

Bank Concentration and Product Market Competition*

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December 7, 2018

Abstract

This paper documents that concentration in the banking sector is associated with less competitive product market outcomes in non-financial sectors. We argue that a distinguishing feature of credit concentration is the higher incidence of competing firms sharing common lenders, which lowers the cost of debt financing in an industry. This is because common lenders internalize potential adverse effects of higher loan rates on the product market behavior among their competing borrowers. Exploiting plausibly exogenous variation in banks' industry market shares stemming from bank mergers, we find that high-market-share lenders charge lower loan rates. The effect is confined to industries with competition in strategic substitutes where negative output externalities would be greatest.

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

Keywords: industry competition, product market, syndicated loans, bank concentration

*We thank Tobias Berg, Giacinta Cestone, Florian Ederer, Alexandra Effenberger, Adrien Matray, Charlotte Ostergaard, Antonio Rosato, Giancarlo Spagnolo, Philip Strahan, Philip Valta and Lucy White, as well as seminar participants at Halle Institute for Economic Research (IWH), Deutsche Bundesbank, the CEPR Third Annual Spring Symposium, and the 2018 EARIE Annual Conference for many helpful suggestions.

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1 Introduction

Recent evidence documents that U.S. industries are becoming increasingly concentrated (Autor, Dorn, Katz, Patterson, and Reenen, 2017; Grullon, Larkin, and Michaely, 2017; Head and Spencer, 2017) and due to higher average market power, economic profits and markups are on the rise (De Loecker and Eeckhout, 2017; Hall, 2018). At the same time, banking-sector concentration is increasing as well (Janicki and Prescott, 2006; Laeven, Ratnovski, and Tong, 2014; Fernholz and Koch, 2016).

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 output and profit margins. Our analysis proceeds in two steps. First, we document, and attempt to establish causality for, the fact that concentration in the credit market is associated with higher industry profits.

In a second step, we shed light on the mechanism underlying the relationship between bank concentration and product market competition. One potential mechanism is that 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 and, as such, limits the number of firms operating in an industry (Cetorelli and Strahan, 2006).

However, we show empirically that higher credit concentration translates to higher markups and lower aggregate output even after accounting for the number of firms active 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 shown more recently by Giannetti and Saidi (2018).

We identify the fact that higher bank concentration leads to a higher incidence of competing firms sharing the same lender as a key determinant of these firms' ability to sustain less competitive outcomes. In particular, even in existing lending relationships, banks may soften credit conditions to avoid aggressive output 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 controlling for industry competition and the number of firms in an industry.

A less competitive outcome is associated with both higher markups and lower industry output. We focus on markup in most of the analysis 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 this relationship can be interpreted causally, we exploit bank mergers as a plausibly exogenous source of variation in banks' industry market shares (similarly to Garmaise and Moskowitz, 2006; Favara and Giannetti, 2017; Giannetti and Saidi, 2018). After instrumenting credit concentration at the industry level with its merger-implied counterpart, we continue to find that higher credit concentration is associated with higher 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 output strategies, 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 rising 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 output 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 on the output decisions of its borrowers. The resulting aggregate 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' output decisions in the same industry, and centralized financing helps firms to implement less competitive outcomes.

We empirically test this hypothesis at the bank-industry-quarter level. Lenders with larger market shares imply a more frequent occurrence of common lenders within industries. In line with our conjecture, we show that lenders that have issued a large share of the loans outstanding in an industry internalize any potential externalities among their borrowers stemming from output effects of higher loan rates, and subsequently charge lower cost of debt. Importantly, high-market-share lenders lower the cost of debt only for firms that compete in strategic substitutes.

By including industry-quarter and bank-quarter 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 – such as fluctuations in industry-level demand for loans – 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

¹ The empirical evidence on this limited-liability effect of debt 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.

out a potential downside by considering firms' decision to share underwriting investment banks, namely the possibility of commercially sensitive information leaking to rival firms, 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 pertains to 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, as in our analysis of credit concentration and industry markups. In particular, we focus on recent mergers and gradual increases in market shares due to these mergers, irrespective of the level of historical market shares of the merging banks. In this manner, we identify a treatment effect that is unlikely to be due to any pre-merger private information held by the merging banks.

We finish our empirical analysis by testing whether sharing common lenders is indeed optimal from the firms' point of view. For this purpose, we infer optimality from firms' decisions to switch to high-market-share lenders when given the opportunity to do so. For identification, we exploit the episode of U.S. branching deregulation as a state-level shock allowing firms to switch to out-of-state banks. We find that firms in deregulated states are more likely to establish new lending relationships with out-of-state banks. Most importantly, the effect is more emphasized for out-of-state banks with high market shares in the same industry as the switching firm. As before, the treatment effect is driven primarily by firms competing in substitutes rather than complements.

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) for-

malize 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 sharing a common lender serves as a commitment device for output decisions and, thus, profits of pre-existing competitors in the same industry. This mechanism complements any effect that bank concentration may have on entry and exit (Cetorelli and Strahan, 2006).

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 multifarious ways. For example, Bhattacharya and Chiesa (1995) consider the possibility that common lenders can facilitate knowledge transfer among competing firms, which would otherwise face the difficulty of legal non-verifiability. In particular, multilateral financing helps to achieve an equilibrium in which only one firm among multiple inventors enters the product market (despite all firms seeking financing for their innovation). The issuance of short-term, rather than long-term, debt plays a crucial role in this mechanism, because it enhances recontracting possibilities at the stage new information is acquired by the common lender.

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 19th/early 20th century).²

Lastly, the idea that debt finance can serve as a coordination mechanism for less competitive output strategies is consistent with recent evidence by Dasgupta and Žaldokas (2018), 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 Profits

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

To measure industry markup, we use Compustat data. In particular, 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.³

² This is because cartels are subject to the moral-hazard problem of individual firms deviating from the collusive equilibrium and undercutting one another. Common lenders to these firms in the same industry have an incentive to discourage such behavior in order to maximize their aggregate gross return. This argument stresses the importance of common financial intermediaries as commitment devices, because these firms would not be able to commit to less competitive outcomes otherwise.

³ 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.

For robustness, we additionally calculate industry-level markup following the procedure laid out in De Loecker and Eeckhout (2017), which is a modified version of the proposed framework 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 above and below the 5th and 95th percentiles within each industry. We provide further details on the estimation procedure in Appendix A.

We also consider industry output. For this purpose, we use data provided by the U.S. Bureau of Economic Analysis (BEA). The BEA provides annual chain-type quantity indices for each industry’s gross output for the period from 1997 to 2015.⁴ We use the most granular BEA industry classification that is available (403 industries). 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 2009, i.e., the index is equal to 100 in 2009.

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 (2018), and 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 obtain transaction-level data on syndicated loans from LPC DealScan. We focus

⁴ See <https://www.bea.gov/industry/industry-economic-accounts-information-guide> for details on the index construction. We match the BEA data with DealScan by translating BEA industry codes to SIC codes. In particular, we go from BEA industry codes to SIC codes via the NAICE code (see <https://www.census.gov/eos/www/naics/concordances/concordances.html>). Note that the match is not unique, i.e., some SIC codes are assigned to multiple BEA industries.

on loans issued to publicly listed or privately held U.S. firms. The sample period is 1990 to 2015.⁵ We exclude financial firms (SIC codes 6000-6999) and public-service firms (SIC codes 8000-9999), and identify bank-industry lending relationships by focusing on the lead arrangers of syndicated loans.⁶

In Panel A of Table 1, we present summary statistics for our main variables at the industry-year level. An important outcome of interest at the industry-year level is the average markup in an industry. Given the specific way industry markup is defined (in line with Bustamante and Donangelo, 2017), we alternatively consider median industry markup or a measure derived from firm-level estimates, described above and henceforth labeled as “DLW,” based on De Loecker and Warzynski (2012) and De Loecker and Eeckhout (2017).

[Table 1 here]

2.2 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 industry markup to concentration in the credit market, as measured by a Herfindahl-Hirschman Index (HHI) over banks’ market shares in terms of credit granted to a given industry.

[Figure 1 here]

After 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.

Motivated by this observation, we scrutinize this effect further by means of regressions at the industry-time level *it*. In particular, we estimate the same regression specification as

⁵ 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 bank market share estimations.

⁶ We use the lender-parent link table provided in Schwert (2018) to match lead arrangers to their respective bank-holding companies.

in the figure, but replace the main explanatory variable by a continuous measure of credit-market concentration:

$$\text{Industry markup}_{it} = \beta \text{Bank-Industry HHI}_{it-1} + \delta_i + \chi_t + \epsilon_{it}, \quad (1)$$

where the outcome variable *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 (as in Bustamante and Donangelo, 2017); *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; and δ_i and χ_t denote industry and year fixed effects, respectively. Standard errors are clustered at the industry level.

The results are in Table 2. In the first column, we find that higher credit concentration is indeed associated with higher industry profits. The effect is robust to controlling for the (lagged) concentration in industry *i* itself (column 2).

We yield virtually the same results in column 3 when we control for the actual number of firms in the industry on the basis of which the markup is calculated. This 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 the number of firms decreases.

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 highest quartile of the distribution of *Bank-Industry HHI*_{it-1} (columns 4 and 5). When moving to the highest quartile of the latter distribution, industry markup increases by 0.009, which corresponds to 6.4% of a standard deviation.

In columns 6 and 7, our results are robust to using as dependent variable the median, rather than the average, industry markup. This suggests that higher industry markup is not driven by higher profits of few dominant firms in the industry.

[Table 2 here]

In the last two columns, we test whether higher markups could be explained by firms' coordinating on lower output. For this purpose, we replace the dependent variable by the BEA's gross-output index.

Indeed, we find that higher concentration in the credit market is not only associated with higher industry markup, but also with lower industry output: when moving to the highest quartile of the credit-concentration distribution, the industry-output index decreases by 5.97 points (for an index that ranges from 59 to 269, see Table 1), which corresponds to 18.4% of a standard deviation, roughly comparable to the effect we document for industry markup. This suggests that firms in the same industry achieve a less competitive outcome by coordinating on their output decisions.

Finally, in Table 3, we show that our findings from the first five columns of Table 2 are robust to using the average industry markup based on firm-level estimates (De Loecker and Warzynski, 2012; De Loecker and Eeckhout, 2017). The main benefit of using industry markups based on DLW is that they can be derived without specifying the mode of product market competition and without price data. Furthermore, the DLW methodology allows for estimating firm-level markups consistently using only the cost of goods sold and capital (fixed assets), both of which are readily available data items in Compustat.

As can be seen in Table 3, the estimates for our main effect exhibit similar economic significance when using DLW industry markups, compared to our estimates in Table 2. When moving to the highest quartile of the distribution of *Bank-Industry HHI*_{*it-1*}, industry markup increases by 0.021, which corresponds to 4.2% of a standard deviation.

[Table 3 here]

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 profitability, 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 2 in Table 2, and include interactions with *Syndicated-loan Usage* $_{it-1}$, which captures the proportion of firms in industry i that is active in the syndicated-loan market in year $t - 1$.

In the first column of Table 4, we see that after controlling for an industry’s HHI in the product market, the effect of credit concentration on industry markup is primarily due to firms active in the syndicated-loan market. This remains to hold true in column 2 where we replace the dependent variable by the average industry markup based on DLW.

[Table 4 here]

These results do not necessarily imply a causal effect of credit concentration on industry markup. In particular, one may be concerned that even after controlling for industry-level HHI, credit concentration follows from higher industry markups, and not vice versa. This may be the case, for example, if a particularly profitable industry exhibits financing needs that are optimally served by very few lenders.

To alleviate such concerns, we use bank mergers as a source of variation in banks’ market shares and, thus, credit concentration, following Garmaise and Moskowitz (2006), Favara and Giannetti (2017), and Giannetti and Saidi (2018). In particular, we build a measure of merger-implied credit concentration based on variation in banks’ market shares due to bank mergers, which are unlikely to be motivated by their desire to increase their market shares for syndicated loans in specific industries. This is because syndicated lending makes only for a portion of banks’ total lending.

We compute *Merger-implied Bank-Industry HHI* $_{it-1}$ as follows. First, we calculate the sum of the two merging banks’ market shares in industry i in the last year before a merger in $t - 1$. Bank market shares are measured over the last five years. In the absence of a merger, this sum is equal to zero. Then, we sum up the squared merger-implied market shares across acquiring (surviving) banks j in industry i in $t - 1$.

As can be seen in column 1 of Table 5, the resulting instrument exhibits a strong correlation with *Bank-Industry HHI*_{*it*-1} in the first stage. The second-stage estimates are in column 2 where the effect of instrumented credit concentration on industry markup remains statistically significant at the 10% level.

[Table 5 here]

3 Coordination through Common Lenders

We next turn to our hypotheses, which we test empirically, for a potential mechanism underlying the relationship between concentration in the credit market and industry markup.

3.1 Hypothesis Development

To explain the relationship between bank concentration and industry profits, we argue that a distinguishing feature of credit concentration is the higher incidence of competing firms sharing common lenders. That is, we conjecture that 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 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 output 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 complements, as argued by Showalter (1995) and Chevalier and Scharfstein (1996) (for empirical evidence, see Chevalier, 1995).

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.⁷

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 precommit to less competitive output. In Poitevin (1989), a common lender can better control the incentive effects of debt and, thus, limit the extent of competition in the output 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 in the model is that marginal returns to production are higher in better states of the world. Therefore, higher cost of debt precommits the firm to a more aggressive stance in the output 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

⁷ 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.

that $\Delta r_k \equiv r_k^{common} - r_k^{separate} < 0$.

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).

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 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 the reduction in loan rates offered by common lenders should be more emphasized in industries in which firms compete in strategic substitutes rather than complements.

Empirically, 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 1: *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 strategic substitutes.*

This explains firms' output decisions and, thus, markups in an industry. In particular, in Poitevin (1989), lower loan rates charged by common lenders lead to less competitive output. 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.

According to Poitevin (1989), this outcome is optimal from both the common lender's and the borrowers' point of view. We test whether it is optimal for firms to contract with a common lender (which we approximate by means of banks with high market shares in a given industry) by analyzing their willingness to switch to a high-market-share lender.

The comparison between high-market-share and low-market-share lenders in the data reflects the comparison between a common lender vs. separate lenders in the model. Firms evaluate the difference in expected profits from borrowing from the same vs. another (i.e., their incumbent) lender. This will be a function of the corresponding difference in interest rates charged, Δr_k , so firms are more likely to switch to a high-market-share lender (from a low-market-share lender) if the resulting cost of debt is subsequently reduced more.

As argued above, the spread between the interest rate charged by a common lender vs. separate lenders is an increasing function of the potential externalities of a higher interest rate. The greater the potential externalities, the lower the loan rate charged by a common lender. The scope for internalizing externalities this way is larger when firms compete in strategic substitutes rather than complements. Therefore, we hypothesize:

Hypothesis 2: *When given the opportunity to switch lenders, firms are more likely to switch to high-market share lenders in their respective industries, and especially so if firms compete in strategic substitutes.*

3.2 Data and Empirical Strategy

We next turn to devising an empirical strategy for testing Hypothesis 1. 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-time ijt panel is 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 .

Banks' market shares are a proxy for the likelihood that any two firms in a given 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. To capture this empirically, we use our explanatory variable $Market\ Share_{ijt-4}$, 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), starting in the year prior to that of quarter t . Our baseline regression specification is:

$$y_{ijt} = \beta Market\ Share_{ijt-4} + \mu_{ij} + \theta_{it} + \psi_{jt} + \epsilon_{ijt}, \quad (2)$$

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 μ_{ij} , θ_{it} , and ψ_{jt} denote bank-industry, industry-quarter, and bank-quarter fixed effects, respectively. Standard errors are clustered at the bank level.

In this setting, industry-period 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-period 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 $Portfolio\ Share_{ijt-4}$ and $Market\ Share_{ijt-4}$ 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 follow Chod and Lyandres (2011) in constructing such a variable. 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:

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

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 value for CSM_k indicates that firms compete in strategic complements, i.e., firm k 's incentives to increase its sales (to maximize its profits) increase in its competitors' sales. A negative value for CSM_k corresponds to competition in strategic substitutes, i.e., firm k 's incentives to increase its sales (to maximize its profits) decrease in its competitors' sales. Thus, we classify industries with a positive (negative) average CSM_k as those in which firms compete in strategic complements (substitutes).

We empirically 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 . We lag CSM_i by one year, i.e., we use CSM_{it-4} in all tests. 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} .

In Panel B of Table 1, we report descriptive statistics at the bank-industry-quarter level. The average (median) bank market share in a given industry is 8% (3%).⁸ The average (median) portfolio share is only 2% (1%). 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

We start by testing Hypothesis 1. The results from estimating (2) are in Table 6. In line with Hypothesis 1, the first column suggests that banks’ higher market shares are associated with significantly lower cost of debt in an industry. We argue that this is due to common lenders’ ability to internalize 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).

[Table 6 here]

To test this, in the second column, we replace banks’ market shares by their portfolio

⁸ These values are above those reported by Giannetti and Saidi (2018). However, in contrast to Giannetti and Saidi (2018), our sample is limited to quarters with non-zero loans granted to industry i by bank j . This restriction is necessary in our setting given that our aim is to analyze (changes) in cost of debt. In our data, loan prices are only observed in quarters with positive issue volume.

shares, i.e., the shares of different industries in banks’ loan portfolios. After doing so, we find a similar quantitative but statistically insignificant effect. In the third column of Table 6, we run a horse race between banks’ market shares and their portfolio shares, and only banks’ higher market shares are significantly linked to lower cost of debt. Notably, 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 the last column where we replace the average all-in-drawn spread as dependent variable by the average usage-weighted spread, as defined in Berg, Saunders, Steffen, and Streititz (2017).⁹

[Table 7 here]

We next test 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. This is because there is greater scope for internalizing externalities of output strategies when firms compete in strategic substitutes. We find this to hold true in Panel A of Table 7 where we dissect our estimate from the third column of Table 6 by the two types of competition. For this purpose, we use the competitive strategy measure (CSM) introduced by Chod and Lyandres (2011), which captures the degree of competitive interaction and the respective sign of the effect of one firm’s output on its competitors’ output decisions.

As can be seen by comparing the second to the third column, the cost of debt charged by high-market-share lenders drops only for strategic substitutes, and with a very similar magnitude as in the first column for the full sample. In terms of economic significance, a

⁹ While the all-in-spread-drawn (AISD) is a reasonable measure for the cost of a term loan, Berg, Saunders, and Steffen (2016) document that the pricing of credit lines is more complex. Most importantly, borrowers do not necessarily have to use the entire loan amount that is committed by the bank, but have the option to draw down the loan. The AISD reflects the payment for the used part of a loan commitment. The all-in-spread-undrawn (AISU) is the spread paid by the borrower on the committed but not used part of the loan commitment. Berg, Saunders, and Steffen (2016) propose to use the “total cost of borrowing” (TCB) as a measure for the total cost of a loan that takes the difference between AISD and AISU as well as other loan-fee components into account. The main drawback of this measure is that it requires matching loan-level data to Compustat data and can, thus, only be estimated for public firms. We follow Berg, Saunders, Steffen, and Streititz (2017), and calculate the usage weighted spread (UWS) as an alternative loan-pricing proxy. This measure is easily computable for our entire loans sample, and also captures the key pricing aspect for lines of credit, i.e., the difference between AISD and AISU.

one-standard-deviation increase in a bank's market share of 0.12 (see Table 1) is associated with a drop in the cost of debt by $0.12 \times 0.22 = 2.64\%$.

Given that we characterize firms in an entire industry as competing in substitutes or complements by means of average values of CSM_{kt-4} , one may wonder to what extent our results are driven by noise, e.g., due to outliers in CSM_{kt-4} within an industry. To address this, in Panel B of Table 7, we require the upper (lower) bound of the 66% or 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).

Comparing the estimates in columns 4 and 6 (columns 5 and 7), the effect of banks' higher market shares on lower cost of debt remains to be confined to strategic substitutes, and the difference in coefficients for strategic substitutes vs. complements widens compared to Panel A.

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 that this is due to the fact that common lenders internalize potential externalities among their borrowers stemming from output effects of higher loan rates. As this is a consequence of banks' maximizing the aggregate debt value of their borrowers, 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 $Market\ Share_{ijt-4}$ 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 8, this is indeed the case, and the effect of banks' market shares on lower loan rates more than doubles for risky industries.

Similarly, high-market-share lenders should be more prone to internalize 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 $Market\ Share_{ijt-4}$ is negative and significant, and carries similar economic significance as the coefficient on the interaction with ROA volatility (column 2).

[Table 8 here]

3.3.2 Bank Mergers as a Source of Variation in Market Shares

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 this potential source of endogeneity underlying banks' market shares, we make use of two alternative identification strategies that exploit plausibly exogenous variation in market shares stemming from bank mergers. Bank mergers are suitable events in our setting. In particular, 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 that mergers are unlikely to occur because of industry-specific developments in this credit market alone.

We start with an intuitive difference-in-differences estimation around bank-merger events. For each bank merger, we construct a 16-quarter event window around the merger m (i.e.,

two years pre and two years post merger). The unit of observation is the bank-merger-quarter level, based on the sample of all completed syndicated loans to industry i in the event window for which the acquiring bank j served as a lead arranger in quarter t . For each event, we define a continuous treatment variable at the industry level, i.e., the increase in the (industry) market share gained by the acquiring bank as a result of the acquisition (calculated using the pre-merger market shares of the target).

The estimation results are reported in Table 9. The estimates in column 1 indicate that controlling for (merger-event) industry fixed effects, acquiring banks increase loan rates following bank mergers. This is consistent with a general increase in bank market power as result of the merger. The effect, however, is significantly weaker for industries with a higher treatment intensity, i.e., for larger market-share gains. In column 2, we additionally include (merger-event) quarter fixed effects to better control for general time trends, and find similar effects. This continues to hold true in column 3 where we replace $\Delta Market Share_{mi}$ by an indicator for any non-zero market-share gain due to a merger.

Finally, in the last two columns, we re-run the same specification as in column 3 for the subsamples of industries in which firms compete in substitutes or complements. In line with our hypothesis, the loan-spread-reducing effect of mergers holds only for firms competing in substitutes (column 4), whereas the corresponding coefficient is neither significant nor negative for firms competing in complements (column 5).

[Table 9 here]

In addition, we present an instrumental-variable methodology in which we make use of bank mergers in a similar fashion as in Section 2.2. In case of a bank merger in $t - 4$, we instrument bank j 's market share in industry i in $t - 4$ by the sum of the two merging banks' historical market shares in industry i starting in quarter $t - 8$, i.e., one year before the merger. Otherwise, our instrument is equal to zero. For the same reasons as those laid out above, we expect the exclusion restriction to hold in the case of our instrument, because we use variation in market shares stemming from syndicated loans in specific industries. Note

that general time-varying conditions at the industry and bank levels (e.g., the merger itself) are captured by industry-time and bank-time fixed effects.

We exploit between-industry variation in market shares within bank mergers, while controlling for the overall effect of the two banks merging itself. In particular, we exploit increases in the merged entity's (surviving bank j) market share in industry i due to the merger. By focusing on (i) recent mergers and (ii) gradual increases in market shares, irrespective of the level of historical market shares of the merging banks, we identify a treatment effect that is unlikely to be due to any pre-merger private information of the merging banks.

The first stage is reported in the first column (third column) of Table 10 for industries in which firms compete in strategic substitutes (complements), and is strong. The estimation results from the second stage are in the second and fourth column, and the estimated coefficient on the instrumented market share of banks is negative and significant solely for firms competing in substitutes (column 2). In sum, these estimates lend further support to a more causal interpretation of banks with higher market shares in industries cutting loan rates as a result of common lenders' internalization of externalities.

[Table 10 here]

Besides ruling out any omitted-variable bias due to endogenous market shares, these more causal estimates also prove useful in addressing concerns of reverse causality. For instance, Valta (2012) shows that concentration in the product market reduces firms' cost of debt. He argues that default risk drops when firms engage in (tacit) collusion, which is subsequently reflected in lower loan spreads. In contrast, our evidence speaks to common lenders enabling higher industry markups through lower cost of debt, rather than industry (tacit) collusion resulting in lower cost of debt, e.g., due to reduced credit risk.

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.¹⁰ In this manner, we find that banks charge lower loan spreads in industries in which they establish larger market shares thanks to mergers with other banks.

4 Inferring Optimality of Common Lenders from Firms' Switching Decisions

We finish our analysis by providing evidence that firms find it optimal to switch to common lenders, enabling them to sustain less competitive outcomes in the product market. To this end, we test whether firms switch to high-market-share lenders, thereby increasing the likelihood of sharing common lenders within an industry, when given the chance to do so.

4.1 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. The staggered state-level banking deregulation wave in the U.S. has been used extensively in the literature, so we only briefly discuss the institutional background here and refer the reader to Rice and Strahan (2010), among others, for an in-depth discussion.

In short, banks had only limited abilities to acquire or open out-of-state branches prior to the passing of the Interstate Banking and Branching Efficiency Act (IBBEA) in 1994, which fully came into effect in 1997. 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

¹⁰ In this regard, our analysis is similar in spirit to Fraisse, Hombert, and Lé (2018).

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.¹¹ As noted above, 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 four, i.e., the most restrictive value, at the beginning of the sample period for all states.¹² The index is then lowered depending on how a state implements potential means to facilitate entry for out-of-state banks.

In our empirical analysis, described in detail below, we use an inverted version of the Rice

¹¹ 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.

¹² 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 $x\%$).

and Strahan (2010) index such that higher index values correspond to less regulated regimes. That is, our index ranges from 0 (highly regulated) to 4 (deregulated). This transformation is simply done to allow for a more natural interpretation of the regression coefficients in our setting, and does not affect our results. 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.

Based on the sample 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 . To characterize a lending relationship, we focus on new syndicated loans with bank j as lead arranger from which firm k did not borrow in the last ten years.

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 . As noted above, we use an index of interstate banking deregulation based on Rice and Strahan (2010) to identify switching opportunities. In our context, the desirability to switch to lender j is a function of its market share in firm k 's industry.

The relaxation of interstate banking barriers opened up the possibility for firms to contract with out-of-state lenders. Hypothesis 2 states that the desirability to switch to an out-of-state lender following a state-level deregulatory shock (in the state in which firm k is incorporated) should be high for out-of-state high-market-share lenders that gained the ability to enter firm k 's geographical market. We capture this empirically by estimating:

$$\begin{aligned}
New\ Rel_{kjt} = & \beta_1 Dereg\ Index_{kt} \times Out-of-State_{kj} \times Market\ Share_{kjt-1} \\
& + \beta_2 Dereg\ Index_{kt} \times Out-of-State_{kj} + \beta_3 Dereg\ Index_{kt} \times Market\ Share_{kjt-1} \\
& + \beta_4 Out-of-State_{kj} \times Market\ Share_{kjt-1} + \beta_5 Market\ Share_{kjt-1} \\
& + \mu_{kj} + \theta_{kt} + \psi_{jt} + \epsilon_{kjt},
\end{aligned} \tag{4}$$

where $New\ Rel_{kjt}$ 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, $Dereg\ Index_{kt}$ is an index of interstate banking deregulation based on Rice and Strahan (2010), which varies at the level of firm k 's state of incorporation over time, $Out-of-State_{kj}$ is a dummy variable indicating bank-firm pairs across different, rather than within the same, states, $Market\ Share_{kjt-1}$ 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 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.

4.2 Results

The results are in Table 11. In column 1, we find that firms are more likely to establish new relationships with out-of-state banks following a deregulatory episode.¹³ Firms are constrained in switching to high-market-share lenders, but do so once this constraint is relaxed.

[Table 11 here]

In the second column, we estimate the full specification (4), and find that this switching effect is indeed even more emphasized for out-of-state banks with large market shares in firm

¹³ 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.

k 's industry. This confirms Hypothesis 2: firms deem it optimal to share a common lender when this gives them the possibility to commit to lower output and to simultaneously profit from cheaper syndicated loans.

Next, we distinguish between firms competing in substitutes and complements. The general 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 rather than complements. This distinction helps us to assess the validity of alternative explanations for our findings. For instance, high-market-share lenders likely have better information about an industry, which could be an important reason for firms switching to them, but this should not be any more or less true for substitutes vs. complements.

To test this, in the last two columns, we split up the sample by firms competing in substitutes (column 3) and complements (column 4). The effect is stronger and significant only for strategic substitutes.

In sum, these estimates suggest that firms' switching behavior is in line with their desire to reap the benefits from contracting with a common lender in their industry so as to profit from lower loan spreads and the possibility to commit to less competitive output decisions.

These results relate to Cetorelli and Strahan (2006), who use the interstate-banking deregulation as a source of variation in bank competition, which they find to increase access to credit for small firms in bank-dependent sectors of production. Our results suggest that the estimates in Cetorelli and Strahan (2006) are actually likely to be understated.

We find that similar banking-deregulatory episodes as in Cetorelli and Strahan (2006), which they justifiedly claim to have increased bank competition, allow firms to switch to lenders with large market shares in their respective industries. This leads to more firms within an industry sharing the same lenders, which allows for lower cost of debt and less competitive output in the product market when the overall concentration in the banking sector increases. In this manner, we do not only reveal firms' preference for sharing the

same lender, but we also point out that even an overall increase in bank competition (due to deregulation allowing firms to switch lenders) has an adverse effect on competition in the product market.

5 Conclusion

In this paper, we show that credit concentration matters for product market competition of non-financial firms. When firms competing in substitutes are more likely to share common lenders, they are charged lower cost of debt and achieve higher industry markups. Our evidence suggests that common lenders serve as a commitment or coordination device for firms' product market decisions.

Our findings warrant the incorporation of product market competition as a policy parameter in the evaluation of real effects of changes in the financial sector. Future research should zoom in on the generalizability of our results.

To characterize lending relationships, we use transaction-level 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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6 Figures

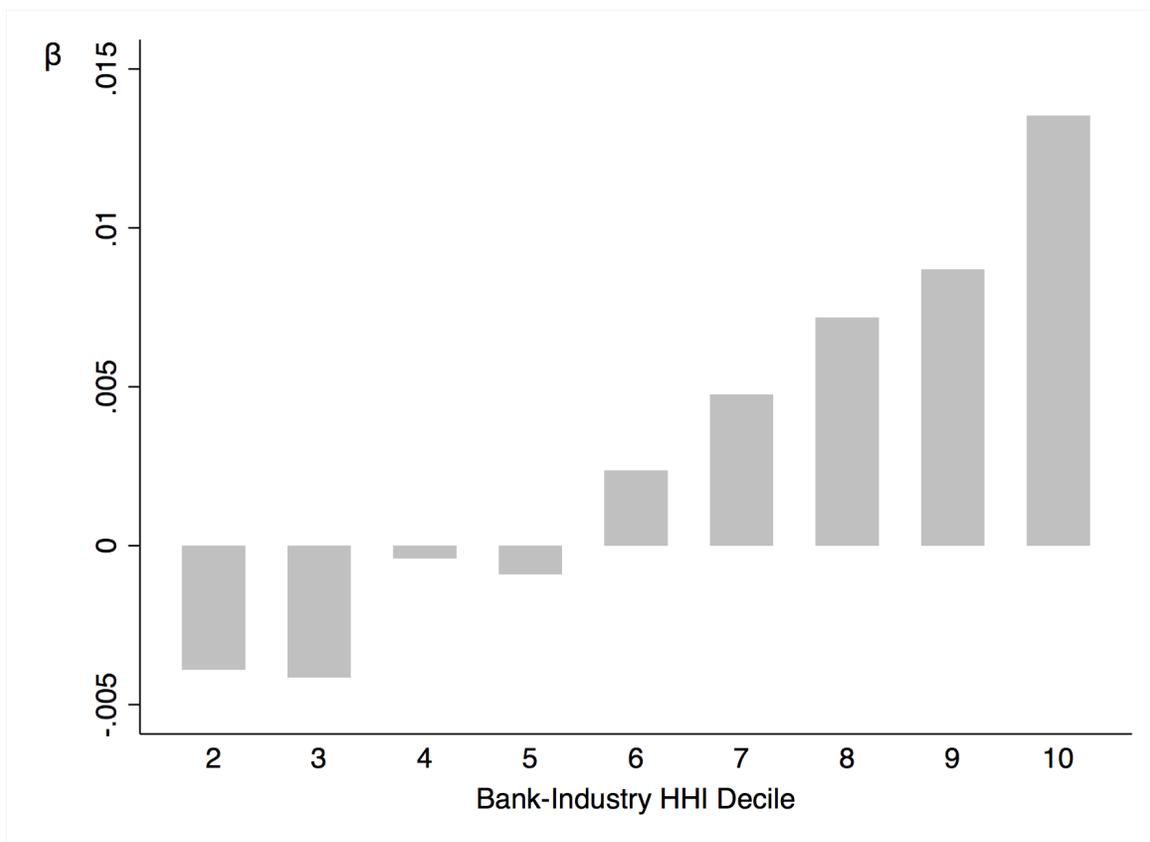


Figure 1: Bank Concentration and Industry Markup

This figure plots the impact of bank concentration on industry markup. Specifically, we plot estimated coefficients from the following regression:

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

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.

7 Tables

Table 1: **Descriptive Statistics**

Panel A reports descriptive statistics on the industry-year level. Panel B reports descriptive statistics on the bank-industry-quarter level. The sample period is 1990 to 2015.

	Min	Median	Max	Mean	Std. Dev	Obs.
Panel A: Industry-year level						
Industry Markup	-0.00	0.29	0.76	0.31	0.14	4,937
Industry Markup (median)	-2.31	0.30	0.91	0.31	0.14	4,937
Industry Markup DLW	-0.07	1.11	1.98	1.06	0.50	4,909
Bank-Industry HHI	0.02	0.20	1.00	0.26	0.18	4,937
High Bank-Industry HHI	0.00	0.00	1.00	0.25	0.43	4,937
Industry HHI	0.02	0.29	1.00	0.36	0.26	4,935
ln(1 + # Firms in Industry)	0.00	2.30	6.91	2.38	1.22	4,935
Industry Output	59.36	110.23	268.50	117.44	32.50	4,878
Panel B: Bank-industry-quarter level						
Spread (in bps)	20.00	225.00	825.00	236.82	143.88	46,676
UWS (in bps)	9.38	130.00	850.00	179.12	155.81	41,852
Market Share	0.00	0.03	1.00	0.08	0.12	46,676
Portfolio Share	0.00	0.01	1.00	0.02	0.05	46,676

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 5 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). In columns 6 to 7, $Industry Markup (median)_{it}$ is the median firm markup in the industry-year. Industries are defined based on three-digit SIC codes. In columns 8 to 9, the dependent variable is $Industry Output_{it}$, i.e., the BEA chain-type quantity index for gross output by industry (the index is equal to 100 in the reference year 2009). 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 the most disaggregated BEA industry definition (403 industries), converted to three-digit SIC code industries. The sample period is 1997 to 2015. $Bank-Industry HHI_{it-1}$ measures the credit concentration in industry i in period t , 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. $Industry HHI_{it-1}$ measures the concentration in industry i in period t , and is defined as the sum of the firms' squared sales-based market shares. $\ln(1 + \# Firms in Industry)_{it-1}$ is the (log) number of firms in the industry. 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	Industry Markup	Industry Markup	Industry Markup	Industry Markup
	(1)	(2)	(3)	(4)	(5)
Bank-Industry HHI	0.031** (0.014)	0.031** (0.014)	0.030** (0.014)		
High Bank-Industry HHI (0/1)				0.009** (0.004)	0.009** (0.004)
Industry HHI		-0.008 (0.018)		-0.008 (0.018)	
$\ln(1 + \# Firms in Industry)$			-0.003 (0.007)		-0.003 (0.007)
Year FE	Yes	Yes	Yes	Yes	Yes
Three-digit SIC Code FE	Yes	Yes	Yes	Yes	Yes
Observations	4,937	4,935	4,935	4,935	4,935
Variable:	Industry Markup (median)	Industry Markup (median)	Industry Output (BEA)	Industry Output (BEA)	
	(6)	(7)	(8)	(9)	
Bank-Industry HHI	0.032* (0.017)		-16.966*** (5.255)		
High Bank-Industry HHI (0/1)		0.011* (0.006)		-5.967*** (1.973)	
Industry HHI					
$\ln(1 + \# Firms in Industry)$	-0.006 (0.010)	-0.007 (0.010)			
Year FE	Yes	Yes	Yes	Yes	
Three-digit SIC Code FE	Yes	Yes	Yes	Yes	
Observations	4,937	4,935	4,878	4,878	

Table 3: **Bank Concentration and Industry Markup – De Loecker and Warzynski (2012) Estimation**

The unit of observation is the industry-year level it . The sample period is 1990 to 2015. The dependent variable is *Industry Markup DLW* $_{it}$, i.e., the average markup by industry-year estimated following De Loecker and Warzynski (2012) and De Loecker and Eeckhout (2017). Industries are defined based on three-digit SIC codes. The sample period is 1990 to 2015. *Bank-Industry HHI* $_{it-1}$ measures the credit concentration in industry i in period t , 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 HHI* $_{it-1}$ measures the concentration in industry i in period t , and is defined as the sum of the firms' squared sales-based market shares. $\ln(1 + \# \text{ Firms in Industry})_{it-1}$ is the (log) number of firms in the industry. 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 DLW				
	(1)	(2)	(3)	(4)	(5)
Bank-Industry HHI	0.058** (0.028)	0.058** (0.028)	0.057** (0.028)		
High Bank-Industry HHI (0/1)				0.021** (0.010)	0.021** (0.010)
Industry HHI		-0.003 (0.037)		-0.002 (0.037)	
$\ln(1 + \# \text{ Firms in Industry})$			-0.004 (0.014)		-0.005 (0.014)
Year FE	Yes	Yes	Yes	Yes	Yes
Three-digit SIC Code FE	Yes	Yes	Yes	Yes	Yes
Observations	4,909	4,909	4,909	4,909	4,909

Table 4: **Bank Concentration and Industry Markup – Syndicated-loan Usage**

The unit of observation is the industry-year level it . The sample period is 1990 to 2015. The dependent variable in column 1 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). The dependent variable in column 2 is *Industry Markup DLW* $_{it}$, i.e., the average markup by industry-year estimated following De Loecker and Warzynski (2012) and De Loecker and Eeckhout (2017). Industries are defined based on three-digit SIC codes. *Bank-Industry HHI* $_{it-1}$ measures the credit concentration in industry i in period t , 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 $t - 5$. *Syndicated-loan Usage* $_{it-1}$ is defined as the total number of firms in industry i 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 $t - 1$. *Industry HHI* $_{it-1}$ measures the concentration in industry i in period t , and is defined as the sum of the firms' squared sales-based market shares. 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 (1)	Industry Markup DLW (2)
Bank-Industry HHI \times Synd. Usage	0.042** (0.016)	0.060** (0.024)
Bank-Industry HHI	-0.002 (0.020)	0.004 (0.036)
Syndicated-loan Usage	-0.015** (0.006)	-0.031*** (0.010)
Industry HHI	-0.009 (0.019)	0.015 (0.038)
Year FE	Yes	Yes
Three-digit SIC Code FE	Yes	Yes
Observations	4,881	4,856

Table 5: **Bank Concentration and Industry Markup – IV Estimates**

The unit of observation is the industry-year level it . The sample period is 1990 to 2015. The sample comprises only banks that merged with at least one other bank anytime during the sample period. The first-stage regression is given in column 1. *Merger-implied Bank-Industry HHI* $_{it-1}$ is defined as the sum of the squared merger-implied market shares, i.e., *Merger-implied Market Share* $_{ijt-2}$. *Merger-implied Market Share* $_{ijt-2}$ is equal to the sum of the two merging banks' market shares in industry i in the last year before a merger in $t-1$. Bank market shares are measured over the last five years. The dependent variable in the second stage 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). Markup is calculated based on Compustat data. Industries are defined based on three-digit SIC codes. *Industry HHI* $_{it-1}$ measures the concentration in industry i in period t , and is defined as the sum of the firms' squared sales-based market shares. Robust standard errors, clustered at the industry level, are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Variable:	Bank-Industry HHI	Industry Markup
	(1)	(2)
Bank-Industry HHI (instrumented)		0.247*
		(0.151)
Merger-implied Bank-Industry HHI	0.116***	
	(0.039)	
Industry HHI	0.111**	-0.032
	(0.044)	(0.031)
Year FE	Yes	Yes
Three-digit SIC Code FE	Yes	Yes
F-statistic	6.62	
Observations	4,256	4,256

Table 6: **Bank 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 in columns 1 to 3 is the logged average all-in-drawn spread of all loans granted to industry i by bank j in period t . The dependent variable in column 4 is the logged average usage weighted spread (UWS). The UWS is defined following Berg, Saunders, Steffen, and Streit (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 Streit (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 term loans or lines of credit, are removed in column 4. $Market Share_{ijt-4}$ 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 $t-23$. 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) (1)	ln(Spread) (2)	ln(Spread) (3)	ln(UWS(25%)) (4)
Market Share	-0.169** (0.075)		-0.176** (0.081)	-0.260** (0.105)
Portfolio Share		-0.016 (0.147)	0.072 (0.158)	0.036 (0.245)
Bank-quarter FE	Yes	Yes	Yes	Yes
Industry-quarter FE	Yes	Yes	Yes	Yes
Bank-industry FE	Yes	Yes	Yes	Yes
Observations	46,676	46,676	46,676	40,317

Table 7: **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 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 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 $t-23$. $Portfolio\ Share_{ijt-4}$ 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 $t-23$. In column 2 (3), the sample is restricted to industries with competition in strategic substitutes (complements). The strategic substitutes (complements) sample refers to all industry-quarters with negative (positive) average CSM_{kt-4} . 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). Robustness tests are reported in Panel B. Here, the strategic substitutes (complements) sample refers to all industry-quarters in which the upper (lower) bound of the 66% or 70% confidence interval for CSM_{kt-4} is negative (positive). Robust standard errors, clustered at the bank level, are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Panel A: Baseline results				
Variable:	ln(Spread)	ln(Spread)		ln(Spread)
		Type of competition		
		Strategic Substitutes	Strategic Complements	
	(1)	(2)	(3)	
Market Share	-0.176** (0.081)	-0.223*** (0.073)	-0.093 (0.148)	
Portfolio Share	0.072 (0.158)	0.299 (0.234)	0.326 (0.340)	
Bank-quarter FE	Yes	Yes	Yes	
Industry-quarter FE	Yes	Yes	Yes	
Bank-industry FE	Yes	Yes	Yes	
Observations	46,676	20,915	18,617	
Panel B: Robustness				
Variable:	ln(Spread)	ln(Spread)		ln(Spread)
		Type of competition		
		Strategic Substitutes	Strategic Complements	
Confidence Interval:	66%	70%	66%	70%
	(4)	(5)	(6)	(7)
Market Share	-0.347** (0.148)	-0.350** (0.144)	0.166 (0.140)	0.248 (0.174)
Portfolio Share	0.658 (0.471)	0.652 (0.575)	-0.387 (0.700)	-0.271 (0.634)
Bank-quarter FE	Yes	Yes	Yes	Yes
Industry-quarter FE	Yes	Yes	Yes	Yes
Bank-industry FE	Yes	Yes	Yes	Yes
Observations	6,722	6,177	5,565	5,008

Table 8: **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 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 $t-23$. $High\ ROA\ Vola_{it-4}$ equals one if $ROA\ Vola_{it-4}$ is in the fourth quartile of the distribution, and zero otherwise. $ROA\ Vola_{it-4}$ is measured over 8 quarters from $t-4$ to $t-11$, where ROA is defined as operating income scaled by total assets. $Low\ Coverage_{it-4}$ equals one if $Coverage_{it-4}$ is in the first quartile of the distribution, and zero otherwise. $Coverage_{it-4}$ is defined as pre-tax income plus interest expenses scaled by interest expenses. 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)	ln(Spread)
	(1)	(2)
Market Share \times High ROA Vola (0/1)	-0.175** (0.068)	
Market Share \times Low Coverage (1/0)		-0.223*** (0.072)
Market Share	-0.151** (0.070)	-0.143** (0.060)
Bank-quarter FE	Yes	Yes
Industry-quarter FE	Yes	Yes
Bank-industry FE	Yes	Yes
Observations	44,573	44,512

Table 9: **Bank Market Share and Cost of Debt – Evidence from Bank Mergers**

This table analyzes the cost of debt around bank-merger events. For each bank merger m , we consider an eight-quarter window prior to the merger (pre-merger window) and an eight-quarter window after the merger (post-merger window), excluding the merger year itself. The unit of observation is the merger-industry-quarter level mit , based on the sample of all completed syndicated loans to industry i in the 16-quarter window around the merger event m for which the acquiring bank served as a lead arranger in quarter t . The sample is limited to quarters with non-zero loans granted to industry i by the acquiring bank. The dependent variable is the logged average all-in-drawn spread of all loans granted to industry i by the acquiring bank in period t . $Post_t$ equals one in the post-merger window, and zero in the pre-merger window. $\Delta Market Share_{mi}$ is the increase in industry market share gained by the acquiring bank through the acquisition. In particular, it is defined as the pre-merger (last year before the merger) market share of the target bank in industry i . $\Delta Market Share > 0_{mi}$ is a dummy variable that equals one if $\Delta Market Share_{mi}$ is positive, and zero otherwise. In column 4 (5), the sample is restricted to industries with competition in strategic substitutes (complements). The strategic substitutes (complements) sample refers to all industry-quarters with negative (positive) average CSM_{kt} in the last year before the merger. 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). 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)	ln(Spread)	ln(Spread)	ln(Spread)	
				Type of competition	
				Strategic Substitutes	Strategic Complements
	(1)	(2)	(3)	(4)	(5)
Post \times Δ Market Share	-1.021* (0.526)	-0.535** (0.234)			
Post \times Δ Market Share > 0			-0.036** (0.015)	-0.070* (0.034)	0.014 (0.017)
Post	0.180*** (0.056)				
Merger-industry FE	Yes	Yes	Yes	Yes	Yes
Merger-period FE	No	Yes	Yes	Yes	Yes
Observations	11,079	11,050	11,050	5,745	4,522

Table 10: **Bank Industry 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 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 sample comprises only banks that merged with at least one another bank anytime during the sample period. The first-stage regressions are given in columns 1 and 3. *Merger-implied Market Share* $_{ijt-2}$ is equal to the sum of the two merging banks' market shares in industry i starting in period $t-2$, which is when a merger between bank j and another bank is completed. The dependent variable in the second stages (columns 2 and 4) is the logged average all-in-drawn spread of all loans granted to industry i by bank j in period t . *Market Share* $_{ijt-1}$ 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 $t-5$ to $t-4$. We instrument this variable by *Merger-implied Market Share*. In columns 1 and 2 (3 and 4), the sample is restricted to industries with competition in strategic substitutes (complements). The strategic substitutes (complements) sample refers to all industry-quarters with negative (positive) average CSM_{kt-4} . 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). 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	ln(Spread)	Market Share	ln(Spread)
	Type of competition			
	Strategic Substitutes	Strategic Substitutes	Strategic Complements	Strategic Complements
	(1)	(2)	(3)	(4)
Merger-implied market share	0.431*** (0.044)		0.373*** (0.030)	
Market Share (instrumented)		-0.669** (0.294)		0.854 (0.584)
Bank-quarter FE	Yes	Yes	Yes	Yes
Industry-quarter FE	Yes	Yes	Yes	Yes
Bank-industry FE	Yes	Yes	Yes	Yes
F-statistic	96.57		153.70	
Observations	20,310	20,310	17,990	17,990

Table 11: **Bank Deregulation and Firms' Switching Lenders**

The unit of observation is the bank-firm-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 correspond 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 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 pairs 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). 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		New Rel	
	(1)	(2)	Type of competition	
			Strategic Substitutes	Strategic Complements
	(1)	(2)	(3)	(4)
Dereg Index x Out-of-State (0/1) x Market Share (ex firm k)		0.048** (0.021)	0.078*** (0.027)	0.007 (0.051)
Dereg Index x Out-of-State (0/1)	0.009*** (0.002)	0.008*** (0.002)	0.005* (0.003)	0.011*** (0.004)
Dereg Index x Market Share (ex firm k)		-0.047** (0.020)	-0.072*** (0.027)	-0.029 (0.050)
Out-of-State (0/1) x Market Share (ex firm k)		-0.097* (0.057)	-0.161** (0.073)	-0.004 (0.147)
Market Share (ex firm k)		0.091* (0.055)	0.155** (0.071)	0.053 (0.145)
Firm-period FE	Yes	Yes	Yes	Yes
Bank-period FE	Yes	Yes	Yes	Yes
Bank-firm FE	Yes	Yes	Yes	Yes
Observations	219,495	219,042	130,470	73,948

A Markup Estimation

This section briefly outlines the markup estimation methodology proposed by De Loecker and Warzynski (2012), DLW henceforth, and De Loecker and Eeckhout (2017). We refer the reader to these papers for an in-depth discussion. The description and notation closely follow De Loecker and Eeckhout (2017).

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 $Q(\cdot)$ that transforms inputs into output:

$$Q(\Omega_{it}, V_{it}, K_{it}) = \Omega_{it} F_t(V_{it}, K_{it}), \quad (\text{A.1})$$

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:

$$\mu_{it} = \theta_{it}^V \frac{P_{it} Q_{it}}{P_{it}^{V_j} V_{it}^j}, \quad (\text{A.2})$$

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.¹⁴ The output elasticity of input has to be estimated. De Loecker and Eeckhout (2017) consider an industry-specific Cobb-Douglas production function with variable inputs and capital:

$$q_{it} = \beta_v v_{it} + \beta_k k_{it} + w_{it} + \varepsilon_{it}, \quad (\text{A.3})$$

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 $w_{it} = h(v_{it}, k_{it})$. Estimation proceeds in two stages. In the first stage, measurement error and unanticipated shocks to sales are purged using

$$q_{it} = \phi_{it}(v_{it}, k_{it}) + \varepsilon_{it}, \quad (\text{A.4})$$

where $\phi = \beta_v v_{it} + \beta_k k_{it} + h(v_{it}, k_{it})$. Productivity is assumed to follow an $AR(1)$ process, $w_{it} = \rho w_{it-1} + \xi_{it}$, giving rise to the moment condition used to obtain the industry-specific output elasticity:

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

where $\xi_{it}(\beta_v)$ is obtained, given β_v , by projecting productivity $w_{it}(\beta_v)$ on its lag $w_{it-1}(\beta_v)$. 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

¹⁴ A breakdown into the different variable-cost positions is not readily available in Compustat, so the reported total cost of production is used.

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).