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:

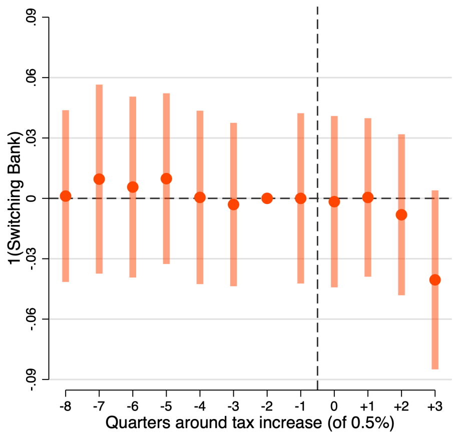
- Crawford et al. (2018) report a default rate of 6% in a sample of Italian small business lines of credit (with maturity 6 months to a year) between 1988 and 1998, which included a financial crisis in 1992.
- Default rates are close to 10% for credit of 13 months maturity

Appendix A.3 Commercial lending of private and public banks

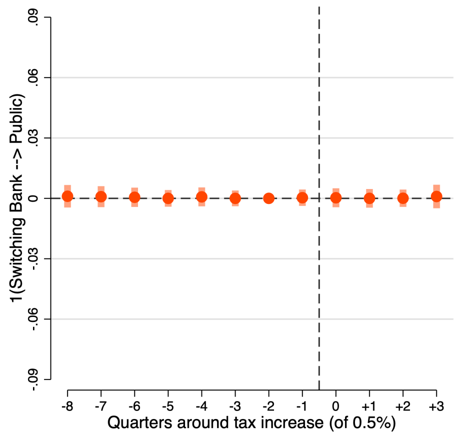
The government banks specialize in the commercial loan market in lending to small firms in small markets. In average (at the median) they lend 20.2% (10.5%) of the outstanding commercial debt in a given province-year—8.8% when the average is weighted by market size. At the borrower-year-level they lend 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 3, where we see no reaction in interest rates to the introduction of the SOLCA tax. And recall that in Figure 3 in Appendix E, 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 Appendix I for



(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.

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.

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.

[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 3).

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, 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

[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.

[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.

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 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;

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

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:

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

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

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

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

[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.

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 Testing Marginal Cost Assumptions

We assume that marginal costs are constant at the loan (borrower-bank-year) level. Notice the generality of this 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.

Moreover, recall that we estimate marginal costs at the borrower-bank-year level. As such, we are not worried about a bias in our estimates of the marginal cost at the margin for the loan size of *ijt*, regardless of the assumption on the cost curves.[1] However, one may worry that our marginal cost assumption could affect our simulated pass-throughs, as quantities adjust, and then $mc_{ijt}(L_{ikt})$ are not generally equal to the new estimates $mc_{ijt}(L_{ijt}^{New})$, except under constant marginal costs. Thus, the constant marginal cost assumption may prove restrictive when performing simulations or counterfactuals.

In particular, given our context, increasing marginal costs imply more incomplete pass-throughs (Weyl and Fabinger, 2013), so our simulations would be biased if true marginal costs are increasing in the quantity demanded by the borrower but we are assuming they are constant. In this circumstance, our simulated pass-through would be biased *away* from those implied by Bertrand-Nash competition and in favor of less competitive conducts. Instead, if underlying marginal cost curves are decreasing in quantity, the bias would go in favor of Bertrand-Nash, while if marginal cost curves are constant, our simulated pass-throughs would be unbiased.

To address this concern, we test the curvature of marginal costs in our data. We first parameterize the marginal cost function as follows:

[1] Indeed, costs given by the following function $C_{ikt}(L_{ikt})$, which allows different borrowers to have different cost curves. For this function, marginal costs are given by $mc_{ikt}(Q_{ikt}) = C'_{ikt}(L_{ikt})$. As marginal costs are recovered at the borrower-bank-year level, the unique estimate will be the same, irrespective of the cost curve $C_{ikt}(\cdot)$, which can have increasing, decreasing, or constant marginal costs.

$$mc_{ijt}(L_{ijt}) = \gamma_j \times L_{ijt} + c_{jt} + c_{it} + c_{ijt}, \tag{C1}$$

where there is a common component in quantity with γ_j capturing the curvature of the marginal cost function for each bank j in loan size L_{ijt}, and we allow for bank-year specific constants through c_{jt}, borrower-specific components in c_{it} and pair-year specific components through c_{ijt}. These capture the heterogeneity discussed above.

To estimate the curvature of the marginal cost curve in quantity, we regress our empirical marginal cost estimates, $\widehat{mc}_{ijt}$, on continuous demand, L_{ijt}, instrumented by the introduction of the SOLCA tax as exogenous demand shifter, without changes in the underlying marginal costs. Specifically, we estimate the instrumental variable model for each bank j:

$$\widehat{mc}_{ijt} = \gamma_j * \widehat{L}_{ijt} + \Gamma * X + \alpha_{jt} + \varepsilon_{ijt} \tag{C2}$$

where α_{jt} are bank-year fixed effects, X are time-varying firm and pair observables (such as pair relationship age, assets of the firm, etc.) and $\widehat{L}_{ijt}$ is instrumented total firm demand corresponding to an implied first stage:

$$\widehat{L}_{ijt} = \gamma_j * Post_t + \Gamma * X + \alpha_{jt} + \varepsilon_{ijt} \tag{C3}$$

where $Post_t$ is an indicator variable that takes the value of one when the SOLCA tax is active (from October 2014), and zero otherwise. The coefficient for γ_j serves as the test of constancy of marginal cost.

We see from Table C1, little evidence of increasing marginal costs, either by pooling data from all banks jointly or by estimating the cost curvature at the bank level. Instead, marginal costs are decreasing at the loan level, meaning that, conditional on the loan being realized, larger loans have lower marginal costs. Such decreasing marginal costs would bias our estimates under our constancy of marginal cost assumption in favor of *more* competitive conduct and *against* collusion. But any bias is likely second-order: though the effects are statistically significant, they appear to be economically small: an increase in the size of the loan by 1 million USD relates to a decrease in marginal costs of 9 USD.

TABLE C1: TEST OF MARGINAL COST ASSUMPTIONS

The table reports the coefficient ($\widehat{\gamma}$) from the instrumental variable model described by Equations C2 and C3, along with the corresponding t-value and observations, for the full data (row 1) and for each lender separately. Data are at the firm-bank-year level for 2010 to 2017. All models include bank-year fixed effects and time-varying firm and relationship controls, including the age of the lending relationship, firm size (assets, wages, revenue, expenditures), firm age, firm tangible capital, and an indicator that takes the value one any of the firm's loans from any bank had ever required a bank write-down, and zero otherwise. The First Stage F-statistic refers to the pooled regression with full data.

Sample	(1) Coefficient ($\widehat{\gamma}$)	(2) T-Value	(3) Ob.s
Full Data	-9.5945	5.2329	17,138
Banco Amazonas	30.1041	3.0106	58
Banco del Austro	-9.3346	1.4787	806
Banco Guayquil	-14.1330	4.4042	1,847
Banco Bolivariano	-20.0432	1.4738	1,137
Citibank Ecuador	1.3372	1.1276	22
Banco Comercial de Manabí	-490.9154	0.6451	114
Banco del Litoral	144.5108	0.5176	14
Banco General Rumiñahui	-24.6680	1.0147	172
Banco Internacional	-9.5143	1.2386	1,443
Banco de Loja	546.7023	0.0380	265
Banco de Machala	-45.4124	0.9832	1,056
Banco del Pacífico	-4.4233	2.0650	579
Banco Pichincha	-5.5910	3.6222	6,722
Produbanco	-14.2807	3.3178	2,241
Banco Nacional de Fomento	-64.3065	0.8653	28
Corporacion Financiera Nacional	0.2986	0.2229	107
ProCredit Bank	-18.3187	1.6589	137
Banco Delbank	26.2148	1.0794	19
Firm-Year FE	Yes		
Bank-Year FE	Yes		
Controls	Yes		
First Stage F Statistic	34.23		

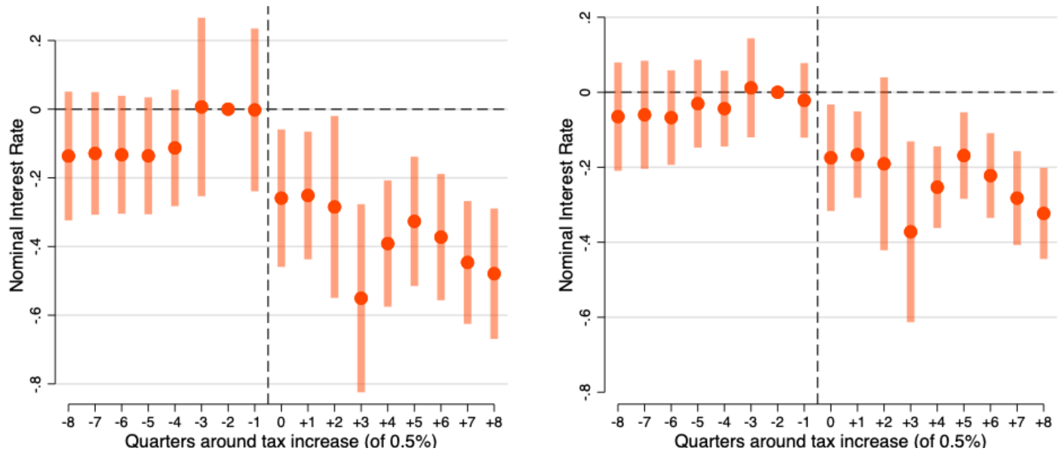
Appendix D Loan Default Prediction

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 D1 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 D1: 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 E Robustness of pass-through estimates

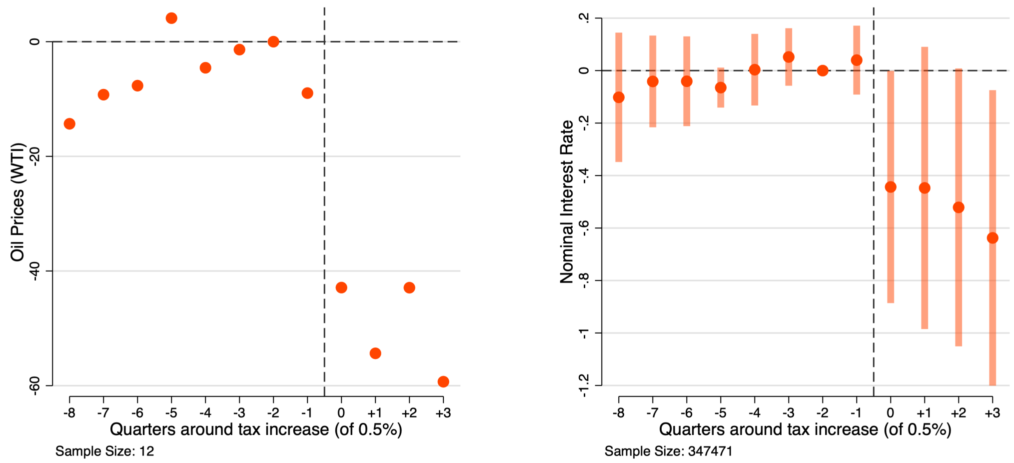


(a) Regular loans; bank & firm FE

(b) Regular loans, bank-firm pair FE

FIGURE E1: DYNAMIC ANALYSIS OF THE SOLCA TAX ON MATURITY AND AMOUNT OF NEW COMMERCIAL DEBT LENT BY PRIVATE BANKS

Replicating Figure 2 in an eight quarter estimation window around the SOLCA tax implementation. It reports the period-by-period difference in average pre-tax nominal interest rates on new commercial loans from private banks around treatment assignment relative to event-time period $t = -2$ (normalized to zero), using firm and bank fixed effects (Panel (a)) or firm $\times$ bank fixed effects (Panel (b)). Data are loan-level. Standard error bars are shown at the 95% confidence level and are clustered at the bank-quarter level.

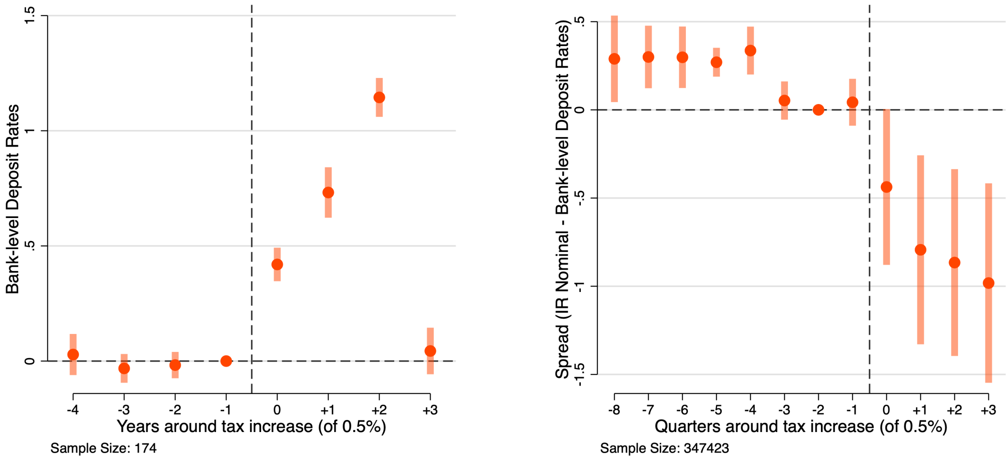


(a) Oil Prices

(b) Interest Rates cont. Oil

FIGURE E2: ROBUSTNESS CONTROLLING FOR OIL PRICES

Panel (a) reports the evolution of quarterly prices of WTI Crude. Panel (b) reports the period-by-period difference in average pre-tax nominal interest rate on new commercial loans from private banks around treatment assignment, controlling for buckets of amount and maturity, default probability, a third-degree polynomial of quarterly WTI Crude prices, and bank-firm pair FE. Standard error bars are shown at the 95% confidence level and are clustered at the bank-quarter level. The relative event-time period $t = -2$ is normalized to zero.



(a) Deposit Rates (b) Spread

FIGURE E3: ROBUSTNESS ON SPREADS

Panel (a) reports the evolution of yearly deposit rates at the bank level around 2014 using bank FE. Yearly deposit rates are calculated by obtaining national average deposit rates by product and calculating bank-level yearly averages across products using product portfolio bank shares. Panel (b) reports the period-by-period difference in average spreads (pre-tax nominal transaction-level interest rate minus yearly bank-level deposit rate average) on new commercial loans from private banks around treatment assignment controlling for buckets of amount and maturity, default probability, a third-degree polynomial of quarterly WTI Crude prices, and bank-firm pair FE. Standard error bars are shown at the 95% confidence level and are clustered at the bank-level in Panel (a) and at the bank-quarter level in Panel (b).

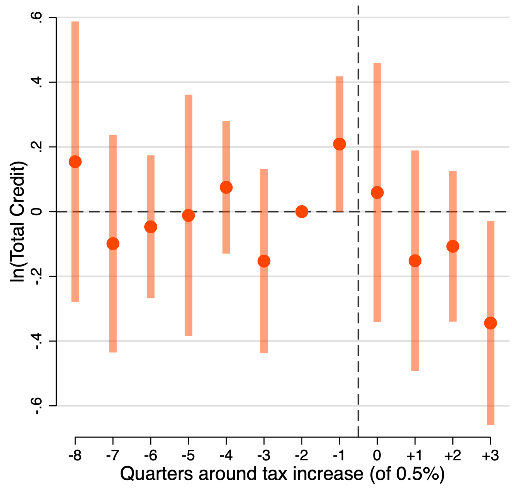
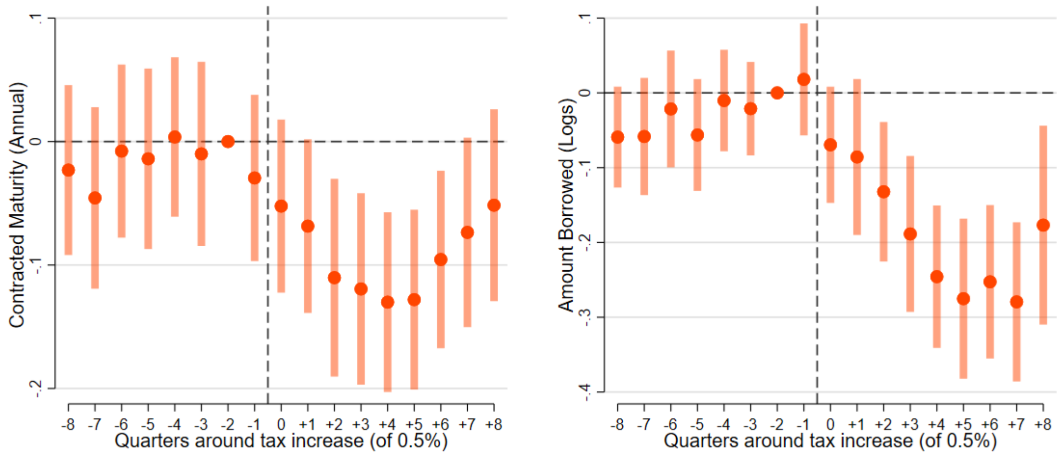


FIGURE E4: DYNAMIC ANALYSIS OF THE INTRODUCTION OF THE SOLCA TAX ON TOTAL COMMERCIAL CREDIT LENT BY PRIVATE BANKS

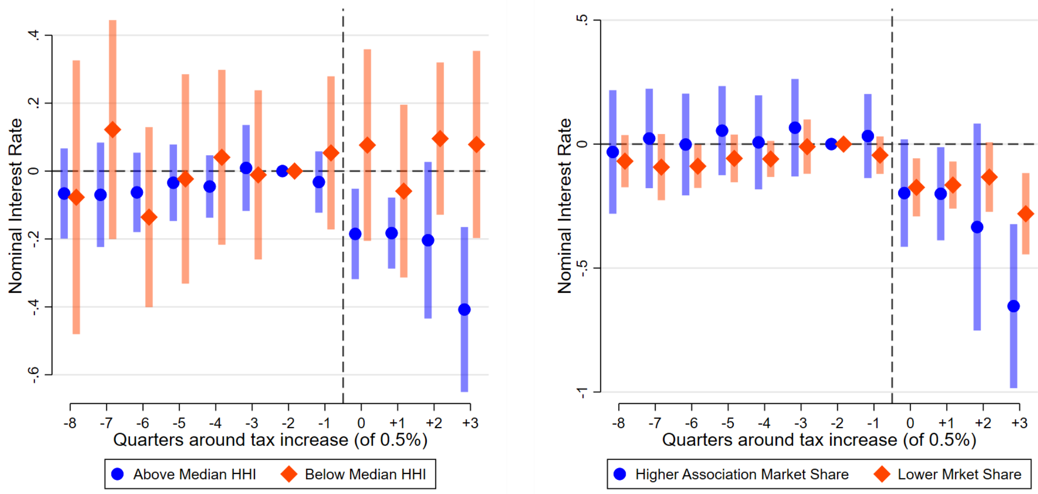
The figure reports the period-by-period difference in total commercial lending from private banks around treatment assignment relative to event-time period $t = -2$ (normalized to zero), using bank fixed effects. Data are bank-quarter level on commercial loans granted by private banks to Ecuadorian corporations. Standard errors bars are shown at the 95% confidence level and are clustered at the bank level.



(a) Regular loans, maturity; bank & firm FE (b) Regular loans, amount, bank & firm FE

FIGURE E5: DYNAMIC ANALYSIS OF THE SOLCA TAX ON MATURITY AND AMOUNT OF NEW COMMERCIAL DEBT LENT BY PRIVATE BANKS

Replicating Figure 4 in an eight quarter estimation around the introduction of the SOLCA tax. It reports the period-by-period difference in average term-to-maturity (Panel (a)) or the natural logarithm of the amount borrowed (Panel (b)) on new commercial loans from private banks around treatment assignment relative to event-time period $t = -2$ (normalized to zero), using firm $\times$ bank fixed effects. Data are loan-level. Standard error bars are shown at the 95% confidence level and are clustered at the bank-quarter level.



(a) Regular loans; bank & firm FE (b) Regular loans; bank-firm pair FE

FIGURE E6: SOLCA TAX PASS-THROUGH BY MARKET CONCENTRATION

The figures report the evolution of yearly, pre-tax nominal interest rates at the loan level around 2014 using firm $\times$ bank fixed effects. Panel (a) splits markets into those with above- and below-median values of lender Herfindahl-Hirschman index defined on loan share. Panel (b) splits markets into those with above- and below-median loan market share by members of the Asociación de Bancos del Ecuador (ASOBANCA). Data are loan-level. Standard error bars are shown at the 95% confidence level and are clustered at the bank-quarter level.

TABLE E1: ROBUSTNESS OF PASS-THROUGH ESTIMATES

The table reports aggregate pass-through estimates to the tax-inclusive 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, twenty buckets of loan amount, and the loan's predicted default probability. Column (1) additionally controls for a third-degree polynomial of quarterly prices of WTI crude oil. Column (2) controls for a third-degree polynomial of province quarterly GDP growth. Column (3) includes quarter fixed effects. Robust standard errors clustered at the bank-quarter level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The table bottom of the table reports testing against the full pass-through null hypothesis ($\rho_o = 1$).

	Outcome: Tax-inclusive interest rate		
	(1)	(2)	(3)
Pass-through (ρ)	0.609	0.408*	0.705*
	(0.387)	(0.214)	(0.372)
WTI Oil Price	0.128***		
	(0.043)		
(WTI Oil Price)^2	-0.002***		
	(0.001)		
(WTI Oil Price)^3	0.000***		
	(0.000)		
Province GDP Growth		-0.013	
		(0.026)	
(Province GDP Growth)^2		-0.003	
		(0.006)	
(Province GDP Growth)^3		-0.000	
		(0.004)	
Pr(Default) Control	Yes	Yes	Yes
Maturity & Amount Controls	Yes	Yes	Yes
Pair Fixed Effect	Yes	Yes	Yes
Year-quarter Fixed Effect	No	No	Yes
Observations	347,471	489,251	489,251
R-squared	0.777	0.749	0.749

Appendix F 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:

$$r_{ikmt} = \gamma_0 + \gamma_x X_{ikmt} + \gamma_2 ln(L_{ikmt}) + \gamma_3 ln(M_{ikmt}) + \lambda_{kmt} + \omega_i^r + \tau_{ikmt}, \tag{F1}$$

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 F1 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 F1 and Appendix Table F2 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 F1 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 F1: PRICE PREDICTION REGRESSIONS

The table reports estimates of Equation F1, 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 3 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.

	(1)	**(2)**	**(3)**	**(4)**
Variable	**IR**	**IR**	**IR**	**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 D, 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 F1. Results are reported in Table F2. 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 F2: 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 F1. The same set of controls are used as in the corresponding Model in Table F1. 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:

$$\begin{aligned} r_{ikmt} &= \tilde{r}_{ikmt} + \tilde{\tau}_{ikmt}, \\ &= \tilde{r}_{kmt} + \tilde{\gamma}_x X_{ikmt} + \tilde{\gamma}_2 ln(L_{ikmt}) + \tilde{\gamma}_3 ln(M_{ikmt}) + \tilde{\omega}_i^r + \tilde{\tau}_{ikmt} \end{aligned} \tag{F2}$$

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 F1. 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.

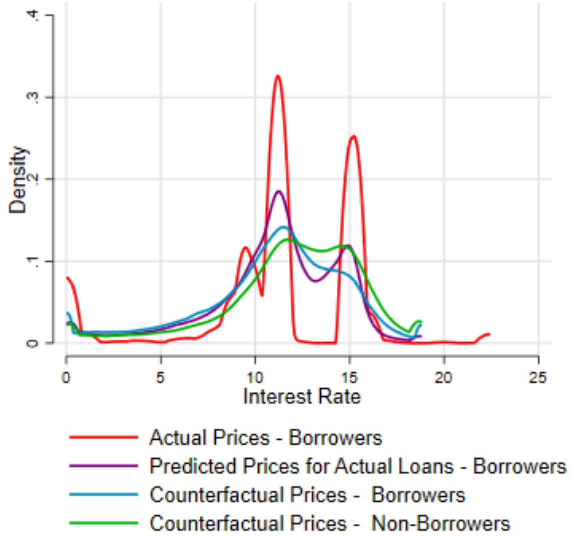


FIGURE F1: DISTRIBUTION OF PREDICTED PRICES

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

Appendix F.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 F3 reports diagnostics on our matching model.

TABLE F3: 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 G Demand Estimates by Region

TABLE G1: 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)
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)

Continued on next page

TABLE G1 – continued from previous page

Region	Variable	Mean	Standard Deviation
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)
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 G2: 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 11. $\widehat{Price}$ 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 H Estimating Demand Elasticities

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

$$\epsilon^L_{ikmt} = \frac{\partial L_{ikmt}}{\partial r_{ikmt}}\frac{r_{ikmt}}{L_{ikmt}} = \frac{\partial ln(L_{ikmt})}{\partial r_{ikmt}} r_{ikmt} = -\alpha_m r_{ikmt} \tag{H1}$$

and

$$\begin{aligned}\epsilon^s_{ikmt} &= \frac{\partial s_{ikmt}}{\partial r_{ikmt}}\frac{r_{ikmt}}{s_{ikmt}} \\ &= -\alpha_m \exp(\mu)\exp(\xi_{kmt} + \psi_i - \alpha_m r_{ikmt} + \beta_{m1}X_{it} + \beta_{m2}X_{ikmt})(1 - s_{ikmt})s_{ikmt} \times \frac{r_{ikmt}}{s_{ikmt}} \\ &= -\alpha_m \exp(\mu)\exp(\xi_{kmt} + \psi_i - \alpha_m r_{ikmt} + \beta_{m1}X_{it} + \beta_{m2}X_{ikmt})(1 - s_{ikmt})r_{ikmt}\end{aligned} \tag{H2}$$

The elasticity for total demand is given by:

$$\begin{aligned}\epsilon^Q_{ikmt} &= \frac{\partial Q_{ikmt}}{\partial r_{ikmt}}\frac{r_{ikmt}}{Q_{ikmt}} = \frac{\partial s_{ikmt}L_{ikmt}}{\partial r_{ikmt}}\frac{r_{ikmt}}{s_{ikmt}L_{ikmt}} \\ &= \frac{\partial s_{ikmt}}{\partial r_{ikmt}}\frac{r_{ikmt}}{s_{ikmt}} + \frac{\partial L_{ikmt}}{\partial r_{ikmt}}\frac{r_{ikmt}}{L_{ikmt}} = \epsilon^s_{ikmt} + \epsilon^L_{ikmt}.\end{aligned} \tag{H3}$$

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

$$\epsilon^{L,j}_{ikmt} = 0 \tag{H4}$$

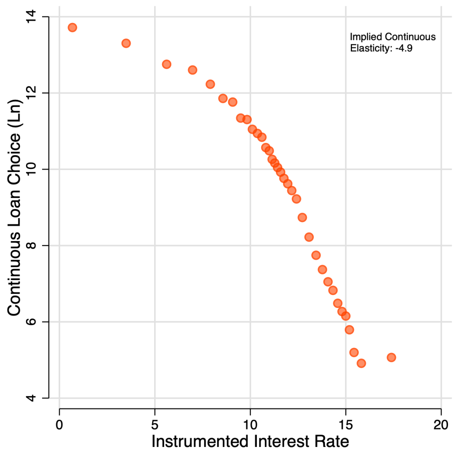
and

$$\begin{aligned}\epsilon^{s,j}_{ikmt} &= \frac{\partial s_{ikmt}}{\partial r_{jkmt}}\frac{r_{jkmt}}{s_{ikmt}} = \alpha_m \exp(\mu)\exp(\xi_{jmt} + \psi_i - \alpha_m r_{ijmt} + \beta_{m1}X_{it} + \beta_{m2}X_{ijmt})s_{ijmt}s_{ikmt} \times \frac{r_{ijmt}}{s_{ikmt}} \\ &= \alpha_m \exp(\mu)\exp(\xi_{jmt} + \psi_i - \alpha_m r_{ijmt} + \beta_{m1}X_{it} + \beta_{m2}X_{ijmt})s_{ijmt}r_{jkmt}\end{aligned} \tag{H5}$$

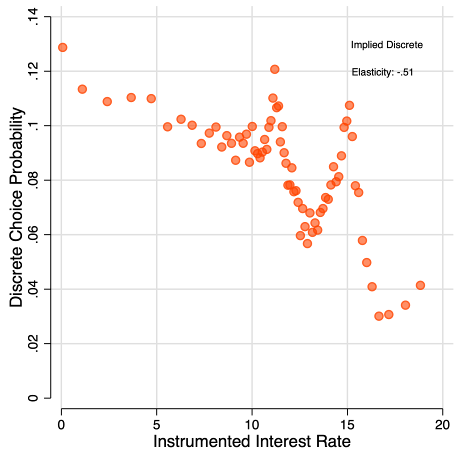
Appendix H.1 Reduced-Form Elasticities

We validate the estimated structural elasticities reported in Table 8 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 H1, 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 H1: 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.

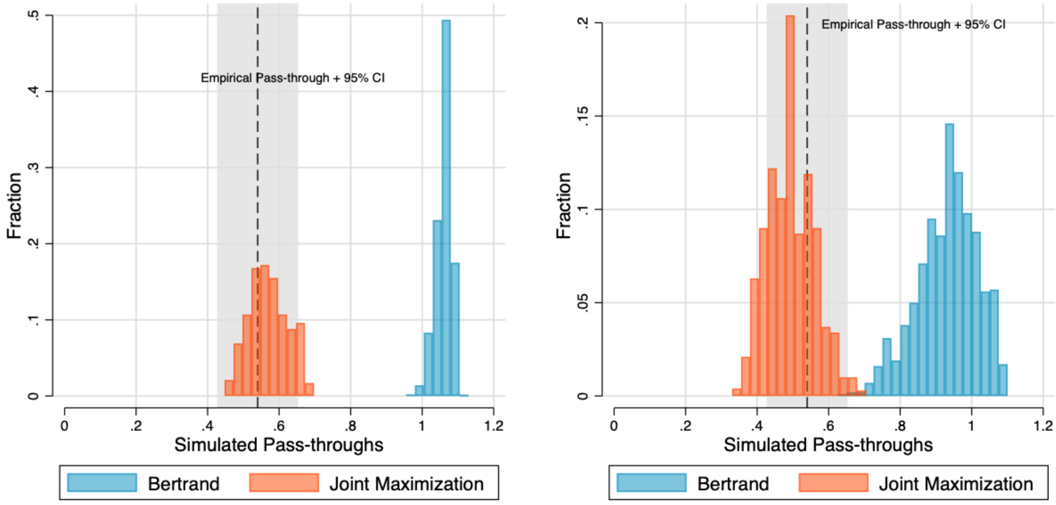
Appendix I Additional Simulations and Counterfactuals

Appendix I.1 Robustness to Modeling Lender-Borrower Relationships

In this appendix, we present a simple exercise to further highlight the identification intuition for conduct υ_m. We simulate the model assuming a conduct parameter $\upsilon_m = 0$, i.e., Bertrand-Nash competition. Next, we separately perform this exercise assuming a conduct parameter $\upsilon_m = 1$, i.e., joint profit maximization as if there were only one monopoly bank in each market.

Figure I1 plots the results of 1,000 bootstrap simulations, where we sampled borrowers with replacement. Panel (a) displays simulated pass-throughs for chosen and potential loans. We estimate that pass-throughs are centered slightly above one under Bertrand-Nash, despite the significant demand heterogeneity documented above. Contrasting this distribution with the empirical point estimate for pass-through of 0.54 and the upper 95% interval at 0.64, we reject that that conduct is Bertrand-Nash in the actual data. Note that this is a sharp test because our discrete-continuous demand model is flexible enough that we can obtain pass-through estimates both above and below one under Bertrand-Nash, which, as documented by Miravete et al. (2023), many discrete-choice models are not able to accommodate.

In contrast, the simulated distribution of pass-throughs under an assumption of competition under joint profit maximization has an average of 0.57 and almost completely overlaps with the empirical estimate of pass-through. Therefore, we fail to reject that conduct is joint maximization in the actual data at the national level. In panel (b), we report the simulated pass-through for only actually chosen banks, i.e., the bank the firm chose to borrow from in our data. Although the spread of the distributions is wider in this exercise, we again observe that the Bertrand-Nash distribution does not overlap with the empirical distribution of pass-through, while the distribution of simulated pass-through under joint maximization completely overlaps with the pass-through observed in the loan data.



(a) All loans

(b) Chosen loans

FIGURE I1: 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.

This exercise also illustrates the flexibility of our discrete-continuous demand model and its ability to match the full support of tax pass-throughs in the data. This contrasts with traditional logit demand models, which limit the shape of the demand curve and struggle to match the entire range of pass-through rates observed, and thereby, attribute mismatches from misspecification in the demand model to the conduct parameter (Miravete et al., 2023). Figure I1 demonstrates that our model can span the tax pass-throughs around one even in the Bertrand-Nash setting, meaning it is flexible enough to capture a wider range of behaviors to simulate the theoretical support of tax pass-through. In panel (b) of FigureI1, we condition on the chosen lending relationship in the data the ability to capture both incomplete and more-than-complete pass-throughs is even more evident.[1]

Appendix I.2 Sensitivity Tests to the Invariant Conduct Assumption

A key assumption of our model and analyses is that conduct is a fundamental market feature that is not itself impacted by the introduction of the SOLCA tax. We rely on this assumption

[1]Given that the objective of our paper is to rely on empirically estimated pass-throughs to calibrate/test conduct, rather than relying on a model to predict unobserved pass-throughs, allowing for further flexibility a la BLP would be counterproductive. If we were to do so we would mechanically bias model-predicted pass-through towards complete or more-than-complete pass-throughs (as shown in Miravete et al. (2023)). Thus, implementing such approach would bias us in favor of finding anti-competitive conduct.

to argue that we can estimate conduct from the empirical pass-through from the single SOLCA tax shock. In this appendix, we provide additional evidence supporting the assumption that the introduction of the SOLCA tax and any anticipated future changes coming from the regulatory environment did *not* affect the competitive and demand structure of the market.

First, we re-simulate tax incidence and marginal excess burden using only years prior to the introduction of the SOLCA tax (2014 and earlier). Appendix Table I1 presents the results, which are qualitatively and quantitatively similar to those presented in Table 13 in the main text, which is estimated on the full sample. In particular, the measured incidence presented in panel (a) of Appendix Table I1 is statistically indistinguishable from the results in panel (a) of Table 13. The interpretation is also unchanged. We find that prior to choosing a bank, unconditional incidence falls on average (median) on the borrower (is equally shared). Once we account for which bank is chosen, the conditional incidence falls primarily on the banks.

For both the ex-ante and ex-post measure in panel (b), we again find that the burden of taxation falls much more on the borrower if one assumes Bertrand Nash competition ($\upsilon_m \equiv 0$) rather than using calibrated conduct estimated on the *pre-tax* data. However, incidence under the assumption of joint-maximization ($\upsilon_m \equiv 1$) is closer to our benchmark results using calibrated conduct. The estimated magnitudes are extremely similar to those estimated under the full sample.

Second, we reconfirm our key result on this pre-tax sample that the loan tax is distortionary (marginal excess burden in panel (a)), but that the predictions of excess burden are much higher if we assume pure Bertrand-Nash competition than if we assume full joint maximization (marginal excess burden in panel (b)). And again, the estimated magnitudes are indistinguishable to those estimated under the full sample.

TABLE I1: ROBUSTNESS OF TAX INCIDENCE TO ESTIMATION ON PRE-SOLCA TAX SUBSAMPLE

This table presents simulated estimates of tax incidence and marginal excess burden through the lens of the model by estimating separately by lender competitive conduct—either the data-calibrated conduct or counterfactual Bertrand-Nash or joint maximization conduct (re-simulating the model imposing a conduct of zero or one, respectively). Different from the corresponding results presented in Table 13 of the main text, here we estimate only on years prior to the introduction of the tax (2014 and earlier). Presented measures are calculated according to incidence Equations 24, 25, and 28. For Bertrand-Nash and joint maximization, we explore results using model-consistent and empirical pass-through estimates. Model (1) presents ex-ante estimates, before the decision of which bank to choose from. Model (2) presents ex-post estimates, conditional on the observed choice of bank. In practice, the difference between Models (1) and (2) is that Model (1) adjusts bank surplus and tax revenue by the choice probability (market share s_{ikmt}). *Marginal excess burden* is defined as the sum of marginal borrower surplus, marginal bank surplus, and marginal tax revenue.

	Mean	**Median**	**Mean**	**Median**
	Unconditional (1)		**Conditional (2)**	
Panel A: The empirical benchmark				
Calibrated Conduct | Empirical Pass-through				
Incidence	2.62	0.95	0.37	0.35
Excess Burden over Marginal Tax Revenue			-0.50	-0.63
Panel B: Counterfactual Simulations				
Joint-Maximization | Simulated Pass-through				
Incidence	2.97	0.99	0.41	0.41
Excess Burden over Marginal Tax Revenue			-0.41	-0.42
Bertrand-Nash | Simulated Pass-through				
Incidence	6.29	1.97	0.89	0.97
Excess Burden over Marginal Tax Revenue			-0.92	-0.97

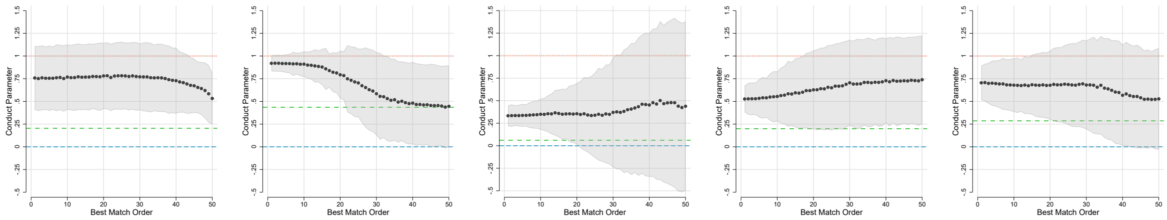
Third, Appendix Table I2 presents the corresponding values for the calibrated conduct parameter estimated over the full sample (Columns 1 and 2 and reproduced from Table 10) and over the pre-SOLCA tax sample (Columns 3 and 4). We again see that the conduct estimates from the two samples are statistically indistinguishable at conventional levels.

TABLE I2: COMPARING CONDUCT PER REGION FROM FULL SAMPLE AND PRE-SOLCA TAX SAMPLE

The table reports how well the pass-throughs in the calibrated model fit those in the observed data and how stable the fit is around the introduction of the SOLCA tax. Conduct parameters estimates are reported by lending region for the full sample (Columns (1) and (2), reproduced from Table 10) and on the sub-sample before the introduction of the SOLCA tax (years 2014 and earlier, in Columns (3) and (4)). The model is separately estimated by region on a random sample of 2,500 firms using a simulated method of moments model that matches empirical to model-estimated tax pass-through. The bootstrapped standard error is based on 1,000 bootstrap samples.

	Full Sample		Pre-SOLCA Sample	
	Mean	Standard Error	Mean	Standard Error
Azuay	0.70	0.12	0.76	0.14
Costa	0.91	0.04	0.92	0.03
Guayas	0.33	0.07	0.33	0.04
Pichincha	0.56	0.07	0.53	0.06
Sierra & Oriente	0.67	0.06	0.71	0.07

Fourth, we re-run our sanity checks for calibrated conduct estimated on the pre-SOLCA tax sample. Appendix Figure I2 reruns the same match order test as for Figure 6 estimated on the full dataset. Specifically, the figure reports for each region the lowest feasible conduct parameter estimates (y-axis) by the degree of match, where zero in the match order (x-axis) represents the conduct that minimizes the squared distance between simulated and observed pass-through in the model and 50 indicates the 50^{th} best match. As in Figure 6, the estimates reported in Appendix Figure I2 are stable, even approaching the worst (50^{th}) match order.



(a) Azuay (b) Costa (c) Guayas (d) Pichincha (e) Sierra

FIGURE I2: REGIONAL CONDUCT BY MATCH; PRE-SOLCA TAX SUBSAMPLE

The figure reports conduct parameter estimates by lending region against the ordered best-ranked matches between empirical and model-estimated tax pass-through. Estimates are based on data before the implementation of the SOLCA tax (Compare to Figure 6, estimated on the full dataset). The best fit is match order one. The model is separately estimated by region on a random sample of 2,500 firms using a simulated method of moments model. The bootstrapped standard errors are estimated using 1,000 bootstrap samples. The dotted line at conduct one corresponds to joint maximization; the dashed line at conduct zero corresponds to Bertrand-Nash competition, and the intermediate conduct corresponds to Cournot competition in each region. Note Region Sierra includes provinces from Oriente as well.

Next, we confirm that simulated pass-through estimated on the pre-SOLCA tax (2014 and earlier) sample is again non-monotonically decreasing over the support of the conduct parameter, both nationwide (Appendix Figure I3) and in each region separately (Appendix Figure I5). In all regions, we observe stability in the first ten to twenty best fitting models. We can reject pure Bertrand-Nash and Cournot competition at the 95% confidence level in the ten best-fitting model estimates for all regions. In Guayas and Pichincha, we can reject joint maximization in the best-fitting models. We fail to reject full joint maximization in three of the five regions. These patterns are consistent with the simulation results reported in Section 5.1. It is clear that banks are not Bertrand-Nash competitive, and results are most consistent with some degree of joint maximization.

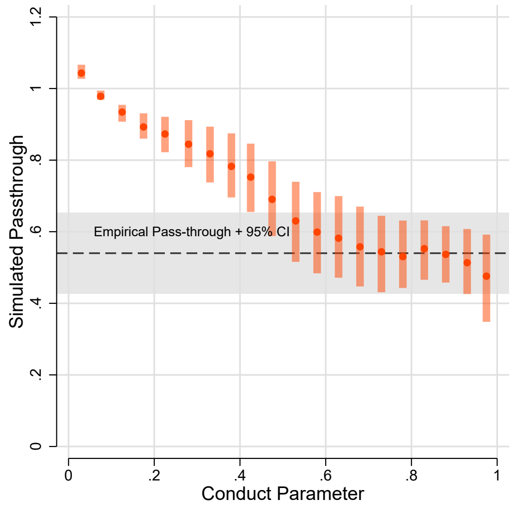


FIGURE I3: AVERAGE NATION-WIDE SIMULATED PASS-THROUGHS BY CONDUCT GRID; PRE-SOLCA TAX SUBSAMPLE

The figure reports the average nation-wide simulated Nash-equilibrium pass-throughs of a tax introduction of 0.5% over a grid of conducts between 0 and 1. Simulations to produce this figure were run on the sub-sample of data before the introduction of the SOLCA tax (compare to Figure 5 estimated on the full dataset). Each region samples 2,500 borrowers. Confidence intervals are clustered at the region-conduct grid level. The dashed line shows the estimated empirical pass-throughs regressions (using data with actual loans) presented in the reduced-form section of the paper, and the shaded area shows the 95% confidence interval.

Finally, we examine the sensitivity of our results to the proximity of the introduction of the SOLCA tax, in September 2014, and a recession that began the first quarter of 2015. Specifically, from around mid-2014 oil supply began to increase due to U.S. shale oil production, OPEC's decision to maintain high output, and weakening global demand from slowing growth in China and Europe and the increasing supply of alternative energy. As a result, the price of heavy crude oil, the type exported by Ecuador, fell from over $100 per barrel in 2014 to below $50 by early 2015. The significant drop in oil prices led to a contraction in Ecuador's GDP in the first quarter of 2015, inducing a recession. This could potentially have impacted pass-through rates of the tax in the latter part of the three-quarter post period we use in estimation.

We therefore re-estimate using pass-throughs from the quarter of the introduction of the tax only, i.e., the third quarter of 2014. The results are reported in Table 4 at both the aggregate, national level and for the individual regions. We continue to estimate incomplete pass-throughs, albeit closer to the complete pass-through of zero and much less precisely. We also are still able to reject that banks are competing Bertrand-Nash at conventional confidence levels, as can be seen from Figure I4 and Figure 5. While we cannot rule out all threats to identification, these represent the most conservative estimates, as all potential adjustment frictions bias towards complete pass-through, in addition to our conservative modeling choices. Thus, that our main results go through is strong evidence of the robustness of our inference.

TABLE I3: PASS-THROUGH ESTIMATES: SHORT-TERM

The table reports aggregate pass-through estimates to the tax-inclusive 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 sample is restricted to include only November and December 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, twenty buckets of loan amount, predicted default probability, and bank-firm FE. Model (1) pools all regional markets. Models (2)-(6) report estimates by regional market. Robust standard errors clustered at the bank-quarter level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Testing is conducted against the full pass-through null hypothesis ($\rho = 1$).

	Outcome: Tax-inclusive interest rate					
	(1)	(2)	(3)	(4)	(5)	(6)
Market	National	Azuay	Costa	Guayas	Pichincha	Sierra
Pass-through (ρ)	0.702*	0.143***	0.563	0.816	0.667	0.831
	(0.159)	(0.307)	(0.373)	(0.184)	(0.289)	(0.453)
Pr(Default) Control	Yes	Yes	Yes	Yes	Yes	Yes
Maturity & Amount Controls	Yes	Yes	Yes	Yes	Yes	Yes
Pair Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	287,070	32,130	12,138	147,977	77,920	16,905

Appendix I.3 Testing the Identification Assumption for Conduct

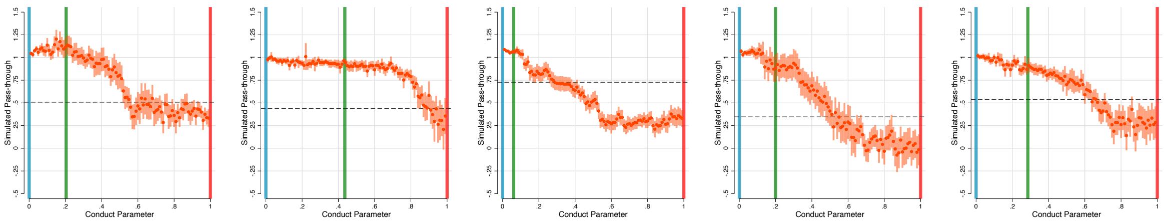
Our model identification assumes a direct relationship between pass-through and the conduct parameter. Specifically, we assume that pass-through is non-constant as competitive conduct, or the degree of joint maximization among banks competing in the same market, increases. For ease of interpretation, it serves to consider this identification assumption through the lens of a simple pass-through formulation borrowed from Weyl and Fabinger (2013). Assuming symmetric imperfect competition, constant marginal cost, and that conduct is invariant to quantity, pass-through is given by:

$$\rho = \frac{1}{1 + \frac{\theta}{\epsilon_{ms}}}, \tag{I1}$$

where θ is the conduct parameter (e.g., $\theta = 1$ under joint maximization and $\theta = 0$ under Bertrand-Nash) and ϵ_{ms} is the curvature of demand. Under this simple model, pass-through is complete in Bertrand-Nash. If measured pass-through is not complete, keeping ϵ_{ms} constant, positive (negative) changes in competitive nature (reflected by moves in θ) will move pass-through closer (farther) from one. If pass-through is incomplete, increases in competition will increase pass-through. Instead, if measured pass-through is more than complete, an increase in competition will decrease pass-through.

We have presented reduced-form evidence in Section 3.3 that pass-through is strongly related with proxies for bank collusion when setting interest rates. Yet, interpretation in our setting is not so straightforward as this reduced-form evidence suggests. Demand curvature may be different across markets, so pass-throughs may differ even if conduct is identical.

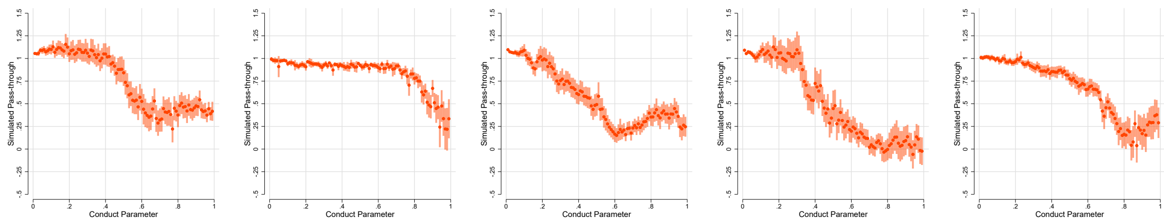
With our estimated model in hand, we can directly test the relationship between conduct and pass-through. Figure I4 replicates Figure 5 in the main paper for each region separately. The exercise is to simulate the pass-through of a 0.5% loan tax like the SOLCA tax over the entire support of the conduct parameter. The y-axis plots simulated pass-through and the x-axis the corresponding conduct parameter. We confirm that in all regions we can reject Bertrand-Nash and Cournot competition. Moreover, we fail to reject joint maximization in four of five regions (all but Pichincha). Finally, we see that pass-through decreases (non-linearly) with conduct and that the relationship is mostly monotonic, especially in the relevant regions required to test against Bertrand-Nash and Cournot. As we report in Figure 5 in the main text, the relationship between pass-through and conduct is also decreasing and monotonic at the national level. Moreover, Figure I5 demonstrates clearly that the same patterns hold if we estimate demand using only pre-tax data.



(a) Azuay (b) Costa (c) Guayas (d) Pichincha (e) Sierra

FIGURE I4: SIMULATED PASS-THROUGH AND COMPETITIVE CONDUCT

The figure reports simulated pass-throughs (y-axis) estimated in 0.1 buckets over the support of the conduct parameter (x-axis). The model is separately estimated by region on a random sample of 2,500 firms. Bootstrapped standard errors are estimated using 1,000 bootstrap samples. The blue vertical bar represents Bertrand-Nash conduct, the green vertical bar represents market-specific Cournot/credit rationing conduct, while the red vertical bar represents joint-maximization. The horizontal dash line represents the point estimate for regional pass-through.Note Region Sierra includes provinces from Oriente as well.



(a) Azuay (b) Costa (c) Guayas (d) Pichincha (e) Sierra

FIGURE I5: RELATIONSHIP BETWEEN SIMULATED PASS-THROUGH AND CONDUCT; PRE-SOLCA TAX SUBSAMPLE

The figure reports simulated pass-through (y-axis) estimated in 0.1 buckets over the support of the conduct parameter (x-axis). The model is separately estimated by region on a random sample of 2,500 firms. Bootstrapped standard errors are estimated using 1,000 bootstrap samples. This figure simulates pass-through on data from before the introduction of the SOLCA tax (compare to Figure I4 estimated on the full sample). Note Region Sierra includes provinces from Oriente as well.

Appendix J Testing Partial Cartels

Appendix J.1 The Corts' Critique

In our main analyses, we utilize a conjectural variation approach to estimate competitive conduct parameters. This approach assumes a market's competitiveness based on lender beliefs about how competitors might react to changes in output or prices. However, this approach has been critiqued in the influential paper by Corts (1999). The first concern is that *static* conduct models that are not special cases are hard to interpret. This is less of a problem in our context as our primary focus is on testing against static benchmarks with well-defined conduct values—differentiated price competition (Bertrand-Nash), credit rationing (Cournot), and joint maximization.

Second, Corts (1999) argues that the conjectural variation approach fails to capture dynamic market behaviors if competitive behaviors change in response to shifts in demand. For example, a sudden and significant increase in demand could disrupt cooperative behavior among competitors as the potential profits from breaking a cartel agreement become increasingly tempting. This critique is less of a concern in our setting as the minor tax increase we focus on is unlikely to have a significant influence on market conduct, unlike the standard practice in the literature of using large demand shifts. Nevertheless, in Internet Appendix Table I1, we examine the robustness of our results by estimating demand on data from the period before the SOLCA tax was introduced. Both qualitatively and quantitatively, the findings align with those presented in the main text.

Appendix J.2 Modeling Partial Cartels

In this section, we describe how we implement the internalization parameter approach of Miller and Weinberg (2017), which permits partial cartels as well as different degrees of internalization interests within the cartel.

Under the internalization framework, the profit of bank k from lender i in market m at time k is given by:

$$\max_{r_{ikmt}} B_{ikmt} = (1 - d_{ikmt})r_{ikmt}Q_{ikmt}(r + \tau_{ikmt}) - mc_{ikmt}Q_{ikmt}(r + \tau_{ikmt}) + \sum_{j \neq k} \upsilon_{kj}[(1 - d_{ijmt})r_{ijmt}Q_{ijmt}(r + \tau_{ijmt}) - mc_{ijmt}Q_{ijmt}(r + \tau_{ijmt})], \tag{J1}$$

where υ_{kj} represents the profit weight (internalization parameter) of how much the profits of j matter for bank k. When $\upsilon_{kj} = 0$ for all $j \neq k$, we are in the Bertrand-Nash world: each firm maximizes profits subject to its residual demand. When $\upsilon_{kj} = 1$ for all $j \neq k$, banks are maximizing industry-wide profits. For other values, we can have asymmetric internalization of profits, allowing for partial cartels and different conduct values (such as Cournot). The first-order condition with respect to r_{ikmt} is then:

$$(1 - d_{ikmt})Q_{ikmt}(r + \tau_{ikmt}) + ((1 - d_{ikmt})r_{ikmt} - mc_{ikmt})\frac{\partial Q_{ikmt}(r + \tau_{ikmt})}{\partial r_{ikmt}} \\ + \sum_{j \neq k} \upsilon_{kj}[((1 - d_{ijmt})r_{ijmt} - mc_{ijmt})\frac{\partial Q_{ijmt}(r + \tau_{ijmt})}{\partial r_{ikmt}}] = 0, \tag{J2}$$

where the first line is the typical Bertrand-Nash formulation for optimal prices, and the second line considers the internalization of competitors' profits.

It is useful to consider the problem in its matrix notation. For banks $k = 1, 2, .., K$, define the matrix of partial derivatives as

$$\frac{\partial Q_{imt}}{\partial r_{imt}} = \begin{bmatrix} \frac{\partial Q_{i1mt}}{\partial r_{i1mt}} & \frac{\partial Q_{i2mt}}{\partial r_{i1mt}} & ... & \frac{\partial Q_{iKmt}}{\partial r_{i1mt}} \\ \frac{\partial Q_{i1mt}}{\partial r_{i2mt}} & \frac{\partial Q_{i2mt}}{\partial r_{i2mt}} & ... & \frac{\partial Q_{iKmt}}{\partial r_{i2mt}} \\ ... & ... & ... & ... \\ \frac{\partial Q_{i1mt}}{\partial r_{iKmt}} & \frac{\partial Q_{i2mt}}{\partial r_{iKmt}} & ... & \frac{\partial Q_{iKmt}}{\partial r_{iKmt}} \end{bmatrix}, \tag{J3}$$

and define the profit-internalization matrix as, where Υ_{mt} is defined for all banks available at market m at time t:

$$\Upsilon_{mt} = \begin{bmatrix} 1 & \upsilon_{12} & ... & \upsilon_{1K} \\ \upsilon_{21} & 1 & ... & \upsilon_{2K} \\ ... & ... & ... & ... \\ \upsilon_{K1} & \upsilon_{K2} & ... & 1 \end{bmatrix}. \tag{J4}$$

Note that given the small size of our study country and the fact that we only have one tax change, we set that $\upsilon_{kjmt} = \upsilon_{kj}$, meaning that for each pair of banks we hold the internalization constant fixed across markets and time. The set of first-order conditions (equation J2) can be then written in matrix notation as:

$$\left[\Upsilon_{mt} \circ \frac{\partial Q_{imt}}{\partial r_{imt}}\right]\tilde{r}_{imt} - \left[\Upsilon_{mt} \circ \frac{\partial Q_{imt}}{\partial r_{imt}}\right]mc_{imt} = -(1 - d_{imt}) \circ Q_{imt}, \tag{J5}$$

where $\circ$ is element-by-element matrix multiplication and $\tilde{r}_{imt} = (1 - d_{imt}) \circ r_{imt}$. This can be further simplified to:

$$\tilde{r}_{imt} = mc_{imt} - \left[\Upsilon_{mt} \circ \frac{\partial Q_{imt}}{\partial r_{imt}}\right]^{-1}(1 - d_{imt}) \circ Q_{imt}. \tag{J6}$$

Prices are such that given the internalization matrix Υ_{mt} and marginal costs mc_{imt}, they constitute a Nash-equilibrium among all banks for borrower i in market m at time t.

For each candidate model m and its internalization matrix Υ^m, we obtain model-consistent marginal costs $mc_{imt}(\Upsilon^m)$ by inverting the equation and relying on prices, estimated default rates $\widehat{d}_{imt}$, and estimated demand parameters.

Appendix J.3 Testing Framework

We begin by rewriting the frameworks of (Backus et al., 2024; Duarte et al., 2024; Dearing et al., 2024) for our specific setting with price discrimination and default. Suppose that equilibrium play in some true model of firm conduct generates data for each borrower i from bank k at time t such that the first-order conditions are given by:

$$p_{ikt} = \widetilde{\Delta}_{ikt} + \widetilde{mc}_{ikt},$$

where p are observed prices, $\widetilde{\Delta}$ is the true markup, which depends on demand primitives and default risk, and $\widetilde{mc}$ are true marginal costs. Then, assuming any specific model m, one can calculate implied markups Δ^m_{ikt} from demand primitives and default risk and back-out implied marginal costs mc^m_{ikt} from the first-order condition of the bank.

For testing, we rely on instruments z_{ikt} (Berry and Haile, 2014) such that $E[\widetilde{mc}_{ikt} z_{ikt}] = 0$, meaning that these instruments are orthogonal to true underlying marginal costs. In particular, we rely on the exogeneity of the introduction of the tax and use indicator functions $z_{ikt} = 1$ if bank k is subject to the tax at time t, and 0 otherwise. The evidence in the reduced-form section of our paper indicates that these instruments are indeed quasi-exogenous.

Consider two alternative models m^1 and m^2. The framework above allows for non-nested testing (Backus et al., 2024; Duarte et al., 2024), where the null hypothesis means that both models fit the data equally well, and the alternative hypothesis that either (1) m^1 or (2) m^2 fits the data better. In particular, the model such that $E[mc^m_{ikt} z_{ikt}] = 0$ fits better the data.

To implement this in practice, we follow *Algorithm 1* in Backus et al. (2024). 1) For any two models $m = m1$ and $m = m2$, we obtain $\widehat{mc}^{m1}_{ikt}$ and $\widehat{mc}^{m1}_{ikt}$, and estimate the following regression:

$$\widehat{mc}^{m}_{ikt} = h_m(X_{ijt}) + \omega^m_{ijt}, \tag{J7}$$

in order to estimate $\widehat{h}_m$ and $\widehat{\omega}^m$, and define $\widehat{\Delta}^{1,2} = \widehat{mc}^{m2}_{ikt} - \widehat{mc}^{m1}_{ikt}$.
We estimate the first-stage relationship as follows:

$$\widehat{\Delta}^{1,2}_{ikt} = g(z_{ikt}) + \eta_{ijt}, \tag{J8}$$

and obtain the corresponding F-statistic to assess instrument validity, and then compute the scalar moment:

$$\widetilde{Q}(\Delta^m) = \left(n^{-1} \sum_{ikt} \widehat{\omega}_{ikt} \widehat{g}(z_{ikt})\right)^2. \tag{J9}$$

We repeat over 500 bootstraps to obtain an estimate of $\widehat{\sigma}$ of the standard error of $\widetilde{Q}(\Delta^1) - \widetilde{Q}(\Delta^2)$, and compute the test statistic:

$$T = \frac{\sqrt{n}(\widetilde{Q}(\Delta^1) - \widetilde{Q}(\Delta^2))}{\widehat{\sigma}}. \tag{J10}$$

A positive and significant test statistic implies model 2 fits the data better than model 1.

Appendix J.4 Testing Results

We perform various non-nested tests. In particular, we test the following models i) the benchmark Bertrand-Nash (i.e., $\upsilon_{kj} = 0\ \forall k, j$), ii) Banking Association Cartel ($\upsilon_{kj} = \kappa\ \forall k \& j \in \{BA\}$), iii) Top 4 Banks in Banking Association Cartel ($\upsilon_{kj} = \kappa\ \forall k \& j \in \{BA \& Top4\}$), iv) All Banks ($\upsilon_{kj} = \kappa\ \forall k \& j$). Model i) is the benchmark that a naive policymaker would follow, ii) is a natural candidate given the heterogeneity in pass-through by banking association membership, iii) restricts ii) to only its top 4 banks, and iv) extends the cartel to a market-wide cartel, in line with our conduct parameter approach.

First, in Table 11, we test Bertrand-Nash against the various cartels. A positive T-test value implies that the cartel models are preferred to Bertrand-Nash, and a high F-test suggests the instruments are relevant, falsifying Bertrand-Nash against the alternative cartels. The instruments are relevant except for low internalization parameters κ in the Full Cartel Model (iv). The T-test shows that **all** cartel models fit the data better than Bertrand-Nash. This result is consistent with our conduct parameter approach, which shows that higher levels of conduct parameters better match the data than Bertrand-Nash.

Second, in Table J1, we test which internalization parameter κ better fits the data *within* a specific cartel model. The instruments are relevant for both Banking Association Cartel (ii) and Top 4 Cartel (iii). In the Banking Association Cartel, we find that the data fits equally well across any κ compared to a full internalization constant $\kappa = 1$. Instead, we reject the null for the Top 4 cartel in favor of a full internalization constant $\kappa = 1$. For the Full cartel model (iv), the instruments are not powerful enough to test high internalization constants, though the evidence is weakly in favor of a full internalization constant $\kappa = 1$.

Third, in Table J2, we test across cartel models, keeping the internalization parameter κ across models constant. The tests show that between a Top 4 cartel and the Banking Association cartel with intermediate levels $\kappa < 1$, they both fit equally well. However, for a full internalization $\kappa = 1$, the Banking Association is rejected in favor of the Top 4 cartel. Instead, when comparing the Full cartel vs the Banking Association cartel, the tests favor the Banking Association cartel at $\kappa = 1$ but do not reject any model for lower parameters. Lastly, the instruments for tests between the Full cartel and the Top 4 cartel are not powered.

Overall, we reject the standard benchmark Bertrand-Nash. Moreover, the tests offer support for strong cartels with internalization parameters $\kappa = 1$. Although the purpose of this paper is not to pinpoint the exact composition of a banking cartel, the evidence favors a Top 4 banking association cartel. Yet, a full banking cartel is also consistent with the data. Given these results, which are consistent with our main conduct parameter approach, we continue with the counterfactual analysis through the conduct approach due to its simplicity for calculating tax incidence and tax deadweight loss.

TABLE J1: WITHIN CARTEL MODEL TESTING USING INTERNALIZATION PARAMETERS

This table presents the results of tests of the internalization constants for a given cartel against a full internalization parameter in the same cartel, in the spirit of (Miller and Weinberg, 2017). Specifically, the internalization constant is tested for the Banking Association (Panel A); Top 4 banks in the Banking Association (Panel B); and a Full cartel of all banks (Panel C). Column 1 presents the weights for the internalization parameter for the null model ($\kappa = 0$ for Bertrand-Nash) and Column 2 presents the weight for the alternative model. Column 3 presents the T-value from testing the alternative versus the null, while Column 4 presents the F-statistic from the first stage, described by Equation J8).

Panel A. κ- versus Partial Banking Association Cartel			
Null Model	**Alternative Model**	**T-test**	**F-stat First Stage**
(1)	(2)	(3)	(4)
0.2	1.0	-.5	41.7
0.4	1.0	-.6	36.9
0.8	1.0	-.6	22.1
Panel B. κ- versus Partial Top 4 Cartel			
Null Model	**Alternative Model**	**T-test**	**F-stat First Stage**
(1)	(2)	(3)	(4)
0.2	1.0	2.7	98.8
0.4	1.0	2.2	86.3
0.8	1.0	3.1	46.7
Panel C. κ- versus Full Cartel			
Null Model	**Alternative Model**	**T-test**	**F-stat First Stage**
(1)	(2)	(3)	(4)
0.2	1.0	1.9	9.8
0.4	1.0	1.8	8.7
0.8	1.0	0.6	2.9

TABLE J2: ACROSS κ-CARTEL MODEL TESTING USING INTERNALIZATION PARAMETERS

This table presents the results of tests across cartel models, within a given internalization constant in the spirit of (Miller and Weinberg, 2017). Specifically, a partial cartel of Top 4 banks in the Banking Association is tested versus an alternative model defined by all banks in the Banking Association (Panel A); a Full cartel of all banks is tested versus an alternative model defined by all banks in the Banking Association (Panel B); and a Full cartel of all banks is tested versus a partial cartel of Top 4 banks in the Banking Association (Panel C). Column 1 presents the weights for the internalization parameter for the null model and Column 2 presents the weight for the alternative model. Column 3 presents the T-value from testing the alternative versus the null, while Column 4 presents the F-statistic from the first stage, described by Equation J8).

Panel A. κ-Partial Top 4 Cartel versus κ-Partial Banking Association Cartel

Null Model	Alternative Model	T-test	F-stat First Stage
(1)	(2)	(3)	(4)
0.2	0.2	0.4	41.5
0.4	0.4	0.3	53.9
0.8	0.8	1.2	63.8
1.0	1.0	-10.3	54.6

Panel B. κ-Full Cartel versus κ-Partial Banking Association Cartel

Null Model	Alternative Model	T-test	F-stat First Stage
(1)	(2)	(3)	(4)
0.2	0.2	-0.8	21.7
0.4	0.4	-0.4	29.5
0.8	0.8	0.3	40.1
1.0	1.0	9.2	26.5

Panel C. κ-Full Cartel versus κ-Partial Top 4 Cartel

Null Model	Alternative Model	T-test	F-stat First Stage
(1)	(2)	(3)	(4)
0.2	0.2	-2.2	2.1
0.4	0.4	-2.5	3.0
0.8	0.8	-6.5	8.1
1.0	1.0	-4.1	7.0