For Online Publication

Appendix A 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 A.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 A.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

$$\Pi_{ikmt} = \overline{\Pi}_{ikmt}(X_{it}, r_{ikmt}, X_{ikmt}, N_{kmt}, \psi_i, \xi_{kmt}; \beta) + \varepsilon_{ikmt}, \tag{A1}$$

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:

$$\Pi_{i0} = \varepsilon_{i0mt}, \tag{A2}$$

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

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

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:

$$s_{ikmt}(\psi_i) = Prob(\Pi_{ikmt} \geq \Pi_{ik'mt}, \forall k' \in M). \tag{A3}$$

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

$$s_{ikmt} = \int s_{ikmt}(\psi_i) dF(\psi_i), \tag{A4}$$

for ψ_i, which has a distribution F.

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

$$L_{ikmt} = -\frac{\partial \Pi_{ikmt}}{\partial r_{ikmt}} = L_{ikmt}(X_{it}, r_{ikmt}, X_{ikmt}, \psi_i, \xi_{kmt}; \beta), \tag{A5}$$

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 A4 and A5, 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 A.3 Credit Supply

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

$$\begin{aligned} \max_{r_{ikmt}} B_{ikmt} &= (1 - d_{ikmt}) r_{ikmt} Q_{ikmt}(r) - mc_{ikmt} Q_{ikmt}(r) \\ \text{s.t. } \upsilon_m &= \frac{\partial r_{ikmt}}{\partial r_{ijmt}} \text{ for } j \neq k, \end{aligned} \tag{A6}$$

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., 2023).[4]

[2] Most borrowers in our setting have only one lender at a given point in time (see Table 3).

[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

Namely, $\upsilon_m = 0$ corresponds to pure Bertrand-Nash competitive conduct while $\upsilon_m = 1$ corresponds to complete joint-maximization. The parameter υ_m can also take intermediate degrees of competition, including Cournot/quantity competition. Intuitively, the parameter captures the degree of correlation in price co-movements in equilibrium.

The first-order conditions for each r_{ikmt} in Equation A6 are then given by:

$$(1-d_{ikmt})Q_{ikmt} + ((1-d_{ikmt})r_{ikmt} - mc_{ikmt})\Big(\frac{\partial Q_{ikmt}}{\partial r_{ikmt}} + \upsilon_m \sum_{j\neq k} \frac{\partial Q_{ikmt}}{\partial r_{ijmt}}\Big) = 0. \tag{A7}$$

Rearranging Equation A7 yields:

$$r_{ikmt} = \frac{mc_{ikmt}}{1-d_{ikmt}} - \frac{Q_{ikmt}}{\underbrace{\frac{\partial Q_{ikmt}}{\partial r_{ikmt}}}_{\text{Bertrand-Nash}} + \underbrace{\upsilon_m \sum_{j\neq k} \frac{\partial Q_{ikmt}}{\partial r_{ijmt}}}_{\text{Alternative Conduct}}}, \tag{A8}$$

which we write using price elasticities:

$$r_{ikmt} = \frac{mc_{ikmt}}{1-d_{ikmt}} - \frac{1}{\frac{\epsilon_{kk}}{r_{ikmt}} + \upsilon_m \sum_{j\neq k} \frac{\epsilon_{kj}}{r_{ijmt}}}. \tag{A9}$$

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 (monopoly), 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 simplicitly 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:

$$\frac{r_{kmt} - mc_{kmt}}{r_{kmt}} = \frac{1}{\epsilon_D^m + (1-\upsilon_m)\sum_{j\neq k} \frac{\partial Q_{kmt}}{\partial r_{jmt}} \frac{r_{jmt}}{Q_{kmt}}}. \tag{A10}$$

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

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.

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

$$\frac{r_{kmt} - mc_{kmt}}{r_{kmt}} = \frac{1}{\epsilon_{kk}(1 - \upsilon_m A_{kmt})}. \tag{A11}$$

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 A.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 A9, we obtain:

$$mc_{ikmt} = r_{ikmt}(1 - d_{ikmt}) + \frac{1 - d_{ikmt}}{\frac{\epsilon_{kk}}{r_{ikmt}} + \upsilon_m \sum_{j \neq k} \frac{\epsilon_{kj}}{r_{ijmt}}}. \tag{A12}$$

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

Traditional approaches in the literature (e.g., Bresnahan, 1982; Berry and Haile, 2014; Backus et al., 2021) 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 monopoly 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

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

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 A7 in terms of semi-elasticities:

$$1 + (r_{ikmt} - \frac{mc_{ikmt}}{1 - d_{ikmt}})\Big(\widetilde{\varepsilon}_{kk} + \upsilon_m \sum_{j \neq k} \widetilde{\varepsilon}_{kj}\Big) = 0, \tag{A13}$$

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

$$\begin{aligned} \rho_{ikmt}(\upsilon_m) \equiv & \frac{\delta r_{ikmt}}{\delta mc_{ikmt}} \\ = & \frac{(\widetilde{\varepsilon}_{kk} + \upsilon_m \sum_{j \neq k} \widetilde{\varepsilon}_{kj})/(1 - d_{ikmt})}{(\widetilde{\varepsilon}_{kk} + \upsilon_m \sum_{j \neq k} \widetilde{\varepsilon}_{kj}) + (r_{ikmt} - mc_{ikmt}/(1 - d_{ikmt}))\Big(\frac{\partial \widetilde{\varepsilon}_{kk}}{\partial r_{ikmt}} + \upsilon_m \sum_{j \neq k} \frac{\partial \widetilde{\varepsilon}_{kj}}{\partial r_{ikmt}}\Big)} \end{aligned} \tag{A14}$$

Therefore, Equations A12 and A14 create a system of two equations and two unknowns (mc_{ikmt}, υ_m), which allows identification of the supply parameters.

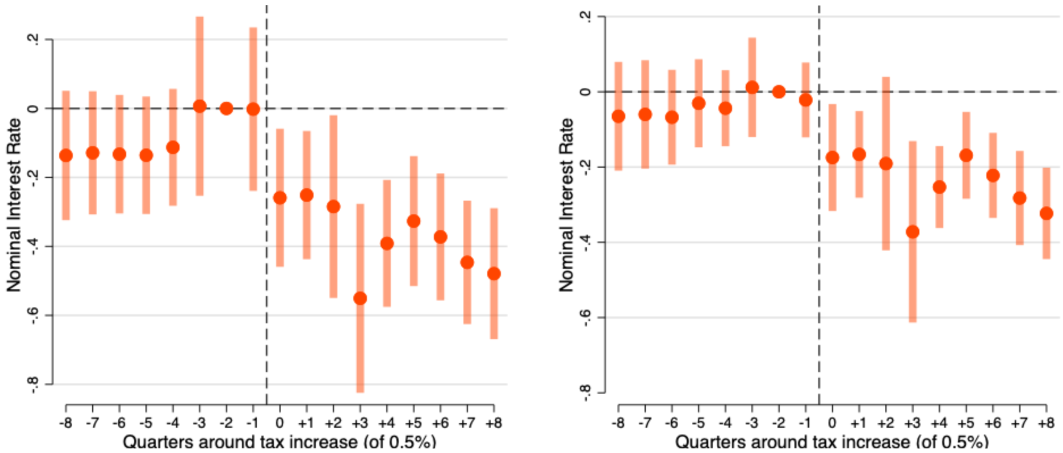
As noted above, we do not have empirical pass-through estimates at the borrower-level. Hence, we create market-level moments. Namely, if we measure pass-throughs at the market level and statically (i.e., just before and after the tax is enacted), the identification argument for our general bank competition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

$$\rho_m(\upsilon_m) \equiv E_{i,k,t}[\rho_{ikmt}(\upsilon_m)]. \tag{A15}$$

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

[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.

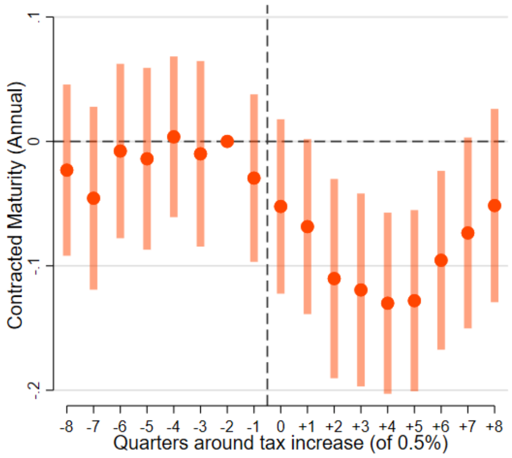
Appendix B Robustness of pass-through estimates



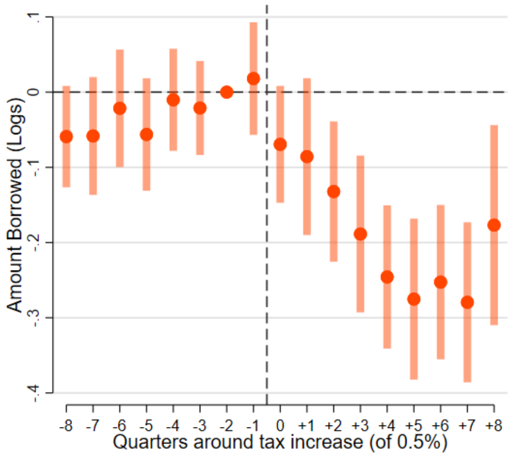
(a) Regular loans; bank & firm FE (b) Regular loans, bank-firm pair FE

FIGURE B1: DYNAMIC ANALYSIS OF THE INTRODUCTION OF THE SOLCA TAX ON PRE-TAX NOMINAL INTEREST RATES OF NEW COMMERCIAL DEBT LENT BY PRIVATE BANKS

The figure replicates Figure 2 in the main text over an estimation window from eight quarters before to eight quarters after the introduction of the SOLCA tax. 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) Regular loans, maturity; bank & firm FE



(b) Regular loans, amount, bank & firm FE

FIGURE B2: DYNAMIC ANALYSIS OF THE INTRODUCTION OF THE SOLCA TAX ON MATURITY AND AMOUNT OF NEW COMMERCIAL DEBT LENT BY PRIVATE BANKS

The figure replicates Figure 4 in the main text over an estimation window from eight quarters before to eight quarters after 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.

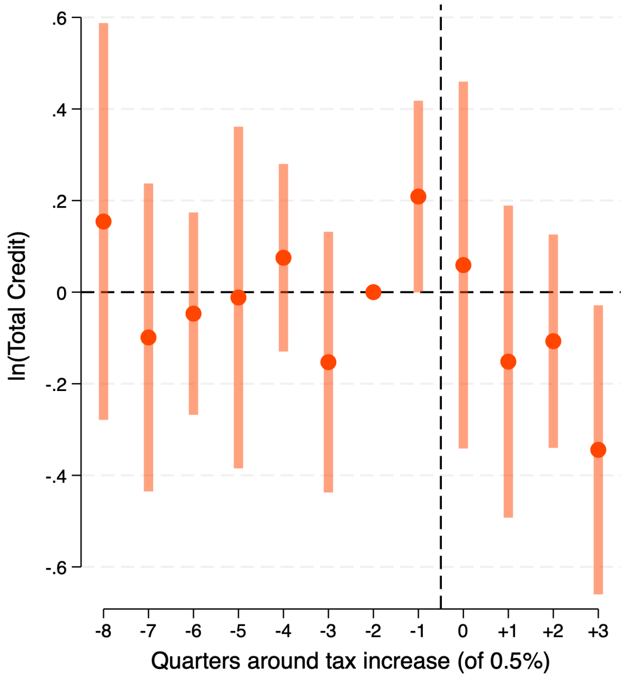


FIGURE B3: DYNAMIC ANALYSIS OF THE INTRODUCTION OF THE SOLCA TAX ON TOTAL COMMERCIAL CREDIT LENT BY PRIVATE BANKS

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.

Appendix C Loan default prediction

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

TABLE C1: COMMERCIAL LOAN DEFAULT MODEL

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

Appendix D Price Prediction

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

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

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

where X_{ikmt} are time-varying controls, including firm-level predictors from firm balance sheets (e.g., assets and 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 that is accessible to both us, the econometricians, and the lenders. We also control for loan-specific variables, such as an indicator for whether any bank classifies the firm as risky in the given time period. Finally, we control for the amount granted (L_{ikmt}) and maturity (M_{ikmt}).

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

Table D1 reports the price regressions. By comparing Model (1) with Model (2) and Model (3) with Model (4), we can see that the fit of the regression, as measured by the R-squared statistic, 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.

Second, in Appendix C, we test the extent to which the variation in prices we cannot explain predicts firms' subsequent default. Specifically, we regress loan default on the same set of controls and the residuals from the regressions reported in Table D1. Results are reported in

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

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

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

TABLE D1: PRICE PREDICTION REGRESSIONS

The table reports estimates of Equation D1, an OLS regression of the nominal interest rate on commercial bank loans (in percentage points) on a series of controls and dummies. An observation is at the loan level. See Table 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

Table D2. We fail to reject the null hypothesis that the residuals have no significant statistical correlation with default once we include firm fixed effects. Instead, the relationship is consistently positive even with firm fixed effects, but not economically large. Indeed, once we account for firm fixed effects, the relationship between prices and default is precisely estimated as zero.

TABLE D2: THE ABILITY OF PRICING RESIDUALS TO PREDICT DEFAULT

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

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

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. See Appendix E for further information and diagnostics on our matching model.

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

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

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

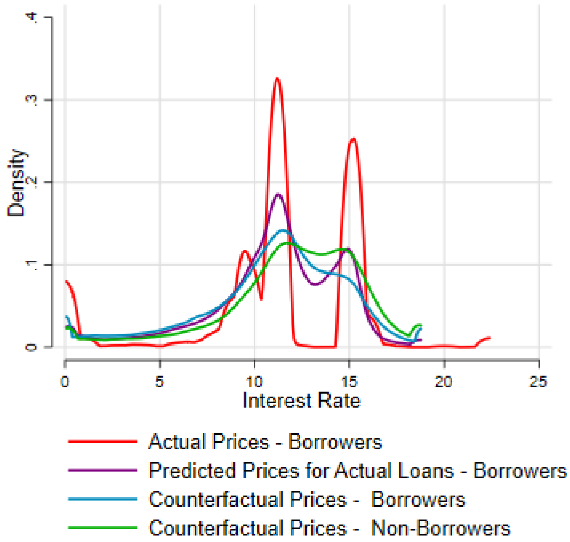


FIGURE D1: DISTRIBUTION OF PREDICTED PRICES

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

Appendix E Firm matching model

TABLE E1: PROPENSITY SCORE MATCHING - BIAS

	Unmatched	Mean			% Reduction	t-test	
VARIABLE	Matched	Treated	Control	% bias	in bias	t	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 F Demand Estimates by Region

TABLE F1: 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)

Continued on next page

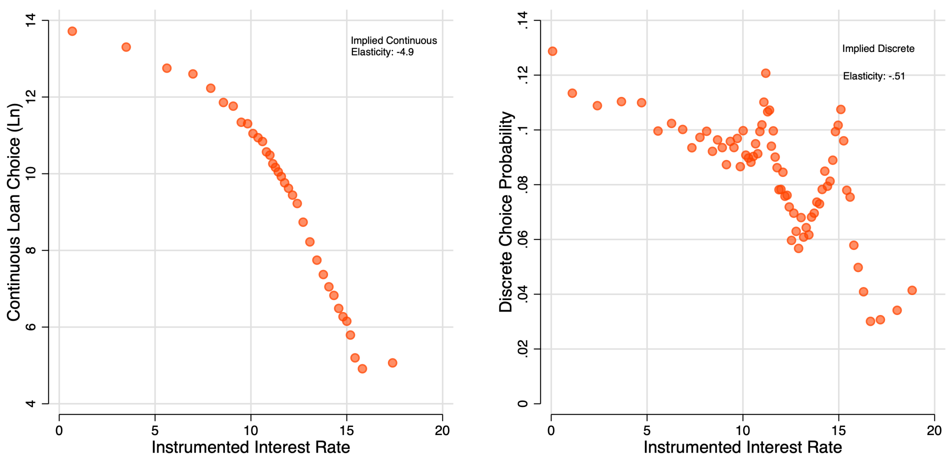
TABLE F1 – continued from previous page

Region	Variable	Mean	Standard Deviation
Guayas	Log(Branches)	0.732	(1.306)
Guayas	Age Firm	0.215***	(0.009)
Guayas	Age Relationship	0.036	(0.042)
Guayas	Assets	0.022	(0.124)
Guayas	Debt	−0.007	(0.070)
Guayas	Expenditures	0.062**	(0.028)
Guayas	Revenue	0.021	(0.031)
Guayas	Wages	0.016	(0.029)
Pichincha	Price	−0.386***	(0.101)
Pichincha	Sigma	1.156***	(0.057)
Pichincha	Scaling Factor	−0.014	(0.321)
Pichincha	Log(Branches)	0.735	(1.377)
Pichincha	Age Firm	0.205***	(0.007)
Pichincha	Age Relationship	0.157***	(0.030)
Pichincha	Assets	0.051	(0.107)
Pichincha	Debt	−0.010	(0.053)
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 F2: 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



(a) Continuous (b) Discrete

FIGURE F1: REDUCED-FORM ELASTICITIES

The figure reports the reduced-form relationship between prices and demand. Panel A presents continuous demand (measured as the log transformation of loan values), while Panel B presents the relationship between prices and discrete-choice demand (measured as the choice probability). Interest rates are instrumented using deliquency rates in microcredit, housing and consumption, as well as interest rates in consumption, micro-lending, commercial credit in other regions. Both figures control for bank, province, and year fixed-effects.

Appendix G Additional Simulations and Counterfactuals

Appendix G.1 Robustness to Modeling Lender-Borrower Relationships

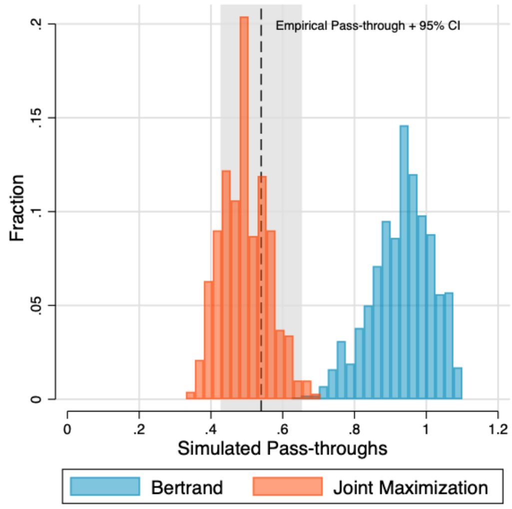


FIGURE G1: DISTRIBUTION OF SIMULATED PASS-THROUGHS FOR CHOSEN BANKS BY CONDUCT

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). Only simulated pass-throughs for loans from the banks the firms actually chose to borrow from are included, in contrast to Figure 6, which displays pass-throughs for chosen and potential loans. Bootstrap estimates come from 1,000 bootstrapped samples of borrower-level estimates of pass-through under each model. The dashed line shows the estimated 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.

Appendix G.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 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 G1 presents the results. The results are qualitatively and quantitatively similar to those presented in Panels A and B of Table 12 in the main text, which is estimated on the full sample.

In particular, the measured incidence presented in Panel A of Appendix Table G1 is statistically indistinguishable from the results in Panel A of Table 12. 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 G1: 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 12 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 27, 28, and 31. 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

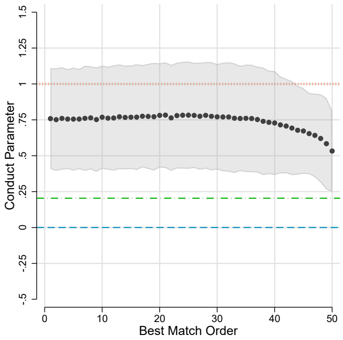
Third, Appendix Table G2 presents the corresponding values for the calibrated conduct parameter estimated over the full sample (Columns 1 and 2 and reproduced from Table 10) and over the pre-SOLCA tax sample (Columns 3 and 4). We again see that the conduct estimates from the two samples are statistically indistinguishable at conventional levels.

TABLE G2: COMPARING CONDUCT PER REGION FROM FULL SAMPLE AND PRE-SOLCA TAX SAMPLE

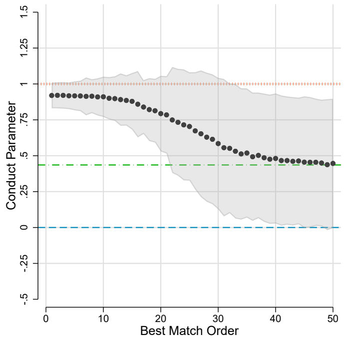
The table reports how well the pass-throughs in the calibrated model fit those in the observed data and how stable the fit is around the introduction of the SOLCA tax. Conduct parameters estimates are reported by lending region for the full sample (Columns (1) and (2), reproduced from Table 10) and on 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

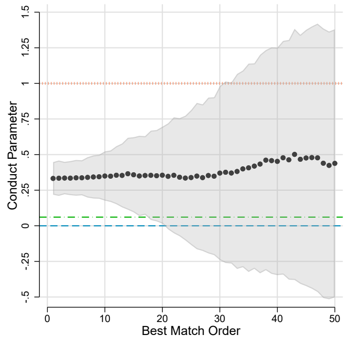
Fourth, we re-run our sanity checks for calibrated conduct estimated on the pre-SOLCA tax sample. Appendix Figure G2 reruns the same match order test as for Figure 5 estimated on the full dataset. Specifically, the figure reports for each region the lowest feasible conduct parameter estimates (y-axis) 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 5, the estimates reported in Appendix Figure G2 are stable, even approaching the worst (50^{th}) match order.



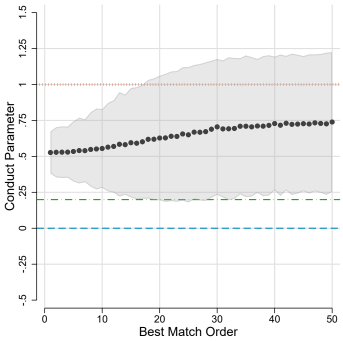
(a) Azuay



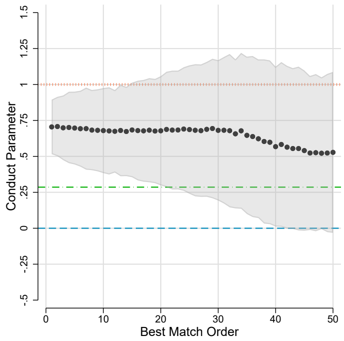
(b) Costa



(c) Guayas



(d) Pichincha



(e) Sierra & Oriente

FIGURE G2: 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 5, 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.

Finally, 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 G3) and in each region separately (Appendix Figure G4). 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 6.2. It is clear that banks are not Bertrand-Nash competitive, and results are most consistent with some degree of joint maximization.

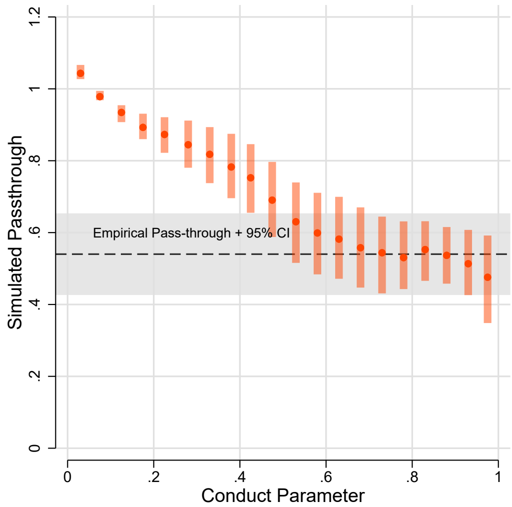
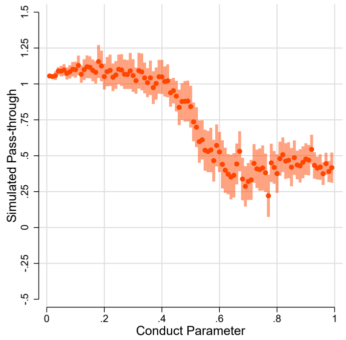
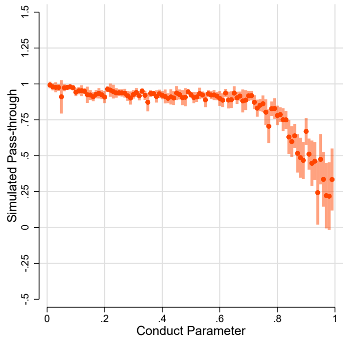


FIGURE G3: AVERAGE NATION-WIDE SIMULATED PASS-THROUGHS BY CONDUCT GRID; PRE-SOLCA TAX SUBSAMPLE

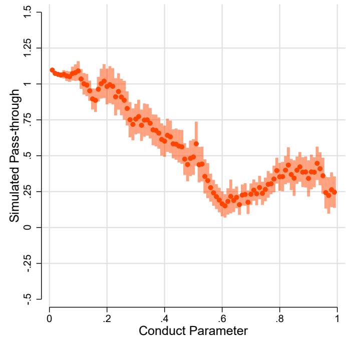
The figure reports the average nation-wide simulated Nash-equilibrium pass-throughs of a tax introduction of 0.5% over a grid of conducts between 0 and 1. Simulations to produce this figure were run on the sub-sample of data before the introduction of the SOLCA tax (compare to Figure 7 estimated on the 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.



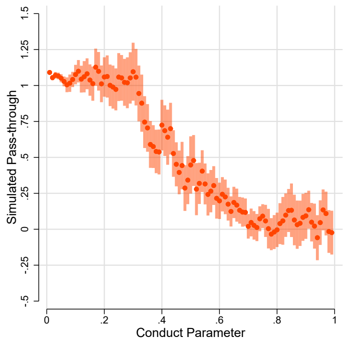
(a) Azuay



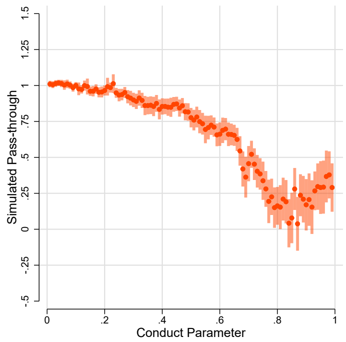
(b) Costa



(c) Guayas



(d) Pichincha



(e) Sierra & Oriente

FIGURE G4: 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 8 estimated on the full sample).

Appendix H 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 H.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 H1 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.

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), 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.

[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 Ferrari et al. (2018)). Interest rate caps place constraints on bank market power and affect the distribution of credit and this is reflected in our model.

TABLE H1: 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