Rising Markups in the Banking Industry

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Abstract

The Industrial Organization literature has traditionally examined market power in specific contexts and timeframes, with limited focus on its evolution over time. While rising markups have been documented in industries such as cereals, cement, and airlines, empirical research on credit markets remains scarce. This study addresses this gap by estimating markups in the Chilean credit market using confidential loan-level data from 2013 to 2019. We develop a structural model that incorporates borrowers' bank choice, loan size, and repayment probability to estimate demand elasticities, marginal costs, and markups. Our findings reveal a 9% increase in market power over the sample period, with larger firms facing markups approximately 17% higher than smaller firms. Additionally, marginal costs decreased by 11%, while firms' price sensitivity declined by 13%. These results highlight the interplay between market concentration, price elasticity, and financial stability, offering valuable insights for policymakers and stakeholders in the banking industry.

1 Introduction

The concept of market power is fundamental to the field of Industrial Organization (IO), with markups serving as a key variable for assessing market power. While the IO literature has traditionally focused on specific situations and moments in time, there is a growing body of evidence documenting rising markups in various industries such as cereals, cement, and airlines (DeLoecker et al., 2020; Döpper et al., 2024; Bet, 2021; Miller et al., 2023). However, there remains a notable gap in the empirical literature regarding the evolution of markups in credit markets.

Studying markups is crucial because higher market power can negatively impact consumer surplus and increase the likelihood of collusion. Conversely, lower market power can lead to reduced prices, greater innovation in financial products, and enhanced financial stability (Repullo, 2004).

This study contributes to closing this gap by examining the evolution of markups in the Chilean credit market. Unlike existing literature, which often overlooks first-degree price discrimination, our study focuses on a market where such type of pricing is prevalent. Using confidential bank data at the loan level from 2013 to 2019, we estimate the demand and supply for commercial loans. This unique dataset allows us to link credit information with firm and bank characteristics, enabling us to identify the prices charged to each firm by the lending bank.

Our structural model incorporates firms' bank choices, loan sizes, and repayment probabilities. On the demand side, we estimate how firms select banks and determine loan amounts, while on the supply side, we assume banks engage in Nash-Bertrand competition with first-degree price discrimination. This approach allows us to estimate demand elasticities, marginal costs, and markups.

Our findings reveal a 9% increase in market power over the sample period, with larger firms facing markups approximately 17% higher than smaller firms. Additionally, marginal costs decreased by 11%, while firms' price sensitivity declined by 13%. These results highlight the interplay between market concentration, price elasticity, and financial stability.

Notably, markup increases coincided with merger events in April 2016 and August 2018, and we observed significant heterogeneity in markup changes across bank sizes, firm sizes, and even within individual banks.

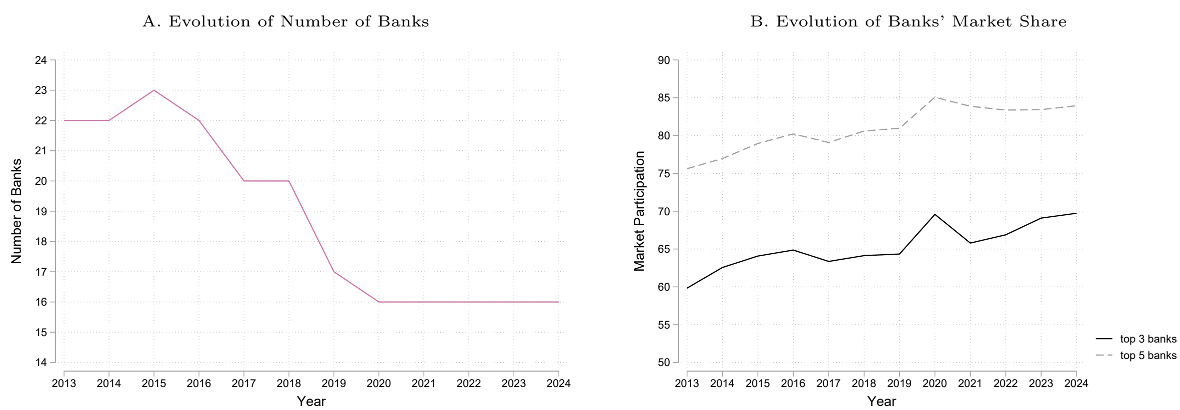
The observed increase in market power can be attributed to several potential mechanisms. First, the mergers that occurred during the sample period likely contributed to higher market concentration, enabling banks to exert greater pricing power. Second, the decline in marginal costs may have allowed banks to maintain or increase markups without significantly raising prices, as cost reductions were not fully passed on to consumers. Third, the observed decline in firms' price sensitivity suggests that borrowers may have faced fewer competitive alternatives or higher switching costs, further reinforcing banks' ability to set higher markups. These mechanisms underscore the complex dynamics between market structure, cost efficiency, and consumer behavior in shaping market outcomes.

These findings provide valuable insights for policymakers and stakeholders in the banking industry, emphasizing the need to balance market concentration and financial stability while fostering competition and innovation in credit markets.

2 The Chilean Banking Industry

The Chilean banking industry is characterized by high and increasing market concentration. In 2024, only 16 banks were active in the market, with six of them accounting for 90% of total loans. Furthermore, the market share of the three largest banks has been steadily rising over the past decade.

Figure 1: Chilean Banking Industry Throughout the Years

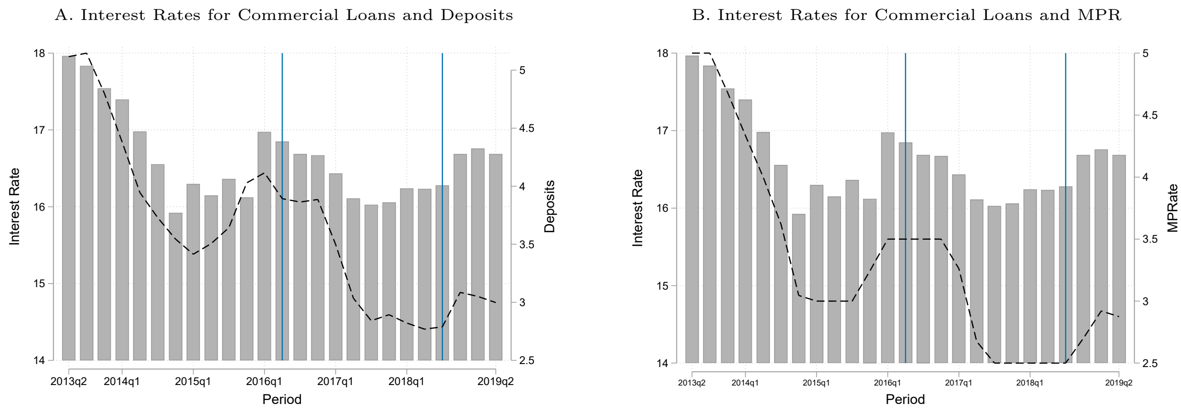


During the sample period, the market experienced significant fluctuations, including the exit of six banks, the entry of two new ones, and two bank mergers. For a merger between two banks to occur in Chile, the National Economic Prosecutor's Office (FNE) acts as the regulatory body to evaluate whether the operation violates free competition laws. Additionally, the integration must be approved by the Financial Market Commission, which oversees the stability and transparency of the financial sector.

Over the past decade, three mergers have been approved, and they have contributed to the increasing concentration of the market, potentially affecting competition, pricing, and consumer choice.

The credit market in Chile presents a significant interest rate margin, with lending rates and deposit rates not fluctuating together comparatively. This disparity may be attributed to changes in the risk profiles of credit portfolios, elevated operational costs, or the degree of competition within the market. Figure 2 illustrates the variation in both rates over the sample period. Notably, funding rates have decreased by nearly 67%, whereas lending rates have only declined by 8%.

Figure 2: Lending Rates and Funding Rates Over Time



3 Data

We utilize several administrative datasets provided by Chilean institutions, including the Financial Market Commission (CMF), the Superintendency of Pensions (SP), and Chile's tax authority (SII). These datasets allow us to merge loan information, with individual data from firms and banks.

From the CMF, we first use loan-level information, which includes bank ID, firm ID, operation date, and loan characteristics such as interest rate, type of interest rate (fixed or variable), loan amount, term, loan type (e.g., installment loan, consumption credit, mortgage credit, lines of credit, leasing, or factoring), and loan currency. Additionally, we use information on the prices of various financial products, such as deposits, consumer credits or others, at bank-period level. We also utilize cumulative debt data provided by the CMF, which includes historical debt information and default data at the firm-period level, enabling us to construct repayment profiles one year ahead of the contracted loan.

Firm and bank characteristics are derived from employer-employee records in the Unemployment Insurance database provided by the Superintendency of Pensions (SP). This includes the total number of workers, the number of workers affiliated with the Unemployment Insurance, firm municipality, and industry classification. From Chile's tax authority, we obtain sales information for firms.

The sample consists of quarterly data from the second quarter of 2013 to the second quarter of 2019, focusing on contracted loans by productive firms. This excludes firms from the financial, educational, health, and public sectors. The sample specifically includes loans for first-time borrowers only, which we clean using credit history data from 2009 until our sample period. The banks involved are financial institutions that are open to taking deposits, and we only use installment loans denominated in Chilean Pesos (CLP$) with fixed interest rates.

Our sample comprises 27,936 firms, of which 26,332 are borrowing firms (Figure 1). We only consider the first credit contracted by each firm during the sample period, after which the firm is excluded from our dataset. Over a total of 25 periods, we have 12 banks lending in at least one quarter. The commercial loans we are considering have an average amount of 51.61 million CLP (approximately 53.2 thousand USD), last on average 21.6 months and have an average interest rate of 16.91.

Table 1: Descriptive Statistics

	obs	mean	s.d.	min	p25	p50	p75	max
FIRMS								
age	27,936	9.79	6.06	1.00	5.00	9.00	14.00	25.00
periods active	27,936	8.90	5.93	0.00	4.00	8.00	13.00	25.00
ever a loan	27,936	0.94	0.23	0.00	1.00	1.00	1.00	1.00
BORROWING FIRMS								
repayment	26,332	0.88	0.32	0.00	1.00	1.00	1.00	1.00
# employees (UI)	26,332	12.67	55.67	1.00	2.00	4.00	10.00	3,668.00
LOANS								
amount (CLP)	26,332	51.61	505.07	0.00	5.60	15.28	35.50	60,000.00
term	26,332	21.60	20.03	0.03	6.03	18.27	36.37	242.30
interest rate	26,332	16.91	7.74	0.00	11.75	15.45	19.99	54.65
< 30 days	18,775	17.81	8.48	0.00	12.01	16.35	21.44	54.65
30 - 90 days	7,264	14.90	4.70	0.00	11.62	14.57	17.57	47.30
90 - 180 days	261	9.05	3.14	0.96	7.19	8.09	10.03	25.49
180 days - 1 year	32	8.12	2.28	2.02	7.06	7.83	9.32	13.76
BANKS								
periods active	12	22.17	4.39	13.00	21.00	25.00	25.00	25.00
market share (#)	12	0.09	0.11	0.00	0.01	0.05	0.11	0.31
market share ($)	12	0.09	0.09	0.01	0.02	0.05	0.13	0.29
BANK-PERIOD								
active	300	0.89	0.32	0.00	1.00	1.00	1.00	1.00
# loans	266	98.99	130.92	1.00	11.00	46.00	124.00	631.00
interest rate	266	14.79	6.75	3.66	10.00	13.48	17.01	36.37
PERIOD								
# banks	25	10.64	1.19	8.00	10.00	11.00	12.00	12.00
# loans	25	1,053.28	476.93	257.00	668.00	1,171.00	1,452.00	1,735.00
# active firms	25	9,939.88	2,812.54	2,905.00	8,625.00	10,744.00	12,150.00	12,879.00

4 The Model

We develop a structural model to analyze the demand and supply of commercial loans, to investigate the evolution of market power within the banking industry. Markups, defined as the difference between the price and the marginal cost of a product, are represented in this context by the disparity between the interest rate charged by banks to firms and the marginal cost incurred by banks for providing the loan.

In the literature we can find different methodologies to estimate markups. The accounting approach which relies on information about gross margins of profits[1], the production approach that estimates markups from the producers' cost minimization problem (the approach DeLoecker et al. (2020) "DLEU" implements), and the demand approach that recovers markups using demand elasticities and the first-order condition from the profits maximization problem (used by Nevo (2001); Döpper et al. (2024) and others.

We estimate markups from a demand approach, modeling demand and supply using a structural model. We assume banks follow a Nash-Bertrand competition and maximize profits to determine the optimal interest rates to charge firms. Our model studies not only intensive but also extensive margin while including loan amount demand. Furthermore, this model will help analyze equilibrium outcomes when new mergers are approved or supply shocks occur.

4.1 Bank choice demand

Firms need to finance projects in different moments in time, often resulting in contracting a loan from a bank. In this context, we assume that firm i evaluates each quarter t whether to contract a loan with bank j or to wait for the next quarter to take it.

To model bank choice demand, we consider only one loan at bank-firm level and select the first loan contracted by each firm in our data. We allow firms to have each quarter a different choice set of banks from where it can contract a loan. A bank is considered available for lending in period t if at least one firm contracts a loan from it during that quarter. Consequently, if a bank has no loans in a given period, it is excluded from the firms' choice set for that quarter. The outside option in this model is represented by the firm's decision not to contract choosing not to contract a loan that quarter.

As we only consider first time-borrowers[2], we assume every firm has the opportunity to choose any bank, thereby eliminating the issue of pre-existing relationships between firms and banks.

We define the indirect utility that firm i gets from taking a loan with bank j in period t as:

$$U_{ijt} = \beta_i p_{ijt} + \eta_i X_{jt} + \xi_{jt} + Y_i + \varepsilon_{ijt} \tag{1}$$

where p_{ijt} is the interest rate set by bank j for firm i in quarter t. In this market, banks set different prices for each firm, resulting in first-degree price discrimination. X_{jt} represents observable bank characteristics that vary each quarter, ξ_{jt} denotes bank characteristics that are unobserved by us as econometricians, and $Y_i = \tau\hat{\gamma}_i$ is a firm fixed effect.

In our model, we allow for heterogeneous price sensitivity across firms, as well as firm-specific preferences for bank characteristics. This approach yields consumer-specific coefficients based on

[1] A recent study employing this approach is Karabarbounis and Neiman (2018).

[2] Once we selected the first loan for all firms, we check if there is debt information in a larger dataset that includes data from 2009.

firm characteristics, including sector, size (number of workers), and firm sales, represented by W_i.

$$\beta_i = \beta^1 + \beta^2 W_i$$
$$\eta_i = \eta^1 + \eta^2 W_i$$

The error term ε_{ijt} represents an idiosyncratic taste shock, and we assume $\varepsilon_{ijt} \sim TIEV$, letting us define the probability[3] that firm i takes a loan from bank j in quarter t as:

$$s_{ijt} = \frac{e^{\beta_i p_{ijt} + \eta_i X_{jt} + \xi_{jt} + Y_i}}{1 + \sum_{k=1}^{J} e^{\beta_i p_{ikt} + \eta_i X_{kt} + \xi_{kt} + Y_i}} \tag{2}$$

4.1.1 Price prediction

An important issue we must address is that we only observe interest rates for contracted loans. We do not know the interest rates that other banks would charge to firms that did not chose them, nor the interest rates that each bank would charge to firms that decided not to take a loan during that period. Therefore, we must predict the prices that each firm would face from every bank, every quarter.

Similar to the approach taken by Crawford et al. (2018), we use out-of-sample data, considering every single loan contracted by firms over ten years with the same characteristics as the product we study (installment loans, fixed rate, in CLP). We conclude that the most effective strategy to predict interest rates is using a linear regression model that includes firm and bank-period fixed effects.

$$p_{ijt} \quad = \quad \hat{p}_{jt} + \hat{\gamma}_i + \hat{\epsilon}_{ijt} \tag{3}$$

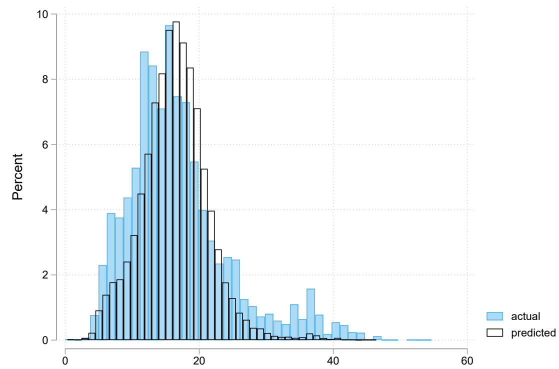
where $\hat{p}_{jt} = \hat{\alpha} + \hat{\omega}_{jt}$, and $\hat{\omega}_{jt}$ is a bank-market fixed effect. In Table 2 and Figure 3, we illustrate the performance of our prediction across the distribution.

Table 2: Actual and Predicted Interest Rates

	mean	sd	min	p1	p10	p25	p50	p75	p90	p99	max
actual	16.91	7.74	0.00	5.03	8.46	11.75	15.45	19.99	26.82	41.01	54.65
predicted	16.39	5.03	0.31	5.37	10.20	13.31	16.34	19.27	22.09	31.25	46.42

[3]This also represents the market share that firm i contributes to bank j in quarter t.

Figure 3: Actual and Predicted Interest Rates Distribution



4.2 Loan amount and repayment

Once we model bank choice demand, we proceed to examine the intensive margin of demand. We assume that firms determine their loan size after deciding to take a loan from a specific bank in a given quarter. This means that we need modeling loan demand conditional on the bank choice demand.

This decision is influenced by the interest rate and firm-specific characteristics related to the amount of funding they require. We represent loan demand as:

$$q_{ijt} = \alpha^q + \beta^q W_i + \lambda^q p_{ijt} + v_{ijt}^q$$

Here, q_{ijt} denotes the loan amount in natural logarithm chosen by firm i from bank j in quarter t. The coefficients α^q, β^q, and λ^q capture the effects of different variables on loan demand. Specifically, W_i represents firm characteristics, p_{ijt} is the interest rate offered by bank j at time t, and v_{ijt}^q is a random error term capturing unobserved factors that may affect the firm's decision.

Our model also considers the firms' probability of repayment one year after contracting a loan. Interest rates are again a very important factor on this decision, we represent the probability of repayment as:

$$R_i = \alpha^R + \beta^R W_i + \lambda^R p_{ijt} + v_{ijt}^R$$

where R_i represents the repayment probability of firm i. W_i again represents firm characteristics, p_{ijt} is the interest rate offered by bank j at time t, and v_{ijt}^R is the error term.

4.3 Supply

Similar to the literature, we assume banks engage in Bertrand-Nash competition when setting interest rates. However, we study a distinct market, where first-degree price discrimination happens, which differs from other studies on the evolution of markups. In studies like Döpper et al. (2024), Atalay et al. (2023), and Brand (2021) with consumer package goods (CPG), Bet (2021) with airlines, or Collard-Wexler and DeLoecker (2015) with steel, price discrimination does not reach the first degree; instead, prices are generally consistent across consumers and time periods.

In contrast, our model allows banks to charge different interest rates to each firm, considering not only observable information available to econometricians but also additional variables that help banks assess firm-specific risk and maximize consumer surplus extraction.

In our model banks maximize profits considering the market share they expect, the loan amount and the probability that firms repay the contracted loans. Banks set interest rates considering the following maximization problem:

$$\max_{p_{ijt}\geq 0} \quad \pi_{ijt} \quad = \quad \sum_{jt}(p_{ijt}R_i - mc_{ijt})s_{ijt}q_{ijt} \tag{4}$$

Solving for the optimal interest rate, we can decompose the interest rate that bank j charges firm i in quarter t the sum of the effective marginal cost and the full markup of the bank j. Notice that the price banks charge to firms, depends on demand elasticities, for bank choice demand, loan demand and also probability of repayment.

$$p_{ijt} = \underbrace{\frac{mc_{ijt}}{R_i + \frac{\frac{\partial R_i}{\partial p_{ijt}}}{\frac{\partial q_{ijt}}{\partial p_{ijt}}\frac{1}{q_{ijt}} + \frac{\partial s_{ijt}}{\partial p_{ijt}}\frac{1}{s_{ijt}}}}}_{\text{effective marginal cost}} + \underbrace{\frac{-1}{\frac{\partial s_{ijt}}{\partial p_{ijt}}\frac{1}{s_{ijt}} + \frac{\partial q_{ijt}}{\partial p_{ijt}}\frac{1}{q_{ijt}} + \frac{\partial R_i}{\partial p_{ijt}}\frac{1}{R_i}}}_{\text{full markup}} \tag{5}$$

5 Estimation

We estimate our model in different parts. First, studying bank choice demand we follow Train (2009) and use a two-step method using maximum likelihood and instrumental variables estimation. Second, with our bank choice demand coefficients and shares, we take care of the endogeneity of choosing loan amount and repayment probability, once the firm took the loan with a bank, correction with a Heckman correction (Dubin and McFadden, 1984).

5.1 Bank choice demand

To estimate bank choice demand, we incorporate our interest rates' prediction (3) on the indirect utility (1), resulting in:

$$U_{ijt} \quad = \quad \lambda\hat{\gamma}_i + \delta_{jt} + \hat{p}_{ijt} \otimes (W_i\beta^2) + X_{jt} \otimes (W_i\eta^2) + \upsilon_{ijt} \tag{6}$$

where $\hat{p}_{ijt} = \hat{\alpha} + \hat{\omega}_{jt} + \hat{\gamma}_i$, $\quad \delta_{jt} = \beta^1 \hat{p}_{jt} + \eta^1 X_{jt} + \xi_{jt}$, $\quad \lambda = \beta^1 + \tau$ and $\upsilon_{ijt} = (\beta^1 + W_i \beta^2) \otimes \hat{\epsilon}_{ijt} + \varepsilon_{ijt} \sim$ TIEV.

Since the demand price parameter, β^1, does not enter the equation (6) except as part of the error term υ_{ijt}. Following Train (2009), we use a two-step method on maximum likelihood and instrumental variables estimation, running equation (6) by ML, and equation (7) by IV in a second-step.

$$\delta_{jt} = \beta^1 \hat{p}_{jt} + \eta^1 X_{jt} + \xi_{jt} \tag{7}$$

One of the main challenges when estimating this model, is taking care of the endogeneity of interest rates. In our case, we conduct an instrumental variable estimation, using as an instrument for $\hat{p_{jt}}$ bank cost shifters, specifically interest rates from deposits at bank-period level.

Once we recover estimates for our model, we can calculate market shares at firm-bank-period level (2) and then calculate price-elasticities for bank choice demand. The own price-elasticity for bank choice demand will be given by:

$$\upsilon^d_{jt} = E\left[\frac{\partial s_{ijt}}{\partial p_{ijt}} \frac{p_{ijt}}{s_{ijt}}\right] = \frac{1}{N} \sum_i \frac{p_{ijt}}{s_{ijt}} (\beta_1 + \beta_2 W_i) s_{ijt} (1 - s_{ijt}) \tag{8}$$

5.2 Loan amount and repayment estimation

For loan demand and repayment estimation, one must consider the problem of endogeneity generated because the firm already decided to take a loan with a specific bank. To solve this issue, we use control functions in the estimation of both.

Using our estimates from bank choice demand and the predicted shares $\hat{s_{ijt}}$, we obtain control functions following (Dubin and McFadden, 1984).

$$cf_{it} \;\; = \;\; \sum_{j \neq i}^{m} \left[\frac{\hat{P}_j ln(\hat{P}_j)}{1 - \hat{P}_j} + ln(\hat{P}_i)\right] \tag{9}$$

where $\hat{P}_j = s_{ijt}$ and $\hat{P}_i$ is s_{ijt} for the selected option by firm i. These control functions are estimated for each firm at quarter level and there will be as many control functions as banks in the choice set for a specific period.

On the other hand, to estimate loan demand and repayment consistently, we instrument the interest rate, since it can share unobservables with both loan amount and repayment, for example how risky the firm can be. In this case, we use a combination of seven different instruments.

First, we consider as a cost shifter variable, the interest rate of deposits, just like the estimation of bank choice demand. But we also include prices of different products for the same bank and quarter, interest rate for consumption credits and mortgages. Second, we include as a quantification of the market itself, the mean of number of workers from other banks in the same period, known as a BLP instrument (Berry et al., 1995). Finally, we include three variables of prices in other markets as instruments, following Nevo (2001) and Hausman (1996) we take into consideration prices that the bank charges in other year, prices in other quarters and prices in other quarters but the same year (a closer market).

Loan demand and repayment probability coefficients will be estimated for each quarter separately using a linear regression for each variable and considering only contracted loans (for whom we have loan amount and true repayment).

$$q_{ij} = \alpha^q + \beta^q W_i + \gamma^q cf_{it} + \lambda^q p_{ij} + v_{ij}^q \tag{10}$$

$$R_{ij} = \alpha^R + \beta^R W_i + \gamma^R cf_{it} + \lambda^R p_{ij} + v_{ij}^R \tag{11}$$

5.3 Supply

In our estimation of supply, we begin by utilizing demand estimates and elasticities from bank choice, loan amount, and repayment behavior. Furthermore, since first-degree discrimination in prices exists, we can compute markups and marginal costs at firm-bank-quarter level.

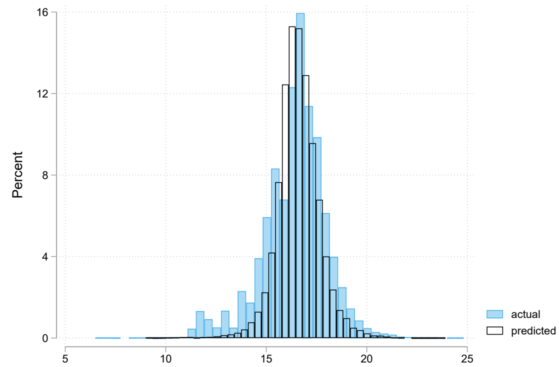
$$p_{ijt} = \frac{mc_{ijt}}{R_i + \frac{\lambda^R}{\frac{\lambda^q}{q_{ijt}} + (\beta^1 + \beta^2 W_i)(1 - s_{ijt})}} + \underbrace{\frac{-1}{\frac{\lambda^q}{q_{ijt}} + (\beta^1 + \beta^2 W_i)(1 - s_{ijt}) + \frac{\lambda^R}{R_i}}}_{\text{full markup}} \tag{12}$$

Notice we will need to predict loan amount and repayment for not contracted loans to study distribution of markups and marginal costs. For loan amount prediction we follow the same strategy as for price prediction in bank choice demand. Not restricting number of loans by firm, we compute firm and bank-period fixed effect, and use both to predict loan amount. In Table 3 and Figure 4 we show how well our prediction behaves along the distribution.

Table 3: Actual and Predicted Loan Amount

	mean	sd	min	p1	p10	p25	p50	p75	p90	p99	max
actual	16.40	1.62	6.50	11.54	14.51	15.54	16.54	17.39	18.17	20.07	24.82
predicted	16.60	1.06	9.00	13.79	15.45	16.00	16.56	17.18	17.83	19.51	23.91

Figure 4: Actual and Predicted Loan Amount Distribution



6 Results

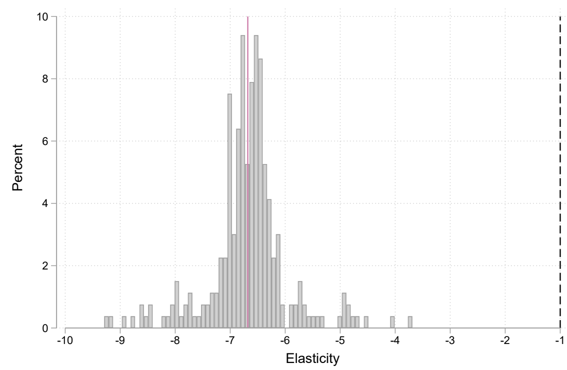
Bank choice estimates are shown in Table 4, firms' sensibility on prices is larger for firms in the retail sector than in other sectors, also is larger for firms with less workers and for firms with no sales registered in our data.

Table 4: Bank Choice Demand Estimates

	coef	std err
interest rate	-0.438	0.086
interest rate × firm size	0.017	0.019
interest rate × manufacturing	0.001	0.005
interest rate × construction	0.000	0.004
interest rate × retail	-0.013	0.003
interest rate × sales 1	0.027	0.007
interest rate × sales 2	0.041	0.007
interest rate × sales 3	0.028	0.007
bank size	0.125	0.027
bank size × firm size	-0.004	0.032
bank size × manufacturing	0.017	0.009
bank size × construction	0.005	0.007
bank size × retail	0.004	0.006
bank size × sales 1	0.137	0.012
bank size × sales 2	0.183	0.011
bank size × sales 3	0.105	0.013
firm size	0.818	0.327
manufacturing	-0.105	0.106
construction	0.051	0.085
retail	0.254	0.071
sales 1	-1.572	0.129
sales 2	-2.251	0.118
sales 3	-1.368	0.132
constant	1.836	1.328

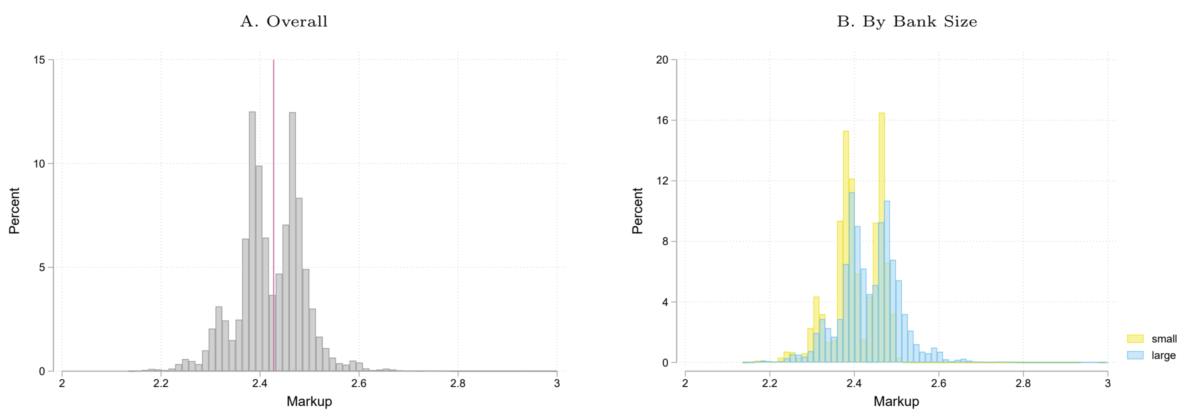
Figure 5 shows that bank choice demand is elastic and that exists heterogeneity across the sample. The elasticity distribution suggests that firms are responsive to changes in interest rates, when a bank charges higher prices they are less likely to choose that bank for a loan. Figure 7 panel A, illustrates the evolution of firms' price elasticity, revealing how firms are becoming less price sensitive during the sample period. This reduction in price-elasticity amounts to a change of 13%. Similar results have been found in other industries, such as in consumer package goods (Döpper et al., 2024; Brand, 2021).

Figure 5: Bank Choice Demand Elasticity



We find that banks' markups have a mean of 2.4 approximately, the distribution seems to be bimodal and also exhibits considerable heterogeneity across the sample. Figure 6 shows how the distribution is slightly different depending on bank size, being larger banks the ones that have bigger markups than smaller ones.

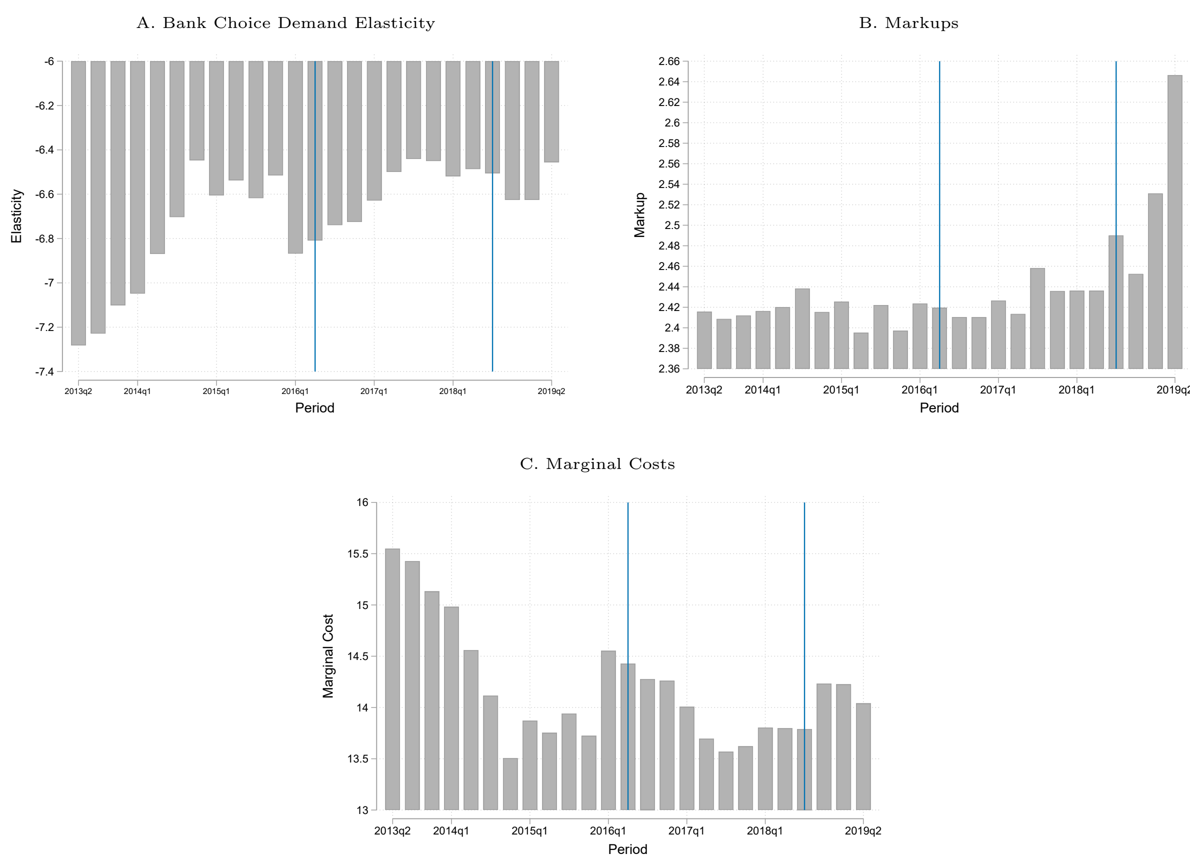
Figure 6: Markup Distribution



Our most significant finding is the increase in markups during our seven-year sample period.

In Figure 7, panel B, reveals that markups remained flat during the first years of the sample, and began to rise following the two mergers that occurred in April 2016 and August 2018 (showed in the figure by the blue lines). Our results show that markups have increased by 8.7% and this change is not uniform across firms or banks. Firms with a larger number of workers face 17% higher markups than smaller firms. Additionally, as Figure 8 demonstrates, some banks have flatter markups over these seven years (panel A and B), while others indicate a steeper increase in their markups (such as panel C and D). Finally, when analyzing banks' marginal costs, we find that they have decreased by 11% during our sample period. However, this reduction is not being passed on to consumers, as markups have been rising.

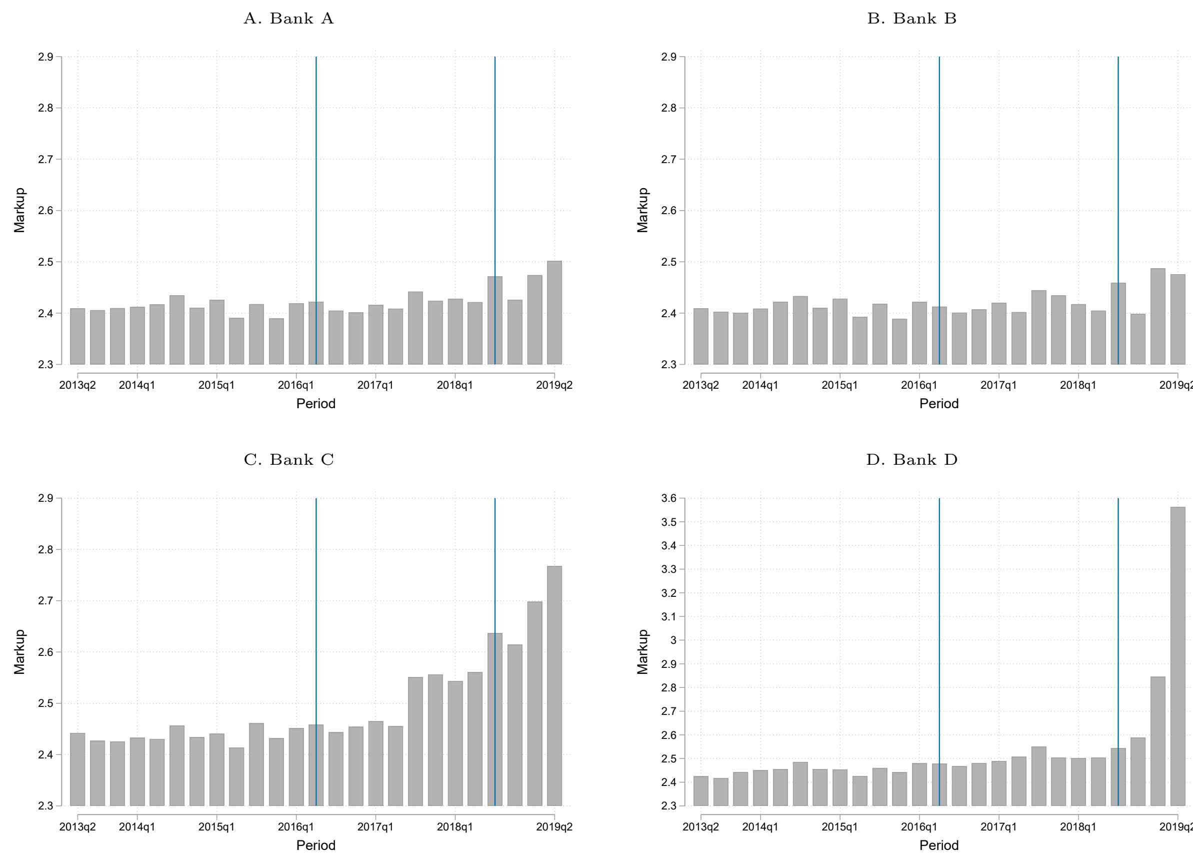
Figure 7: Variables Over Time



Our results go in the same direction as the current literature. In different industries there has been found that markups are increasing over the past decades (DeLoecker et al., 2020; Atalay et al., 2023; Miller et al., 2023; Brand, 2021; Miller et al., 2023). One possible mechanism discussed in the literature is the decrease in the consumers' price sensibility (Döpper et al., 2024; Brand, 2021), which is also shown by our results. In addition, our findings in decreasing marginal costs are also an important factor that can explain part of this increase in market power (Döpper et al., 2024;

Ganapati, 2024). Finally, the market structure of the Chilean banking sector, may be having an important role in the rise of market power. Our results suggest that mergers are drivers of the increasing markups consistent with what Miller et al. (2023) found, they conclude that the main drivers of higher markups are plant closures and mergers.

Figure 8: Markups Over Time, by Bank



7 Conclusions

This study provides new insights into the evolution of market power in the Chilean banking industry by estimating markups using a structural model of demand and supply for commercial loans. Our findings reveal a 12% increase in market power over the sample period, driven by factors such as mergers, declining marginal costs, and reduced price sensitivity among borrowers. Larger firms were found to enjoy significantly higher markups compared to smaller firms, highlighting the uneven distribution of market power across firm sizes.

The results underscore the complex interplay between market concentration, cost efficiency, and borrower behavior. While the evidence suggests that mergers have contributed to higher markups, the reduced elasticity of loan demand suggests that borrowers are becoming less responsive to price changes over time. As a consequence, the cost reductions that have been found are not entirely passed through to consumers in the form of lower interest rates. These dynamics have important implications for competition, financial stability, and consumer welfare in the credit market.

Policymakers should carefully consider the trade-offs between fostering competition and maintaining financial stability when evaluating future mergers or regulatory changes. Encouraging transparency, reducing switching costs, and promoting innovation in financial products could help mitigate the adverse effects of rising market power while ensuring a more competitive and inclusive banking sector.

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A Additional Figures

Figure A.1: Bank Choice Demand Elasticity by Sector

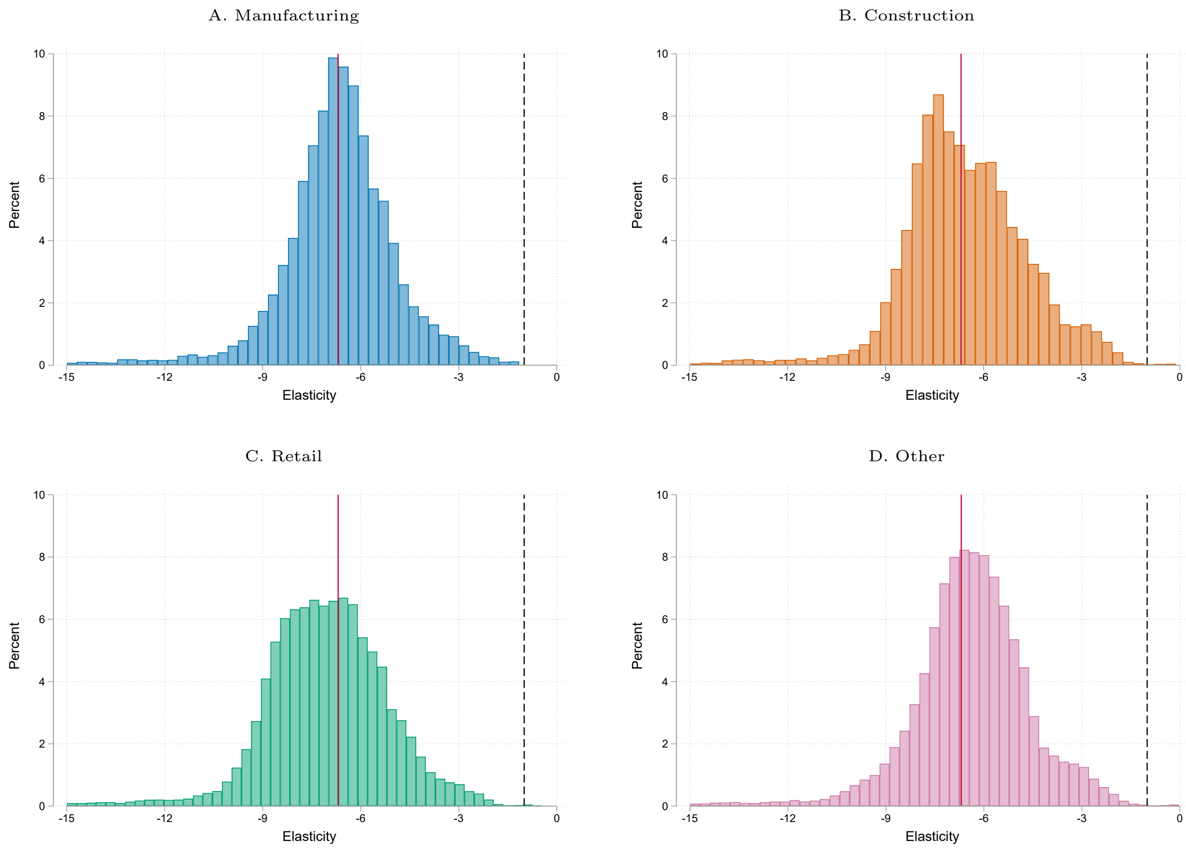


Figure A.2: Bank Choice Demand Elasticity by Sales

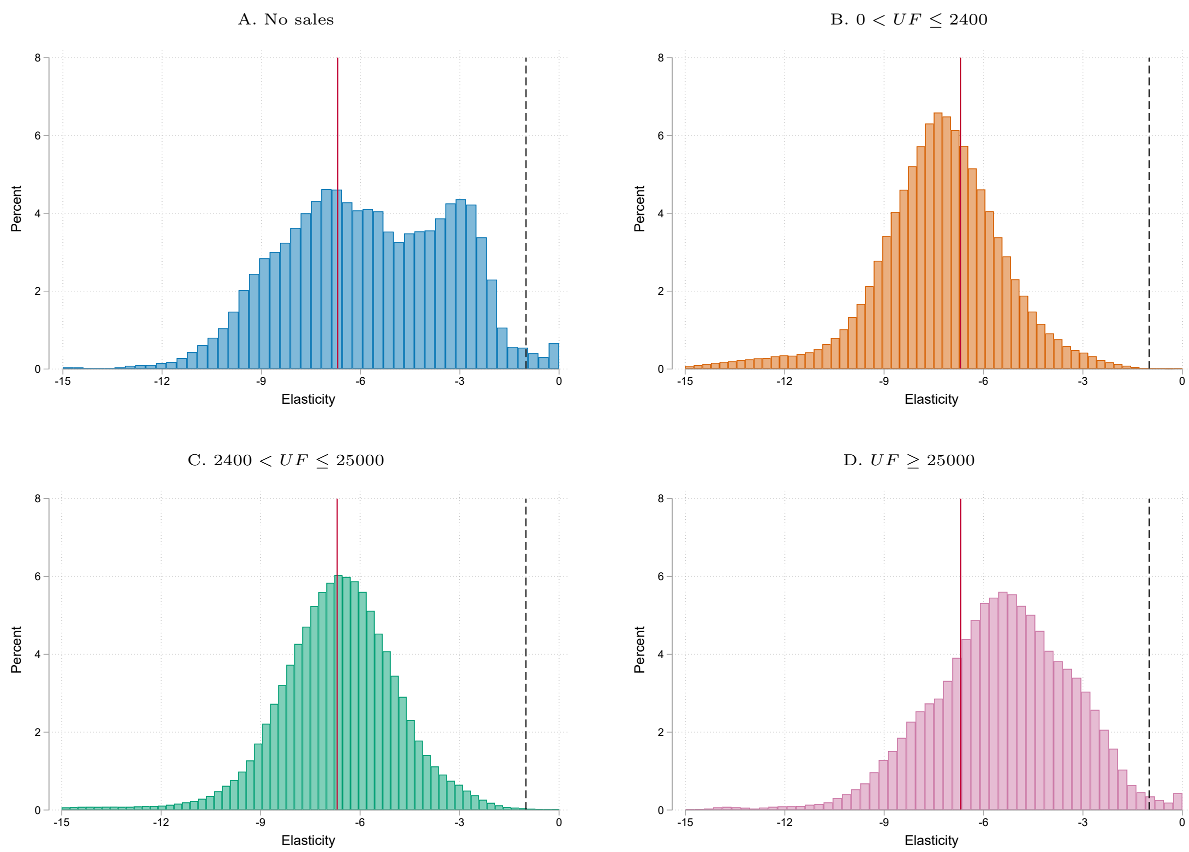


Figure A.3: Markups by Firm Size

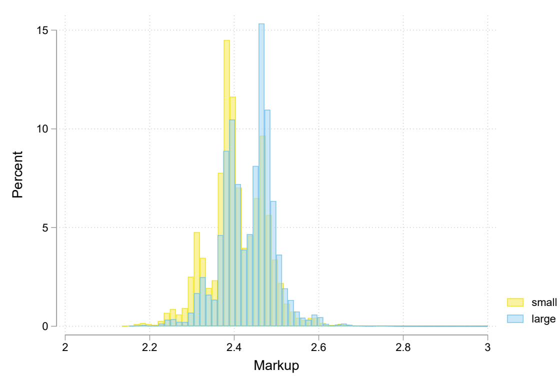


Figure A.4: Markups by Firm Sector

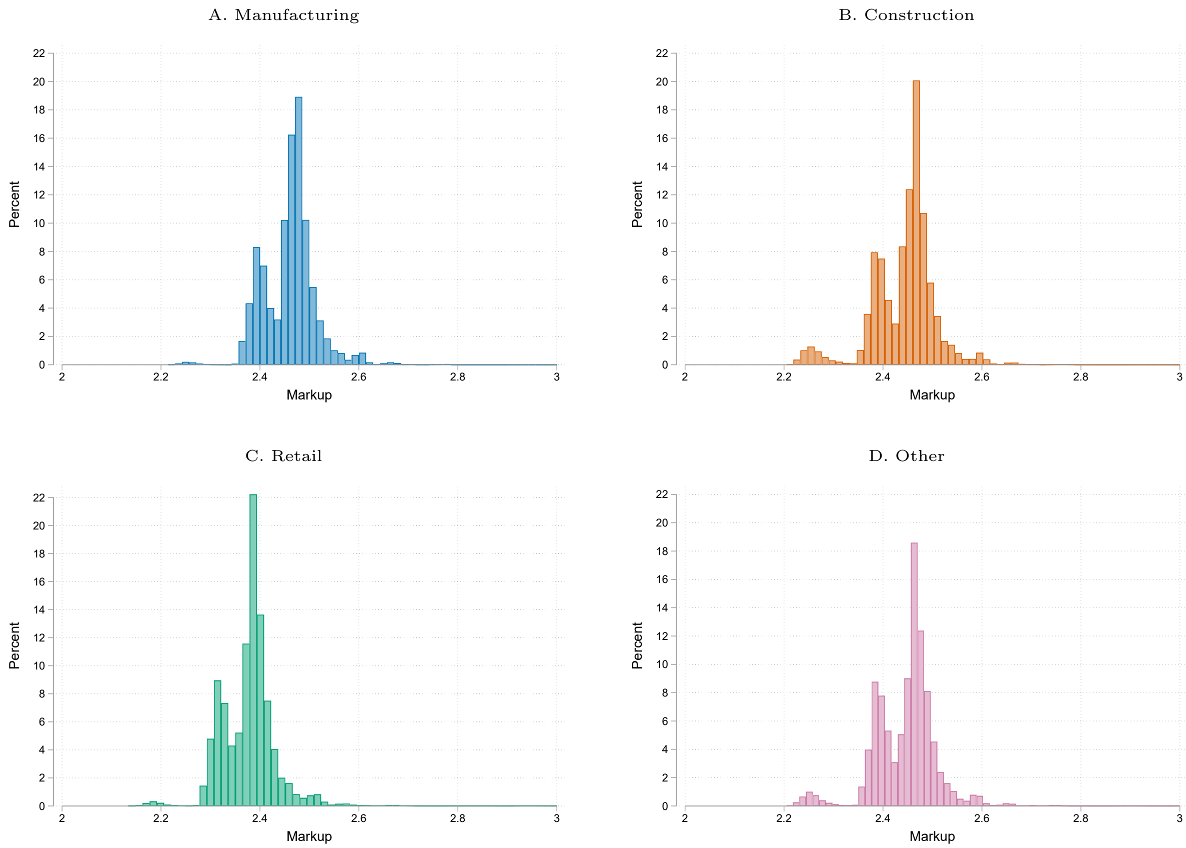


Figure A.5: Markups by Firm Sales

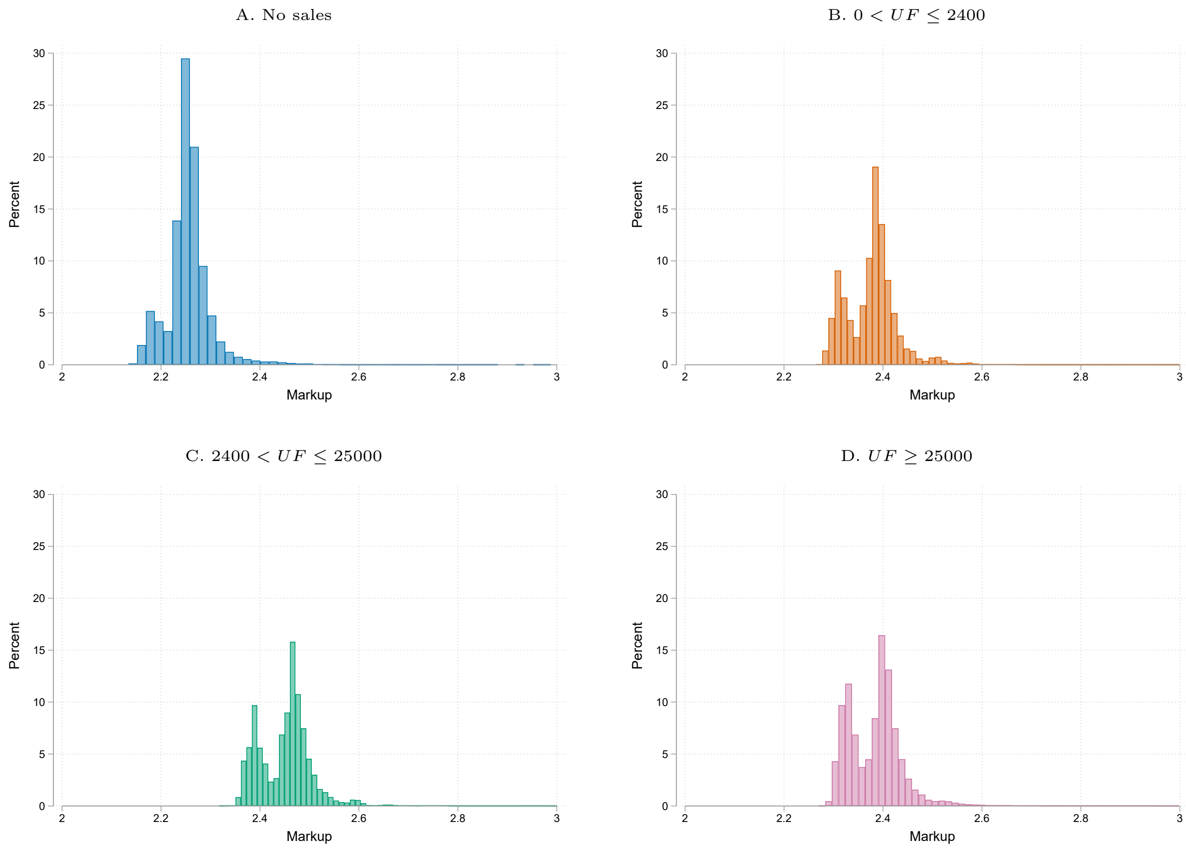
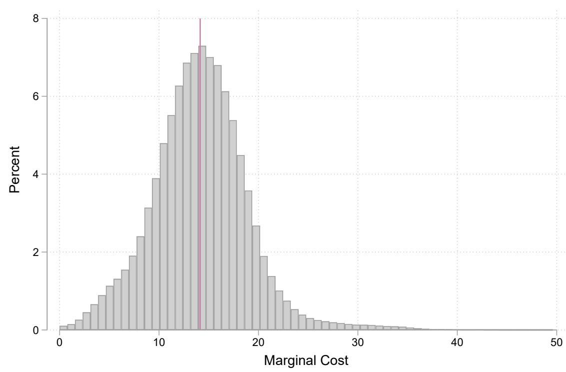


Figure A.6: Marginal Costs Distribution



B Additional Tables

Table B.1: Loan Demand 2nd Stage

period	coef	std err	F test
2013q2	-0.14	0.02	25.19
2013q3	-0.16	0.02	60.85
2013q4	-0.16	0.02	36.14
2014q1	-0.14	0.02	48.71
2014q2	-0.14	0.02	70.03
2014q3	-0.09	0.03	16.57
2014q4	-0.15	0.02	36.00
2015q1	-0.12	0.02	37.48
2015q2	-0.21	0.02	34.29
2015q3	-0.14	0.02	49.86
2015q4	-0.22	0.02	38.99
2016q1	-0.14	0.03	27.01
2016q2	-0.16	0.02	43.24
2016q3	-0.19	0.02	65.15
2016q4	-0.20	0.01	79.96
2017q1	-0.15	0.01	98.19
2017q2	-0.19	0.02	24.84
2017q3	-0.10	0.02	80.36
2017q4	-0.16	0.01	144.83
2018q1	-0.17	0.01	184.86
2018q2	-0.21	0.01	122.59
2018q3	-0.07	0.02	78.76
2018q4	-0.23	0.03	44.81
2019q1	-0.09	0.02	84.12
2019q2	-0.14	0.02	123.89