Bank market power and credit allocation

Felipe Brugués Rebecca De Simone[†]

First version: February 27, 2023

Latest version: December 19, 2024

Abstract

We study how bank competition affects commercial lending, extending the findings in Brugués and De Simone (2024). We find that 26% of observed markups are due to joint profit maximization and that moving to Bertrand-Nash would reduce equilibrium prices by 17%, increase loan use by 21% (intensive margin), and increase overall credit demand by 13% (extensive margin). These distortions vary greatly by borrower characteristics and dwarf those of financial transaction taxes. Through partial equilibrium instrumental variable regressions, we find large effects on firm size and productivity. We aggregate this partial equilibrium effect through a general equilibrium model of firm dynamics to measure the dynamic effects of credit and firm growth. Overall, our findings suggest that the lack of competition in banking has first-order implications for credit and misallocation.

A large body of evidence has documented the importance of bank market power in determining credit access and the pass-through of shocks to rates (Crawford et al., 2018; Drechsler et al., 2017; Benetton and Fantino, 2021; Eisenschmidt et al., 2023; Brugués and De Simone, 2024), linking banking to a broader literature on market power that finds increasing markups throughout the world in recent years (De Loecker and Eeckhout, 2018). While market power generates distortions to output in any industry, its effect on lending is of first-order concern due to the importance of the financial sector in determining firm growth. In this paper, we decompose the source of market power of banking into demand-side, supply-side, and risk factors and explore the effects of supply-side market power in the allocation of credit, and subsequently its effects on firm growth and an aggregate allocative efficiency.

[†]The authors are from the Business School of Instituto Tecnológico Autónomo de México and the London Business School, respectively. They can be reached at felipe.brugues@itam.mx and rdesmone@london.edu. Previous versions of this paper circulated as: *How do banks compete? Lessons from an Ecuadorian loan tax*.

Specifically, we extend our findings in Brugués and De Simone (2024), which tests the mode of competition of commercial credit in Ecuador and finds evidence against traditional modes of competition (i.e., differentiated price or quantity competition) in favor of collusion of the cartels, to characterize the welfare and incidence effects of lender competition using counterfactual experiments. Our empirical contribution is two-fold. First, we show that the lack of bank competition have large effects on prices, inflating price above what demand-side market power and risk-adjustments would imply, reducing demand for credit. Second, the reduction in credit from supply-side forces have significant implications for firm-level growth and aggregate allocative efficiency, reducing aggregate yearly TFPR by around 0.7% (around 56% the TFPR growth in our study period).

Our empirical approach relies on a generalized structural model of demand and supply of credit, which nests traditional modes of competition (e.g., Bertrand-Nash) used in the literature (Crawford et al., 2018; Benetton et al., 2024; Ioannidou et al., 2022; Benetton, 2021) but also allows for collusion between banks. We use the estimated demand model and out-of-model pass-through estimates from a 2014 loan tax reform in Ecuador to identify best fit mode of competition. In line with Brugués et al. (2024), which finds that Bertrand-Nash and Cournot are rejected in favor of collusion between banks, we explore the implications of joint-maximization behavior of banks relative to Bertrand-Nash. In particular, we show that our estimated model better matches empirical pass-throughs under joint-maximization rather than Bertrand-Nash.

Having established better fit of a joint-maximization model, we turn to explore its implications for credit allocation and terms. We find that a lack of competition among banks substantially distorts the credit market as between 20 to 25% of markups are coming from supply-side conduct, rather than demand-side elasticities or default risk. Addressing supply-side market power, for instance through effective anti-trust policy would have substantial effects on credit allocations, as loan markups would be 26% lower if banks priced competitively under traditional differentiated pricing strategy, loan use would increase by 21%, and bank credit access would expand 13% relative to what we see in the data. This implies large *contemporaneous* inefficiencies coming from supply-side market power, similar to those that would be generated by a monopoly that reduces total output inefficiently to capture larger profits. Our estimates suggests that for every additional dollar captured by the banks in terms of profits, three dollars are lost in terms of borrower surplus.

We find that the supply-side distortions are not distributed equally among borrowers. While marker power generates deadweight loss everywhere, small and young firms, as well as new relationships, are mainly affected between 1.5 to 2 times more than the median firm. This implies that easing these supply-side financial frictions would have allocative effects in the economy.

To quantify and aggregate these effect over all firms, we identify the causal impact on firm revenue productivity (TFPR) of supply-side credit shocks, by instrumenting firm-level credit using with bank-level marginal cost shocks orthogonal to firm demand on credit. We find that an exogenous increase in credit of 20% (similar to what we would expected from anti-trust policy), leads to an increase in future TFPR of 0.4%. Therefore, besides the contemporaneous effects on efficiency, supply-side bank market power have misallocation effects on the economy due to depressed firm productivity.

We apply the framework of Petrin and Levinsohn (2012), Rotemberg (2019), and Bau and Matray (2023) to estimate aggregate effects and decompose them into allocative efficiency effects and reallocation across firms. We estimate that implementing an antitrust policy that shifts competitive behavior from what we observe in the data to Bertrand-Nash competitive conduct—wherein banks do not joint maximize when setting prices—would increase total productivity growth by 0.71%. Most of this growth would come from improving allocative efficiency (0.46%) and the remainder from reduced misallocation through credit reallocation across firms (0.25%). To put this effect magnitude in context, it represents 56% of Ecuador's average total revenue productivity (TFPR) growth over our sample period from 2010 to 2017. And this magnitude is similar to that estimated by Rotemberg (2019) in a major credit subsidy program in India, which made 15% of all firms eligible for subsidies. Even so, we have likely underestimated the welfare impact of lender competition since we do not account for the dynamic effects on firm growth.

Our main contribution is to the literature exploring the welfare and incidence effects of market power. We are the first to quantify the welfare and aggregate effects of lender competition on credit markets. There is empirical evidence of lender collusion and its effects (Cornaggia et al. (2015); Hatfield and Wallen (2023); Jiang et al. (2023)), some of which show that tax pass-throughs vary by market concentration in lending markets (Scharfstein and Sunderam (2017); Drechsler et al. (2017); Benetton and Fantino (2021)).

In particular, Hatfield and Wallen (2023) consider the impact of bank collusion in the deposit market through multi-market contact but does not take a modeling approach that allows quantification of otherwise unobservable bank competition. Ciliberto and Williams (2014) also considers the effect of collusion through multi-market contact in the airline industry but does not allow for a fully flexible collusion (conduct) parameter. More generally, while suggestive, pass-through heterogeneity is consistent with many conduct values—including no collusion—if there is demand curvature heterogeneity. Establishing the impact of lender competition and illuminating the source of bank pricing power requires a model. Finally, Brugués and De Simone (2024) uses our setting and model to study how the welfare impact of financial taxes and subsidies depends on lender market power but does not quantify the welfare and aggregate impacts of lender competition itself.

A rich structural lending literature characterizes the demand-side sources of lender pricing power: Crawford et al. (2018) and Cox et al. (2023) in commercial lending; Egan et al. (2017) in deposits; Robles-Garcia (2021) and Benetton (2021) in mortgages, Yannelis and Zhang (2023) in auto lending, and Cuesta and Sepúlveda (2024) in consumer lending. Yet this literature focuses on demand-side sources of market power using Bertrand-Nash models and on the role of lending market frictions in explaining observed prices. Instead, we generalize the models of Crawford et al. (2018) and Benetton (2021) to decompose loan markups into their demand- and supply-side sources and use counterfactual experiments to explore the effects of the latter. In summary, relative to this literature, this paper illuminates the source of bank pricing power, quantifies the welfare impacts of lender competition, establishes the mechanism of this effect, and demonstrates how it varies across the firm-size distribution.

Finally, we contribute to a macro-economic literature quantifying the role of specific frictions or policies on allocative efficiency, including from banking deregulation (Sraer and Thesmar (2023)); capital adjustment costs (Asker et al. (2014)); financial frictions (Buera et al.

(2015), Midrigan and Xu (2014), and Catherine et al. (2022)). The closest paper to ours is Rotemberg (2019), who decomposes the aggregate effects of a credit subsidy in India into allocative efficiency effects and reallocation across firms. We simulate the impact of an antitrust policy that moved banks from the equilibrium competitive conduct we observe in the data to Bertrand-Nash competition. We then calculate the allocation efficiency and reallocation impact of the policy.

The rest of the paper is organized as follows. Section 1 describes the SOLCA tax, the Ecuadorian credit market, and our data sources. It then reports empirical pass-through estimates. Section 2 presents our baseline model of commercial lending and describes how we identify the conduct parameter using pass-through from the SOLCA tax. Section 3 documents our estimation strategy. Section 3.3 tests conduct against benchmark competition models. Section 4 uses counterfactual experiments to demonstrate how banks' market power affects loan pricing, the distribution of credit, and borrower and lender welfare. Section 5 reports the effect of increased lender competition on firm growth, productivity, and aggregate efficiency. Section 6 concludes.

1 Pass-Through of the 2014 SOLCA Tax in Ecuador

1.1 The SOLCA Tax

In September 2014, the Ecuadorian National Assembly introduced a loan tax to raise funds for free cancer treatment centers run by the Sociedad de Lucha contra el Cáncer (SOLCA). This SOLCA tax applies to all loans from private banks, and the bank collects it from the borrower as a one-time payment at loan grant. The tax amount varies with loan maturity: loans with a maturity of one year or longer incur the full 0.5% tax, while shorter-term loans are taxed proportionally.[1] The introduction of the tax was unexpected by both borrowers and financial institutions in Ecuador. In this section, we estimate the pass-through of this tax to the interest rates of new commercial loans using a micro dataset combining Ecuador's regulatory credit

[1]The tax rate for loans with maturities less than one year is calculated as $0.5\% \times X/12$, where X is the loan's maturity in months.

registry and firm financial statements for the entire distribution of corporations in Ecuador.

1.2 The Dataset

Brugués and De Simone (2024) details the construction of the data. We focus on regular commercial loans issued to corporations regulated by Ecuador's business bureau. Data are quarterly and span the period from January 2010 to December 2017. Table 1 describes the data. All measurements expressed in currency are in 2010 U.S. dollars.

The data include 457,623 firm-year observations, corresponding to 31,903 unique corporations. Of these, 97,796 firm-year observations relate to active firm-year borrowers, whereas 359,827 observations pertain to non-borrowing firm-years. The main takeaways from Table 1 are that Ecuador is representative of other bank-dependent economies, especially in that primarily safe, formal firms access bank credit at high interest rates in a market where long-term relationship lending is the norm and where banks wield pricing power that affects both the allocation of credit and credit terms. Indeed, most borrowers have only one lender at a given point.[2] We incorporate these insights into our model and tests.

[Place Table 1 here.]

1.3 Estimating Direct Tax Pass-Through

We follow the preferred specification of Brugués and De Simone (2024) to recover the direct pass-through of the introduction of the SOLCA tax to loan interest rates. Specifically, we estimate the regression:

$$rTax_{likt} = \rho tax_{likt} + \sum_{j=1}^{20} \beta_a^j 1\{A \in h\} + \sum_{j=1}^{20} \beta_m^j 1\{M \in z\} + \alpha_d DP_{likt} + \alpha_{ik} + \varepsilon_{likt}, \tag{1}$$

indent for loan l contracted by firm i from bank k at time t. Where we regress the tax-inclusive, annualized interest rate ($rTax$) of new loans on the tax amount in percentage terms (tax), de-

[2] See Appendix A for more detailed descriptions of the Ecuadorian commercial loan market.

fined as:

$$\text{tax}_{likt} = \begin{cases} 0 & \text{before 2024Q4} \\ 0.5\% & \text{after 2024Q4 if } M \geq 1 \\ 0.5\% \times M & \text{after 2024Q4 if } M < 1 \end{cases} \tag{2}$$

where M is the loan's maturity in years.

This specification properly accounts for the kink in the tax percentage at a loan maturity of one year. The pass-through, ρ_o, captures how final, tax-inclusive prices change with respect to the amount of the tax for each loan.

Control variables include flexible, semi-parametric controls for the amount (A) and maturity (M) of the loan using 20 buckets; the loan maturity, M, with its 20 corresponding buckets; bank-firm pair fixed effects α_{ik} controlling for changes in lender composition and other relationship-specific unobservables; the predicted default probability DP; and time-varying unobservables captured by ε.[3] The estimation window is from eight quarters before the introduction of the tax through three quarters afterward, excluding October 2014. Robust standard errors are clustered at the bank-quarter level.

The first row of Table 2 reports the estimated direct pass-through, $\widehat{\rho}$, of the tax to tax-inclusive interest rates on commercial loans granted by private banks. We conduct hypothesis testing against the complete pass-through null hypothesis ($\rho_o = 1$). If $\widehat{\rho} < 1$ it indicates incomplete pass-through and $\widehat{\rho} > 1$ corresponds to more-than-complete pass-through. We find that there is, on average, incomplete pass-through of the tax in aggregate. In particular, the borrower pays slightly more than half of the SOLCA bank tax on the average loan while the bank shoulders the rest by reducing the equilibrium interest rate.

[Place Table 2 here.]

The remainder of Table 2 reports direct pass-through estimates by region.[4] In all regions we find point estimates that indicate incomplete pass-through. We will use these point estimates to

[3] Appendix C describes how we model the default probability.

[4] We choose as regional markets the top three largest provinces—Pichincha, Guayas, and Azuay—and aggregate the remaining, smaller provinces into two regions capturing the coast (Costa), and highlands and Amazonian basin (Sierra/Oriente) regions.

validate market-level conduct.

The identification assumption for recovering an unbiased pass-through estimate is that within the estimation window, interest rates prior to the tax shock are a counterfactual for interest rates afterward so that any interest rate response is attributable entirely to the tax. Borrower-lender pair fixed effects control for any compositional effect of the tax on borrowing while loan-level covariates control for any effect through loan terms or expected loan default. Brugués and De Simone (2024) provides evidence that interest rates did not anticipate the introduction of the SOLCA tax, a placebo test in state-owned banks whose loans were not subject to the tax in our sample period, extensive robustness tests, and evidence that the empirical pass-through varies with reduced-form proxies for competition.

2 Quantitative Model of Commercial Lending

We utilize the direct pass-through of the SOLCA tax to identify a quantitative model of demand and supply in the commercial loan market that enables us to characterize bank competition and its impacts directly. This section outlines our model's design and estimation; for a comprehensive overview, refer to Appendix B and Brugués and De Simone (2024).

Our model is informed by the environment described in Table 1, featuring small-to-medium-sized, single-establishment firms engaged in relationship lending with traditional, deposit-funded banks. We assume that borrowers and lenders are risk neutral, borrowers have the freedom to choose from any bank in their local market, that the marginal cost of lending is constant within each loan-year (Backus et al., 2024; Duarte et al., 2024; Dearing et al., 2024), and the returns on borrowers' investments can be parameterized.[5]

Our model captures both discrete and continuous demand elements, allowing the testing of all the benchmark conduct models in the literature. Firm i in period t decides whether to borrow from one of the banks k actively lending in market m. The indirect profit function for borrower

[5] In Brugués and De Simone (2024), we relax the assumption that the borrowers can borrow from any bank that has lent in the market, and we rigorously test the marginal cost assumption empirically using pair-level estimates of marginal costs and a demand shifter.

i choosing bank k in market m at time t is defined as:

$$\Pi_{ikmt} = \overline{\Pi}_{ikmt}(X_{it}, r_{ikmt}, X_{ikmt}, N_{kmt}, \psi_i, \xi_{kmt}; \beta) + \varepsilon_{ikmt}, \tag{3}$$

where $\overline{\Pi}_{ikmt}$ represents the indirect profit function at the optimized values of loan usage, L_{ikmt}. X_{it} denotes observable characteristics of the firm, r_{ikmt} is the interest rate, X_{ikmt} represents time-varying characteristics of the bank-firm borrowing relationship, N_{kmt} is the time-varying branch availability offered by the bank in market m, ψ_i captures unobserved borrower characteristics, ξ_{kmt} captures unobserved bank characteristics that affect all firms borrowing from bank k, ε_{ikmt} is an idiosyncratic taste shock, and β collects the demand parameters common to all borrowers in market m. If the firm chooses not to borrow, it gets the value of its outside option, $\Pi_{i0} = \varepsilon_{i0mt}$, normalized to zero indirect profit. Firms select bank k that gives them their highest expected indirect profit, such that the demand probability is $s_{ikmt} = Prob(\Pi_{ikmt} \geq \Pi_{ik'mt}, \forall k' \in m)$.

Given the set K_{imt} of banks in local market m at time t available for firm i, the total expected demand is pinned down by $Q_{ikmt}(r) = s_{ikmt}(r)L_{ikmt}(r)$. This relationship-level expected demand is the product of firm i's probability of demanding a loan from bank k, s_{ikmt}, and its expected loan use, L_{ikmt}, given posted interest rates $r = \{r_{i1mt}, ..., r_{1Kmt}\}$. Continuous loan demand is determined by Hotelling's lemma such that input demand is given by $L_{ikmt} = -\partial\Pi_{ikmt}/\partial r_{ikmt}$.

On the supply side, banks choose borrower-specific interest rates to maximize their period-t profits. Specifically, bank k offers interest rate r_{ikmt} to firm i to maximize bank profits B_{ikmt}, subject to the market conduct and one-time tax τ_{ikmt}, which is zero before the introduction of the tax and $\tau_{ikmt} \in (0, 0.5]$ afterward as a function of the contracted maturity of the loan. Formally, the bank's problem is:

$$\max_{r_{ikmt}} B_{ikmt} = (1 - d_{ikmt})r_{ikmt}Q_{ikmt}(r + \tau_{ikmt}) - mc_{ikmt}Q_{ikmt}(r + \tau_{ikmt}) \tag{4}$$
$$\text{subject to } \upsilon_m = \frac{\partial r_{ijmt}}{\partial r_{ikmt}} \text{ for } j \neq k,$$

Where d_{ikmt} represents banks' expectations of the firm's default probability at the time of loan issuance. The model accounts for selection risk by allowing flexibility in marginal costs at the borrower-pair-year level and by incorporating heterogeneity in default rates based on borrower characteristics (Cabral et al., 2018; Benetton et al., 2024; Einav et al., 2021).

The market conduct parameter, $\upsilon_m = \frac{\partial r_{ijmt}}{\partial r_{ikmt}}$ $(j \neq k)$, measures collusion incentives by modeling the degree of correlation in price co-movements (Weyl and Fabinger, 2013; Kroft et al., 2024). The conduct parameter ranges from zero to one, where several values correspond to well-defined models of competition: $\upsilon_m = 0$ corresponds to Bertrand-Nash, $\upsilon_m = 1$ to complete joint maximization, and other values indicate intermediate degrees of competition, including those corresponding to Cournot competition. Thus, by including the conduct constraint, we allow banks to compete on price and quantity/credit rationing.

The related first-order conditions for each r_{ikmt} are:

$$(1 - d_{ikmt})Q_{ikmt} + ((1 - d_{ikmt})r_{ikmt} - mc_{ikmt})\Big(\frac{\partial Q_{ikmt}}{\partial r_{ikmt}} + \upsilon_m \sum_{j \neq k} \frac{\partial Q_{ikmt}}{\partial r_{ijmt}}\Big) = 0. \tag{5}$$

Rearranging Equation 5 and substituting in price elasticities we derive the pricing equation:

$$r_{ikmt} = \frac{mc_{ikmt}}{1 - d_{ikmt}} - \frac{1}{\underbrace{\frac{\epsilon_{kk}}{r_{ikmt}}}_{\text{Bertrand-Nash}} + \underbrace{\upsilon_m \sum_{j \neq k} \frac{\epsilon_{kj}}{r_{ijmt}}}_{\text{Alternative Conduct}}}. \tag{6}$$

This pricing equation incorporates a marginal cost term and a markup comprised of two components: the own-price elasticity markup (retained under pure Bertrand-Nash) and a term capturing the importance of cross-price elasticities. To the extent $\upsilon_m > 0$, the second term implies that the bank takes into account the joint losses from competition when setting loan rates. As υ_m increases, banks' behavior increasingly aligns with joint maximization, resulting in higher profit-maximizing prices, r_{ikmt}.

By inverting Equation 6, we obtain:

$$mc_{ikmt} = r_{ikmt}(1 - d_{ikmt}) + \frac{1 - d_{ikmt}}{\frac{\epsilon_{kk}}{r_{ikmt}} + \upsilon_m \sum_{j \neq k} \frac{\epsilon_{kj}}{r_{ijmt}}}. \tag{7}$$

This equation demonstrates that observing prices, quantities, demand, and default parameters alone is insufficient to identify pair-specific marginal costs since conduct, υ_m, is also unobserved. Without information on υ_m, we can only bound marginal costs using the fact that

$\upsilon_m \in [0, 1]$. To overcome this difficulty, we follow insights from the public finance literature that the pass-through of taxes and marginal costs to final prices are tightly linked to competition conduct—the pass-through function depends on demand elasticities, demand curvature, interest rates, marginal costs, and default rates (Weyl and Fabinger, 2013). Therefore, conditional on demand estimates, only one conduct value rationalizes a given observed pass-through.

In practice, we observe aggregate pass-through rates at various market levels—city, province, regional, or national. By taking the expected value of these pass-through rates for different markets, we introduce an additional moment for each market to uniquely identify the conduct parameter υ_m for that market. We utilize the empirical analog of these market moments to calibrate best-fit conduct empirically.

3 Model Estimation

3.1 Demand Parameters

Appendix E describes our maximum likelihood demand estimation procedure, interprets our parameter estimates, and assesses model fit. Brugués et al. (2024) reports extensive robustness tests using alternative demand-estimation procedures. We face two key empirical challenges. The first is that we observe the terms of granted loans while our demand model requires a menu of prices from all available banks to all potential borrowers in each market. To address this long-standing problem in the literature, we predict the prices of unobserved, counterfactual loans following the strategy of Adams et al. (2009), Crawford et al. (2018), and Ioannidou et al. (2022). Details are reported in Appendix D. Second, to address measurement error and endogeneity in the price parameter, we follow the literature using cost-based and Hausman-style instruments that capture variation in marginal costs at the bank level that are orthogonal to individual-level demand.

Table 3 reports the aggregate demand parameter estimates, reported as the mean and standard deviation of the point estimates aggregated across regions. The standard deviations are bootstrapped by estimating each region-level parameter using 1,000 bootstrap samples, averaging those estimates, and then calculating the standard deviation across the bootstrap samples.

[Place Table 3 here.]

The estimates are sensible. Higher interest rates are associated with a reduction in loan demand, while an increase in the number of bank branches leads to higher loan demand. The parameter sigma captures unobserved heterogeneity, while the scaling factor vertically adjusts the indirect utility to match the ratio of borrowers to non-borrowers. We observe that older firms are more likely to borrow, and that longer lending relationships increase the likelihood of borrowing. Additionally, larger firms—measured by assets, revenues, or wages—tend to borrow more, as do firms with higher expenses. In contrast, firms exhibiting higher leverage are less likely to seek loans. The demand parameter estimates at the regional level reflect similar patterns, as shown in Appendix Table E1.

To assess demand sensitivity to prices, we calculate own- and cross-demand elasticities, presented in Table 4.[6] The *Continuous* elasticity reflects the intensive margin with respect to interest rates, while *Discrete* pertains to discrete-choice elasticity with respect to interest rates. Our findings show that a one percent price increase results in an average (median) decrease of 4.63% (4.5%) in loan usage (continuous) and 6.01% (0.55%) in market share.[7] The *Total* elasticity combines continuous and discrete measures. It displays significant borrower heterogeneity. Critically, our model is flexible enough to capture this borrower heterogeneity. This is vital since this demand heterogeneity may help explain differences in pass-throughs (Miravete et al., 2023). Finally, the *Cross* elasticity indicates that a one percent increase in interest rates boosts competitors' market shares by 0.17% (0.01%). We validate these structural elasticities using a reduced-form instrumental variable approach, as shown in Appendix Figure E1, with median structural elasticities closely matching reduced-form estimates. The rest of the paper uses the estimated and identified model to quantify the distributional and welfare impacts of lender collusion and to explore the resulting aggregate efficiency and output losses.

[Place Table 4 here.]

[6] Refer to Appendix E.2 for details.

[7] While these estimates are slightly more elastic than those found in Crawford et al. (2018) and Ioannidou et al. (2022), they align closely with Benetton (2021) and Benetton et al. (2024).

3.2 Model Fit

In Table 5, we present descriptive statistics on the fit of the model. We focus on market shares (discrete choice), loan use (continuous choice), prices, and default rates.[8] The table shows that the model fits the mean data well, with a perfect fit for market shares, loan use, and default rates. Our model under-predicts prices by a small margin. Naturally, our model predicts less variation across all measures than in the data.

[Place Table 5 here.]

3.3 Supply-side Conduct Parameters

After estimating demand, we calibrate best-fit conduct considering only two modes of competition: Bertrand-Nash ($\upsilon_m = 0$) and joint-maximization ($\upsilon_m = 1$). For each mode of conduct, we obtain marginal costs (mc^{υ}_{ikmt}) consistent with the parameters obtained through the inverted pricing Equation 7, as well as demand and default functions. Then, for each borrower, we simulate the introduction of a 0.5% tax to all the banks in their choice set and recalculate Nash equilibrium prices consistent with marginal costs (mc^{υ}_{ikmt}), demand and default. After obtaining equilibrium prices, we calculate pair-level pass-through estimates for each mode of conduct as the difference in prices before and after the tax, adjusted by the tax rate.

Figure 1 illustrates the results of 1,000 bootstrap simulations, where we sampled borrowers with replacement. Panel (a) displays simulated pass-throughs for both chosen and potential loans. We estimate that pass-throughs are centered slightly above one under Bertrand-Nash despite the significant demand heterogeneity documented above. By comparing this distribution to the empirical point estimate of pass-through at 0.54 and the upper 95% interval at 0.64, we reject the hypothesis that conduct is Bertrand-Nash in the actual data. This serves as a sharp test because our discrete-continuous demand model is flexible enough to obtain pass-through estimates both above and below one under Bertrand-Nash—a feature that many discrete-choice models, as pointed out by Miravete et al. (2023), cannot accommodate. In contrast, the simulated distribution of pass-through rates under the assumption of joint profit maximization has

[8] In Appendix C, we discuss our empirical strategy to estimate default rates.

an average of 0.57, which nearly overlaps with the empirical estimate. As a result, we fail to reject the assumption that conduct is characterized by joint maximization at the national level.

[Place Figure 1 here.]

In panel (b), we present the simulated pass-through rates for only those banks that were actually chosen by borrowers in our data. Although the spread of the distributions is wider in this case, we again find that the Bertrand-Nash distribution does not overlap with the empirical pass-through distribution. Conversely, the distribution of simulated pass-throughs under joint maximization entirely coincides with the pass-through rates observed in the loan data.

We repeated the best-fit exercise at the regional level. In Table 6. We again find joint maximization better matches the empirical pass-throughs at *each* regional level.

[Place Table 6 here.]

4 Effects of bank market power on credit and prices

This section examines how banks' market power affects loan pricing, the distribution of credit, and borrower and lender welfare. We start by assessing the impact of competitive conduct on lenders and borrowers by simulating two contrasting competitive scenarios. We first consider a setting where banks engage in Bertrand-Nash competition ($\upsilon_m = 0$), competing independently without collusion. We then analyze a scenario of joint profit maximization ($\upsilon_m = 1$), where banks in each market act as a single cartel. Panels (a) through (c) Table 7 summarize the results.

[Place Table 7 here.]

Under the Bertrand-Nash competition assumption, banks set prices based solely on their own-price elasticities of demand, as is evident from Equation 7. Panel (a) of Table 7 presents the borrower-specific marginal costs of banks in this scenario. The average marginal cost for each additional dollar lent is 8.82%, with a median of 9.3%. These costs reflect expenses related to funding, monitoring, screening, and other economic activities associated with lending. Panel (c) reports that the average (median) markup—the difference between prices and marginal costs—under the Betrand-Nash conduct assumption is 2.43 percentage points, with a median of 2.30 percentage points. The associated Lerner indices are 0.23 on average and 0.21 at the median.

When banks engage in joint profit maximization, they internalize the effects of their pricing decisions on competitors, effectively behaving as a cartel. Under this scenario, prices are a function of both own-price and cross-price elasticities. Panel (b) reveals that marginal costs decrease significantly under joint profit maximization, averaging 4.87 percentage points with a median of 3.10 percentage points. This represents reductions of 50.57% and 55.75%, respectively, compared to the Bertrand-Nash scenario. The decrease in marginal costs suggests that, under joint maximization, the model attributes a larger portion of the loan price to markups resulting from anti-competitive behavior and less to marginal costs relative to the Bertrand-Nash benchmark. Our model-free estimate of bank marginal costs, reported in Table 1 at around 4%, aligns more closely with the marginal costs under joint profit maximization. This alignment implies that assuming competitive conduct when some degree of collusion exists may lead to overestimating lenders' marginal costs.

Consistent with the lower marginal costs, the model predicts substantially higher markups under joint profit maximization. Panel (c) shows that the average markup increases to 6.38 percentage points, with a median of 4.79 percentage points. The corresponding Lerner indices rise to 0.61 on average and 0.68 at the median, more than doubling compared to the Bertrand-Nash scenario. This significant increase may explain why existing literature often reports relatively low markups; for instance, Benetton (2021) finds markups of 18% of the average interest rate, while Crawford et al. (2018) reports markups as low as 5%.

By examining the ratio of markups under joint maximization to those under Bertrand-Nash competition, we decompose markups into portions attributable to anti-competitive conduct, demand-side preferences and frictions (such as switching costs and product differentiation), and risk adjustments due to borrower default probabilities. We find that, on average, 25.46% of the markup is due to anti-competitive conduct, with a median of 19.18%. Demand-side factors account for the majority of the markup—70.27% on average and 72.62% at the median. Risk adjustments contribute a smaller share, averaging 4.26% with a median of 0.33%.

These pricing differences have significant economic implications for borrowers. Panel (d) of Table 7 illustrates that, under the Bertrand-Nash competition scenario, the intensive margin of credit demand—the amount borrowed—would increase by an average of 21.39% and a median of 20.29% due to lower loan prices. Additionally, the extensive margin—the decision to borrow or not—would also be affected. The proportion of firms not borrowing decreases from 3.3% to 2.9%, representing a 13% increase in the number of firms obtaining loans under competitive conditions. Moreover, this increase in credit availability is accompanied by only a slight rise in the average risk of the borrower pool (adverse selection). Specifically, the average risk increases by 0.45 percentage points as lower prices attract riskier borrowers who were previously excluded due to higher costs.

In addition to estimating how price changes affect credit, our model allows us to assess the welfare effects of anti-competitive behavior by comparing changes in borrower surplus to changes in lender profits. Panel (e) of Table 7 shows that borrowers would gain significantly under Bertrand-Nash competition, with an average increase in surplus of $41,907 and a median of $3,717 (in 2010 USD). In contrast, lenders would experience a decrease in profits per borrower, averaging $100,346 with a median of $3,347. Despite the increased loan volume, the reduction in loan prices adversely affects lender profitability, which may explain why banks do not price closer to a Bertrand-Nash equilibrium in the data.

As a last test, an incidence analysis reveals that, while the average loss for lenders appears to be much larger than the gains, borrowers actually benefit more per dollar than lenders lose. Our measure of incidence is the change in borrower surplus divided by the change in lender surplus. Using this metric, we find that for every dollar of profit lost by banks, borrowers gain an average of $2.81 in surplus, with a median of $1.62. These findings suggest that for the empirical equilibrium in the data—characterized by some degree of joint maximization and elevated loan prices—to be efficient, social welfare weights would need to heavily favor lender surplus over borrower surplus. This suggests that distortions introduced by reduced lender competition, by limiting credit access and increasing borrowing costs, also lead to resource misallocation and welfare losses in the broader economy. Policies aimed at enhancing competition in the banking sector could mitigate these effects, promoting more efficient credit allocation.

4.1 Heterogeneity in Incidence and Welfare Effects

Given the significant real effects we have documented, the distributional effects of competition in the commercial lending market are of first-order concern as they can illuminate from a different angle the extent that bank conduct causes misallocation of credit across the economy (Hsieh and Klenow, 2009). We exploit access to micro-level data on borrowers and our counterfactual exercise of moving to Bertrand-Nash competition to offer insights into the distributive incidence and welfare costs of the financial tax.

[Place Figure 2 here.]

Figure 2 plots the incidence of competition estimates, or the negative ratio between the effect on borrower surplus to that on lender surplus ($\frac{-\Delta CS}{\Delta PS}$), from moving to Bertrand-Nash from the equilibrium in the data. This is the same measure that we used in Table 7 to summarize the distortions from lack of competition. To interpret the figure, any incidence above one indicates that for every dollar extra in lender profits, more than one dollar of borrower surplus is destroyed in deadweight loss. The larger the incidence, the more distortive is the lack of competition.

In panel (a), we see that incidence decreases sharply in firm size (as measured by assets), indicating that small firms face much higher distortions due to lack of competition. Panel (b) reports the same result from another angle. It answers the question: for every extra dollar in lender surplus, how much of it was deadweight loss and how much was transfers in surplus between lenders and borrowers? In the figure, the closer the number is to zero, the smaller the distortion. We see that for every dollar in borrower surplus from moving to Bertrand-Nash, around 50 cents came from lowering distortions and 50 cents are from transfers from lenders to borrowers.

Consistent with the top panels, panel (c) reports that younger firms would benefit more from increased lender competition. Finally, panel (d) reports that those with longer-term relationships with their banks would benefit less from a move to Bertrand-Nash competition. This is not obvious, as it is an extant question whether the benefits to firms from relationship lending outweigh any relationship hold-up effect from increased switching costs (Sharpe, 1990;

Rajan, 1992). Thus, we see that the incidence of competition is greatly heterogeneous across borrower demographics, impacting firm growth through its effect on the unequal distortion of credit across the corporate sector.

Finally, Brugués and De Simone (2024) show that more lender competition generates more distortions (a larger Harberger triangle delineating deadweight loss) from financial taxes like the SOLCA tax. On the other hand, we have concluded that the lack of competition in the best-fit model is distortive. Figure 3 measures the trade-off between the welfare impacts of competition on tax incidence and the direct welfare impacts of noncompetitive lender conduct. Specifically, it plots the additional Harberger triangle in tax versus the Harberger triangle from competition across the covariate distribution. In panel (a), we see that the increased distortion from implementing a loan tax are around 9%, on average, the size of the Harberger triangles from lack of competition. Panel (b) reports a similar relationship which is almost constant across the firm-age distribution. Panel (c) also tells us that the increased distortion from competition is larger than the decreased distortion from loan taxes in a collusive lending market. In this relationship, we again see that the main benefits from collusion on tax welfare accrue to long-term relationship borrowers, although even for the longest relationships the gains from greater lender competition far outweigh the tax welfare impacts. Overall, the magnitude of the distortion from lack of lender competition is much larger than the lower tax distortion benefit from raising revenue in a collusive lending market. To our knowledge, we are the first to directly make this comparison in the growing literature that documents the benefits of lender market power in credit markets (Petersen and Rajan, 1995; Mahoney and Weyl, 2017; Crawford et al., 2018; Yannelis and Zhang, 2023).

[Place Figure 3 here.]

5 Effects of bank market power on firm growth

In this section, we proposed a framework to extrapolate the estimated effects on the credit of improved competition (i.e., moving from joint maximization to Bertrand-Nash), predicted to increase the intensive margin of credit by 20%, to measure its potential effect on firm-level outcomes and aggregated to obtain economy-wide effects. The counterfactual exercise proceeds in three steps.

First, through standard production function estimation tools (Ackerberg et al., 2015), we obtain firm-level productivity (TFPR) estimates by exploiting the balance sheet and income statement for the studied firms. Second, through an instrumental variable approach aimed at capturing supply-side credit shocks, we measure the effect of credit on future TFPR. Third, following Petrin and Levinsohn (2012), Rotemberg (2019), and Bau and Matray (2023), we obtain aggregate productivity growth estimates of improved competition.

5.1 Production function estimation

Following the standard in the production function estimation literature (Bau and Matray, 2023), we assume firms have a Cobb-Douglas revenue production function given by:

$$Revenue_{it} = TFPR_{it} K_{it}^{\alpha^k} L_{it}^{\alpha^l} M_{it}^{\alpha^m}, \tag{8}$$

for firm i and year t. The variables $Revenue_{it}$, K_{it}, L_{it}, M_{it} represent total sales, capital, number of workers, and expenditures, while $TFPR_{it}$ is the firm-specific unobserved revenue productivity. We measure capital as the book value of physical assets and expenditures as the sum of materials, energy, and fuel. We implement Ackerberg et al. (2015) to estimate the revenue production function to deal with the endogeneity issues of input choice and productivity and estimate revenue production estimates at the economy-wide level.

Table 8 reports the results. In Column (1), we use the total wage bill to measure labor and obtain elasticity estimates similar to those reported in Brugués et al. (2024), who also study production functions in Ecuador but who do not observe the number of employees. This similarity suggests our underlying data is consistent with previous studies. In Column (2), we present our preferred specification using the number of employees to measure labor. We find results in line with previous literature (De Loecker et al., 2016; Gandhi et al., 2020): an elasticity of 0.7 for intermediate inputs, 0.32 for labor, and 0.12 for capital. TFPR is estimated as the residual in observed sales minus predicted sales based on the production function.

[Place Table 8 here.]

5.2 Effects of credit supply shocks on productivity

With the estimates of TFPR in hand, we proceed to measure the effects of *supply-side* shocks to credit on firm-level productivity. Causal estimates of supply-side shocks to credit would allow us to approximate the effects of an exogenous supply-side change to interest rates from increased competition on the firm.

An influential literature has demonstrated the importance of isolating *supply-side* shocks to study the effect of credit on firm productivity (Amiti and Weinstein (2018); Manaresi and Pierri (2024)). The key intuition is that credit demand shocks are likely correlated with productivity demand shocks, as productivity shocks increase demand for all inputs. Thus, these estimates based on demand-side shocks are likely biased. As a result, the literature has developed tools that decompose loan movements into bank, firm, industry, and common shocks (Amiti and Weinstein, 2018). We follow an alternative route that takes advantage of the *supply-side instruments* used to estimate demand, which, as discussed above, capture bank-level marginal cost shocks that are orthogonal to the firm. Our approach follows two steps.

First, we use these instruments to create measures of instrumented credit based on supply-side shocks. We implement the following instrumental variable regression at the firm level:

$$L_{ispt} = \alpha r_{ispt} + \gamma_t + \gamma_s + \gamma_p + \varepsilon_{ijpt}, \tag{9}$$

for firm i in sector s and province p. L_{ispt} is total firm-level demand for credit, and r_{ispt} is firm-level average interest. Both are aggregated over all potential sources of finance in a given year. The fixed effects γ's capture time-varying trends, and sectoral and regional differences in total credit. We instrument interest rates r_{ispt} by aggregating the firm-level instruments constructed for demand estimation. In particular, we use the average prices of the matched banks in other provinces for commercial credit, mortgages, micro-lending, and delinquencies in non-commercial credit products. The instrumental variable approach for credit at the firm level gives results consistent with the structural demand approach above. We obtain an interest coefficient of -0.34 (0.024) with a strong first-stage F-stat of 320.

Then, in the spirit of the control function approach, we obtain estimates of predicted loan levels based on the supply-side determinants by netting out the residuals from the instrumental variable regression. As the instruments are purely supply-side, the residuals will contain all demand-side determinants of credit, leaving us with credit use based purely on supply-side shocks.

Second, we regress firm-level TFPR on the instrumented supply-side credit using the following specification:

$$Y_{ispt} = \beta_c ln(\widehat{Credit})^{supply}_{ispt} + \beta_x X_{ispt} + \gamma + \varepsilon_{ispt}, \tag{10}$$

where Y_{ispt} is 1-period future TFPR or the difference in TFPR between $t + 1$ and t, X_{ispt} are controls such as growth rate in input or contemporaneous TFPR, $ln(\widehat{Credit})^{supply}_{ispt}$ is instrumented credit based purely on supply shocks, and γ are fixed effects at the year, sector, province or firm-level, depending on the specification.

Table 9 presents the results of the effects of supply-side credit shocks on future firm-level TFPR. Odd-numbered columns control for year, sector, and province fixed effects, while even-numbered columns control for year and firm fixed effects. Column (1) presents the effect of credit shocks at time t on TFPR at time $t+1$, controlling for TFPR at time t. The coefficient indicates that a one percent increase in credit stemming from supply shocks increases future TFPR by 0.02%. Column (2) shows the results are robust to controlling for firm fixed effects. Instead, in Columns (3) to (6), we report first-difference effects and again find similar estimates, even after controlling for input usage trends in models (5) and (6). These estimates are quantitatively similar to those reported in Manaresi and Pierri (2024). These effects then imply that there are non-negligible effects of improving competition in banking on firm growth. Taking the average increase in credit due to lower prices of 20%, implies a 0.4% increase in firm productivity on a year-to-year basis.

[Place Table 9 here.]

5.3 Aggregating the Effects

As competition policy on banking can potentially affect firm productivity, we now proceed to measure the aggregate effects over all firms. We apply the framework of Petrin and Levinsohn (2012) and Rotemberg (2019), which decompose the aggregate effects into allocative efficiency effects and reallocation across firms. The change in aggregate productivity growth (APG) is given by:

$$APG = \sum_i (D_i \Delta \ln(TFPR_i)) + \sum_i D_i \Big[\sum_{Input} (\alpha_{Input_i} - s_{Input_i}) \Delta \ln Input_i \Big], \tag{11}$$

where D_i is firm's i share of total sales in the economy, α_{Input_i} is the firm's elasticity of revenue with respect to $Input$, s_{Input_i} is the revenue share of the input. The variables $\Delta \ln(TFPR_i)$ and $\Delta \ln Input_i$ are the estimated causal change in productivity and input from a policy. The objects here can be estimated using a production function, an instrumental variable approach, or straight from the data.

In particular, the weights D_i and revenue shares s are taken from the data, while α_{Input_i} is taken from the production function estimation results. The change in productivity $\Delta \ln(TFPR_i$ is approximated by the total change in credit from the policy estimated at the firm level through the simulation approach multiplied by the average treatment effect of credit on TFPR ($beta_c$ in equation 10, namely $\Delta ln(Credit)^{BN} \times \beta_c$. To obtain $\Delta \ln Input_i$, we run equation 10 by replacing the dependent variable for the relevant input and approximate total change in a similar fashion to productivity.

Table 10 shows the calibrated parameters, the distribution of empirical values obtained from the data, the distribution of predicted change in credit following the antitrust policy, and the aggregate effects of the policy. We find that total productivity growth increases by 0.71%, with a large effect coming from improvements in allocative efficiency (0.46%) and the remainder in reallocation across firms (0.25%). While apparently modest, these effects are similar to those estimated by Rotemberg (2019) in a large subsidy program of credit in India, which made 15% of all firms eligible for subsidies. Moreover, though modest in size, they represent a significant share (56%) of the average TFPR growth between 2010 and 2017 in Ecuador, which amounted to 1.26. Moreover, these effects do not consider the dynamic effects on firm growth. Therefore, the adverse effects of market power on firm growth are substantial.

[Place Table 10 here.]

6 Conclusion

In this paper, we study how bank competition affects commercial lending by using the 2014 introduction of a loan tax in Ecuador to identify a quantitative model of commercial lending that allows us to decompose loan markups into their demand- and supply-side components. By counterfactual varying lender competitive conduct (supply-side markups), we find that 26% of observed markups are due to joint profit maximization and that moving to Bertrand-Nash would reduce equilibrium prices by 17%, increase loan use by 21% (intensive margin), and increase overall credit demand by 13% (extensive margin). These distortions vary greatly by borrower characteristics and dwarf those of financial transaction taxes. Through partial equilibrium instrumental variable regressions, we find large effects on firm size and productivity. We aggregate this partial equilibrium effect through a general equilibrium model of firm dynamics to measure the dynamic effects of credit and firm growth.

Overall, our findings suggest that the lack of competition in banking has first-order implications for credit and misallocation. Despite recent evidence documenting some benefits from lender pricing power, policies such as antitrust measures, reducing barriers to entry, and enhancing loan pricing transparency are welfare-improving. These insights extend beyond Ecuador, providing a framework for understanding and addressing similar dynamics in other bank-dependent economies.

References

Ackerberg, Daniel A, Kevin Caves, and Garth Frazer, "Identification properties of recent production function estimators," *Econometrica*, 2015, *83* (6), 2411–2451.

Adams, William, Liran Einav, and Jonathan Levin, "Liquidity constraints and imperfect information in subprime lending," *American Economic Review*, 2009, *99* (1), 49–84.

Amiti, Mary and David E Weinstein, "How much do idiosyncratic bank shocks affect investment? Evidence from matched bank-firm loan data," *Journal of Political Economy*, 2018, *126* (2), 525–587.

Asker, John, Allan Collard-Wexler, and Jan De Loecker, "Dynamic inputs and resource (mis) allocation," *Journal of Political Economy*, 2014, *122* (5), 1013–1063.

Atkin, David and Dave Donaldson, "Who's getting globalized? The size and implications of intranational trade costs," *R&R, Econometrica*, 2015.

Backus, Matthew, Christopher Conlon, and Michael Sinkinson, "Common ownership and competition in the ready-to-eat cereal industry," *R&R, Econometrica*, 2024.

Bau, Natalie and Adrien Matray, "Misallocation and capital market integration: Evidence from India," *Econometrica*, 2023, *91* (1), 67–106.

Benetton, Matteo, "Leverage regulation and market structure: A structural model of the UK mortgage market," *Journal of Finance*, 2021, *76* (6), 2997–3053.

_, Alessandro Gavazza, and Paolo Surico, "Mortgage pricing and monetary policy," *conditionally accepted, American Economic Review*, 2024.

_ and Davide Fantino, "Targeted monetary policy and bank lending behavior," *Journal of Financial Economics*, 2021, *142* (1), 404–429.

Bergquist, Lauren Falcao and Michael Dinerstein, "Competition and entry in agricultural markets: Experimental evidence from Kenya," *American Economic Review*, 2020, *110* (12), 3705–47.

Berry, Steven T and Philip A Haile, "Identification in differentiated products markets using market level data," *Econometrica*, 2014, *82* (5), 1749–1797.

Bresnahan, Timothy F, "The oligopoly solution concept is identified," *Economics Letters*, 1982, *10* (1-2), 87–92.

Brugués, Felipe and Rebecca De Simone, "Taxation when markets are not competitive: Evidence from a loan tax," *Working paper*, 2024.

Brugués, Felipe, Javier Brugués, and Samuele Giambra, "Political connections and misallocation of procurement contracts: evidence from Ecuador," *Journal of Development Economics*, 2024, *170*, 103296.

Buera, Francisco J, Joseph P Kaboski, and Yongseok Shin, "Entrepreneurship and financial frictions: A macrodevelopment perspective," *Annual Review of Economics*, 2015, *7* (1), 409–436.

Cabral, Marika, Michael Geruso, and Neale Mahoney, "Do larger health insurance subsidies benefit patients or producers? Evidence from Medicare Advantage," *American Economic Review*, 2018, *108* (8), 2048–2087.

Catherine, Sylvain, Thomas Chaney, Zongbo Huang, David Sraer, and David Thesmar, "Quantifying reduced-form evidence on collateral constraints," *The Journal of Finance*, 2022, *77* (4), 2143–2181.

Ciliberto, Federico and Jonathan W Williams, "Does multimarket contact facilitate tacit collusion? Inference on conduct parameters in the airline industry," *RAND Journal of Economics*, 2014, *45* (4), 764–791.

Cornaggia, Jess, Yifei Mao, Xuan Tian, and Brian Wolfe, "Does banking competition affect innovation?," *Journal of Financial Economics*, 2015, *115* (1), 189–209.

Cox, Natalie, Ernest Liu, and Daniel Morrison, "Market Power in Small Business Lending: A Two Dimensional Bunching Approach," *Forthcoming at Journal of Financial Economics*, 2023.

Crawford, Gregory S, Nicola Pavanini, and Fabiano Schivardi, "Asymmetric information and imperfect competition in lending markets," *American Economic Review*, 2018, *108* (7), 1659–1701.

Cuesta, José Ignacio and Alberto Sepúlveda, "Price regulation in credit markets: A trade-off between consumer protection and credit access," *R&R, Econometrica*, 2024.

Dearing, Adam, Lorenzo Magnolfi, Daniel Quint, Christopher J Sullivan, and Sarah B Waldfogel, "Learning Firm Conduct: Pass-Through as a Foundation for Instrument Relevance," 2024.

Drechsler, Itamar, Alexi Savov, and Philipp Schnabl, "The deposits channel of monetary policy," *Quarterly Journal of Economics*, 2017, *132* (4), 1819–1876.

Duarte, Marco, Lorenzo Magnolfi, Mikkel Sølvsten, and Christopher Sullivan, "Testing firm conduct," *Quantitative Economics*, 2024, *15* (3), 571–606.

Egan, Mark, Ali Hortaçsu, and Gregor Matvos, "Deposit competition and financial fragility: Evidence from the US banking sector," *American Economic Review*, 2017, *107* (1), 169–216.

Einav, Liran, Amy Finkelstein, and Neale Mahoney, "The IO of selection markets," in "Handbook of industrial organization," Vol. 5, Elsevier, 2021, pp. 389–426.

Eisenschmidt, Jens, Yiming Ma, and Anthony Lee Zhang, "Monetary policy transmission in segmented markets," *Journal of Financial Economics*, 2023.

Gandhi, Amit, Salvador Navarro, and David A Rivers, "On the identification of gross output production functions," *Journal of Political Economy*, 2020, *128* (8), 2973–3016.

Hatfield, John William and Jonathan Wallen, "Many markets make good neighbors: Multimarket contact and deposit banking," *Working paper. https://www. hbs. edu/faculty/Pages/item. aspx*, 2023.

Hsieh, Chang-Tai and Peter J Klenow, "Misallocation and manufacturing TFP in China and India," *The Quarterly Journal of Economics*, 2009, *124* (4), 1403–1448.

Ioannidou, Vasso, Nicola Pavanini, and Yushi Peng, "Collateral and asymmetric information in lending markets," *Journal of Financial Economics*, 2022, *144* (1), 93–121.

Jiang, Liangliang, Ross Levine, and Chen Lin, "Does competition affect bank risk?," *Journal of Money, Credit and Banking*, 2023, *55* (5), 1043–1076.

Kroft, Kory, Jean-William Laliberté, René Leal-Vizcaíno, and Matthew J Notowidigdo, "Salience and taxation with imperfect competition," *Review of Economic Studies*, 2024, *91* (1), 403–437.

Loecker, Jan De and Jan Eeckhout, "Global market power," Technical Report, National Bureau of Economic Research 2018.

_ , Pinelopi K Goldberg, Amit K Khandelwal, and Nina Pavcnik, "Prices, markups, and trade reform," *Econometrica*, 2016, *84* (2), 445–510.

Mahoney, Neale and E Glen Weyl, "Imperfect competition in selection markets," *Review of Economics and Statistics*, 2017, *99* (4), 637–651.

Manaresi, Francesco and Nicola Pierri, "The Asymmetric Effect of Credit Supply on Firm-Level Productivity Growth," *Journal of Money, Credit and Banking*, 2024, *56* (4), 677–704.

Midrigan, Virgiliu and Daniel Yi Xu, "Finance and misallocation: Evidence from plant-level data," *American Economic Review*, 2014, *104* (2), 422–458.

Miravete, Eugenio J, Katja Seim, and Jeff Thurk, "Pass-through and tax incidence in differentiated product markets," *International Journal of Industrial Organization*, 2023, p. 102985.

Petersen, Mitchell A and Raghuram G Rajan, "The effect of credit market competition on lending relationships," *Quarterly Journal of Economics*, 1995, *110* (2), 407–443.

Petrin, Amil and James Levinsohn, "Measuring aggregate productivity growth using plant-level data," *The Rand Journal of Economics*, 2012, *43* (4), 705–725.

Rajan, Raghuram G, "Insiders and outsiders: The choice between informed and arm's-length debt," *Journal of Finance*, 1992, *47* (4), 1367–1400.

Robles-Garcia, Claudia, "Competition and incentives in mortgage markets: The role of brokers," *Unpublished working paper*, 2021.

Rotemberg, Martin, "Equilibrium effects of firm subsidies," *American Economic Review*, 2019, *109* (10), 3475–3513.

Scharfstein, David and Adi Sunderam, "Market power in mortgage lending and the transmission of monetary policy," *Unpublished working paper. Harvard University*, 2017.

Sharpe, Steven A, "Asymmetric information, bank lending, and implicit contracts: A stylized model of customer relationships," *Journal of Finance*, 1990, *45* (4), 1069–1087.

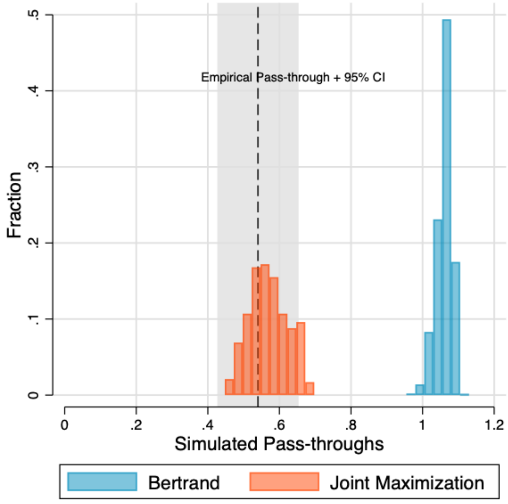
Sraer, David and David Thesmar, "How to use natural experiments to estimate misallocation," *American Economic Review*, 2023, *113* (4), 906–938.

Train, Kenneth E, *Discrete choice methods with simulation*, Cambridge university press, 2009.

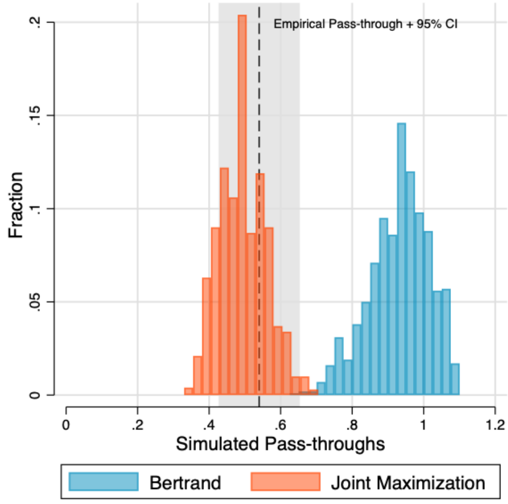
Weyl, E Glen and Michal Fabinger, "Pass-through as an economic tool: Principles of incidence under imperfect competition," *Journal of Political Economy*, 2013, *121* (3), 528–583.

Yannelis, Constantine and Anthony Lee Zhang, "Competition and selection in credit markets," *Journal of Financial Economics*, 2023, *150* (2), 103710.

7 Figures and Tables



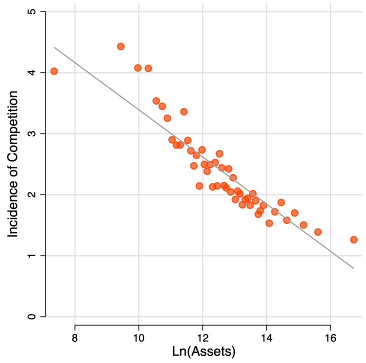
(a) All loans



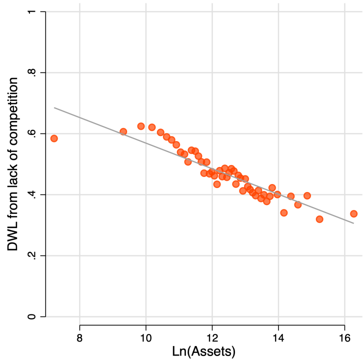
(b) Chosen loans

FIGURE 1: DISTRIBUTION OF SIMULATED PASS-THROUGHS BY CONDUCT

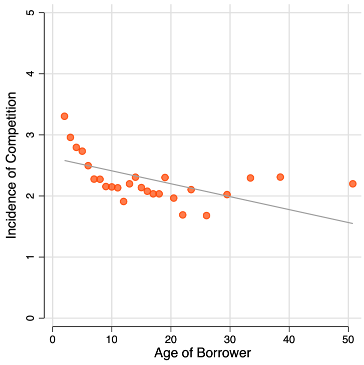
The figure reports the distribution of average nation-wide, bootstrapped, simulated Nash-equilibrium pass-throughs of the introduction of a loan tax of 0.5% by mode of conduct (Bertrand-Nash in blue and Joint Maximization in Orange). Panel (a) displays simulated pass-throughs for chosen and potential loans while Panel (b) displays pass-throughs only for loans actual lent. Bootstrap estimates come from 1,000 bootstrapped samples of borrower-level estimates of pass-through under each model. The dashed line shows the empirical pass-throughs regressions (using actual loan data) presented in the reduced-form section of the paper, and the shaded area shows the 95% confidence intervals.



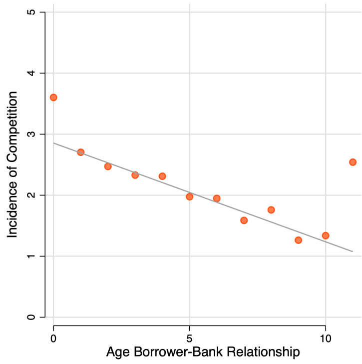
(a) Incidence: Assets



(b) DWL: Assets



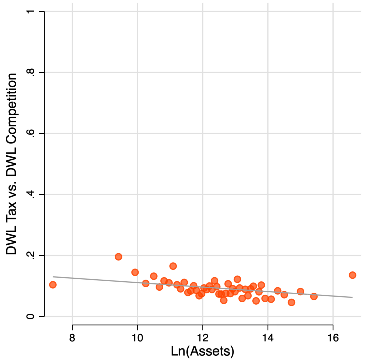
(c) Incidence: Firm Age



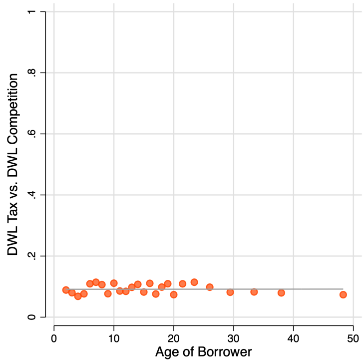
(d) Incidence: Relationship Length

FIGURE 2: HETEROGENEITY IN INCIDENCE AND DEADWEIGHT LOSS OF COMPETITION BY FIRM SIZE, AGE, AND LENDING RELATIONSHIP LENGTH

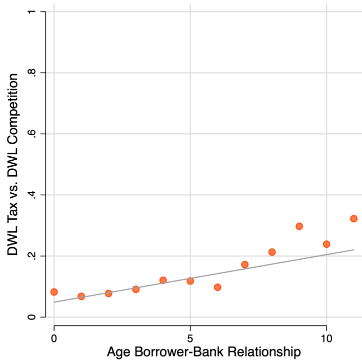
The figure examines the heterogeneity in the welfare impact of moving from the best-fit model to Bertrand-Nash competition. Panels (a), (c), and (d) of the figure report binscatter plots on the incidence of competition estimates ($-\Delta CS/\Delta PS$) by firm size (ln assets), firm age, and bank-firm relationship length. Panel (b) reports the deadweight loss from lender competition net the deadweight loss from the SOLCA tax.



(a) Assets



(b) Firm Age



(c) Relationship Age

FIGURE 3: HARBERGER TRIANGLES COMPARISON FOR FINANCIAL TAX AND COMPETITION BY FIRM SIZE (ASSETS), FIRM AGE, AND BANK-FIRM RELATIONSHIP AGE

The figure reports binscatter plots on the comparison between the Harberger Triangles (deadweight loss) generated by financial taxes benchmarked over the Harberger Triangles from collusive prices by firm size (ln assets), firm age, and bank-firm relationship age.

TABLE 1: DESCRIPTIVE STATISTICS

The table describes the commercial loan dataset. *Firm-Level Data* are at the firm-year level for 2010 to 2017. *Firm Age* is years from incorporation date. *Total Assets* and *Total Sales* are reported in millions of 2010 USD. *Total Wages* are all wages reported to the company regulator for both contract and full-time employees in millions of 2010 USD. *Total Debt* is the sum of short- and long-term debt in millions of 2010 USD. *Leverage* is total debt over beginning-of-period total assets. *Number Bank Relationships* are the number of banks the firm has borrowed from in a calendar year. *Age Bank Relationship* is years from the first loan with a bank. *Loan-Level Data* are at the loan-year level for 2010 to 2017, where only newly-granted commercial loans are included. *Interest Rate* is the nominal, annualized interest rate at issuance, in percent. *Loan Amount* is the size of the loan in millions of 2010 USD at issuance. *Annual Loan Maturity* is years-to-maturity at issuance. *1(Loan with rating < B)* takes the value one if the bank has applied a risk weight on the loan lower than B, i.e., the loan expects non-zero write-down on the loan. *1(Default Observed)* takes the value one if the loan defaults at any point after issuance. *Deposit Interest Rates* is a weighted average of bank-year deposits, where weights are the nationwide average rates for deposits at each horizon. Continuous variables are winsorized at the 1% and 99% levels.

Variable	**Mean**	**Median**	**SD**	**Min.**	**Max.**	**Obs.**
	Panel A: Firm-Level Data: Active Borrowers					
Firm Age	12.25	9.00	11.14	0.00	96.00	97,796
Total Assets	2.05	0.40	4.22	0.00	20.66	97,796
Total Sales	2.57	0.62	4.86	0.00	23.14	97,796
Total Wages	0.36	0.10	0.63	0.00	2.98	97,796
Total Debt	1.31	0.28	2.61	0.00	12.65	97,796
Leverage	0.66	0.71	0.28	0.00	1.19	97,796
Number of Bank Relationships	1.38	1.00	0.79	1.00	7.00	97,796
Number Loans	8.88	2.00	100.66	1.00	9,195.00	97,796
	Panel B: Firm-Level Data: Non Active Borrowers					
Firm Age	9.92	7.00	10.09	0.00	93.00	359,827
Total Assets	0.46	0.05	1.73	0.00	20.66	359,827
Total Sales	0.43	0.03	1.70	0.00	23.14	359,827
Total Wages	0.07	0.01	0.25	0.00	2.98	359,827
Total Debt	0.26	0.02	1.01	0.00	12.65	359,827
Leverage	0.54	0.58	0.40	0.00	1.19	359,827
	Panel C: Loan-Level Data					
Age Bank Relationship	2.31	2.00	2.41	0.00	16.00	885,229
Loan Interest Rate	9.20	8.95	3.48	1.08	25.50	885,229
Loan Amount	0.10	0.01	1.73	0.00	4.66	885,229
Annual Loan Maturity	0.51	0.25	0.80	0.00	27.39	885,229
1(Loan with Rating < B)	0.02	0.00	0.14	0.00	1.00	885,229
1(Default Observed)	0.00	0.00	0.06	0.00	1.00	885,229
	Panel D: Bank-Level Data					
Deposit Interest Rates	4.68	4.47	0.46	3.89	6.26	1,951

TABLE 2: DIRECT PASS-THROUGH ESTIMATES

The table reports pass-through estimates by lending region to the interest rates of commercial loans around the introduction of the 2014 SOLCA tax in Ecuador. Data are at the loan-level. The estimation window is from eight quarters before the introduction of the tax through three quarters afterward, excluding October 2014. The main independent variable is the tax rate, measured as 0.5 adjusted proportionally by term-to-maturities if maturity is less than 1 year. The dependent variable is the tax-inclusive interest rate, which is the sum of the nominal, annualized interest rate plus the tax rate. Both are in percentage points. Regressions control for twenty buckets of term-to-maturity, and twenty buckets of loan amount, predicted default probability, and bank $\times$ firm (pair) fixed effects. The model is estimated at the aggregate level and then separately by region. Robust standard errors are clustered at the bank-quarter level.

	Pass-through (ρ)	**Standard Error**	**Observations**	**P-value (Pass-through = 1)**
Aggregate	0.536	0.150	347,471	0.002
Azuay	0.508	0.276	39,610	0.072
Costa	0.438	0.344	15,139	0.104
Guayas	0.727	0.160	176,907	0.090
Pichincha	0.346	0.301	95,380	0.031
Sierra	0.537	0.401	20,435	0.251

TABLE 3: DEMAND PARAMETERS

The table presents the mean and standard deviation of estimated parameters across markets (provinces). The coefficient for *Price* comes from an instrumental variable approach that corrects for price endogeneity and measurement error in predicted prices for non-observed offers. The standard deviation is calculated as the standard error of the parameter values obtained by estimating the model on 1,000 bootstrap samples.

Variable	**(1) Mean**	**(2) Standard Error**
Price	-0.24	0.08
Sigma (unobserved heterogeneity)	0.81	0.05
Scaling factor (to match proportion borrowers)	1.06	0.39
Log(Branches)	2.26	1.02
Age Firm	-0.03	0.01
Age Relationship	0.39	0.04
Assets	0.24	0.11
Debt	-0.01	0.05
Expenditures	0.06	0.04
Revenues	-0.02	0.04
Wages	0.01	0.03

TABLE 4: LOAN DEMAND, OWN-PRODUCT AND CROSS-PRODUCT DEMAND ELASTICITIES

The table reports the loan-level estimated elasticities for realized and non-realized loans. Continuous elasticity is the intensive margin elasticity with respect to interest rates. Discrete elasticity is the discrete-choice elasticity with respect to interest rates. Total is the sum of continuous and discrete. Cross elasticity is the discrete bank substitution elasticity with respect to interest rates.

Elasticities	**Mean**	**Median**	**Std. Dev.**	**Min.**	**Max.**	**Count**
Continuous	-4.63	-4.50	2.68	-9.58	-0.86	628,450
Discrete	-6.01	-0.55	11.33	-42.80	0.00	628,450
Total	-10.71	-7.31	10.21	-44.68	-2.81	628,450
Cross	0.17	0.01	0.36	0.00	1.38	627,704

TABLE 5: DESCRIPTION OF MODEL FIT

The table presents measures of model fit regarding market shares, loan use, prices, and default rates. Differences in observations are because loan use, prices, and default are only measured for actual, realized loans. Market shares and loan use come from the structural demand model, discussed in section **??**. Estimation methodology for default is available in **??** and for prices in **??**.

Parameter	**Mean**	**Std. Dev.**	**Count**
Observed Market Share	0.06	0.25	681,722
Model Market Share	0.06	0.15	681,722
Observed Loan Use	9.43	2.33	39,560
Predicted Loan Use	9.42	1.49	39,586
Observed Prices	11.27	4.42	39,586
Predicted Prices	11.21	3.54	39,586
Observed Default	0.02	0.14	39,586
Predicted Default	0.02	0.04	39,586

TABLE 6: SIMULATED VS. ACTUAL PASS-THROUGH BY REGION

The table shows the region-level empirical and simulated pass-through. The empirical pass-through are estimates of the pass-through by lending region to the interest rates of commercial loans around the introduction of the 2014 SOLCA tax in Ecuador. Data are at the loan-level for 2010 to 2017, excluding October 2014. The main independent variable is the tax rate, measured as 0.5 adjusted proportionally by term-to-maturities if maturity is less than 1 year. The dependent variable is the tax-inclusive interest rate, which is the sum of the nominal, annualized interest rate plus the tax rate. Both are in percentage points. Regressions control for twenty buckets of term-to-maturity, and twenty buckets of loan amount, predicted default probability, and bank × firm (pair) FE. To produce the simulated pass-through we use the estimated supply and demand parameters from our model to simulate pass-throughs of the introduction of the 0.5% tax rate for each mode of conduct (Bertrand-Nash and joint maximization), while flexibly accounting for demand heterogeneity. The tax shock is modeled as a 0.5 percentage point linear increase in the bank-borrower-specific marginal costs of lending. Then, for each borrower, we use their estimated demand functions to solve for the Nash equilibrium of prices implied by the system of equations of first-order conditions (Equation 5) for all banks in their choice set, under the assumption that $\upsilon_m = 0$ under Bertrand-Nash and $\upsilon_m = 1$ under joint maximization. Columns (2) and (3) describe the results of following this rpocess for 1,000 bootstrap simulations, where we sampled borrowers with replacement.

Region	(1) **Empirical**	(2) **Joint Maximization**	(3) **Bertrand-Nash**
Azuay	0.508	0.294	0.974
Costa	0.438	0.443	0.626
Guayas	0.727	0.719	1.104
Pichincha	0.346	0.404	1.063
Sierra	0.537	0.542	0.819

TABLE 7: MOVE TO BERTRAND-NASH COMPETITION

This table presents the estimated borrower-bank-loan specific (panel A) marginal costs under two modes of conduct (Bertrand Nash: Not Accounting for Conduct; and Joint Maximization: Accounting for Conduct). Panel B presents predicted prices and contrasts them with equilibrium prices after shutting down conduct $\upsilon_m = 0$. Panel C shows the markups under Bertrand and Joint Maximization, as well as the equilibrium markups after shutting down conduct. It also presents the decomposition of markups into Conduct, Preferences, and Risk. Panel D shows the intensive and extensive margin effects from shutting down conduct to zero. It also reports the change in risk profile due to the entrance of borrowers. Panel E presents estimates of the welfare effects and incidence of joint maximization.

	Mean	**Median**
	Panel A: Marginal Costs	
Marginal Cost - Not Accounting for Conduct	8.82	9.30
Marginal Cost - Accounting for Conduct	4.87	3.10
% Change in Marginal Cost	-50.57	-55.75
	Panel B: Prices	
Prices - Predicted	11.25	11.56
Prices - Move to Bertrand-Nash	9.43	10.34
% Change in Equilibrium Prices	-17.18	-5.36
	Panel C: Markups	
Markup - Not Accounting for Conduct	2.43	2.30
Markup - Accounting for Conduct	6.38	4.79
Markup - Move to Bertrand-Nash	4.56	2.43
% Share of Markup due to Conduct	25.46	19.18
% Share of Markup due to Preferences	70.27	72.62
% Share of Markup due to Risk	4.26	0.33
	Panel D: Intensive & Extensive Margin	
% Change in Continuous Loan Use - Move to Bertrand-Nash	21.39	20.29
Market Share Outside Option - Predicted Prices	0.033	
Market Share Outside Option - Move to Bertrand-Nash	0.029	
% Change in Risk in Borrowers (Adverse Selection))	0.45	
	Panel E: Welfare and Incidence	
USD Change in Borrower Surplus (ΔCS)	41,907.85	3,717.17
USD Change in Lender Surplus (ΔPS)	-100,346.58	-3,347.45
Incidence of Competition (-ΔCS/ΔPS)	2.81	1.62

TABLE 8: PRODUCTION FUNCTION ESTIMATION

The table reports the elasticities of a Cobb-Douglas revenue production function with capital, intermediate inputs, and labor as inputs. The model is estimated following Ackerberg et al. (2015) and implemented using *acfest* in Stata.

	(1)	(2)
Labor	0.499	0.321
	(0.020)	(0.032)
Expenditures	0.527	0.701
	(0.016)	(0.006)
Capital	0.042	0.120
	(0.003)	(0.005)
Labor Measured in	Wages	# Employees
Observations	581,559	334,732

TABLE 9: CREDIT SUPPLY SHOCKS AND FIRM PRODUCTIVITY

The table reports the effects of credit, instrumented by supply-side shocks, on firm ln(TFPR). Firm-level ln(TFPR) is calculated via production function estimation following Ackerberg et al. (2015). Variable names starting with *F.* indicate one period forward, while *L.* indicate one period lag. Δ indicates one-period difference in the variable between t and $t-1$. Credit is measured using the bank regulator database summing over all sources of credit. Capital is book value of fixed assets, Expenditures is total intermediate inputs, and # of Employees is the total number of individuals working at the firm as reported by the firms. Instrumented Credit is obtained from an instrumental variable regression of ln(Credit) on firm-level average interest rates, instrumented by the average prices of their supplying banks in other products and regions, to capture the supply-side shocks, and obtained through linear forecasting based on the instrumental variable approach. Instrumented coefficient for ln(Credit) on interest rate, aggregate at the firm-level, is -0.34 (0.024) and the first-stage F-stat is 320.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	F. ln(TFPR)	F. ln(TFPR)	F. Δ ln(TFPR)	F. Δ ln(TFPR)	F. Δ ln(TFPR)	F. Δ ln(TFPR)
Instrumented ln(Credit)	0.0208***	0.0189***	0.0175***	0.0224**	0.0162***	0.0259**
	(0.00508)	(0.00703)	(0.00467)	(0.00953)	(0.00503)	(0.0109)
L. Δ Expenditures					0.0686***	0.0783***
					(0.00524)	(0.00707)
L. Δ Capital					-0.0554***	-0.0737***
					(0.00550)	(0.00738)
L. Δ # Employees					0.124***	0.137***
					(0.00928)	(0.0101)
ln(TFPR)	0.441***	-0.0125				
	(0.00844)	(0.0107)				
Constant	1.674***	2.945***	0.0436**	0.0596*	0.0281	0.0680*
	(0.0312)	(0.0394)	(0.0171)	(0.0354)	(0.0186)	(0.0403)
Observations	70,065	63,285	70,065	63,285	61,157	54,531
R-squared	0.343	0.625	0.016	0.175	0.034	0.195
Year FE	YES	YES	YES	YES	YES	YES
Sector FE	YES	NO	YES	NO	YES	NO
Province FE	YES	NO	YES	NO	YES	NO
Firm FE	NO	YES	NO	YES	NO	YES

Robust standard errors clustered at the firm-level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

TABLE 10: AGGREGATE EFFECTS OF MOVING TO BERTRAND-NASH

This table reports the aggregate efficiency effects of moving to Bertrand-Nash, mediated by a decrease in prices and an increase in credit demand.

APG Estimated and Calibrated Targets			
Target	Elasticity to Credit	Input Elasticity	Mean Shares of Revenue
TFPR	0.02	–	–
Capital	0.09	0.12	0.06
Expenditures	0.02	0.70	0.62
Labor	0.10	0.32	0.27
	p25	Median	p75
% Change in Credit	3.42	20.28	61.19
APG Estimates (%)			
Type of Effect of Credit	Total Effect	Allocative Efficiency	Reallocation
Heterogenous	0.71	0.46	0.25
Homogenous at 20%	0.35	0.23	0.12

Internet Appendix

Appendix A The Ecuadorian Banking Sector

Overall, Ecuador is typical of similar middle-income, bank-dependent economies studies in the literature. Over our sample, from 2010 to 2017, the Ecuadorian financial system was comprised of 24 banks: four large banks (Pichincha, Guayaquil, Produbanco and Pacıifico), nine medium-sized banks (Bolivariano, Internacional, Austro, Citibank, General Rumiñahui, Machala, Loja, Solidario and Procredit), nine small banks, and two international banks (Citibank and Barclays).[1] The Superintendencia de Bancos y Seguros (SB; Superintendent of Banks and Insurance Companies) is the regulator for the sector.[2]

Interest rates on new credits are regulated by a body under the control of the legislature, the Junta de Política y Regulación Monetaria y Financiera. It defines maximum interest rates for credit segments. For commercial credit, maximum interest rates are defined according to the size of the loan and the size of the company.[3] Finally, depositors are protected by deposit insurance from the Corporación del Seguro de Depósitos (Deposit Insurance Corporation (COSEDE)).

Appendix A.1 Market characteristics' relationship to interest rates

We test the representativeness of Ecuadorian commercial lending by checking the correlations between average equilibrium interest rates and market characteristics at the aggregated bank-province-year level. Table A1 reports the results. Model 1 employs year fixed effects (FE), Model 2 utilizes province and year FE, and Model 3 runs estimates with both year and bank FE.

[1]Note: size is measured according to the bank's assets.

[2]This does not include microlenders, who are regulated by the Superintendencia de Economía Popular y Solidaria (Superintendent of the Popular and Solidarity Economy). Micro loans are granted on worse terms than regular commercial loans and access to the two markets is strictly bifurcated by law. In our study we focus on the regular commercial lending sector.

[3]Interest rate caps are common around the world—as of 2018 approximately 76 countries (representing 80% of world GDP) impose some restrictions on interest rates, according to the World Bank. They are particularly prevalent in Latin America and the Caribbean but are also observed on some financial products offed in Australia, Canada and the United States (see **?**). Interest rate caps place constraints on bank market power and affect the distribution of credit and this is reflected in our model.

TABLE A1: INTEREST RATE AND MARKET CHARACTERISTICS

The table reports correlations between average nominal interest rates on new commercial credit and market characteristics. Data are at the bank-province-year level for 2010 to 2017, for years in which the bank offered any loan in a given province. The variables include the natural log transformation of: *# Branches* is the number of open branches in the province; *# Other Private Branches* is the total number competing branches active in the province. *# Clients* is the sum of unique clients; *Av. Loan* is the average loan size at issuance; *Av. Maturity* is average annualized term-to-maturity at issuance; *Av. Interest Rate* is the nominal, annualized interest rate at issuance, in percent; *# Loans per Client* is the average number of loans extended per firm from a given bank; *HHI* is the Herfindahl-Hirschman Index at the province-year level. Data from state-owned banks are excluded. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Variable	**(1) Av. IR**	**(2) Av. IR**	**(3) Av. IR**
Ln(Av. Loan)	-0.567***	-0.605***	-0.557***
	(0.045)	(0.047)	(0.054)
Ln(Av. Maturity)	-0.624***	-0.585***	-0.551**
	(0.185)	(0.194)	(0.226)
Ln(# Branches)	-0.438***	-0.402***	-0.363**
	(0.136)	(0.135)	(0.151)
Ln(# Other Branches)	-0.046	0.044	0.014
	(0.053)	(0.071)	(0.075)
Ln(HHI Value)	0.704***	0.546	0.352*
	(0.210)	(0.365)	(0.212)
Ln(# Loans per Client)	-0.604***	-0.606***	-0.475***
	(0.048)	(0.048)	(0.053)
Ln(# Clients)	0.506***	0.576***	0.272***
	(0.051)	(0.063)	(0.051)
Constant	11.990***	13.080***	14.680***
	(1.863)	(2.925)	(1.892)
Year FE	Yes	Yes	Yes
Province FE	No	Yes	No
Bank FE	No	No	Yes
Observations	1,734	1,734	1,734
R-squared	0.298	0.345	0.415

The general patterns we observe between market access and loan pricing align with those documented in existing literature in Latin America and elsewhere. Across all our models, we find that average interest rates tend to decline with increasing loan size and maturity. Banks that have a higher number of branches in a given market on average offer lower rates—potentially indicating that banks expand in markets in which they have an efficiency advantage. Conversely, we find a weak and statistically insignificant link between loan pricing and the number of competing branches within a province or across different markets served by the same bank. This suggests that mere access to competing banks through larger branches does not significantly influence a bank's average pricing strategy.

Moreover, we uncover a positive correlation between market concentration, as proxied by the Herfindahl-Hirschman Index (HHI) based on commercial lending share, and average interest rates. Even within individual banks, more concentrated markets command higher rates. Furthermore, we observe that interest rates tend to be lower when the bank and borrower interact frequently, as measured by the number of loans per borrower. However, larger banks (as indicated by the number of borrowers) generally charge higher interest rates. This could be due to the diverse needs (borrower preference heterogeneity) that leads firms to borrow from specific banks, despite steeper prices.

Appendix A.2 Loan default in our data relative to in the literature

In our dataset of commercial loans to non-micro, formal firms, we observe very low levels of average default.

Here, we benchmark against default in related papers:

- Crawford et al. (2018) report a default rate of 6% in a sample of Italian small business lines of credit (with maturity 6 months to a year) between 1988 and 1998, which included a financial crisis in 1992.

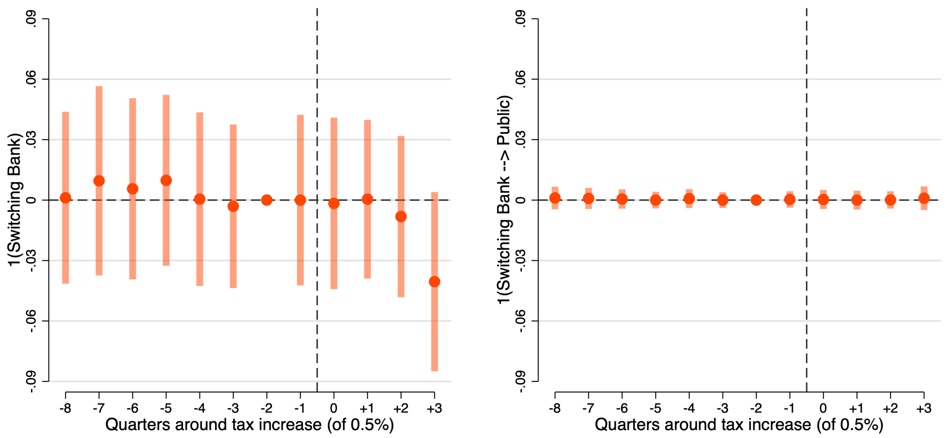
- Default rates are close to 10% for credit of 13 months maturity

Appendix A.3 Commercial lending of private and public banks

The government banks specialize in the commercial loan market in lending to small firms in small markets. In average (at the median) they lend 20.2% (10.5%) of the outstanding commercial debt in a given province-year—8.8% when the average is weighted by market size. At the borrower-year-level they lend 2.3% (0%) on average (at the median). Thus, there is some degree of competition between the public and private banking sector in commercial lending and there are possible indirect effects of the SOLCA tax on public commercial lending. In this paper we take this seriously by including the private banks in the model estimation.

While theoretically salient, however, the existence of the public commercial loan market does not appear to be first order in practice in this setting. This is suggested by Figure **??**, where we see no reaction in interest rates to the introduction of the SOLCA tax. And recall that in Figure **??** in **??**, we see that there was also no significant effect on loan maturity or amount borrowed in loans lent by public banks.

Moreover, we see no evidence that there was significant switching of firms around the introduction of the tax, either between any banks or from borrowing taxed private-sector loans to borrowing untaxed public-sector loans. To test this, we first define the variable *Switch*, which takes the value one if the loan borrowed in period t is from a different bank, public or private, than the last loan borrowed. The left-hand panel of Figure A1 reports the evolution in the probability of switching lenders around the introduction of the SOLCA tax relative to the probability two quarters before the tax was introduced. We see no significant difference either leading up to the tax or immediately after its introduction. If anything, there is a decrease in the probability of switching lenders three quarters after the introduction of the tax, though it is not significant at conventional confidence levels. This may reflect the macroeconomic shock from falling oil prices that sent Ecuador into recession in the first quarter of 2015 (see **??** for further information on this recession and its potential to affect our results). of In the right-hand panel of Figure A1 we similarly see no evidence of a change in the probability of switching to borrowing from a public bank. Overall, we see no evidence that the existence of a public source of commercial loans that were not subject to the SOLCA tax had a significant impact on the pass-through of the tax or on lender competition in the private commercial loan market. This is due to the enforced separation between the two markets necessitated to reserve the subsidized interest rates of public commercial loans for micro businesses.



(a) Prob. switch bank (b) Prob. switch to public bank

FIGURE A1: DYNAMIC ANALYSIS OF THE INTRODUCTION OF THE SOLCA TAX ON THE PROBABILITY OF SWITCHING LENDERS

The figure reports the period-by-period difference in outcomes around the introduction of the SOLCA tax relative to event-time period $t = -2$ (normalized to zero). The outcome in Figure (a) is the probability that a new commercial loan is borrowed from a different bank than the last loan in the period relative to at $t = -2$. For Figure (b) the outcome is the probability that a new loan is borrowed from a different bank than the last loan and that new lender is a public, state-owned bank. Data are loan-level and include bank fixed effects. Standard error bars are shown at the 95% confidence level and are clustered at the bank-quarter level.

Appendix B A Model of Commercial Lending with General Competitive Conduct

In this appendix, we describe our quantitative model of commercial lending in more detail than was possible in Section 2.

Appendix B.1 Setup

We consider local markets M with K lenders (private banks) and I borrowers (small-to-medium-sized, single establishment firms). Let k be the index for banks, i for borrowers, m for local markets, and t for the month. Both lenders and borrowers are risk neutral. To isolate the effect of bank joint profit maximization (conduct) on pricing and pass-throughs, we first rely on two simplifying assumptions: (1) borrowers can choose from any bank in their local market, and (2) borrowers' returns on investment can be parameterized.

Appendix B.2 Credit Demand

In a given period t, borrower i has to decide whether to borrow and, if so, from which bank k in their market m. If the firm chooses not to borrow, it gets the value of its outside option, normalized to $k = 0$. Then, conditional on borrowing, the firm simultaneously chooses from all the banks available to them (discrete product choice) and the loan amount (continuous quantity choice), given their preferences.

The (indirect) profit function for borrower i choosing bank k in market m at time t is

$$\Pi_{ikmt} = \overline{\Pi}_{ikmt}(X_{it}, r_{ikmt}, X_{ikmt}, N_{kmt}, \psi_i, \xi_{kmt}; \beta) + \varepsilon_{ikmt}, \tag{B1}$$

where $\overline{\Pi}_{ikmt}$ is the indirect profit function of the optimized values of loan usage, L_{ikmt}. It is equivalent to an indirect utility function in the consumer framework. X_{it} are observable characteristics of the firm, for example, its assets or revenue. r_{ikmt} is the nominal interest rate.[1] X_{ikmt} are time-varying characteristics of the bank-firm pair, such as the age of the relationship. N_{kmt} is time-varying branch availability offered by the bank in market m. ψ_i captures unobserved (both by the bank and the econometrician) borrower characteristics, such as the shareholders' net worth and the management's entrepreneurial ability. ξ_{kmt} captures unobserved bank characteristics that affect all firms borrowing from bank k. ε_{ikmt} is an idiosyncratic taste shock. Finally, β collects the demand parameters common to all borrowers in market m.

If the firm does not borrow, it receives the profit of the outside option:

$$\Pi_{i0} = \varepsilon_{i0mt}, \tag{B2}$$

where we have normalized the baseline indirect profit from not borrowing to zero.

The firm chooses the financing option that gives it the highest expected return.[2] The firm therefore picks bank k if $\Pi_{ikmt} > \Pi_{ik'mt}$, for all $k' \in M$. The probability that firm i chooses bank k given their value for unobserved heterogeneity ψ_i is given by:

$$s_{ikmt}(\psi_i) = Prob(\Pi_{ikmt} \geq \Pi_{ik'mt}, \forall k' \in M). \tag{B3}$$

Integrating over the unobserved heterogeneity yields the unconditional bank-choice probability:

$$s_{ikmt} = \int s_{ikmt}(\psi_i) dF(\psi_i), \tag{B4}$$

for ψ_i, which has a distribution F.

Given the selected bank, the firm chooses optimal quantity L_{ikmt}, which we obtain using Hotelling's lemma:[3]

$$L_{ikmt} = -\frac{\partial \Pi_{ikmt}}{\partial r_{ikmt}} = L_{ikmt}(X_{it}, r_{ikmt}, X_{ikmt}, \psi_i, \xi_{kmt}; \beta), \tag{B5}$$

where the function excludes N_{kmt}, the number of branches that bank k has in the local area market of firm i. This establishes the only exclusion restriction the model requires: branch density affects the choice of the bank but not the continuous quantity choice. We verify this restriction empirically in our setting.

Putting everything together, the demand model is defined jointly by Equations B4 and B5,

[1] Different from Benetton (2021), we let the price vary by borrower-bank.

[2] Most borrowers in our setting have only one lender at a given point in time (see Table 1).

[3] Benetton (2021) uses Roy's identity, which states that product demand is given by the derivative of the indirect utility with respect to the price of the good, adjusted by the derivative of the indirect utility with respect to the budget that is available for purchase. This adjustment normalizes for the utility value of a dollar. As firms do not necessarily have a binding constraint, especially when making investments, we instead use Hotelling's lemma, which is the equivalent to Roy's identity for the firm's problem. This lemma provides the relationship between input demand and input prices, acknowledging that there is no budget constraint and no need to translate utils into dollars.

which describe the discrete bank choice and the continuous loan demand, respectively. Then the total expected demand, given rates of all banks in market m, is $Q_{ik}(r) = s_{ik}(r)L_{ik}(r)$. This expected demand is given by the product of the model's demand probability and the expected loan use by i from a loan from bank k.

Appendix B.3 Credit Supply

Each bank offers price r_{ikmt} to firm i to maximize bank profits B_{ikmt}, subject to conduct:

$$\max_{r_{ikmt}} B_{ikmt} = (1 - d_{ikmt})r_{ikmt}Q_{ikmt}(r + \tau_{ikmt}) - mc_{ikmt}Q_{ikmt}(r + \tau_{ikmt}) \tag{B6}$$
$$\text{s.t. } \upsilon_m = \frac{\partial r_{ikmt}}{\partial r_{ijmt}} \text{ for } j \neq k,$$

where d_{ikmt} are banks' expectations of the firm's default probability at the time of loan grant.

We introduce the market conduct parameter $\upsilon_m = \frac{\partial r_{ikmt}}{\partial r_{ijmt}}$ $(j \neq k)$ on the supply side to allow for different forms of equilibrium competition. Specifically, υ_m measures the degree of competition (joint profit maximization) in the market (Weyl and Fabinger, 2013; Kroft et al., 2024).[4] Namely, $\upsilon_m = 0$ corresponds to pure Bertrand-Nash competitive conduct while $\upsilon_m = 1$ corresponds to complete joint-maximization. The parameter υ_m can also take intermediate degrees of competition, including Cournot/quantity competition. Intuitively, the parameter captures the degree of correlation in price co-movements in equilibrium.

The first-order conditions for each r_{ikmt} in Equation B6 are then given by:

$$(1 - d_{ikmt})Q_{ikmt} + ((1 - d_{ikmt})r_{ikmt} - mc_{ikmt})\Big(\frac{\partial Q_{ikmt}}{\partial r_{ikmt}} + \upsilon_m \sum_{j\neq k} \frac{\partial Q_{ikmt}}{\partial r_{ijmt}}\Big) = 0. \tag{B7}$$

Rearranging Equation B7 yields:

$$r_{ikmt} = \frac{mc_{ikmt}}{1 - d_{ikmt}} - \frac{Q_{ikmt}}{\underbrace{\frac{\partial Q_{ikmt}}{\partial r_{ikmt}}}_{\text{Bertrand-Nash}} + \underbrace{\upsilon_m \sum_{j\neq k} \frac{\partial Q_{ikmt}}{\partial r_{ijmt}}}_{\text{Alternative Conduct}}}, \tag{B8}$$

which we write using price elasticities:

$$r_{ikmt} = \frac{mc_{ikmt}}{1 - d_{ikmt}} - \frac{1}{\frac{\epsilon_{kk}}{r_{ikmt}} + \upsilon_m \sum_{j\neq k} \frac{\epsilon_{kj}}{r_{ijmt}}}. \tag{B9}$$

Much like a regular pricing equation, the model splits the price equation into a marginal cost term and a markup. In our case, the markup is composed of two terms: the usual own-price elasticity markup ($\epsilon_{kk} = \partial Q_{ikmt}/\partial r_{ikmt} r_{ikmt}/Q_{ikmt}$) plus a term that captures the importance of the cross-price elasticities ($\epsilon_{kj} = \partial Q_{ikmt}/\partial r_{ikmt} r_{ijmt}/Q_{ikmt}$). The model, therefore, nests the

[4] Besides two main distinctions: (1) pair-specific pricing and (2) use of Hotelling's lemma instead of Roy's identity, the demand setting presented here follows very closely Benetton (2021). An alternative model would closely follow the setting of Crawford et al. (2018), which allows for pair-specific pricing. However, our model differs substantially from both cases, as we no longer assume banks are engaged in Bertrand-Nash competition in prices, i.e., we don't assume all bank pricing power comes from inelastic demand. Instead of assuming the specific mode of competition, we follow a more general approach that nests several types of competition: Bertrand-Nash, Cournot, perfect competition, collusion, etc.

Bertrand-Nash pricing behavior of Crawford et al. (2018), Benetton (2021) and others, but allows for deviations of alternative conduct. For $\upsilon_m > 0$, the bank considers the joint losses from competition. The higher the value υ_m, the more competitive behavior is consistent with full joint-maximization (full cartel), and the higher the profit-maximizing price r_{ikmt}. In our model, the possibility of default re-adjusts prices upward to accommodate the expected losses from non-repayment.

To build intuition further, we discuss additional interpretations of the competitive conduct parameter. First, note that in a symmetric equilibrium *market* demand elasticity is $\epsilon_D^m = -\frac{r}{Q}\sum_j \frac{\partial Q_{kmt}}{\partial r_{jmt}}$. Suppose for simplicity that prices and marginal costs are symmetric within a given bank, and there is no default. Then the following markup formula describes the pricing equation:

$$\frac{r_{kmt} - mc_{kmt}}{r_{kmt}} = \frac{1}{\epsilon_D^m + (1-\upsilon_m)\sum_{j\neq k} \frac{\partial Q_{kmt}}{\partial r_{jmt}} \frac{r_{jmt}}{Q_{kmt}}}. \tag{B10}$$

This simplified formulation demonstrates that the markup is an interpolation between joint maximization that targets aggregate demand elasticity and Bertrand-Nash maximization that targets the elasticity of the bank's residual demand.

Alternatively, one can define the firm-level diversion ratio $A_k \equiv -[\sum_j \frac{\partial Q_{kmt}}{\partial r_{jmt}}]/[\frac{\partial Q_{kmt}}{\partial r_{kmt}}]$. As this equation indicates, the diversion ratio in our context is the extent to which borrowers switch to borrowing from another bank in response to a change in loan price, where a higher value indicates a higher propensity to switch. We can then express the markup formula as

$$\frac{r_{kmt} - mc_{kmt}}{r_{kmt}} = \frac{1}{\epsilon_{kk}(1-\upsilon_m A_{kmt})}. \tag{B11}$$

We now see that the diversion ratio describes the opportunity cost of raising prices. Then the markup equation indicates that banks internalize these opportunity costs when bank competitive conduct is not pure Bertrand-Nash (zero). In particular, they internalize the cannibalization effects on their profits when lowering prices, thus generating upward price pressure.

As a last note, it is worth highlighting the generality of our marginal cost assumption. While we stipulate that marginal costs are constant for each loan, the model allows for considerable heterogeneity. First, we allow marginal cost to be borrower specific. For example, some borrowers may be easier to monitor so that the bank will have a lower marginal cost of lending to them. Second, we allow the marginal cost to be bank-dependent, capturing differences in efficiency across banks. Third, we allow for differences across markets, permitting geographical dispersion such as that related to the density of the bank's local branches. Fourth, we account for pair-specific productivity differences by indexing marginal costs at the pair level. This would control for factors such as bank specialization in lending to specific sectors. Fifth, although marginal costs are constant for a given borrower, the pool of borrowers will affect the total cost function of the firm, allowing them to be decreasing, increasing, or constant, depending on the selection patterns of borrowing firms. Lastly, we allow all of this to vary over time.

Appendix B.4 Discussion of identification of the conduct parameter

We first explain why we cannot separately identify the conduct and marginal cost parameters without tax pass-through. Then, we discuss solutions used in the literature and provide an alternative approach to overcome the identification issues that is well suited to the lending setting.

First, we establish that our model alone does not allow separate identification of the supply parameters. Suppose that the econometrician has identified the demand and default parameters, either through traditional estimation approaches or because the econometrician has direct measurements of these objects using an experimental design.[5] By inverting Equation B9, we obtain:

$$mc_{ikmt} = r_{ikmt}(1 - d_{ikmt}) + \frac{1 - d_{ikmt}}{\frac{\epsilon_{kk}}{r_{ikmt}} + \upsilon_m \sum_{j \neq k} \frac{\epsilon_{kj}}{r_{ijmt}}}. \tag{B12}$$

This equation indicates that, different from Crawford et al. (2018) or Benetton (2021), observations of prices, quantities, demand, and default parameters alone cannot identify pair-specific marginal costs. The reason for this is that conduct, υ_m, is also an unknown. Without information on υ_m, we can only bound marginal costs using the fact that $\upsilon_m \in [0, 1]$.

Traditional approaches in the literature (e.g., Bresnahan, 1982; Berry and Haile, 2014; Backus et al., 2024) propose to separately identify (or test) marginal costs and conduct by relying on instruments that shift demand without affecting marginal costs. Through this method, it is possible to test whether markups under different conduct values (e.g., zero conduct corresponding to perfect competition or conduct of one for the full cartel case) are consistent with observed prices and shifts in demand. A commonly used set of instruments are demographic characteristics in the market. For example, the share of children in a city will affect demand for cereal but is unlikely to affect the marginal costs of production. However, in our setting, pair-specific frictions affect marginal costs, such as adverse selection and monitoring costs. Thus, relying on demand shifter instruments is unlikely to satisfy the exclusion restriction. For instance, borrower observable characteristics like firm growth rates, assets, or even the age of the CEO will be correlated with changes in the borrower-specific marginal cost.

To overcome this difficulty, we follow insights from the public finance literature (Weyl and Fabinger, 2013), which demonstrate that the pass-through of taxes and marginal costs to final prices are tightly linked to competition conduct. Thus, by relying on reduced-form pass-through estimates from the introduction of the SOLCA tax, we can create one additional identifying equation that allows us to separate marginal costs from conduct.[6] The reason we can recover conduct with information on pass-through estimates is that, given estimates of demand elasticities (or curvatures), the relationship between conduct and pass-through is monotonic. Therefore, for a given observation of pass-through, and holding demand elasticities constant, only one conduct value could rationalize any given pass-through.

To obtain an expression for pass-through as a function of conduct υ_m, express Equation B7 in terms of semi-elasticities:

$$1 + (r_{ikmt} - \frac{mc_{ikmt}}{1 - d_{ikmt}})\Big(\widetilde{\varepsilon}_{kk} + \upsilon_m \sum_{j \neq k} \widetilde{\varepsilon}_{kj}\Big) = 0, \tag{B13}$$

[5] We discuss our strategy for identifying the demand and default parameters below.

[6] While to our knowledge, this approach is novel in the lending literature, papers in the development (Bergquist and Dinerstein, 2020) and trade (Atkin and Donaldson, 2015) literatures have used pass-through to identify the modes of competition in agricultural and consumer goods markets.

with $\widetilde{\varepsilon}_{kj} = (\partial Q_{ikmt}/\partial r_{ijmt})/Q_{ikmt}$. Applying the implicit function theorem yields:

$$\begin{aligned}\rho_{ikmt}(\upsilon_m) \equiv & \frac{\delta r_{ikmt}}{\delta mc_{ikmt}} \\ = & \frac{(\widetilde{\varepsilon}_{kk} + \upsilon_m \sum_{j\neq k} \widetilde{\varepsilon}_{kj})/(1-d_{ikmt})}{(\widetilde{\varepsilon}_{kk} + \upsilon_m \sum_{j\neq k} \widetilde{\varepsilon}_{kj}) + (r_{ikmt} - mc_{ikmt}/(1-d_{ikmt}))\left(\frac{\partial \widetilde{\varepsilon}_{kk}}{\partial r_{ikmt}} + \upsilon_m \sum_{j\neq k} \frac{\partial \widetilde{\varepsilon}_{kj}}{\partial r_{ikmt}}\right)}\end{aligned} \tag{B14}$$

Therefore, Equations B12 and B14 create a system of two equations and two unknowns (mc_{ikmt}, υ_m), which allows identification of the supply parameters.

As noted above, we do not have empirical pass-through estimates at the borrower-level. Hence, we create market-level moments. Namely, if we measure pass-throughs at the market level and statically (i.e., just before and after the tax is enacted), the identification argument for our general bank competition model is:

$$\rho_m(\upsilon_m) \equiv E_{i,k,t}[\rho_{ikmt}(\upsilon_m)]. \tag{B15}$$

Therefore, we add one moment for each market to identify one additional parameter υ_m.

Appendix C Loan Default Prediction

We predict default at the loan level by regressing the event of a loan becoming 90 days or more behind payment on lagged firm-level covariates that predict default in the literature, including firm age at the grant of the loan, the loan's term-to-maturity and the amount that was borrowed, the nominal interest rate on the loan, total firm wages, assets, revenue, and debt, tangibility (property plant and equipment scaled by total assets), the total number of bank relationships and their age at the grant of the loan, if bank internal ratings on any of the firm's bank debt has ever been rated as risky or a doubtful collection (less than an A rating), if the loan is classified as a microcredit, and an indicator that takes the value one if a firm has only one lender relationship, and firm, province-year and sector-year fixed effects. Table C1 reports the estimated default models. Column (4) is our preferred specification that we use to construct the regression control *Pr(Loan Default)*, which is defined as the difference between the observed propensity to default on a loan and the residuals of this predictive regression.

TABLE C1: COMMERCIAL LOAN DEFAULT MODEL

VARIABLES	(1) 1(Default)	(2) 1(Default)	(3) 1(Default)	(4) 1(Default)
Firm Age at Grant	-0.008***	-0.007***	-0.009***	-0.008***
	(0.001)	(0.001)	(0.001)	(0.001)
Term-to-Maturity (Months)	-0.047***	-0.058***	-0.062***	-0.062***
	(0.008)	(0.008)	(0.008)	(0.009)
Ln(Amount borrowed)	-0.015***	-0.025***	-0.024***	-0.027***
	(0.005)	(0.005)	(0.005)	(0.005)
Nominal Interest Rate	0.023***	0.027***	0.025***	0.024***
	(0.002)	(0.002)	(0.003)	(0.003)
Ln(Total Wages)	-0.017***	-0.016***	-0.013***	-0.018***
	(0.004)	(0.004)	(0.005)	(0.005)
Ln(Total Assets)	-0.005	-0.004	0.003	0.005
	(0.008)	(0.008)	(0.008)	(0.008)
Ln(Total Revenue)	-0.032***	-0.032***	-0.033***	-0.032***
	(0.004)	(0.004)	(0.004)	(0.005)
Ln(Total Debt)	-0.055***	-0.050***	-0.057***	-0.054***
	(0.007)	(0.007)	(0.007)	(0.008)
Leverage Ratio	0.064**	0.057**	0.112***	0.121***
	(0.027)	(0.028)	(0.028)	(0.029)
Tangibility Ratio	0.424***	0.412***	0.394***	0.316***
	(0.037)	(0.039)	(0.040)	(0.042)
Total Bank Relationships	-0.009	-0.019**	-0.025***	-0.013
	(0.008)	(0.008)	(0.009)	(0.009)
Age of Relationship at Grant	-0.145***	-0.135***	-0.155***	-0.152***
	(0.007)	(0.007)	(0.007)	(0.008)
1(Below A Rating) = 1	2.017***	2.103***	2.160***	2.189***
	(0.027)	(0.028)	(0.029)	(0.030)
1(Microcredit) = 1	0.144**	0.141**	0.094	0.081
	(0.065)	(0.067)	(0.070)	(0.071)
1(Only 1 Bank) = 1	0.133***	0.167***	0.154***	0.163***
	(0.030)	(0.031)	(0.032)	(0.033)
Constant	-1.772***	-1.485***	-2.275***	-2.275***
	(0.074)	(0.131)	(0.248)	(0.284)
Observations	442,662	423,609	420,624	418,688
Bank FE	No	Yes	Yes	Yes
Province x Year FE	No	No	Yes	Yes
Industry x Year FE	No	No	No	Yes
McFadden's Pseudo-R2	0.532	0.549	0.566	0.575
ROC Area	0.961	0.968	0.970	0.971

Appendix D Price Prediction

A key empirical challenge to estimating our model is that we observe the terms of granted loans while our demand model requires prices from all available banks to all potential borrowers. To address this common problem, we predict the prices of unobserved, counterfactual loans as in Adams et al. (2009), Crawford et al. (2018), and Ioannidou et al. (2022).

The idea is to model banks' pricing decisions by flexibly controlling for unobserved and observed information about borrower risk. We employ ordinary least squares regressions for price prediction. The main specification for price prediction is:

$$r_{ikmt} = \gamma_0 + \gamma_x X_{ikmt} + \gamma_2 ln(L_{ikmt}) + \gamma_3 ln(M_{ikmt}) + \lambda_{kmt} + \omega_i^r + \tau_{ikmt}, \tag{D1}$$

where X_{ikmt} are time-varying controls, including firm-level predictors from firm balance sheets (e.g., assets, debts) and income statements (e.g., revenue, capital, wages, expenditures) and the length of the borrower-lender relationship in years. These control for the hard information accessible to both the econometrician and the lender. We also control for loan-specific variables, such as an indicator for whether any bank classifies the firm as risky in the given time period. Finally, we control for the amount granted (L_{ikmt}) and maturity (M_{ikmt}).

Next, ω_i^r and λ_{kmt} represent firm and bank-market-year fixed effects. These fixed effects capture additional unobserved (to us) borrower heterogeneity and market shocks that affect prices because banks can observe them.[1] Finally, τ_{ikmt} are prediction errors. By combining predicted coefficients, we then predict the prices $\tilde{r}_{ijmt}$ that would have been offered to borrowing firms from banks they did not select. Our strategy is to use this combination of detailed microdata and high-dimensional fixed effects to control for the fact that banks likely have more hard, and especially soft, information about borrowers than we do as econometricians.[2]

Table D1 reports the price regressions. Comparing column (1) with column (2) and column (3) with column (4), demonstrates that the fit of the regression (R-squared) increases only marginally when we use separate bank, year and province fixed effects versus dummies for the interaction of the three variables. The largest improvement in the fit occurs when we include firm fixed effects, strongly supporting the hypothesis that banks use fixed firm attributes unobservable to the econometrician as a key determinant of loan pricing. In this specification, we can explain approximately 65% of the variation in observed commercial loan prices.[3]

Banks in Ecuador certainly can and do use soft information when pricing loans. How big a problem is this for our price prediction empirical exercise? We carry out two tests to explore the effect of this unobservable empirically. First, Ecuadorian lenders report that they rely most heavily on hard information in author-conducted interviews. They rank firm revenue and performance and past repayment decisions as the primary factors determining lending terms. These are all hard data directly observable in our data.

[1] Note that we are thus predicting based on data from firms that borrowed multiple times.

[2] Table D1 and Appendix Table D2 fully replicate Tables 2 and 3 of Crawford et al. (2018) using our dataset. It motivates our decision to use the pricing model used in Equation D1 with firm fixed effects as our preferred specification.

[3] This is comparable to the 71% R-squared achieved by Crawford et al. (2018) and much higher than that typical in the empirical banking literature.

TABLE D1: PRICE PREDICTION REGRESSIONS

The table reports estimates of Equation D1, an OLS regression of the nominal interest rate on commercial bank loans (in percentage points) on a series of controls and dummies. An observation is at the loan level. See Table 1 for variable definitions. Standard errors are clustered at the bank-province-year level and reported in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

Variable	(1) IR	(2) IR	(3) IR	(4) IR
Ln(Total Assets)	-0.310***	-0.392***	-0.0259***	-0.0309***
	(0.00545)	(0.00538)	(0.00703)	(0.00711)
Ln(Total Debt)	0.0886***	0.119***	0.00922	0.00882
	(0.00488)	(0.00480)	(0.00601)	(0.00605)
Ln(Total Revenue)	0.124***	0.151***	0.0247***	0.0274***
	(0.00384)	(0.00378)	(0.00421)	(0.00424)
Ln(Capital)	-0.0173***	-0.0287***	-0.00565***	-0.00106
	(0.00136)	(0.00135)	(0.00160)	(0.00163)
Ln(Wages)	0.0778***	0.0632***	-0.0137***	-0.0141***
	(0.00242)	(0.00239)	(0.00336)	(0.00338)
Ln(Expenditures)	-0.227***	-0.244***	-0.0293***	-0.0275***
	(0.00343)	(0.00339)	(0.00401)	(0.00404)
Age of Relationship at Grant	-0.232***	-0.195***	-0.158***	-0.159***
	(0.00216)	(0.00223)	(0.00296)	(0.00317)
Ln(Amount Borrowed)	-0.384***	-0.284***	-0.172***	-0.141***
	(0.00178)	(0.00191)	(0.00201)	(0.00206)
Ln(Maturity)	-0.428***	-0.539***	-0.470***	-0.514***
	(0.00312)	(0.00318)	(0.00301)	(0.00310)
Constant	17.39***	17.18***	11.48***	11.10***
	(0.0277)	(0.0276)	(0.0566)	(0.0575)
Bank FE	Yes	No	Yes	No
Province FE	Yes	No	Yes	No
Year FE	Yes	No	Yes	No
Bank-Province-Year FE	No	Yes	No	Yes
Firm FE	No	No	Yes	Yes
Observations	757,375	757,192	749,112	748,916
R-squared	0.309	0.361	0.636	0.648

Second, in Appendix C, we test the extent to which the variation in prices we cannot explain predicts firms' subsequent default. Specifically, we regress loan default on the same set of controls and the residuals from the regressions reported in Table D1. Results are reported in Table D2. We fail to reject the null hypothesis that the residuals have no significant statistical correlation with default once we include firm fixed effects. Instead, the relationship is consistently positive even with firm fixed effects, but not economically large. Indeed, once we account for firm fixed effects, the relationship between prices and default is precisely estimated as zero.

TABLE D2: THE ABILITY OF PRICING RESIDUALS TO PREDICT DEFAULT

VARIABLES	(1) 1(Default)	(2) 1(Default)	(3) 1(Default)	(4) 1(Default)
Residuals	0.0676***			
	(0.00843)			
Residuals		0.0729***		
		(0.00879)		
Residuals			0.00209	
			(0.00673)	
Residuals				0.00898
				(0.00676)
Constant	0.0406***	0.0414***	0.0388***	0.0396***
	(0.00400)	(0.00423)	(0.00426)	(0.00452)
Bank FE	Yes	No	Yes	No
Province FE	Yes	No	Yes	No
Year FE	Yes	No	Yes	No
Bank-Province-Year FE	No	Yes	No	Yes
Firm FE	No	No	Yes	No
Observations	757,375	757,192	749,112	748,916
R-squared	0.031	0.050	0.024	0.043

Notes. The table reports estimates from an OLS regression of a indicator variable that takes the value of one if the firm defaults on a commercial bank loan and zero otherwise on the residuals of the pricing regressions reported in Table D1. The same set of controls are used as in the corresponding Model in Table D1. The observation is at the loan level. Residuals are divided by 100 to aid interpretation of the reported coefficients. Standard errors are clustered at the bank-province-year level and reported in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

Observed and unobserved prices for borrowing and non-borrowing firms are defined as:

$$\begin{aligned} r_{ikmt} &= \tilde{r}_{ikmt} + \tilde{\tau}_{ikmt}, \\ &= \tilde{r}_{kmt} + \tilde{\gamma}_x X_{ikmt} + \tilde{\gamma}_2 ln(L_{ikmt}) + \tilde{\gamma}_3 ln(M_{ikmt}) + \tilde{\omega}_i^r + \tilde{\tau}_{ikmt} \end{aligned} \tag{D2}$$

where $\tilde{\tau}_{ikmt}$ will be unobserved for non-chosen banks and non-borrowing firms, and $\tilde{r}_{kmt} = \tilde{\gamma}_0 + \tilde{\lambda}_{kmt}$. We present the resulting distribution of prices for borrowers' actual choices and non-chosen banks, as well as non-borrowers' prices, in Figure D1. As shown in the figure, our model predicts well the areas with greater mass as well as the support of the distribution of observed prices. Moreover, our model predicts similar prices for non-chosen options for borrowers but higher prices (around 8%) for non-borrowers.

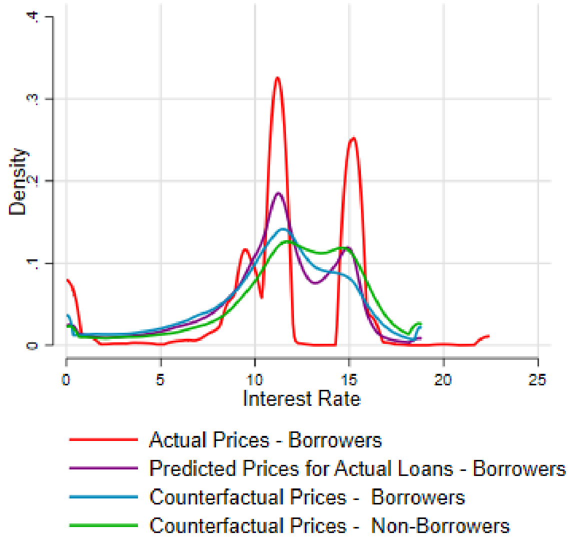


FIGURE D1: DISTRIBUTION OF PREDICTED PRICES

The figure reports the distributions of predicted prices for borrowers' actual choices, borrowers' not chosen alternatives, and non-borrowers.

Appendix D.1 Firm matching model

We employ a propensity score matching approach to predict prices for firms that do not borrow in our sample. In this we follow the strategy taken in the literature to solve this empirical challenge, including in Adams et al. (2009) and Crawford et al. (2018). Specifically, we match borrowing firms to non-borrowing firms that are similar in their observable characteristics and then assign a borrowing firm's fixed effect, $\tilde{\omega}_i^r$, to the matched non-borrowing firm. We follow the same procedure to predict the loan size and term-to-maturity. Table D3 reports diagnostics on our matching model.

TABLE D3: PROPENSITY SCORE MATCHING - BIAS

VARIABLE	Unmatched Matched	Mean Treated	Mean Control	% bias	% Reduction in bias	t-test t	t-test p>t
Age - Bucket 1	U	0.15514	0.30536	-36.3		-31.39	0
	M	0.15514	0.1535	0.4	98.9	0.96	0.335
Debt - Bucket 1	U	0.0732	0.2202	-42.5		-41.51	0
	M	0.0732	0.07302	0.1	99.9	0.14	0.885
Assets - Bucket 1	U	0.07314	0.2064	-39.2		-37.77	0
	M	0.07314	0.07338	-0.1	99.8	-0.19	0.85
Sales - Bucket 1	U	0.06344	0.20687	-42.9		-42.98	0
	M	0.06344	0.06287	0.2	99.6	0.49	0.622
Wages - Bucket 1	U	0.07463	0.23165	-44.7		-43.88	0
	M	0.07463	0.07328	0.4	99.1	1.1	0.273
Age - Bucket 2	U	0.3794	0.38096	-0.3		-0.25	0.804
	M	0.3794	0.38004	-0.1	58.9	-0.28	0.778
Debt - Bucket 2	U	0.42281	0.45483	-6.5		-5	0
	M	0.42281	0.42459	-0.4	94.4	-0.77	0.443
Assets - Bucket 2	U	0.43583	0.4655	-6		-4.61	0
	M	0.43583	0.43622	-0.1	98.7	-0.17	0.868
Sales - Bucket 2	U	0.3731	0.46048	-17.8		-13.91	0
	M	0.3731	0.37428	-0.2	98.7	-0.52	0.606
Wages - Bucket 2	U	0.38894	0.48385	-19.2		-15	0
	M	0.38894	0.3898	-0.2	99.1	-0.38	0.707
Age - Bucket 3	U	0.46546	0.31368	31.5		23.59	0
	M	0.46546	0.46646	-0.2	99.3	-0.42	0.671
Debt - Bucket 3	U	0.50399	0.32497	37		27.74	0
	M	0.50399	0.50238	0.3	99.1	0.68	0.495
Assets - Bucket 3	U	0.49102	0.32811	33.6		25.25	0
	M	0.49102	0.4904	0.1	99.6	0.26	0.792
Sales - Bucket 3	U	0.56346	0.33265	47.7		36.03	0
	M	0.56346	0.56285	0.1	99.7	0.26	0.794
Wages - Bucket 3	U	0.53643	0.2845	53		39.22	0
	M	0.53643	0.53692	-0.1	99.8	-0.21	0.835

Notes. The table compares the control and treatment groups before and after propensity score matching over a variety of firm-level characteristics.

Appendix E Estimating the Model

This section describes our estimation strategy, interprets our parameter estimates, and assesses model fit.

We write the (indirect) profit function $\overline{\Pi}_{ik}$ using the parametric form:

$$\overline{\Pi}_{ikmt} = \exp(\mu)\exp(\xi_{kmt} + \psi_i - \alpha_m r_{ikmt} - \alpha_m \tau(M_{ikmt}) + \beta_{m1} X_{it} + \beta_{m2} X_{ikmt}) + \gamma_N N_{ikmt}, \tag{E1}$$

where N_{ikmt} is the branch network in the local market and $\tau(M_{ikmt})$ captures the tax rate determined by contract maturity M_{ikmt}. Bank-market-year fixed effects, $\exp(\xi_{kmt})$, control for borrower preferences across banks (horizontal differentiation). The borrower's unobserved propensity to borrow is captured by ψ_i, their dislike of higher prices by α_m, and their likelihood to borrow at all by time-varying for characteristics, X_{it}. The likelihood a firm will borrow from a specific bank is also a function of relationship characteristics X_{ikmt} and N_{ikmt}.

A key empirical challenge is that we observe the terms of granted loans while our demand model requires a menu of prices from all available banks to all potential borrowers in each market. To address this long-standing problem in the literature, we predict the prices of unobserved, counterfactual loans following the strategy of Adams et al. (2009), Crawford et al. (2018), and Ioannidou et al. (2022). Details are reported in Appendix D. Plugging in predicted prices from estimating Appendix Equation D2, we obtain the following indirect profit function:

$$\begin{aligned}
\Pi_{ikmt} &= \exp(\mu)\exp\Big(\underbrace{\xi_{kmt} - \alpha_m \tilde{r}_{kmt}}_{\tilde{\xi}_{kmt}} + \underbrace{(\beta_{m1} - \alpha_m \tilde{\gamma}_{x1})}_{\tilde{\beta}_{m1}} X_{it} + \underbrace{(\beta_{m2} - \alpha_m \tilde{\gamma}_{x2})}_{\tilde{\beta}_{m2}} X_{ikmt} && \text{(E2)}\\
&\qquad - \alpha_m \tilde{\gamma}_2 ln(L_{ikmt}) - \alpha_m \tilde{\gamma}_3 ln(M_{ikmt}) - \alpha_m \tau(M_{ikmt}) - \alpha_m \tilde{\omega}_i^r + \underbrace{\psi_i - \alpha_m \tilde{\tau}_{ikmt}}_{\tilde{\psi}_{ikmt}}\Big)\\
&\qquad + \gamma_N N_{ikmt} + \varepsilon_{ikmt}\\
&= \exp(\mu)\exp\Big(\tilde{\xi}_{kmt} + \tilde{\beta}_{m1} X_{it} + \tilde{\beta}_{m2} X_{ikmt} - \alpha_m \tilde{\gamma}_2 ln(L_{ikmt}) - \alpha_m(\tilde{\gamma}_3 + \tilde{\tau}) ln(M_{ikmt}) && \text{(E3)}\\
&\qquad - \alpha_m \tilde{\omega}_i^r + \tilde{\psi}_{ikmt}\Big) + \gamma_N N_{ikmt} + \varepsilon_{ikmt}
\end{aligned}$$

In the last equality, we use a log-linear approximation of the function $\tau(M_{ikmt})$.[1] We assume the idiosyncratic taste shocks ε_{ikmt} are i.i.d. Type-I Extreme Value and that the borrower's unobservable characteristic heterogeneity, $\tilde{\psi}_{ikmt} = \psi_i - \alpha_m \tilde{\tau}_{ikmt}$, follows a normal distribution with mean zero and variance σ_b^2. Notice that, in principle, we could estimate the demand price parameter α_m from any of the variables $\tilde{\gamma}_2 L_{ikmt}$, and $\tilde{\omega}_i^r$. Yet, due to the noise created by the estimated parameters—following a traditional measurement error on the independent variable argument—the coefficient on α_m would be biased. For that reason, we follow the conventional route and estimate α_m from $\tilde{\xi}_{kmt}$ through a second-stage instrumental variable approach that relies on exogenous variation in average prices at the bank-market-year level that addresses concerns of measurement error and endogeneity.

Before we describe our instrumental variable strategy to identify α_m, we describe our maximum likelihood demand estimation procedure. First, we derive the maximum likelihood function. Under the assumption that the taste shock ε_{ikmt} is distributed i.i.d. Type-I Extreme Value,

[1] Given the context, the function is equal to $\tau(M_{ikmt}) = 0.5 \min\{1, M_{ikmt}\}$.

the conditional probability that the firm i chooses bank j is given by:

$$s_{ikmt}(\psi_i) = \frac{\exp(\Pi_{ikmt})}{1 + \sum_j \exp(\Pi_{ijmt})}, \tag{E4}$$

where the indirect profit from not borrowing has been normalized to 0. The unconditional probability is given by

$$S_{ikmt} = \int s_{ikmt}(\psi_i) dF(\psi_i). \tag{E5}$$

Given actual bank choices, we obtain the loan demand function, L_{ikmt}, by Hotelling's lemma:[2]

$$\ln(L_{ikmt}) = \ln(\exp(\mu)\alpha_m) + \xi_{kmt} - \alpha_m r_{ikmt} + \beta_{m1} X_{it} + \beta_{m2} X_{ikmt} + \psi_i \tag{E6}$$

Adding and subtracting $\alpha_m \tilde{r}_{kmt}$, we get:

$$\ln(L_{ikmt}) = \ln(\exp\mu)\alpha_m) + \tilde{\xi}_{kmt} - \alpha_m(r_{ikmt} - \tilde{r}_{kmt}) + \beta_{m1} X_{it} + \beta_{m2} X_{ikmt} + \psi_i. \tag{E7}$$

From Equation E7 and assuming normality for ψ_i, the probability of the conditional loan demand is:

$$f(ln(L_{ikmt})|k, k \neq 0) = \tag{E8}$$
$$\frac{1}{\sqrt{2\pi\sigma^2}} \times \exp\left[-\frac{\left(\ln(L_{ikmt}) - \ln(\exp(\mu)\,\alpha_m) - \tilde{\xi}_{kmt} + \alpha_m(r_{ikmt} - \tilde{r}_{kmt}) - \beta_{m1} X_{it} - \beta_{m2} X_{ikmt}\right)^2}{2\sigma^2} \right].$$

Note that as the branch network enters linearly in the indirect utility, it does not appear in input demand. Hence, this assumption implies an exclusion restriction: branch density affects the likelihood of borrowing but not its intensity.[3]

The joint log likelihood that firm i borrows a loan size L_{ik} from bank k is given by:

$$\ln(\mathcal{L}) = \sum_{t=0}^{T} \sum_{m=0}^{M} \sum_{j=0}^{J_m} \sum_{k=0}^{K_m} 1_{ikmt}[\ln(S_{ikmt}) + \ln(f(\ln(L_{ikmt})|k, k \neq 0))], \tag{E9}$$

where 1_{ik} is an indicator equal to 1 if borrower i chooses the loan offered by bank k and 0 otherwise. This likelihood function deals with the simultaneity issues created by the discrete-continuous choice, where the firm picks a bank and the loan size.

We implement this maximum likelihood demand estimation procedure in three steps. First, we obtain the values for the bank-market constants, $\tilde{\xi}_{kmt}$, and the coefficients $\tilde{\beta}$ and β from the indirect profit function. In the first iteration ($r = 1$), we set coefficients to a guess based on the estimation of a Logit model. In the subsequent iterations, we obtain the coefficients through gradient search. Second, we implement the instrumental variable approach described below to calculate α_m from the estimate of $\tilde{\xi}_{kmt}$. Third, we repeat this procedure for 1,000 bootstrap samples for each region to obtain standard errors for all coefficients.[4]

[2]Here, we took the derivative of Equation E1 with respect to the interest rate.

[3]This assumption is the same as Benetton (2021) and Benetton et al. (2024). Like them, the assumption is supported in the data (Appendix Appendix A).

[4]An alternative approach is to use the control function of Train (2009). The first step of this method is to regress predicted and observed prices on the variables that enter the discrete and continuous demand equations.

We now describe how we estimate α_m while controlling for the endogeneity of demand and prices and potential measurement error. We estimate the equation:

$$\tilde{\xi}_{kmt} = -\alpha_m \tilde{r}_{kmt} + \beta_b X_{kmt} + \epsilon_{kmt}, \tag{E10}$$

where we recover the market-level price coefficient through an instrumental variable approach of recovered bank-market-year fixed effects on bank-market-year prices. Specifically, we instrument predicted bank-market, time-varying prices ($\tilde{r}_{kmt}$) with the following variables: the average commercial price for bank k in other markets n, the average price for consumer loans in other markets, the average price for entrepreneur loans in other markets, and the aggregate default rate in non-commercial loan products, such as micro-lending, mortgages, and consumption. These cost-based and Hausman-style instruments capture variation in marginal costs at the bank level that are orthogonal to individual-level demand.

The identification assumptions of our instrumental variable strategy are that none of the instruments are weak (relevance) and that all impact demand only through their effect on price (exclusion).

Below, we report the demand estimates pooled across regions and we re-produce the region-level instrumented price parameters estimates alongside first-stage Cragg-Donald Wald F-statistics for the first stage against the null hypothesis of instrument irrelevance. In aggregate, the instruments relate well with the bank-market interest rates, with a model R-squared of 0.43. Moreover, market-specific F-statistics, reported in Table E2, are high. This is strong evidence that our instruments are relevant.

The exogeneity of the instruments cannot be directly tested. We argue that the instruments are set in response to common bank-level factors but do not affect a specific firm's demand for a loan in the market except through their effect on the interest rate. Encouragingly, when we performed Sargan-Hansen over-identification tests for our instrumental variable strategy, we failed to reject the null hypothesis that the error term is uncorrelated with the instruments.

Appendix E.1 Estimated Demand Parameters

Table E1 reports estimates at the regional level. These more granular estimates demonstrate the same patterns as in Table 3, while estimates and their direction continue to be sensible.

TABLE E1: DEMAND PARAMETERS

The table presents the mean and standard deviation of estimated parameters by region. The coefficient for *price* comes from an instrumental variable approach that corrects for price endogeneity and measurement error in predicted prices for non-observed offers. The standard deviation is calculated as the standard error of the parameter values obtained by estimating the model on 1,000 bootstrap samples. Corresponding nationwide estimates are presented in Table 7. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

Region	Variable	Mean	Std. Dev.
Azuay	Price	−0.245***	(0.055)
Azuay	Sigma	1.602***	(0.032)
Azuay	Scaling Factor	−0.027	(0.337)

Continued on next page

We would then include the residuals as controls in the joint maximum likelihood. In practice, the number of steps will be similar to the algorithm described above. The only benefit is that this algorithm performs the instrumental variable estimation at the same time as the gradient search process.

TABLE E1 – continued from previous page

Region	Variable	Mean	Standard Deviation
Azuay	Log(Branches)	0.869	(1.951)
Azuay	Age Firm	0.376***	(0.007)
Azuay	Age Relationship	0.183***	(0.037)
Azuay	Assets	0.109	(0.136)
Azuay	Debt	−0.025	(0.063)
Azuay	Expenditures	0.165***	(0.045)
Azuay	Revenue	0.003	(0.043)
Azuay	Wages	0.123***	(0.028)
Costa	Price	−0.048**	(0.021)
Costa	Sigma	1.421***	(0.034)
Costa	Scaling Factor	−0.046	(0.403)
Costa	Log(Branches)	0.827	(1.166)
Costa	Age Firm	0.204***	(0.007)
Costa	Age Relationship	0.148***	(0.033)
Costa	Assets	0.019	(0.060)
Costa	Debt	−0.005	(0.030)
Costa	Expenditures	0.060*	(0.036)
Costa	Revenue	0.023	(0.035)
Costa	Wages	0.063**	(0.026)
Guayas	Price	−0.434***	(0.158)
Guayas	Sigma	−0.069	(0.065)
Guayas	Scaling Factor	−0.016	(0.350)
Guayas	Log(Branches)	0.732	(1.306)
Guayas	Age Firm	0.215***	(0.009)
Guayas	Age Relationship	0.036	(0.042)
Guayas	Assets	0.022	(0.124)
Guayas	Debt	−0.007	(0.070)
Guayas	Expenditures	0.062**	(0.028)
Guayas	Revenue	0.021	(0.031)
Guayas	Wages	0.016	(0.029)
Pichincha	Price	−0.386***	(0.101)
Pichincha	Sigma	1.156***	(0.057)
Pichincha	Scaling Factor	−0.014	(0.321)
Pichincha	Log(Branches)	0.735	(1.377)
Pichincha	Age Firm	0.205***	(0.007)
Pichincha	Age Relationship	0.157***	(0.030)
Pichincha	Assets	0.051	(0.107)
Pichincha	Debt	−0.010	(0.053)

Continued on next page

TABLE E1 – continued from previous page

Region	Variable	Mean	Standard Deviation
Pichincha	Expenditures	0.207***	(0.039)
Pichincha	Revenue	0.002	(0.037)
Pichincha	Wages	−0.003	(0.032)
Sierra	Price	−0.091***	(0.012)
Sierra	Sigma	1.168***	(0.038)
Sierra	Scaling Factor	−0.033	(0.545)
Sierra	Log(Branches)	0.865	(1.321)
Sierra	Age Firm	0.225***	(0.008)
Sierra	Age Relationship	0.152***	(0.040)
Sierra	Assets	−0.009	(0.095)
Sierra	Debt	−0.026	(0.043)
Sierra	Expenditures	0.395***	(0.044)
Sierra	Revenue	0.012	(0.037)
Sierra	Wages	0.078**	(0.034)

TABLE E2: OVER-IDENTIFICATION TESTS FOR INSTRUMENTED PRICE PARAMETER

The table shows the region-level estimated price parameter, from the demand-side estimation of the indirect profit function in Equation E1. $\widehat{Price}$ are the estimates of the instrumented price parameter. *t-statistic* is the associated t-statistic for a test against the null of zero. *F-statistic* is the Cragg-Donald Wald F statistic for the first-stage against the null that the excluded instruments are irrelevant in the first-stage regression. Finally, *P-value over-identification* is the p-value for a Sargen-Hansen test of over-identifying restrictions with the null hypotheses that the error term is uncorrelated with the instruments.

Region	$\widehat{Price}$	t-statistic	F-statistic	P-value over-identification
Azuay	-0.245	-4.473	246.393	0.249
Costa	-0.048	-2.302	1,755.901	0.214
Guayas	-0.434	-2.748	816.356	0.341
Pichincha	-0.386	-3.827	304.962	0.753
Sierra	-0.091	-7.714	3,840.642	0.666

Appendix E.2 Estimating Demand Elasticities

The discrete-continuous model of loan demand (intensive margin) elasticity and product share (extensive margin) demand elasticity are given, respectively, by:

$$\epsilon^{L}_{ikmt} = \frac{\partial L_{ikmt}}{\partial r_{ikmt}} \frac{r_{ikmt}}{L_{ikmt}} = \frac{\partial ln(L_{ikmt})}{\partial r_{ikmt}} r_{ikmt} = -\alpha_m r_{ikmt} \tag{E11}$$

and

$$\begin{aligned}
\epsilon^{s}_{ikmt} &= \frac{\partial s_{ikmt}}{\partial r_{ikmt}} \frac{r_{ikmt}}{s_{ikmt}} \\
&= -\alpha_m \exp(\mu) \exp(\xi_{kmt} + \psi_i - \alpha_m r_{ikmt} + \beta_{m1} X_{it} + \beta_{m2} X_{ikmt})(1 - s_{ikmt}) s_{ikmt} \times \frac{r_{ikmt}}{s_{ikmt}} \\
&= -\alpha_m \exp(\mu) \exp(\xi_{kmt} + \psi_i - \alpha_m r_{ikmt} + \beta_{m1} X_{it} + \beta_{m2} X_{ikmt})(1 - s_{ikmt}) r_{ikmt} \qquad \text{(E12)}
\end{aligned}$$

The elasticity for total demand is given by:

$$\begin{aligned}
\epsilon^{Q}_{ikmt} &= \frac{\partial Q_{ikmt}}{\partial r_{ikmt}} \frac{r_{ikmt}}{Q_{ikmt}} = \frac{\partial s_{ikmt} L_{ikmt}}{\partial r_{ikmt}} \frac{r_{ikmt}}{s_{ikmt} L_{ikmt}} \\
&= \frac{\partial s_{ikmt}}{\partial r_{ikmt}} \frac{r_{ikmt}}{s_{ikmt}} + \frac{\partial L_{ikmt}}{\partial r_{ikmt}} \frac{r_{ikmt}}{L_{ikmt}} = \epsilon^{s}_{ikmt} + \epsilon^{L}_{ikmt}. \qquad \text{(E13)}
\end{aligned}$$

Regarding cross-price elasticities with respect to prices of competitor j, we obtain the following expression:

$$\epsilon^{L,j}_{ikmt} = 0 \qquad \text{(E14)}$$

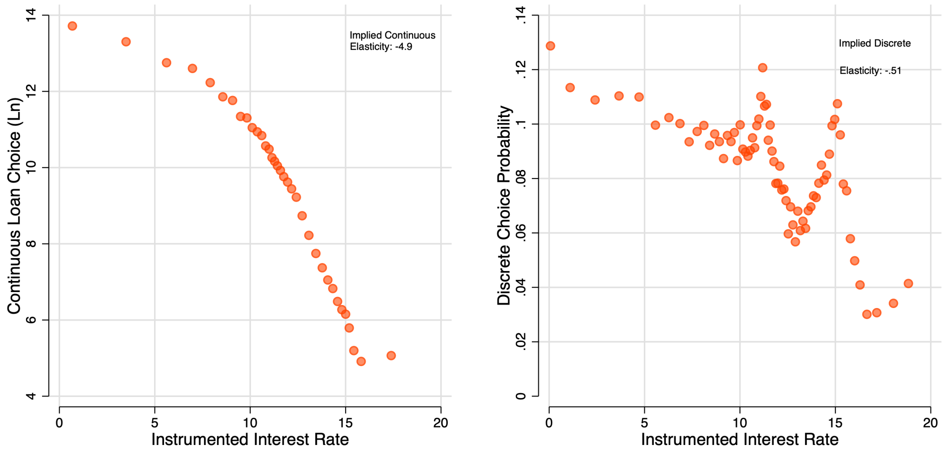
and

$$\begin{aligned}
\epsilon^{s,j}_{ikmt} &= \frac{\partial s_{ikmt}}{\partial r_{jkmt}} \frac{r_{jkmt}}{s_{ikmt}} = \alpha_m \exp(\mu) \exp(\xi_{jmt} + \psi_i - \alpha_m r_{ijmt} + \beta_{m1} X_{it} + \beta_{m2} X_{ijmt}) s_{ijmt} s_{ikmt} \times \frac{r_{ijmt}}{s_{ikmt}} \\
&= \alpha_m \exp(\mu) \exp(\xi_{jmt} + \psi_i - \alpha_m r_{ijmt} + \beta_{m1} X_{it} + \beta_{m2} X_{ijmt}) s_{ijmt} r_{jkmt} \qquad \text{(E15)}
\end{aligned}$$

Appendix E.3 Reduced-Form Elasticities

We validate the estimated structural elasticities reported in Table 4 using a reduced-form instrumental variable approach. Specifically, we regress demand on instrumented loan interest rates, controlling for bank, province, and year fixed-effects. Instruments include delinquency rates in microcredit, housing and consumption, and interest rates in consumption, micro-lending, commercial credit in other regions.

We report the relationship between the instrumented interest rate and continuous demand (ln(loan value)) in panel (a) of Figure E1, while panel (b) presents the relationship with discrete-choice demand (choice probability). The corresponding implied elasticities are reported in the upper right corner of each panel. Reassuringly, the median structural elasticities match the reduced-form estimates for elasticities that we calculate using an instrumental variable approach in regression form.



(a) Continuous (b) Discrete

FIGURE E1: REDUCED-FORM ELASTICITIES

The figure reports the reduced-form relationship between prices and demand, controlling for bank, province, and year fixed-effects. Panel A presents continuous demand (ln(loan value)), while Panel B presents discrete-choice demand (choice probability). Interest rates are instrumented using delinquency rates in microcredit, housing and consumption, and interest rates in consumption, micro-lending, commercial credit in other regions.