Yes
State-quarter FE	Yes	Yes	Yes	Yes
Bank-quarter FE	Yes	Yes	Yes	Yes
Loan-purpose FE	Yes	Yes	Yes	Yes
Loan-type FE	Yes	Yes	Yes	Yes
Loan characteristics	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	Yes
First-stage F-stat	404.48	131.82		
Observations	105,644	101,993	105,644	101,993
Adj R^2	0.79	0.83		

Table C6: **Underwriting Market Share and Cost of Debt**

The unit of observation is the bank-industry-quarter level *ijt*, based on the sample of all completed syndicated loans from 1990 to 2015 granted to industry i for which bank j served as a lead arranger in quarter t. Furthermore, the sample is limited to quarters with non-zero loans granted to industry i by bank j. The dependent variable is the logged (volume-weighted) average all-in-drawn spread of all loans granted to industry i by bank j in period t. *Market Share*$_{ijt-4}$ is the proportion of bank j's total loan volume to industry i over the aggregate loan volume in industry i, measured over five years (20 quarters) from $t-4$ to $t-23$. *Underwriting Share*$_{ijt-4}$ is the proportion of bank j's total number of debt and equity underwriting mandates in industry i over the aggregate number of debt and equity issuances in industry i, measured over over five years (20 quarters) from $t-4$ to $t-23$. p-values based on robust standard errors, clustered at the bank level, are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Variable:	ln(Spread)$_{ijt}$	ln(Spread)$_{ijt}$	ln(Spread)$_{ijt}$	ln(Spread)$_{ijt}$
	(1)	(2)	(3)	(4)
Market Share$_{ijt-4}$ × Underwrit. Share$_{ijt-4}$				0.351*
				(0.100)
Market Share$_{ijt-4}$	-0.557***		-0.542***	-0.576***
	(0.000)		(0.000)	(0.000)
Underwriting Share$_{ijt-4}$		-0.223***	-0.076	-0.159***
		(0.007)	(0.249)	(0.005)
Bank-quarter FE	Yes	Yes	Yes	Yes
Industry-quarter FE	Yes	Yes	Yes	Yes
Observations	58,694	58,694	58,694	58,694
Adj R^2	0.55	0.55	0.55	0.55

Table C7: **Bank Deregulation and Firms' Switching Lenders**

The unit of observation is the firm-bank-year level kjt. The sample period is 1994 to 2008. *Dereg Index*$_{kt}$ is an index of interstate banking deregulation based on Rice and Strahan (2010). We invert the Rice-Strahan index such that higher index values corresond to less regulated regimes. Therefore, the index ranges from 0 (highly regulated) to 4 (deregulated) based on regulatory changes in the state in which the borrower firm k is incorporated. *Out-of-State*$_{kj}$ is a dummy variable that indicates interstate bank-firm pairs, i.e., firms that are incorporated in a different state than the lender. *Market Share (ex firm k)*$_{kjt-1}$ is the market share of bank j in firm k's industry in year $t-1$. Market shares are defined as the proportion of bank j's total loan volume to borrowers that are in the same industry as firm k (*excluding* loans to firm k itself) over the aggregate loan volume in the industry (*excluding* loans to firm k). Market shares are lagged by one year and measured over five years, i.e., $t-1$ to $t-5$. The dependent variable *New Rel*$_{kjt}$ is a dummy variable that equals one if firm k obtains a loan from bank j (as lead arranger) in year t from which the firm has not borrowed in the last ten years, and zero otherwise. The sample is restricted to bank-firm pairs for which a new lending relationship is established at any point during the sample period. In column 3 (4), the sample is restricted to industries with competition in strategic substitutes (complements). The strategic substitutes (complements) sample refers to all bank-firm paris for which the average estimated CSM_{kt-1} is negative (positive). The Competitive Strategy Measure (CSM) is a measure of the degree of competitive interaction (see Section 3.2 and Chod and Lyandres, 2011, for details). p-values based on robust standard errors, clustered at the firm level, are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Variable:	New Rel$_{kjt}$	New Rel$_{kjt}$	New Rel$_{kjt}$	New Rel$_{kjt}$
			Type of competition	
			Strategic Substitutes	Strategic Complements
	(1)	(2)	(3)	(4)
Dereg Index$_{kt}$ × Out-of-State$_{kj}$ × Market Share (ex firm k)$_{kjt-1}$		0.026	0.056**	-0.059
		(0.218)	(0.040)	(0.278)
Dereg Index$_{kt}$ × Out-of-State$_{kj}$	0.009***	0.009***	0.005*	0.013***
	(0.000)	(0.000)	(0.055)	(0.000)
Dereg Index$_{kt}$ × Market Share (ex firm k)$_{kjt-1}$		-0.030	-0.056**	0.034
		(0.147)	(0.037)	(0.521)
Out-of-State$_{kj}$ × Market Share (ex firm k)$_{kjt-1}$		-0.079	-0.165**	0.129
		(0.141)	(0.017)	(0.385)
Market Share (ex firm k)$_{kjt-1}$		0.092*	0.172**	-0.056
		(0.079)	(0.011)	(0.704)
Firm-period FE	Yes	Yes	Yes	Yes
Bank-period FE	Yes	Yes	Yes	Yes
Bank-firm FE	Yes	Yes	Yes	Yes
Observations	233,055	232,629	126,540	85,245
Adj R^2	0.12	0.12	0.12	0.13

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