How do banks compete? Lessons from an Ecuadorian loan tax

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Abstract

We study how bank competition affects commercial lending using a quantitative model. The model generalizes previous characterizations of bank competition by allowing banks a wide variety of competitive behavior — from setting prices as joint profit maximizers to pricing competitively under Bertrand-Nash competition where demand-side frictions determine markups (e.g., moral hazard). Recent literature suggests markups under Bertrand-Nash can incentivize banks to address frictions (e.g., monitor). Pricing power from joint maximization is unambiguously harmful. We use passthrough estimates from the surprise introduction of a loan transaction tax in Ecuador, and data on the universe of commercial credit, to identify the model. We reject pure Bertrand-Nash competition but fail to reject joint maximization. Counterfactual analyses show 26% of observed markups are due to joint profit maximization and that moving to Bertrand-Nash would reduce equilibrium prices by 17%, increase loan use by 21% (intensive margin), and increase overall credit demand by 13% (extensive margin).

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1 Introduction

How do banks compete in the market for commercial loans? How does this impact the efficiency and allocation of credit? Existing research suggests the answers are far from clear-cut. For example, we know bank pricing power can distort existing borrower relationships and investment efficiency (Sharpe, 1990; Rajan, 1992; Nelson, 2020).[1] At the same time, there is evidence that bank pricing power can also benefit borrowers if it results from banks specializing products to meet borrower demands, motivates bank monitoring, decrease adverse selection through screening, or reduces inter-temporal frictions that prevent efficient risk sharing (Petersen and Rajan, 1995; Mahoney and Weyl, 2017; Crawford et al., 2018; Yannelis and Zhang, 2021). Despite the diverging effects of market power, the literature assumes that bank pricing power originates from inelastic demand for credit, for example, from specializing products or demand frictions. However, it is also possible that bank pricing power stems from bank behavior on the supply side, factors such as banks internalizing their competitors' reaction to price changes, e.g., pricing power from softened competition.

Thus, there are significant open questions on how banks compete, the source of their pricing power, and the distributional effects of heterogeneity in that power. Addressing this gap is important for at least three reasons. First, assuming this channel is not at work may bias models, leading researchers to overstate the marginal costs of lending. In particular, since in lending, pair-specific frictions affect marginal costs, such as adverse selection and monitoring costs, this means that models trying to isolate the size and effect of these frictions will tend to overestimate their effect on prices. Second, it is not clear that the effect of bank pricing power is ambiguous if it results from joint profit maximization. Third, the policy responses available to mitigate the ill effects of bank pricing power differ based on their source.[2]

Our main contribution is that instead of assuming the specific mode of competition, we follow a more general approach that nests several types of competition (market "conduct"):

[1]Most researchers define a competitive market outcome as one where price equals the marginal cost of the highest cost unit supplied to the market. Following this convention, if the market price of credit is above this marginal cost of lending, then we consider banks are exercising market power.

[2]For example, if markups are positive because of bank product differentiation, but banks are competitive, it would be best to reduce barriers to entry or perhaps expand the offerings of state-owned banks. But if markups are positive primarily because banks collude, traditional antitrust regulation becomes an additional policy tool.

Bertrand-Nash (the literature standard), Cournot, joint maximization, etc.[3] We do this by exploiting tax passthroughs as additional identifying moments. These allow us to overcome the main empirical difficulty in the literature: separating the conduct parameter characterizing bank competition from marginal costs while at the same time accounting for bank differentiation of loan products to meet heterogeneous borrower preferences. Thus, we can decompose loan markups into demand-side preferences and supply-side conduct. In this way, we generalize the characterization of lender pricing power in the existing literature on imperfect competition in lending markets.[4] These models commonly assume that banks compete in Bertrand-Nash, so all pricing power comes from borrower preferences and frictions preventing borrower adjustment. Yet we find that 26% of loan markups derives from inefficiently low competition among banks that offer substitute products. Moreover, given a substantial literature documenting passthroughs of monetary policy to interest rates (Scharfstein and Sunderam, 2016; Di Maggio et al., 2017; Drechsler et al., 2017; Benetton and Fantino, 2021; Wang et al., 2022), our methodology is readily applicable to other countries and settings.

We study the commercial lending market in Ecuador, using administrative data on all commercial loans granted from 2010 to 2017. This data and setting provide several advantages. First, we observe the entire commercial loan universe in Ecuador. Second, the surprise introduction of a loan transaction tax in 2014, known as the "SOLCA Tax," allows us to estimate tax passthroughs to final interest rates on commercial loans.[5] This tax was not anticipated, and the Ecuadorian legislature designed it to fill funding gaps in public cancer treatment, indicating its introduction is plausibly exogenous to the ex-ante bank-firm match decisions and contract characteristics. The tax thus acts as an exogenous shock to the marginal cost of lending, which is likely uncorrelated with shocks to credit demand. By combining a structural model of credit demand and supply and reduced-form passthrough estimates, we can identify whether and how bank joint maximization affects the distribution and efficiency of loans.

Specifically, we construct a rich structural model of the Ecuadorian commercial lending

[3]Following terminology from the Industrial Organization (IO) literature, we shall refer to this as the "conduct" parameter from this point.

[4]In particular, our model is closest to, and generalizes, Crawford et al. (2018) and Benetton (2021).

[5]SOLCA stands for *Sociedad de Lucha contra el Cáncer*. It is a public agency and hospital offering free cancer treatment.

market in which banks compete on interest rates for heterogeneous borrowers. We model the demand side as a discrete/continuous choice, in which heterogeneous borrowing firms discretely choose a bank and make a continuous choice on loan size based on their price sensitivities and other characteristics, like firm size. On the supply side, we model prices in a flexible model of asymmetric, imperfect competition, which can cover a wide variety of conduct (from joint maximization to Nash-Bertrand pricing). The model differentiates banks on the number of physical branches they have in a market, their firm-specific borrower-lender relationship length, and their differing borrower-specific marginal lending costs. For example, sources of heterogeneity in marginal costs of lending include heterogeneity in screening and monitoring costs and specialization in lending to firms in specific commercial sectors. Besides differentiation, interest rates depend on heterogeneous risks of default as well as aggregate market conduct. Given all of these sources of differentiation, our model allows for full price discrimination across borrowers. Using the model, we demonstrate how passthrough estimates serve as an additional identifying moment, allowing us to identify and estimate demand parameters, borrower-specific marginal costs, and conduct. With this, we can back out the division of surplus between firms and banks and show how market characteristics and bank conduct determine this division.[6]

Why has the existing literature assumed that the conduct parameter is zero? To estimate bank conduct, we need (1) the price elasticity of demand and (2) the bank's marginal cost of lending. However, marginal cost is not readily observable.[7] Thus, we need a model to estimate the borrower-specific marginal cost of lending. Another difficulty is that a model alone does not allow us to rule out that unobservable differences in marginal costs of lending, rather than firm conduct, explain any observed difference in lending interest rates. That is, marginal costs and conduct are not separately identified even with a rich dataset that observes prices and quantities. Moreover, we must distinguish the effect of bank conduct from the impact

[6]This exercise is in the spirit of Atkin and Donaldson (2015), who demonstrate how to use observable passthrough to determine the division of surplus between consumers and intermediaries stemming from international trade. Our contribution is also related to the literature that uses structural methods to study imperfect competition and frictions in lending markets (including Crawford et al. (2018) and Cox et al. (2020) in commercial lending).

[7]Berry et al. (2019) show that estimating conduct by regressing prices (a market outcome) on measures of market concentration (e.g., the Herfindahl–Hirschman index) is highly problematic.

of differences between markets with high margins due to inelastic demand for the market as a whole (Corts, 1999).

To deal with these difficulties, we apply insights from the seminal work by Bresnahan (1982) and Lau (1982), which identify conduct through shifters in demand that are uncorrelated with changes in marginal costs. However, we do not apply the usual methodology directly, which relies on cross-market variation in demographic characteristics as instruments for demand (e.g., Backus et al., 2021). In lending markets, demographic characteristics strongly correlate with marginal costs of lending. Instead, we connect this literature in industrial organization to the public finance literature that determines a tight relationship between conduct and tax/marginal cost passthroughs (Weyl and Fabinger, 2013). One could interpret these passthroughs as *known* changes in marginal costs that serve as the instruments for changes in demand without additional changes to borrower-specific marginal costs. An alternative intuition is that passthroughs serve as an additional moment condition. For a market with N borrower-bank pairs, together with banks' first-order condition —a function of marginal cost and conduct— we create a system of $N+1$ equations to exactly identify N pair-specific marginal costs and one market-level conduct parameter.

What aspect of bank competition are we capturing with the conduct parameter? The conduct parameter measures the competitive behavior of firms in a very general way. The bank's conduct has been micro-founded in the IO literature as capturing the firm's (here bank's) expectation about how its competitors will change industry output in response to the firm's price changes in equilibrium (an idea at least as old as Bowley (1924)). The conduct parameter then captures the degree of correlation in price co-movements. Specifically, if the conduct parameter is greater than zero, the bank considers the joint losses from competition when setting its own price. The bank internalizes the cannibalization effects of lowering its own prices, thus generating upward price pressure. Conduct equal to one corresponds to monopoly price-setting behavior from joint maximization of bank profits with its competitors. In this situation, rather than pricing according to their own residual demand elasticity (the traditional pricing strategy under Bertrand-Nash), all the banks set interest rates to maximize profits subject to aggregate demand. The larger the value of the conduct parameter in the intermediate region between zero and one, the higher the profit-maximizing price, and the more bank price-setting behavior is consistent with joint maximization.

Empirically, we document that borrowers and lenders, on average, split the tax cost, implying incomplete passthrough and variable markups. On average, the borrower pays approximately 30 to 50% of the loan tax, while the bank bears the remainder of the tax incidence by reducing the loan interest rate. This incomplete passthrough is indicative of imperfect competition. If the lender were pricing at the marginal cost of lending, they could not profitably adjust interest rates downwards in response to the new tax. Moreover, we document substantial heterogeneity in this passthrough that cannot be explained by risk of default and contract characteristics (e.g., loan size and term-to-maturity).[8] For instance, we find that passthroughs are more muted in more concentrated markets or markets with banks with a greater degree of multi-market contact, which has been shown in the literature to aid with tacit collusion (Ciliberto and Williams, 2014). These passthrough heterogeneity results are consistent with previous studies in high-income countries that demonstrate passthroughs vary by market concentration (Scharfstein and Sunderam, 2016; Drechsler et al., 2017; Benetton and Fantino, 2021). While suggestive, these reduced-form estimates do not illuminate the source of bank pricing power.

Our model enriches this insight by quantifying bank market power and revealing how banks compete. After estimating credit demand following standard tools in the literature (Train, 1986; Benetton, 2021), we use the estimated demand parameters and the reduced-form passthrough to test for conduct. We find that observed passthrough rates are highly inconsistent with Bertrand-Nash but consistent with joint maximization. We then use counterfactual experiments to decompose market power in terms of preferences (product differentiation, or Bertrand-Nash competition) and bank conduct and to gauge the losses from suppressed competition. In our preliminary results, we find that 26% of the markup is attributed to conduct and that traditional approaches would overestimate marginal costs by 50%. In the counterfactual move to Bertrand-Nash, interest rates decrease by 17% (from 11.25 to 9.43 percentage points). As a result, firm investment increases by 21% on the intensive margin. At the same time, 13% of firms in the

[8]Variation in borrowing costs that are unexplained by borrower risk is characteristic of a wide variety of settings (e.g., Banerjee and Duflo (2010) for evidence across the developing world, Gilchrist et al. (2013) in the USA, and Cavalcanti et al. (2021) in Brazil). Thus, while Ecuador offers a unique setting and unusually rich data to characterize bank competition, its banking sector is representative of many credit markets.

sample that were not financing investments through the banking sector would now be willing to borrow at lower interest rates.

2 Related Literature

We contribute to the literature that studies imperfect competition and frictions in lending markets, especially the growing literature using structural methods from empirical industrial organization and trade. Studies focusing on small business lending include Crawford et al. (2018), who examine the interaction of imperfect competition and adverse selection frictions, and Cox et al. (2020), who study how bank concentration impacts how banks and borrowers split the surplus from loan guarantees when interest rates are capped. Other applications to financial markets include deposits (Egan et al. (2017)), mortgages (Robles-Garcia (2021); Benetton (2021)), auto lending (Yannelis and Zhang (2021)); and consumer lending (Cuesta and Sepúlveda (2021)). Differently from existing models, we separately identify bank competition by estimating a flexible bank conduct parameter using passthrough from the introduction of the SOLCA loan transaction tax in Ecuador. This exercise is in the spirit of Atkin and Donaldson (2015), who demonstrate how to use observable passthrough to determine the division of surplus between consumers and intermediaries stemming from international trade, and of Bergquist and Dinerstein (2020), who use experimentally estimated passthroughs in agricultural markets to test for collusion of intermediaries.

We also contribute to an extensive literature studying the welfare and distributional effects of the passthrough of taxes (and regulatory costs equivalent to taxes) on prices in product markets and consumer surplus (Nakamura and Zerom (2010); Fabra and Reguant (2014); Ganapati et al. (2020)). However, the distributional effects of taxes in lending markets and how this depends on the market structure of the banking industry is less studied.[9] Yet market structure is crucial to understanding tax passthrough as the statutory incidence typically differs from the actual incidence (Weyl and Fabinger, 2013). This paper takes a public finance perspective to understand how bank concentration impacts commercial loan contracts and how financial tax

[9] In a recent paper Jiménez et al. (2020) show how the statutory incidence of mortgage taxes affects prices, without variation on the tax rate.

policy is affected by bank concentration.

Moreover, our setting and model are general enough to yield insights for any uniform increase in firm borrowing costs. Thus, we can speak to an extensive literature documenting passthroughs of monetary policy to interest rates (Scharfstein and Sunderam, 2016; Di Maggio et al., 2017; Drechsler et al., 2017; Benetton and Fantino, 2021; Wang et al., 2022). This literature has long struggled with identification because interest rate changes are highly endogenous to both credit supply and demand.[10] The introduction of a transaction tax, especially one passed at the last minute with minimal debate, is a much cleaner natural experiment but a rare occurrence in the developed markets where most of the studies of interest rate passthrough have been set. Our results suggest that in the presence of imperfect bank competition, the passthrough of the cost shock portion of the interest rate increase is incomplete and that heterogeneity in bank market power significantly impacts who bears the burden of the shock.

Finally, we contribute to the literature on the economic effects of credit misallocation, notably by Banerjee and Moll (2010) and Moll (2014). Our model allows counterfactual experiments to characterize how the distribution of credit changes when bank competition does.

3 Institutional Background and Data

3.1 Loan Transaction Tax

As in many developing countries, especially in Latin America, Ecuador has relied on bank levies to finance government expenditure (Kirilenko and Summers, 2003). Some of these bank levies targeted bank debits, such as those introduced in Ecuador's economic crisis of 1999. Since 1964 Ecuador has also used bank levies to raise funds specifically to fund cancer treatment (Sociedad de Lucha contra el Cáncer or SOLCA taxes), with taxes on financial operations that range from 0.25 to 1% of the value of the transaction or loan. In 2008, the Ecuadorian government eliminated all taxes on financial transactions, including the SOLCA taxes. As a result, the government funded cancer treatment and research under the regular budget.

[10] See Kleimeier and Sander (2017) for a discussion of the challenges of empirically pinning down the effect of competition on interest rate passthrough.

However, in September 2014, the Ecuadorian National Assembly approved the final version of a new finance law "Código Orgánico Monetario y Financiero," which standardized and consolidated the existing regulation of the banking, finance, and insurance sectors. This law contained a last-minute amendment that reintroduced the SOLCA tax to cover shortfalls in funding cancer treatment.[11] Both contemporary coverage and conversations with banks and businesses in Ecuador characterize the tax as a surprise to both borrowers and banks.[12]

The new tax became active at the end of October 2014. From that point, new loans granted by private banks in Ecuador must pay a tax on the entire value of the new credit.[13] The tax's exact value depends on the loan's maturity. Credit with maturities of one year or longer pay the entire tax of 0.5%, whereas taxes for all maturities less than one year are calculated proportionally.[14] The tax is levied on the borrower for each new loan (the statutory incidence) and is collected and remitted by the banks to the tax authority at loan grant.

3.2 Datasets

We constructed a comprehensive and detailed data set from administrative databases collected by the Superintendencia de Bancos (bank regulator) and the Superintendencia de Compañías (business bureau) of Ecuador. The data are quarterly and cover the period between January 2010 and December 2017.

3.2.1 Loan Dataset

The primary data are the universe of new and outstanding commercial bank loans made by all banks operating in Ecuador. There are 27 private commercial banks (25 Ecuadorian and two foreign) in our sample. In addition, six state-owned banks also lend commercial credit, primarily micro-loans to small businesses. The dataset covers all loans granted by either type

[11]Other notable changes of the law were that it defined the regulation of mobile money payments and strengthened anti-money laundering regulation.

[12]See, for example, contemporary coverage in the two major Ecuadorian newspapers: "Código revive impuesto de 0,5% para créditos para beneficiar a SOLCA," by the editorial staff, published the 29th of July 2014, in *El Universo*; and "El Código Monetario pasó con reformas de última hora," by Mónica Orozco, published the 25th of July 2014 in *El Comerico*.

[13]The tax was levied not only on commercial loans but all credit card, auto, and mortgage loans. Throughout our sample, 2010-2017, only new credit by private banks was subject to the SOLCA tax. Loans granted by public (state-owned) banks were not taxed.

[14]Let X be the maturity in months. Then, the tax on loans with maturities shorter than a year is $0.5\% \times X/12$.

of bank from 2010 to 2017.

This dataset is not a credit registry—since banks cannot use it to observe information on other banks' loans or borrowers—but it contains similar information. The Ecuadorian bank regulator, the Superintendencia de Bancos y Seguros, maintains the database from quarterly bank filings that report information on new loans and the performance of ongoing loans. The data include the loan amount, type, interest rate, term-to-maturity, and the internal bank risk rating at the grant date. We can also measure repayment performance from information on outstanding loans.

From this dataset, we focus on commercial credit not classified as microloans. We also consider only those loans lent to firms that are registered as corporations and are thus regulated by the Superintendencia de Compañías. This choice excludes loans to sole proprietorships. Finally, in our main analyses and when estimating our model, we excluded loans from state-owned banks. This specialization matches our firm data (below) and allows us to specialize our model of commercial credit. For example, market entry and competition within the microlending sector differ considerably from commercial lending by private banks.

3.2.2 Firm Dataset

We combine the bank loan data with annual firm-level data on every firm regulated by the Ecuadorian business bureau (the Superintendencia de Compañías). This dataset covers firms' balance sheets, income statements, shareholding structure, and wages. Specifically, the data include yearly information on firm revenue, assets, inputs, wage bills, total debt, the location of headquarters, its primary industrial sector, firm age, and a dynamic list of all shareholders and top management. We have directly linked the databases through a unique firm identifier.

3.3 Descriptive Statistics

Table 1 reports credit statistics at the bank-province-year level. The average (median) bank offers \$59M (\$1.4M) of commercial credit to corporations in a given year. We can see that, in common with most low- and middle-income, bank-dependent economies, a few banks dominate the commercial loan market. While some banks have several clients—the average bank lends to 83 corporations in a year—there are also banks with very few commercial clients, as the median bank has 11 firm clients a year. In total, banks offer 517 (24) loans a year.

[Place Table 1 here.]

Table 2 presents descriptive statistics on market access and lending by market concentration. Highly concentrated markets have fewer branches, fewer competing banks (and fewer competing branches). Similarly, branches of banks in highly-concentrated markets are smaller, have fewer clients, offer fewer loans in total and per client, offer (slightly) shorter maturities, and charge higher interest rates.

[Place Table 2 here.]

Next, Table 3 reports summary statistics on the full merged commercial loan dataset covering 2010 to 2017. The top panel summarises the data at the firm-year level. There are 457,623 firm-year observations for 31,903 unique corporations. Of these, 97,796 firm-year observations are of active firm-year borrowers, while 359,827 observations are of for non-borrowing firm-years. The average borrowing firm is about twelve years out from incorporation and has, on average, $2M in assets, though the distribution is very skewed—the median firm has only $400,000 in total assets. Total sales are similarly skewed, with average (median) sales of $2.6M ($620,000). The average (median) borrowing firm is highly leveraged, with a total debt-to-assets ratio of 0.66 (0.71). Instead, non-borrowing firms are younger, around ten years since incorporation. They are also smaller, with mean (median) assets of $460,000 ($50,000) and mean (median) sales of $430,000 ($30,000). Non-borrowing firms are also less leveraged, with a total debt-to-assets ratio of 0.54 (0.58).

[Place Table 3 here.]

In the data, 29% of firms access commercial credit (although only 14% of firms are actively borrowing in a given year). The bottom panel describes the data at the loan level for the universe of commercial (non-micro) loans to corporations granted between 2010 and 2017. The average (median) firm has 1.38 (1) bank relationships within a given borrowing year. The average (median) borrower-lender relationship has lasted 2.31 (2) years. Most clients repeatedly borrow from the same bank, with the average client borrowing 9 (2) times in a year. On average, each loan is $100,000 ($10,000) and has a six (three) month term-to-maturity. The average (median) loan carries a 9.20% (8.95%) annualized nominal interest rate. The bank only writes down the value of about two percent of the loans in our sample. However, actual default in our sample is rare; it occurs on average less than 1% of the time (in the total sample, including sole-proprietorships and micro-loans, default happens 3% of the time). The overall picture is of a small number of safe firms that can access formal bank debt at relatively high prices and low maturities.

Finally, Table 4 reports correlations between the average equilibrium interest rate and market characteristics at the aggregate, bank-province-year level. Model 1 uses year fixed effects (FE), Model 2 includes province and year FE, and Model 3 estimates with year and bank FE.

[Place Table 4 here.]

The general relationships between market access and prices are consistent with patterns documented in the existing literature. Across specifications, we see that average interest rates tend to decrease in loan size and maturity. Banks offering greater access within a given market (as measured by the number of branches) tend to offer lower prices — perhaps reflecting that banks expand in markets in which they have an efficiency advantage. We find a weak and insignificant relationship between prices and the number competing branches available, in the cross-section, within a province, and across-markets within a given bank. This suggests that by itself, access to competing banks through larger branches do not impact the average pricing strategy of the bank. Moreover, we find a positive correlation between the concentration of bank markets, as measured by the Herfindahl-Hirschman Index (HHI), and the average interest rate. Even within a given bank, more concentrated markets have higher prices. Lastly, interest rates tend to be lower when borrowers interact often with the bank (as measured by the number of loans per borrower). Still, larger banks (as measured by the number of borrowers) tend to charge higher interest rates, which may reflect borrower preference heterogeneity that leads them to pick certain banks, despite higher prices.

The main takeaways are that (1) Ecuador is highly representative of lower- and middle-income economies, especially in that (2) a small number of safe, formal firms access most formal credit at high interest rates (3) in a market where long-term relationship lending is the norm and (4) where banks wield pricing power that affects both the allocation of credit and credit terms. We incorporate these insights into our model, presented next, and our empirical specifications.

4 A Model of Commercial Lending

We have presented clear evidence that banks have market power in Ecuador and that it affects the allocation of credit and credit terms. In this section, we describe our quantitative model of commercial lending that will allow us to pin down the bank conduct parameter and directly characterize bank competition and its effects.

4.1 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 parties are risk-neutral. To isolate the effect of bank joint profit maximization (conduct) on pricing and passthroughs, 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.

4.2 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

$$\Pi_{ikmt} = \overline{\Pi}_{ikmt}(X_{it}, r_{ikmt}, X_{ikmt}, N_{kmt}, \psi_i, \xi_{kmt}; \beta) + \varepsilon_{ikmt}, \tag{1}$$

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 interest rate.[15] 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 managements' 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:

$$\Pi_{i0} = \varepsilon_{i0mt}, \tag{2}$$

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.[16] 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:

$$s_{ikmt}(\psi_i) = Prob(\Pi_{ikmt} \geq \Pi_{ik'mt}, \forall k' \in M). \tag{3}$$

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

$$s_{ikmt} = \int s_{ikmt}(\psi_i) dF(\psi_i), \tag{4}$$

for ψ_i having a distribution F.

Given the selected bank, the firm chooses optimal quantity L_{ikmt}, which we obtain using

[15]In contrast to Benetton (2021), we let the price vary by borrower-bank.

[16]The vast majority of borrowers have only one lender at a given point in time (see Table 3).

Hotelling's lemma:[17]

$$L_{ikmt} = -\frac{\partial \Pi_{ikmt}}{\partial r_{ikmt}} = L_{ikmt}(X_{it}, r_{ikmt}, X_{ikmt}, \psi_i, \xi_{kmt}; \beta), \tag{5}$$

where the function excludes N_{kmt}, the number of branches that bank k has in the local area market of firm i.

The demand model is defined jointly by Equations 4 and 5, which describe the discrete bank choice and the continuous loan demand, respectively. The model only requires one exclusion restriction: branch density affects the choice of the bank but not the continuous quantity choice.

Let the total expected demand given rates of all banks in market m be $Q_{ik}(r) = s_{ik}(r)L_{ik}(r)$. 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.

On the supply side, we allow for different forms of competition by introducing the market conduct parameter $\upsilon_m = \frac{\partial r_{ikmt}}{\partial r_{ijmt}}$ $(j \neq k)$. υ_m measures the degree of competition (joint profit maximization) in the market (Weyl and Fabinger, 2013; Kroft et al., 2020).[18] Namely, $\upsilon_m = 0$ corresponds to Bertrand-Nash, $\upsilon_m = 1$ to joint-maximization, and other values measure intermediate degrees of competition. Intuitively, the parameter captures the degree of correlation in price co-movements. Below, we discuss additional interpretations of the parameter.

Assume each bank offers price r_{ikmt} to firm i to maximize bank profits B_{ikmt}, subject to

[17] 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 use instead 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.

[18] 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.

conduct:

$$\max_{r_{ikmt}} B_{ikmt} = (1 - d_{ikmt}) r_{ikmt} Q_{ikmt}(r) - mc_{ikmt} Q_{ikmt}(r) \tag{6}$$
$$\text{s.t. } \upsilon_m = \frac{\partial r_{ikmt}}{\partial r_{ijmt}} \text{ for } j \neq k,$$

where d_{ikmt} are banks' expectations of the firm's default probability at the time of loan grant. The related first-order conditions for each r_{ik} are then given by:

$$(1 - d_{ikmt})Q_{ikmt} + ((1 - d_{ikmt})r_{ikmt} - mc_{ikmt})\Big(\frac{\partial Q_{ikmt}}{\partial r_{ikmt}} + \upsilon_m \sum_{j \neq k} \frac{\partial Q_{ikmt}}{\partial r_{ijmt}}\Big) = 0. \tag{7}$$

Rearranging Equation 7 yields:

$$r_{ikmt} = \frac{mc_{ikmt}}{1 - d_{ikmt}} - \frac{Q_{ikmt}}{\underbrace{\frac{\partial Q_{ikmt}}{\partial r_{ikmt}}}_{\text{Bertrand-Nash}} + \underbrace{\upsilon_m \sum_{j \neq k} \frac{\partial Q_{ikmt}}{\partial r_{ijmt}}}_{\text{Alternative Conduct}}}, \tag{8}$$

which we write using price elasticities:

$$r_{ikmt} = \frac{mc_{ikmt}}{1 - d_{ikmt}} - \frac{1}{\frac{\epsilon_{kk}}{r_{ikmt}} + \upsilon_m \sum_{j \neq k} \frac{\epsilon_{kj}}{r_{ijmt}}}. \tag{9}$$

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 closer is behavior consistent with 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, 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 prices and marginal costs are symmetric within a given bank, and there is no default. Then the following markup formula describes the pricing equation:

$$\frac{r_{kmt} - mc_{kmt}}{r_{kmt}} = \frac{1}{\epsilon_D^m + (1 - \upsilon_m) \sum_{j \neq k} \frac{\partial Q_{kmt}}{\partial r_{jmt}} \frac{r_{jmt}}{Q_{kmt}}}. \tag{10}$$

In other words, 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 $A_k \equiv -[\sum_j \frac{\partial Q_{kmt}}{\partial r_{jmt}}]/[\frac{\partial Q_{kmt}}{\partial r_{kmt}}]$, and express the markup formula as

$$\frac{r_{kmt} - mc_{kmt}}{r_{kmt}} = \frac{1}{\epsilon_{kk}(1 - \upsilon_m A_{kmt})}. \tag{11}$$

We can interpret diversion ratios as the opportunity cost of raising prices. Then the markup equation indicates that in bank conduct other than Bertrand-Nash, banks internalize these opportunity costs. In particular, they internalize the cannibalization effects of lowering prices, thus generating upward price pressure.

As a last note, it is worth highlighting the generality of our marginal cost assumption. While we are forcing marginal costs to be *constant* within each specific borrower, we allow for a large degree of heterogeneity. First, we allow marginal cost to depend on the buyer's identity. For example, some buyers 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 also represent possible 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, thereby 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.

5 Identification of the conduct parameter

This section lays out the identification argument for our general bank competition model. We first clarify why we cannot separately identify the conduct and marginal cost parameters without tax passthrough. 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.[19] By inverting Equation 9, we obtain:

$$mc_{ikmt} = r_{ikmt}(1 - d_{ikmt}) + \frac{1 - d_{ikmt}}{\frac{\epsilon_{kk}}{r_{ikmt}} + \sum_{j \neq k} \frac{\epsilon_{kj}}{r_{ijmt}}}. \tag{12}$$

This equation indicates that, contrary to 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 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 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

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

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 passthrough of taxes and marginal costs to final prices are tightly linked to competition conduct. Thus, by relying on reduced-form passthrough estimates from the introduction of the SOLCA tax, we can create one additional identifying equation that allows us to separate marginal costs from conduct.[20] The reason we can recover conduct with information on passthrough estimates is that, given estimates of demand elasticities (or curvatures), the relationship between conduct and passthrough is monotonic. Therefore, for a given observation of passthrough, and holding demand elasticities constant, only one conduct value could rationalize any given passthrough.

To obtain an expression for passthrough as a function of conduct υ_m, express Equation 7 in terms of semi-elasticities:

$$1 + (r_{ikmt} - \frac{mc_{ikmt}}{1 - d_{ikmt}})\Big(\widetilde{\varepsilon}_{kk} + \upsilon_m \sum_{j \neq k} \widetilde{\varepsilon}_{kj}\Big) = 0, \tag{13}$$

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

$$\begin{aligned} \rho_{ikmt}(\upsilon_m) \equiv& \frac{\delta r_{ikmt}}{\delta mc_{ikmt}} \\ =& \frac{(\widetilde{\varepsilon}_{kk} + \upsilon_m \sum_{j\neq k} \widetilde{\varepsilon}_{kj})/(1 - d_{ikmt})}{(\widetilde{\varepsilon}_{kk} + \upsilon_m \sum_{j\neq k} \widetilde{\varepsilon}_{kj}) + (r_{ikmt} - mc_{ikmt}/(1 - d_{ikmt}))\Big(\frac{\partial \widetilde{\varepsilon}_{kk}}{\partial r_{ikmt}} + \upsilon_m \sum_{j \neq k} \frac{\partial \widetilde{\varepsilon}_{kj}}{\partial r_{ikmt}}\Big)} \end{aligned} \tag{14}$$

Therefore, Equations 12 and 14 create a system of two equations and two unknowns (mc_{ikmt}, υ_m), which allows identification of the supply parameters.

In practice, we only observe passthroughs aggregated at some more granular level, such as the level of the market in which banks compete (whether that be defined at the city, province, regional or national level).[21] For instance, if we measure passthroughs at the market level and statically (i.e., just before and after the tax is enacted), the corresponding identifying equation

[20] 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 passthrough to identify the modes of competition in agricultural and consumer goods markets.

[21] In future versions we shall vary the market definition continuously, we have already found all results robust to defining the market at the province or regional level.

is:

$$\rho_m(\upsilon_m) \equiv E_{i,k,t}[\rho_{ikmt}(\upsilon_m)]. \tag{15}$$

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

5.1 Estimating the tax passthrough

In this section, we measure the passthrough of the SOLCA bank transaction tax described in Section 3.1 on contracted nominal interest rates. First, we demonstrate that the SOLCA tax affected new commercial loan terms, that there was no contemporary effect on loans from public banks that were not subject to the SOLCA tax, and that loan terms were not changing before the introduction of the tax.

The first step of our analysis is to characterize how the surprise introduction of the SOLCA tax in October 2014 affects subsequent new commercial loan terms, including nominal interest rates, maturity, and loan size. We do so by levying event studies that transparently show the evolution of the outcome of interest over time, allowing us to validate that the SOLCA tax was unexpected by borrowers and banks.

Consider the following model for loan l contracted by firm f from bank b at time t.

$$r_{lfbt} = \sum_{k=-8}^{3} \delta_k 1\{t \in k\} + \beta_a ln(A_{lfbt}) + \beta_m ln(M_{lfbt}) + \alpha_f + \alpha_b + \eta DP_{lfbt} + \varepsilon_{lfbt}, \tag{16}$$

where r is the interest rate, A is the amount borrowed, M is the maturity in years, α_f is firm fixed-effects, α_b is bank fixed-effects, DP is predicted default probability, and ε are time-varying unobservables.[22] Periods k are quarters around 2014 quarter 4, the quarter of October 2014, when the SOLCA tax came into force.

We control for loan term-to-maturity, as maturity has a direct negative effect on contracted nominal interest rates (see Table 4). Moreover, as shown below, the policy negatively affected the contracted maturity. Its exclusion would lead to an upward bias in the estimated coefficients δ_k, i.e., a bias away from finding no effect. In addition, we include bank and firm fixed effects

[22]See Appendix B for more details on how we predict loan default and construct the regressor DP.

to control for unobserved, time-invariant heterogeneity in the determinants of interest rates. We also control for the loan amount. To prevent partial treatment from biasing the coefficients, we drop all new loans granted in October 2014, when the tax came into effect. For identification, we must normalize one of the coefficients δ_k to zero. We normalize two quarters ahead of the introduction (-2 in event time) to zero.

The coefficient of interest, δ_k, identifies the average percent change in nominal interest rates on new loans from introducing the tax. If δ_k is negative, then prices (and markups) are decreased in response to the introduction of the SOLCA tax. This would indicate an incomplete passthrough of the tax to borrowers because banks bore some of the burden by lowering loan interest rates.[23] If, instead, δ_k is positive, there is more-than-complete passthrough, as the firm bears both the full cost of the tax and pays a higher interest rate. Lastly, if δ_k is zero, there is complete passthrough of the tax to borrowers—the borrowers pay the entire tax, and the bank does not adjust the interest rate. If we assume a constant marginal cost, either incomplete or more-than-complete passthrough is evidence of imperfect competition in the commercial bank lending market.[24]

We start by analyzing the dynamic specifications to get a sense of the magnitude and timing of the effect of the introduction of the SOLCA tax on commercial loan contracts. This specification also allows us to visually test for pre-trends. The identification assumption is that interest rates would have evolved on average similarly in the absence of the tax as they were evolving before the tax was introduced. For this to hold, it is thus crucial that bank loan terms were not set in anticipation of the tax. Figure 1 presents the evolution around the introduction of the tax of the coefficients from modeling Equation 16, i.e., from testing the effect of the tax on nominal interest rates of loans granted by private commercial lenders.

[Place Figure 1 here.]

The two panels are for regular loans. These are primarily borrowed by corporations regu-

[23]Recall that the statutory incidence is the firm, i.e., the law mandates that the firm pays the tax, which is collected and remitted to the Tax Authority by the bank at loan grant. But the economic incidence, i.e., which party actually bears the tax burden, need not be the same as the statutory burden. In this case, to the extent the bank lowers interest rates, they are covering some of the cost of the tax.

[24]With additional assumptions, in particular constant demand curvature, incomplete passthrough implies that the demand curve is log-concave while over-complete passthrough can indicate that the demand curvature is log-convex.

lated by the Ecuadorian Business Bureau ("SA" firms, for Sociedad Anónima, or RUC firms, for the name of their unique firm identifier).[25]

We can see that for eight quarters before the introduction, average nominal interest rates remained relatively flat and we cannot statistically distinguish any of the pre-event coefficients from the normalized period (-2). Immediately after the introduction of the tax, nominal interest rates jump downward by around 0.2 percentage points, with a slight downward post-event trend. The magnitude of this jump suggests that, on average, the passthrough is (0.5-0.2) / 0.5 = 0.6, i.e., the lender and borrower approximately split the tax burden.[26] Estimated effects are similar if we use pair (bank-firm) fixed effects instead of separate bank and firm fixed effects, as shown in the right panel of Figure 1.[27] This specification provides further evidence that the effects are not driven by compositional effects of borrower risk, as the effects are within already active firm-bank pairs.

We present various robustness specifications in Appendix Figure A1. In Panels (a) and (b), we extend the time horizon to 8 quarters after the introduction of the tax to document that the effect on nominal prices is persistent. While the longer-horizon figures clearly demonstrate passthrough incompleteness, we are also concerned that as the time window increases, there will be increasingly more confounders that will affect prices, thereby plausibly contaminating the passthrough estimate. Therefore, we prefer to rely on shorter time windows for our main results.

As a placebo test, we perform our baseline event study on a sample of loans lent by government banks, which were not subject to the SOLCA tax. For these loans, the path of interest rates is indeed strikingly different. Figure 2 shows cyclical levels of nominal interest rates, none of which are significant at conventional levels before or after the introduction of the tax. This placebo test strengthens our confidence that commercial loan prices were not set in antic-

[25]The most commonly used forms of business structures in Ecuador are stock corporations (SA) and limited liability companies (SL). The main differences between these two kinds of enterprises are that shares may be freely negotiated in stock corporations, while quotas of limited liability companies may only be transferred with the unanimous consent of all the partners or quota holders. As a consequence, quotas of limited liability companies may not be seized or sold in a public auction. However, profits declared as dividends may be subject to seizure by debtors of the partners of limited liability companies.

[26]Note that this interpretation assumes a 0.5% tax on all loans. Recall that loans with a term-to-maturity of less than one year have a proportionally reduced tax rate. We address this below.

[27]Our granular dataset allows us to observe individual bank-firm relationships. Bank-by-firm fixed effects control for additional supply factors, such as firm-specific monitoring skills or pair-specific match quality.

ipation of the SOLCA tax, confirming the institutional fact that the tax was a surprise and that other factors were not impacting interest rates not subject to the SOLCA tax just after it was introduced.

[Place Figure 2 here.]

The introduction of the SOLCA tax could affect loan contract terms other than interest rates. Figure 3 reports the event study analysis where the outcome is loan term-to-maturity (left panel) and the amount borrowed (right panel). The left panel of Figure 3 shows that the maturity of new commercial debt decreased after the SOLCA tax was implemented. This finding is intuitive, given that the tax schedule features a kink at the one-year maturity. In the right-hand panel, we see that the amount borrowed also decreased in response to the tax, significantly by three quarters from its introduction. In contrast with the effect on prices, changes in amount and maturity are rather gradual, aiding in the interpretation that interest rates are indeed a primary channel in which banks compete. Appendix Table A2 looks over a longer post period. This reveals that unlike the average interest rate, which does not revert up to eight quarters after the SOLCA tax was implemented, both amount and especially maturity revert towards their pre-tax levels.

[Place Figure 3 here.]

Note that the theory of tax incidence under imperfectly competitive markets (Weyl and Fabinger, 2013; Pless and van Benthem, 2019) links price passthrough to market conduct. Therefore, we are primarily interested in precisely estimating how the tax affected interest rates. However, both maturity and amount are set in conjunction with interest rates and cannot be ignored. For example, from Table 4, presenting correlations between the nominal interest rate on new debt and other contract features and market characteristics, we see a robust negative relationship between both amount and maturity and interest rates. Since there is also a negative effect of the policy on maturity and amount, excluding these other loan contract features from the regressions would bias estimates upward, mechanically pushing the estimates toward full passthrough. We, therefore, include contemporaneous maturity and loan amount in all regressions.

5.2 Estimating the Tax passthrough Directly

The event study specification described by Equation 16 is useful because it allows us to test for any evidence of pre-trends in contract terms in anticipation of the introduction of the SOLCA tax and to examine the evolution of the response. However, because there is a kink in the tax percentage at a loan maturity of one year, we can only recover an imprecise average passthrough. We address this by directly measuring the passthrough of the tax to the cost of borrowing. Specifically, we estimate how final, tax-inclusive prices change with respect to the amount of the tax for each loan. We estimate for loan l contracted by firm f from bank b at time t:

$$rTax_{lfbt} = \rho tax_{lfbt} + \sum_{k=1}^{20} \beta_a^k 1\{A \in j\} + \sum_{k=1}^{20} \beta_m^k 1\{M \in z\} + \alpha_d DP_{lfbt} + \alpha_f + \alpha_b + \varepsilon_{lfbt}, \qquad (17)$$

where $rTax$ is the tax-inclusive interest rate and tax is the tax amount in percent.[28] Following the structure of the SOLCA tax, for loans with a maturity of one year or longer tax is 0.5% after the reform and zero beforehand. For loans with less than a one-year maturity, tax is $0.5\% \times M$, where M is the loan's maturity in years. Then $rTax$ is the nominal interest rate in percent plus tax—the tax-inclusive price of borrowing. A is the amount borrowed with corresponding buckets, M is the loan maturity with its corresponding buckets, α_f is firm fixed-effects, α_b is bank fixed-effects, DP is the predicted default probability, and ε are time-varying unobservables. As mentioned above, we control semi-parametrically for maturity and amount rather than log-linearly as it will offer more conservative estimates.[29] The time window is from eight quarters before the introduction of the tax to three quarters afterward. In this specification, ρ is the passthrough rate. Complete passthrough corresponds to $\rho = 1$; $\rho < 1$ indicates incomplete passthrough, and $\rho > 1$ corresponds to more-than-complete passthrough.

Model (1) of Table 5 reports the direct passthrough of the tax to tax-inclusive interest rates

[28] Papers that run this type of empirical specification are: Atkin and Donaldson (2015); Pless and van Benthem (2019); Genakos and Pagliero (2022); and Stolper (2021).

[29] Indeed, in specifications with log-linear controls, passthroughs are consistently lower than with the semi-parametric controls.

on commercial loans granted by private banks using a specification with bank and firm fixed effects and flexible controls for the amount and maturity of the loan using 20 buckets. The interpretation of the coefficient on *Tax* is that there is, on average, incomplete passthrough of the tax. In particular, the borrower pays approximately 35% of the SOLCA transaction tax on the average loan while the bank shoulders the rest by reducing the interest rate. Model (2) adds the probability of loan default, and the point estimate remains statistically indistinguishable from that of Model (1).

[Place Table 5 here.]

Models (3) and (4) differ from Models (1) and (2) in that the estimation includes bank-firm pair fixed effects instead of separate bank and firm fixed effects. Note that this specializes our analysis to lending relationships with new loans both before and after the SOLCA tax was introduced (established lending relationships). The passthrough remains incomplete, but the borrower now shoulders a higher proportion of the tax—slightly more than half rather than around a third of the tax burden. The point estimate is again statistically indistinguishable with and without including the probability of loan default as a control.

5.3 Heterogeneity by Market Conduct

We now turn to provide evidence that passthrough may be indicative of differences in market power and conduct across markets. For this, we use firm and market characteristics.

To explore heterogeneity in the estimated treatment effect, we consider the following model:

$$\begin{aligned} rTax_{lfbt} =& \rho tax_{lfbt} + \delta_h tax_{lfbt} \times X_{lfbt} + \sum_{k=1}^{20} \beta_a^k 1\{A \in j\} + \\ & \sum_{k=1}^{20} \beta_m^k 1\{M \in z\} + \alpha_d DP_{lfbt} + \alpha_{fb} + \varepsilon_{lfbt}, \end{aligned} \tag{18}$$

where Xt_{lfbt} is some market or firm characteristic, such as number of lenders, relationship age with lender by treatment time, size, etc. Coefficient δ_h captures the heterogeneity in the treatment effect. We use the same time windows as in the event-studies, namely, 8 quarters before and 3 quarters after the policy.

We define the following variables as pre-treatment characteristics. *Relationship Age* is defined as the difference in years between the first recorded bank loan a borrower has with each of its banks and October 2014. Relationships that are created after the policy are assigned an age of 0. Variable *Large* is an indicator that is equal to 1 if a firm was in the top 10% of firms in terms of average assets before the policy was introduced, while *FirmSize* is the continuous pre-assets measure. The variable *Only One Lender* is an indicator equal to 1 if the firm borrowed from only one bank prior to the tax implementation date, while # *Lenders* is the continuous count of unique bank relationships the firm has engaged in. Variable # *Av. City Active Lenders* counts the average number of banks that have at least one lending relationship in the firm's city, while # *Potential Lenders* captures the maximum number of banks that where active at some point in the firm's province. Variables *HHI City* and $HHI - Province$ measure the average yearly Herfindahl-Hirschman index (HHI) in the firm's city and province, respectively. Lastly, *Multimarket Contact* measures the average number of other markets (provinces) in which banks in the market interact.[30] To facilitate comparison and have standard units, we standardize all continuous variables.

For ease of interpretation, it serves to study a simple passthrough formulation from Weyl and Fabinger (2013), copied here. Assuming symmetric imperfect competition, constant marginal cost, and that conduct is invariant to quantity, passthrough is given by:

$$\rho = \frac{1}{1 + \frac{\theta}{\epsilon_{ms}}}, \tag{19}$$

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, passthrough is complete in Bertrand-Nash. If measured passthrough not complete, keeping ϵ_{ms} constant, positive (negative) changes in competitive nature (reflected by moves in θ) will move passthrough closer (farther) from one. If passthrough is incomplete, increases in competition will increase passthrough. Instead, if measured passthrough is more than complete, an increase in competi-

[30]This is in the spirit of Ciliberto and Williams (2014), which shows that multimarket contact may facilitate tacit collusion and reduce competition.

tion will decrease passthrough.

Of course, interpretation in our setting is not so straightforward. Demand curvature may be different across markets, so passthroughs may differ even if conduct is identical. Yet, to develop intuition, we present heterogeneity in passthroughs and show that passthroughs do move in the direction predicted in the simple model above.

Table 6 presents the results. In Columns (1) and (2), we show the interaction with firm size. Although the continuous measure in (1) is noisy, we find in both columns that larger firms have passthroughs closer to the competitive benchmark. In Column (3), we see that older relationships also have passthroughs closer to one. In Columns (4) and (5), we present firm-specific measures of bank access, and find that (although noisy), firms that have less access to banks have passthroughs that diverge from the benchmark.

In the remaining columns, we present evidence that directly relates to competition in the local markets. In Columns (6) and (7), we study passthrough heterogeneity in terms of the availability of lenders in the market and find that markets with more lenders have passthroughs that approach Bertrand-Nash. Instead, if we measure competition using city or province HHI, we find that passthroughs move away from Bertrand-Nash. Lastly, we find that areas with a greater number of banks that operate simultaneously in multiple other markets have passthroughs in line with less competitive conduct.

[Place Table 6 here.]

Overall, these results show the potential use of passthrough heterogeneity to capture heterogeneity in competition across markets. Indeed, all measures of competition show consistent results. However, this suggestive rather than conclusive evidence that markets are not competitive. First, it may be that conduct is very close to Bertrand-Nash, yet markets differ widely in their demand determinants. More concentrated markets may be smaller or in distant markets in which firms' investment needs are scant, either of which would affect the shape and curvature of the demand for capital. While the bank-firm pair fixed effects and the controls for contract terms may capture some of this cross-market heterogeneity in demand, it might be insufficient if demand curves are non-linear.

5.4 Passthroughs by Region

While in practice, one could estimate passthroughs at the lowest market level, e.g., province or city, some markets are small (with down to 200 observations), yielding noisy estimates. For that reason, we aggregate small provinces into regions and leave large provinces on their own. In particular, we estimate passthrough for the provinces Azuay, Guayas, and Pichincha, which are the largest, and aggregate across provinces for the regions Costa and Sierra/Oriente. Table 7 presents the direct tax passthroughs by region. Although noisy for the smaller regions, we consistently find point estimates that indicate incomplete passthrough. We will use these point estimates to estimate conduct at the regional level.

[Place Table 7 here.]

6 Estimating the Model

In this section, we lay out our model estimation strategy.

6.1 Price Prediction

The first empirical challenge 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 Crawford et al. (2018).

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:

$$r_{ikmt} = \gamma_0 + \gamma_x X_{ikmt} + \gamma_2 ln(L_{ikmt}) + \gamma_3 ln(M_{ikmt}) + \lambda_{kmt} + \omega_i^r + \tau_{ikmt}, \tag{20}$$

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 of 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.[31] Finally, τ_{ikmt} are prediction errors. By combining predicted coefficients, we then predict prices $\tilde{r}_{ijmt}$ of the terms 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.[32]

Table 8 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.[33]

[Place Table 8 here.]

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? Anecdotally, Ecuadorian lenders report that they rely most heavily on hard information. In fact, private banks must publish their lending guidelines, and they universally 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.

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

[32] Table 8 and Appendix Table A2 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 20 with firm fixed effects as our preferred specification.

[33] 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.

Second, in Appendix B, 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 8. We fail to reject the null hypothesis that the residuals have no significant statistical correlation with default once we include firm fixed effects. On the contrary, 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.

For firms that do not borrow from banks in our sample, we employ a propensity score matching approach, as used in Adams et al. (2009) and Crawford et al. (2018) to solve the same empirical challenge. 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 C.1 for further information and diagnostics on our matching model.

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

$$\begin{aligned} r_{ikmt} &= \tilde{r}_{ikmt} + \tilde{\tau}_{ikmt}, \\ &= \tilde{r}_{kmt} + \tilde{\gamma}_x X_{ikmt} + \tilde{\gamma}_2 ln(L_{ikmt}) + \tilde{\gamma}_3 ln(M_{ikmt}) + \tilde{\omega}_i^r + \tilde{\tau}_{ikmt} \end{aligned} \tag{21}$$

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 4. 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.

[Place Figure 4 here.]

6.2 Demand

We follow Train (1986) and Benetton (2021) in writing the (indirect) profit function $\overline{\Pi}_{ik}$ using the parametric form:[34]

$$\overline{\Pi}_{ikmt} = \exp(\mu)\exp(\xi_{kmt} + \psi_i - \alpha_m r_{ikmt} + \beta_{m1}X_{it} + \beta_{m2}X_{ikmt}) + \gamma_N N_{ikmt}, \tag{22}$$

where N_{ikmt} is the branch network in the local market. Plugging in predicted prices from Equation 21, we obtain the following indirect profit function:

$$\begin{aligned}\Pi_{ikmt} &= \exp(\mu)\exp\Big(\underbrace{\xi_{kmt} - \alpha_m\tilde{r}_{kmt}}_{\tilde{\xi}_{kmt}} + \underbrace{(\beta_{m1} - \alpha_m\tilde{\gamma}_{x1})}_{\tilde{\beta}_{m1}}X_{it} + \underbrace{(\beta_{m2} - \alpha_m\tilde{\gamma}_{x2})}_{\tilde{\beta}_{m2}}X_{ikmt} \qquad (23)\\ &\quad - \alpha_m\tilde{\gamma}_2 ln(L_{ikmt}) - \alpha_m\tilde{\gamma}_3 ln(M_{ikmt}) - \alpha_m\tilde{\omega}_i^r + \underbrace{\psi_i - \alpha_m\tilde{\tau}_{ikmt}}_{\tilde{\psi}_{ikmt}}\Big)\\ &\quad + \gamma_N N_{ikmt} + \varepsilon_{ikmt}\\ &= \exp(\mu)\exp\Big(\tilde{\xi}_{kmt} + \tilde{\beta}_{m1}X_{it} + \tilde{\beta}_{m2}X_{ikmt} - \alpha_m\tilde{\gamma}_2 ln(L_{ikmt}) - \alpha_m\tilde{\gamma}_3 ln(M_{ikmt}) \qquad (24)\\ &\quad - \alpha_m\tilde{\omega}_i^r + \tilde{\psi}_{ikmt}\Big) + \gamma_N N_{ikmt} + \varepsilon_{ikmt}\end{aligned}$$

We assume the idiosyncratic taste shocks ε_{ikmt} are i.i.d. Type-I Extreme Value, and that the borrower's unobservable characteristic heterogeneity, $\tilde{\psi}_{ikmt} = \psi_i - \alpha_m\tilde{\tau}_{ikmt}$, follows a Normal distribution with mean zero and variance σ_b^2. Notice that, in principle, we could estimate the demand price parameter α_m from any of the variables $\tilde{\gamma}_2 L_{ikmt}$, $\tilde{\gamma}_3 M_{ikmt}$, and $\tilde{\omega}_i^r$. Yet, due to the noise created by the estimated parameters—following a traditional measurement error on the independent variable argument—the coefficient on α_m would be biased. For that reason, we follow the conventional route and estimate α_m from $\tilde{\xi}_{kmt}$ through a second-stage instrumental variable approach that relies on exogenous variation in average prices at the bank-market-year level that addresses concerns of measurement error and endogeneity.

Before we describe our instrumental variable strategy to identify α_m, we describe our maximum likelihood demand estimation procedure. First, we derive the maximum likelihood func-

[34] Noting that they use indirect utility rather than profit.

tion. The conditional probability that the firm i chooses bank j is given by

$$s_{ikmt}(\psi_i) = \frac{\exp(\Pi_{ikmt})}{\sum_j \exp(\Pi_{ijmt})}, \tag{25}$$

while the unconditional probability is given by

$$S_{ikmt} = \int s_{ikmt}(\psi_i))dF(\psi_i). \tag{26}$$

Given actual bank choices, we can use Hotelling's lemma to obtain the loan demand function L_{ikmt}:[35]

$$\ln(L_{ikmt}) = \ln(\exp \mu\alpha_m) + \xi_{kmt} - \alpha_m r_{ikmt} + \beta_{m1} X_{it} + \beta_{m2} X_{ikmt} + \psi_i \tag{27}$$

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

$$\ln(L_{ikmt}) = \ln(\exp \mu\alpha_m) + \tilde{\xi}_{kmt} - \alpha_m(r_{ikmt} - \tilde{r}_{kmt}) + \beta_{m1} X_{it} + \beta_{m2} X_{ikmt} + \psi_i. \tag{28}$$

From Equation 28 and the normality assumption for ψ_i, the probability of the conditional loan demand is

$$f(ln(L_{ikmt})|k, k \neq 0) = \tag{29}$$
$$\frac{1}{\sqrt{2\pi\sigma^2}} \times \exp\left[- \frac{\left(\ln(L_{ikmt}) - \ln(\exp \mu\alpha_m) - \tilde{\xi}_{kmt} + \alpha_m(r_{ikmt} - \tilde{r}_{kmt}) - \beta_{m1} X_{it} - \beta_{m2} X_{ikmt} \right)^2}{2\sigma^2} \right].$$

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

$$\ln(\mathcal{L}) = \sum_{t=0}^{T} \sum_{m=0}^{M} \sum_{j=0}^{J_m} \sum_{k=0}^{K_m} 1_{ikmt}[\ln(S_{ikmt}) + \ln(f(\ln(L_{ikmt})|k, k \neq 0))], \tag{30}$$

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

[35] Here, we took the derivative of Equation 22 with respect to the interest rate.

We implement this maximum likelihood demand estimation procedure in three steps. First, we obtain the values for the bank-market constants $\tilde{\xi}_{kmt}$ and the coefficients $\tilde{\beta}, \beta$ from the indirect profit function. In the first iteration $r = 1$, this is just a guess from a Logit model. In the subsequent iterations, we obtain the coefficients through gradient search. Second, we implement the instrumental variable approach described below to calculate α_m from the estimate of $\tilde{\xi}_{kmt}$. Third, we repeat this procedure for 400 bootstrap samples for each region to obtain standard errors for all coefficients.[36]

Next, we estimate α_m while controlling for the endogeneity of demand and prices, and for potential measurement error. We implement an instrumental variable approach for the equation:

$$\tilde{\xi}_{kmt} = -\alpha_m \tilde{r}_{kmt} + \beta_b X_{kmt} + \epsilon_{kmt}. \tag{31}$$

Specifically, we instrument predicted bank-market time-varying prices $\tilde{r}_{kmt}$ with the following variables: the average commercial price for bank k in other markets n, the average price for consumer loans in other markets, the average price for entrepreneur loans in other markets, and the aggregate default rate in non-commercial loan products, such as micro-lending, mortgages, and consumption. In the aggregate, the instruments relate well with the bank-market interest rates.

6.2.1 Demand Elasticities

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

$$\epsilon^L_{ikmt} = \frac{\partial L_{ikmt}}{\partial r_{ikmt}} \frac{r_{ikmt}}{L_{ikmt}} = \frac{\partial ln(L_{ikmt})}{\partial r_{ikmt}} r_{ikmt} = -\alpha_m r_{ikmt} \tag{32}$$

[36] An alternative approach is to use the control function from Train (2009). The first step of this method is to regress predicted and observed prices on the variables that enter the discrete and continuous demand equations. We would then include the residuals as controls in the joint maximum likelihood. In practice, the number of steps will be similar to the algorithm described above. The only benefit is that this algorithm performs the instrumental variable estimation at the same time as the gradient search process.

and

$$
\begin{aligned}
\epsilon^{s}_{ikmt} &= \frac{\partial s_{ikmt}}{\partial r_{ikmt}} \frac{r_{ikmt}}{s_{ikmt}} \\
&= -\alpha_m \exp \mu \exp(\xi_{kmt} + \psi_i - \alpha_m r_{ikmt} + \beta_{m1} X_{it} + \beta_{m2} X_{ikmt})(1 - s_{ikmt}) s_{ikmt} \times \frac{r_{ikmt}}{s_{ikmt}} \\
&= -\alpha_m \exp \mu \exp(\xi_{kmt} + \psi_i - \alpha_m r_{ikmt} + \beta_{m1} X_{it} + \beta_{m2} X_{ikmt})(1 - s_{ikmt}) r_{ikmt} \qquad (33)
\end{aligned}
$$

The elasticity for total demand is given by:

$$
\begin{aligned}
\epsilon^{Q}_{ikmt} &= \frac{\partial Q_{ikmt}}{\partial r_{ikmt}} \frac{r_{ikmt}}{Q_{ikmt}} = \frac{\partial s_{ikmt} L_{ikmt}}{\partial r_{ikmt}} \frac{r_{ikmt}}{s_{ikmt} L_{ikmt}} \\
&= \frac{\partial s_{ikmt}}{\partial r_{ikmt}} \frac{r_{ikmt}}{s_{ikmt}} + \frac{\partial L_{ikmt}}{\partial r_{ikmt}} \frac{r_{ikmt}}{L_{ikmt}} = \epsilon^{s}_{ikmt} + \epsilon^{L}_{ikmt}. \qquad (34)
\end{aligned}
$$

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

$$
\epsilon^{L,j}_{ikmt} = 0 \qquad (35)
$$

and

$$
\begin{aligned}
\epsilon^{s,j}_{ikmt} &= \frac{\partial s_{ikmt}}{\partial r_{jkmt}} \frac{r_{jkmt}}{s_{ikmt}} = \alpha_m \exp \mu \exp(\xi_{jmt} + \psi_i - \alpha_m r_{ijmt} + \beta_{m1} X_{it} + \beta_{m2} X_{ijmt}) s_{ijmt} s_{ikmt} \times \frac{r_{ijmt}}{s_{ikmt}} \\
&= \alpha_m \exp \mu \exp(\xi_{jmt} + \psi_i - \alpha_m r_{ijmt} + \beta_{m1} X_{it} + \beta_{m2} X_{ijmt}) s_{ijmt} r_{jkmt} \qquad (36)
\end{aligned}
$$

6.3 Supply

The supply side parameters (mc_{ik}, υ_m) are estimated using optimal pricing formulae through the inverted Equation 12 and the passthrough Equation 14 as the targeting moment.

7 Estimation Results

7.1 Demand Parameters

Table 9 collects the demand parameter estimates, reported as the mean and standard error of the point estimates with each market (region). Standard errors are bootstrapped by estimating each region-level parameter on 400 bootstrap samples and then taking the standard deviation across bootstrap sample and within region.

[Place Table 9 here.]

Generally speaking, the signs of the estimates are as expected, but there is great heterogeneity across markets. The price parameter captures the sensitivity of demand to interest rates. We estimate it through the instrumental variable approach discussed above. As expected, higher interest rates have a negative effect on the demand for loans for a given bank. To understand the sensitivity of demand to prices, we calculate own- and cross-demand elasticities, reported in Table 10. We find that a 1% increase in price leads to a 4.69% decrease in loan use (continuous) and a 6.01% decrease in market share.[37] Moreover, a 1% increase in interest rates increases competitors' market shares by 0.17%. At this point, it is worth highlighting the large demand heterogeneity across borrowers. Some borrowers are slightly inelastic, with elasticities up to -2.81, whereas others are highly elastic, with estimates down to -44.68. It is vital that we capture this borrower heterogeneity, as it may help explain differences in passthroughs.

[Place Table 10 here.]

The remaining demand parameters presented in Table 9 are sensible. The parameter sigma captures unobserved heterogeneity, while the scaling factor captures vertical shifts in the indirect utility to match the ratio of borrowers to non-borrowers. Next, the parameter for bank branches shows more demand for loans from banks with a greater physical presence in a given market. The other parameters show that: (1) older firms are more likely to borrow; (2) borrowers are more likely to choose to borrow from banks the longer their lending relationship; (3)

[37] Compared to the structural lending literature, these estimates are slightly more elastic than those from Crawford et al. (2018) and Ioannidou et al. (2022) but are close in magnitude to those from Benetton et al. (2021).

larger firms, measured by assets or revenues, are more likely to borrow; (4) firms with greater expenses or wage bills are more likely to borrow; and (5), firms with higher leverage are less likely to borrow. In Appendix D we report the demand estimates pooled across regions and we re-produce the region-level instrumented price parameters estimates alongside first-stage Cragg-Donald Wald F-statistics for the first stage against the null hypothesis of instrument irrelevance and the results of Sargen-Hansen over-identification tests for our instrumental variable strategy against the null hypothesis that rhe error term is uncorrelated with the instruments.

7.2 Model Fit

In Table 11, we present descriptive statistics on the fit of the model. We focused on market shares (discrete choice), loan use (continuous choice), prices, and default rates. The table shows that the model fits the mean data well, with a perfect fit for market shares, loan use, and default rates. Our model under-predicts prices by a small margin. Across all measures, our model predicts less variation than in the data.

[Place Table 11 here.]

7.3 Supply Side Parameters

As a first exercise, 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. We then compare the model-implied marginal costs and markups under these two scenarios.

First, we report banks' borrower-specific marginal costs under the usual assumption of Bertrand-Nash competition ($\upsilon_m = 0$). Recall that this is the standard assumption in the banking literature and that its advantage is it allows us to invert the first order condition of the seller (as in Equation 12) to backup prices by setting $\upsilon_m = 0$ and using only the own-price elasticities of demand. We find average (median) marginal costs of 9.07 (9.55) percent for each extra dollar lent, which accounts for funding, monitoring, screening, and other economic costs. The corresponding average (median) markup—the gap between prices and marginal costs—is 2.19 (2.12) percentage points or 19.47% (18.84%) of the average interest rate of 11.25%.

Next, we take advantage of cross-elasticity estimates and back-out marginal costs and markups under the assumption of full joint maximization, i.e., $\upsilon_m = 1$. As expected, marginal costs decrease. Specifically, average (median) marginal costs decrease by 4.06 (6.37) percentage points or a 50.57 (55.75) percent decrease relative to the Bertrand-Nash case. In other words, compared to joint maximization, assuming Bertrand-Nash competition leads the model to attribute a greater portion of the price to higher marginal costs than in the data. In contrast, under the assumption of joint maximization, the model attributes some of the markup to anti-competitive behavior, i.e., the FOC from the banks' problem loads on both the effect of borrower demand elasticity on quantity demanded and on the impact of internalizing the profit maximization of competitors. So naturally, the markup the model estimates under the assumption of joint maximization is larger: the model returns an average (median) estimated markup of 6.24 (4.56) percentage points or 55.46 (39.44) percent of the average interest rate. This represents more than a 100 percent increase in the markup relative to the markup estimated under the assumption of Bertrand-Nash competition.

[Place Table 12 here.]

7.4 Testing Conduct

We now use the estimated supply and demand parameters for each mode of conduct to simulate passthroughs of the introduction of the 0.5% tax rate. The goal of this section is to obtain distributions of passthroughs consistent with each conduct while at the same time flexibly accounting for demand heterogeneity. We then can compare these simulated distributions with the passthrough distribution from the actual data.

To obtain model-consistent passthroughs, we start with our estimates of bank-borrower-specific marginal costs of lending under each mode of conduct. Then, following the isomorphism between tax and marginal cost passthroughs documented by the public finance literature, we model the introduction of the tax as a 0.5 percentage point linear increase in the marginal costs for each pair. Then, for each borrower, we use their estimated demand functions to solve for the Nash equilibrium of prices implied by the system of equations of first-order conditions (Equation 7) for all banks in their choice set, under the assumption that $\upsilon_m = 0$ under Bertrand-

Nash and $\upsilon_m = 1$ under joint maximization. Finally, we measure the simulated passthroughs by comparing model equilibrium and observed prices.

Figure 5 plots the results of 1,000 bootstrap simulations, where we sampled borrowers with replacement. We estimate that passthroughs are centered slightly above one under Bertrand-Nash, despite the significant demand heterogeneity documented above. Contrasting this distribution with the empirical point estimate for passthrough 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 our discrete-continuous demand model is flexible enough that we can obtain passthrough estimates both above and below one under Bertrand-Nash, which, as documented by Miravete et al. (2022), many discrete-choice models are not able to accommodate.

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

[Place Figure 5 here.]

Table 13 presents the result from another angle. Column (1) reproduces the region-level passthrough estimates from Table 5. Columns (2) and (3) report the passthrough estimates by region from using the model to simulate the introduction of the 0.5% tax rate under joint maximization and Bertrand-Nash conduct, respectively. We again observe that joint maximization matches the observed empirical moments very well. Indeed, apart from Azuay, the joint maximization estimates match the empirical estimates extremely closely. Recall that we did not fit the data to the passthrough moments, so that this result is a powerful confirmation of our precise failure to reject that the observed tax passthrough in the data is the result of joint maximization conduct. On the other hand, the simulated tax passthrough under Bertrand-Nash competition do not match the empirical passthrough moments well.

[Place Table 13 here.]

7.5 Implications of conduct for markups and credit allocation

We now evaluate the implications of anti-competitive (non-zero) conduct for markups (prices) and credit allocation. Recall we found an average marginal cost difference of 50.57 percent between the marginal costs estimated under a conduct of joint-maximization ($\upsilon_m = 1$) versus a conduct of Bertrand-Nash ($\upsilon_m = 0$). This result already demonstrates (sensibly) that prices would be, on average lower the less a bank internalizes the profit maximization of its competitors when setting its own price, controlling for other loan contract features. Firms facing a lower cost of borrowing would, in turn, increase their investment and demand rates, ceteris paribus. To quantify the effects of moving to Bertrand-Nash from the equilibrium we estimated in the actual data, we obtain Nash-equilibrium prices under the original choice set considering marginal costs as if banks engaged in joint maximization but shutting down the internalization parameter υ_m to zero.

Return to Table 12 to view the results, reported in Panels B and C. First, we see that equilibrium prices would be an average (median) 17.18 (5.36) percent lower than observed prices in the data. This represents a decrease in average (median) markup from 6.24 to 4.42 percentage points (from 4.56 to 2.27). The bank-borrower-specific ratio between the markups under joint maximization and the markups after the move to Bertrand-Nash allows us to decompose the portion of markup due to anti-competitive conduct. We find that on average (median) 26.27 (20.64) percent of the markup is due to conduct.

These increases in prices and markups come with real economic effects for borrowers, which we can observe in Table 12, Panel D. Using the continuous part of loan demand (Equation 27), we can estimate the change in demand for each borrower under new equilibrium prices. Due to the lower prices, we find that the intensive margin of credit demand would increase on average (median) by 21.39 (20.29) percent. Furthermore, by using the discrete part of the model, we estimate the equilibrium market share for the outside option and find that the extensive margin of credit demand would also increase, moving from 3.3 percent of the firms not borrowing to 2.9 percent, or a 13 percent increase in the number of firms borrowing.

7.6 Calibrating Conduct for each Market

In progress.

7.7 Tax Incidence, Tax Revenue, and Conduct

In progress.

7.8 Policy Analysis

In progress.

8 Conclusion

In this paper we investigate the impact of bank competition on commercial lending using the introduction of a surprise loan tax in Ecuador and a structural model of commercial lending. The model takes into account a mix of continuous and discrete credit demand, and looks at the different ways that banks compete for borrowers, from setting prices for maximum joint profits to competing under the Bertrand-Nash model. This model improves upon previous studies by differentiating between competition and differences in marginal lending costs, allowing the identification of a parameters describing bank conduct. We estimate the model and its results using data from all commercial credit transactions in Ecuador. Our preliminary findings show that the Bertrand-Nash competition model is not supported, but the joint profit maximization model is. Specifically, we estimate that 26% of the price markups are due to anti-competitive behavior in joint profit maximization. If competition were based on Bertrand-Nash, prices would decrease by 17%, loan usage would increase by 26% (intensive margin), and overall credit demand would increase by 13% (extensive margin). In future work we will fully calibrate the conduct parameter for each market and investigate how it varies with empirical market, borrower, bank and lending relationship characteristics. We will also run counterfactual policy experiences through the lens of our model that will allow us to explore the impact of potential government policies to support competition in lending on equilibrium prices and the distribution of firms and investment.

These results already have several important implications for policymakers and the literature. Most importantly, it is not without loss of generality that existing models assume Bertrand-Nash competition among lenders. When we relax this assumption and take it to the data we find that a substantial amount of bank pricing power is better explained by collusive behavior from joint profit maximization. This is important because pricing power coming from Bertrand-Nash conduct, e.g., from bank product specialization or banks investing in existing relationships have been show to have positive as well as negative effects on credit terms and borrower outcomes ((Petersen and Rajan, 1995; Mahoney and Weyl, 2017; Crawford et al., 2018; Yannelis and Zhang, 2021)). However, it is not clear there are any positive consequences for borrowers from pricing power derived from joint profit maximization. Moreover, the emphasis of policy responses to address bank market power will differ depending on market conduct. For example, traditional anti-trust tools or measures to increase pricing transparency are likely to be effective when pricing power derives from joint maximization conduct whereas lowering specific frictions may become more important if conduct is closer to Bertrand-Nash. Indeed, in simulations we find that loan prices are significantly lower under a Bertrand-Nash counterfactual relative to a joint maximization conduct scenario, suggesting large gains from targeted policy even if the theoretical first-best perfect competition benchmark is unrealistic. We will explore this further empirically in the next iteration of this paper.

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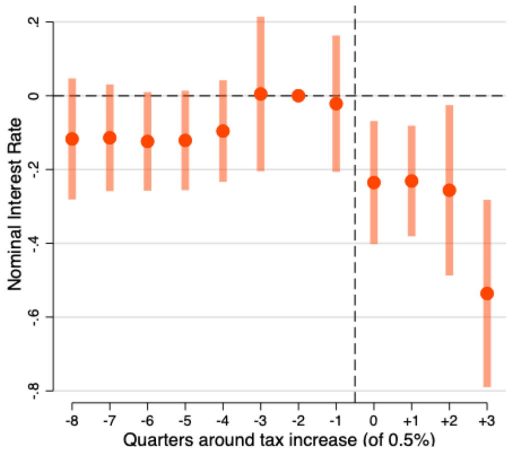
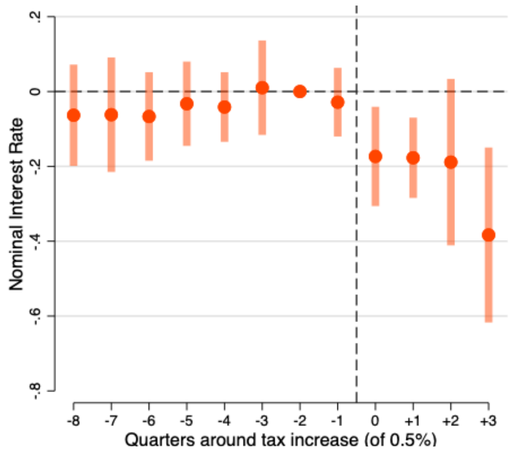
9 Tables and Figures



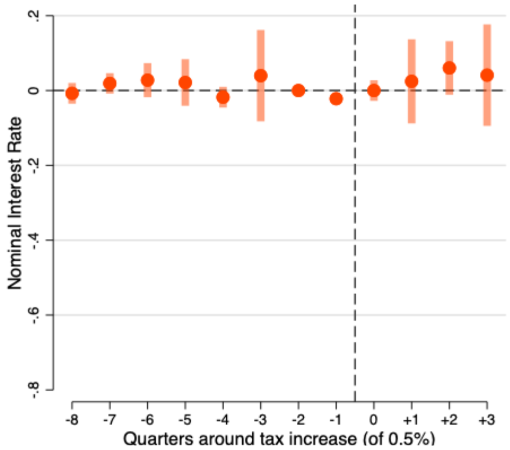
(a) Regular loans; bank & firm FE



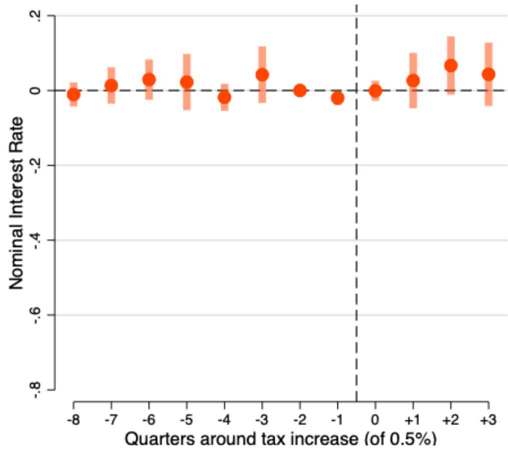
(b) Regular loans, bank-firm pair FE

FIGURE 1: DYNAMIC ANALYSIS OF THE INTRODUCTION OF THE SOLCA TAX ON NOMINAL INTEREST RATES OF NEW COMMERCIAL DEBT LENT BY PRIVATE BANKS

The figure reports the period-by-period difference in average nominal interest rates from private banks around treatment assignment relative to event-time period $t = -2$ (normalized to zero), using firm FE plus bank FE (Panel (a)) and firm × bank FE (Panel (b)). Data are loan-level on commercial loans granted by private banks to Ecuadorian corporations. The figure tests for both treatment effects and looks for evidence of significant differences in outcomes before treatment assignment (pre-trends). Standard errors bars are shown at the 95% confidence level and are clustered at the bank-quarter level.



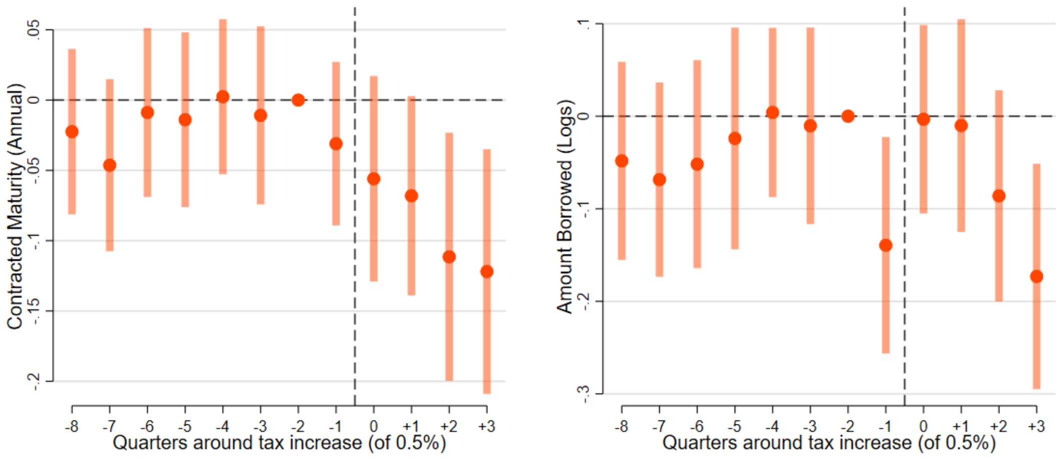
(a) Regular loans; bank & firm FE



(b) Regular loans, bank-firm pair FE

FIGURE 2: DYNAMIC ANALYSIS OF THE INTRODUCTION OF THE SOLCA TAX ON NOMINAL INTEREST RATES OF NEW COMMERCIAL DEBT LENT BY STATE-OWNED BANKS

The figure reports the period-by-period difference in average nominal interest rates from state-owned banks around treatment assignment relative to event-time period $t = -2$ (normalized to zero), using firm FE plus bank FE (Panel (a)) and firm $\times$ bank FE (Panel (b)). Data are loan-level on commercial loans granted by state-owned banks to Ecuadorian firms. Standard errors 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 3: DYNAMIC ANALYSIS OF THE INTRODUCTION OF THE SOLCA TAX ON MATURITY AND AMOUNT OF NEW COMMERCIAL DEBT LENT BY PRIVATE BANKS

The figure reports the period-by-period difference in average term-to-maturity (Panel (a)) or the log of amount borrowed (Panel (b)) for new loans around treatment assignment relative to event-time period $t = -2$ (normalized to zero). Both specifications control for bank FE and firm FE. Data are loan-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-quarter level.

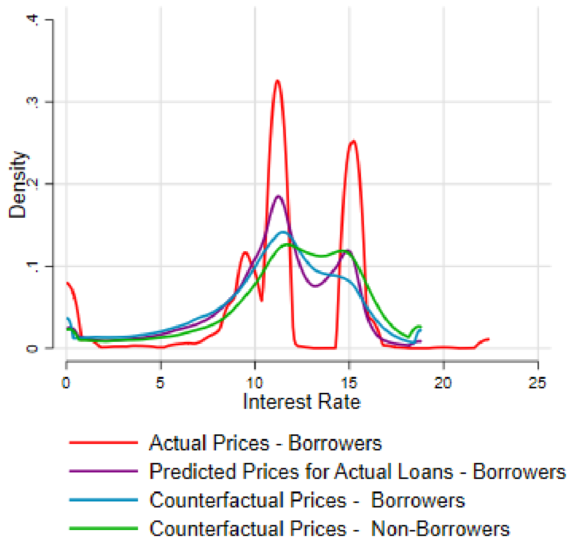


FIGURE 4: DISTRIBUTION OF PREDICTED PRICES

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

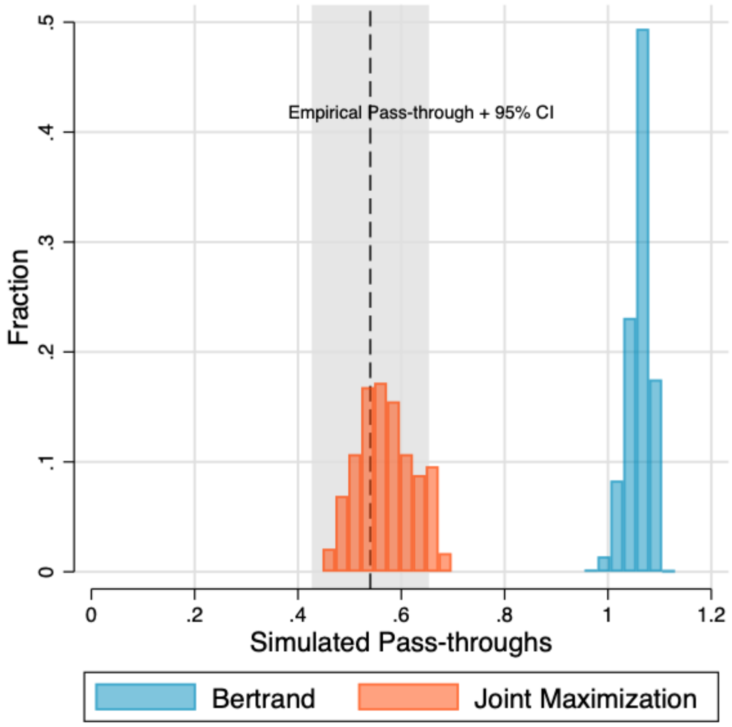


FIGURE 5: DISTRIBUTION OF SIMULATED PASSTHROUGHS BY CONDUCT

The figure reports the distribution of nation-wide bootstrapped average simulated Nash-equilibrium passthroughs of a tax introduction of 0.5% by mode of conduct (Bertrand-Nash in blue and Joint Maximization in Orange). Bootstrap estimates come from 1,000 bootstrapped samples of borrowers-level estimates of passthrough under each model. The dashed line shows the estimated empirical passthroughs regressions (using data with actual loans) presented in the reduced-form section of the paper, and the shaded area shows the 95% confidence interval.

TABLE 1: AGGREGATE-LEVEL CREDIT CHARACTERISTICS

The table describes the commercial loan market in aggregate. 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. *Total volume* is the sum of the dollar value of all loans extended. *# Clients* is the sum of unique clients. *# Loans* is the count of loans extended. Data from both private and state-owned banks are included.

Variable	**Mean**	**Median**
Total Volume	59,100,000	1,420,334
# Clients	83.82	11.00
# Loans	517.78	24.00
Observations	1,771	1,771

TABLE 2: CHARACTERISTICS BY MARKET CONCENTRATION (HHI)

The table describes the commercial loan market by market concentration. 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. Data are cut above and below median HHI value (2243.18), measured across all years in the data. *Panel A* presents branch information. *# Branches* is the number of open branches in the province. *# Other Private Banks* is the number of other private banks active in the province. *# Other Private Branches* is the total number competing branches active in the province. *Panel B* presents credit information. *Total Volume* is the sum of the dollar value of all loans extended. *# Clients* is the sum of unique clients. *# Loans* is the count of loans extended. *Av. Loan* is the average loan size. *Av. Maturity* is average annualized term-to-maturity at issuance. *Av. Interest Rate* is the nominal, annualized interest rateat issuance, in percent. *# Loans per Client* is the average number of loans extended per firm from a given bank. Data from state-owned banks are excluded.

Variable	**Below Median HHI**	**Above Median HHI**
	Panel A: Branch Information	
# Branches	5.16	2.69
# Other Private Banks	15.93	10.45
# Other Private Branches	104.13	43.32
Observations	891	880
	Panel B: Credit Information	
Total Volume	105,000,000	12,600.000
# Clients	141.53	25.37
# Loans	937.30	93.01
Av. Loan	182,430.30	99,334.42
Av. Maturity	1.09	0.92
Av. Interest Rate	9.99	11.01
# Loans per Client	114.79	12.97
Observations	891	880

TABLE 3: DESCRIPTIVE STATISTICS

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

Variable	**Mean**	**Median**	**SD**	**Min.**	**Max.**	**Obs.**
	Panel A: Firm-Level Data: Active Borrowers					
Firm Age	12.25	9.00	11.14	0.00	96.00	97,796
Total Assets	2.05	0.40	4.22	0.00	20.66	97,796
Total Sales	2.57	0.62	4.86	0.00	23.14	97,796
Total Wages	0.36	0.10	0.63	0.00	2.98	97,796
Total Debt	1.31	0.28	2.61	0.00	12.65	97,796
Leverage	0.66	0.71	0.28	0.00	1.19	97,796
	Panel B: Firm-Level Data: Non Active Borrowers					
Firm Age	9.92	7.00	10.09	0.00	93.00	359,827
Total Assets	0.46	0.05	1.73	0.00	20.66	359,827
Total Sales	0.43	0.03	1.70	0.00	23.14	359,827
Total Wages	0.07	0.01	0.25	0.00	2.98	359,827
Total Debt	0.26	0.02	1.01	0.00	12.65	359,827
Leverage	0.54	0.58	0.40	0.00	1.19	359,827
	Panel C: Loan-Level Data					
Number of Bank Relationships	1.38	1.00	0.79	1.00	7.00	97,796
Number Loans	8.88	2.00	100.66	1.00	9,195.00	97,796
Age Bank Relationship	2.31	2.00	2.41	0.00	16.00	135,091
Loan Interest Rate	9.20	8.95	3.48	0.00	25.50	885,229
Loan Amount	0.10	0.01	1.73	0.00	466.00	885,229
Annual Loan Maturity	0.51	0.25	0.80	0.00	27.39	885,229
1(Loan with Rating < B)	0.02	0.00	0.14	0.00	1.00	885,229
Default Observed	0.00	0.00	0.06	0.00	1.00	744,257

TABLE 4: 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 log-measures 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 is excluded. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

	(1)	**(2)**	**(3)**
Variable	**Av. IR**	**Av. IR**	**Av. IR**
log(Av. Loan)	-0.567***	-0.605***	-0.557***
	(0.045)	(0.047)	(0.054)
log(Av. Maturity)	-0.624***	-0.585***	-0.551**
	(0.185)	(0.194)	(0.226)
log(# Branches)	-0.438***	-0.402***	-0.363**
	(0.136)	(0.135)	(0.151)
log(# Other Branches)	-0.046	0.044	0.014
	(0.053)	(0.071)	(0.075)
log(HHI Value)	0.704***	0.546	0.352*
	(0.210)	(0.365)	(0.212)
log(# Loans per Client)	-0.604***	-0.606***	-0.475***
	(0.048)	(0.048)	(0.053)
log(# 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

TABLE 5: AGGREGATE PASSTHROUGH ESTIMATES

The table reports aggregate passthrough estimates to the interest rates of commercial loans around the introduction of the 2014 SOLCA tax in Ecuador. Data are at the loan-level for 2010 to 2017, excluding October 2014. The main independent variable is the tax rate, measured as 0.5 adjusted proportionally by term-to-maturities if maturity is less than 1 year. The dependent variable is the tax-inclusive interest rate, which is the sum of the nominal, annualized interest rate plus the tax rate. Both are in percentage points. Regressions control for twenty buckets of term-to-maturity, and twenty buckets of loan amount. Regressions (2) and (4) control for predicted default probability. Regression (1) and (2) control for bank FE and firm FE, whereas (3) and (4) for bank × firm (pair) FE. 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 passthrough null hypothesis ($\rho = 1$).

	Outcome: Tax-inclusive interest rate			
	(1)	(2)	(3)	(4)
Passthrough (ρ)	0.357***	0.335***	0.529***	0.536***
	(0.144)	(0.166)	(0.137)	(0.150)
Pr(Default) Control	No	Yes	No	Yes
Maturity & Amount Controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	No	No
Firm FE	Yes	Yes	No	No
Pair FE	No	No	Yes	Yes
Observations	385,128	352,574	378,747	347,471
R-squared	0.721	0.711	0.783	0.777

TABLE 6: HETEROGENEITY IN DIRECT TAX PASSTHROUGH

The table reports heterogeneity in aggregate passthrough 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, and twenty buckets of loan amount, predicted default probability, and bank × firm (pair) FE. Interacted variables are: *Firm Size* is the standardized average level of assets pre-October 2014; *1(Large)* is an indicator equal to one if *Firm Size* is above median; *Relationship Age* measures the standardized number of years since first bank-firm interaction; *1(One Lender)* is an indicator equal to one if firm one had one lender relationship prior to October 2014; *# Lenders* is the standardized measure of lenders prior to October 2014; *# Av. City Active Lenders* is the standardized measure of average number of active lenders per year prior to October 2014; *# Potential Lenders* is the standardized measure of maximum number of active lenders as of October 2014; *HHI Province* is the standardized measure of Herfindahl-Hirschman Index per year per province prior to October 2014; *HHI City* is the standardized measure of Herfindahl-Hirschman Index per year per city prior to October 2014; *Multimarket Contact* is the standardized measure of average number, across all bank pairs active in the province, of other provinces in which banks jointly operate in. Robust standard errors clustered at the bank-quarter level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. For the main effect, testing is conducted against the full passthrough null hypothesis (ρ = 1). For the interaction term, testing is against the no-effect null hypothesis.

	Outcome: Tax-inclusive interest rate									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Passthrough (ρ)	0.567**	0.317***	0.547**	0.596*	0.565**	0.676	0.441***	0.550**	0.603**	0.529**
	(0.207)	(0.210)	(0.203)	(0.221)	(0.212)	(0.209)	(0.207)	(0.195)	(0.200)	(0.203)
Interacted with	*Firm Size*	*1(Large)*	*Relationship Age*	*1(One Lender)*	*# Lenders*	*# Av. City Active Lenders*	*# Potential Lenders*	*HHI Province*	*HHI City*	*Multimarket Contact*
	0.146	0.406*	0.207**	-0.332*	0.136	0.583***	0.459***	-0.565***	-0.413***	-0.226**
	(0.117)	(0.207)	(0.0827)	(0.185)	(0.125)	(0.177)	(0.117)	(0.113)	(0.0860)	(0.0923)
Pair FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Amount Bucket	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Maturity Bucket	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Default Risk Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	344,964	344,964	347,471	347,471	347,471	347,471	347,471	347,471	347,463	347,471
R-squared	0.776	0.776	0.777	0.777	0.777	0.777	0.777	0.777	0.777	0.777

TABLE 7: PASSTHROUGH PER REGION

The table reports passthrough estimates by lending region to the interest rates of commercial loans around the introduction of the 2014 SOLCA tax in Ecuador. Data are at the loan-level for 2010 to 2017, excluding October 2014. The main independent variable is the tax rate, measured as 0.5 adjusted proportionally by term-to-maturities if maturity is less than 1 year. The dependent variable is the tax-inclusive interest rate, which is the sum of the nominal, annualized interest rate plus the tax rate. Both are in percentage points. Regressions control for twenty buckets of term-to-maturity, and twenty buckets of loan amount, predicted default probability, and bank × firm (pair) FE. The model is separately estimated by region. Robust standard errors are clustered at the bank-quarter level.

	Passthrough (ρ)	**S.E.**	**Observations**	**P-value** (**Passthrough = 1**)
Azuay	0.508	0.276	39,610	0.072
Costa	0.438	0.344	15,139	0.104
Guayas	0.727	0.160	176,907	0.090
Pichincha	0.346	0.301	95,380	0.031
Sierra	0.537	0.401	20,435	0.251

TABLE 8: PRICE PREDICTION REGRESSIONS

The table reports estimates of Equation 20, 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**
log(Total Assets)	-0.310***	-0.392***	-0.0259***	-0.0309***
	(0.00545)	(0.00538)	(0.00703)	(0.00711)
log(Total Debt)	0.0886***	0.119***	0.00922	0.00882
	(0.00488)	(0.00480)	(0.00601)	(0.00605)
log(Total Revenue)	0.124***	0.151***	0.0247***	0.0274***
	(0.00384)	(0.00378)	(0.00421)	(0.00424)
log(Capital)	-0.0173***	-0.0287***	-0.00565***	-0.00106
	(0.00136)	(0.00135)	(0.00160)	(0.00163)
log(Wages)	0.0778***	0.0632***	-0.0137***	-0.0141***
	(0.00242)	(0.00239)	(0.00336)	(0.00338)
log(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)
Log(Amount Borrowed)	-0.384***	-0.284***	-0.172***	-0.141***
	(0.00178)	(0.00191)	(0.00201)	(0.00206)
Log(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 9: 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 400 bootstrap samples. *, **, 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***	(0.030)
Azuay	Scaling Factor	−0.027	(0.351)
Azuay	Log(Branches)	0.869	(2.346)
Azuay	Age Firm	0.376***	(0.007)
Azuay	Age Relationship	0.183***	(0.037)
Azuay	Assets	0.109	(0.138)
Azuay	Debt	−0.025	(0.063)
Azuay	Expenditures	0.165***	(0.045)
Azuay	Revenue	0.003	(0.043)
Azuay	Wages	0.123***	(0.027)
Costa	Price	−0.048**	(0.021)
Costa	Sigma	1.421***	(0.035)
Costa	Scaling Factor	−0.046	(0.424)
Costa	Log(Branches)	0.827	(1.134)
Costa	Age Firm	0.204***	(0.007)
Costa	Age Relationship	0.148***	(0.034)
Costa	Assets	0.019	(0.062)
Costa	Debt	−0.005	(0.030)
Costa	Expenditures	0.060*	(0.036)
Costa	Revenue	0.023	(0.035)
Costa	Wages	0.063**	(0.027)
Guayas	Price	−0.434***	(0.158)
Guayas	Sigma	−0.069	(0.066)
Guayas	Scaling Factor	−0.016	(0.343)
Guayas	Log(Branches)	0.732	(1.685)
Guayas	Age Firm	0.215***	(0.009)
Guayas	Age Relationship	0.036	(0.042)
Guayas	Assets	0.022	(0.125)
Guayas	Debt	−0.007	(0.071)
Guayas	Expenditures	0.062**	(0.028)
Guayas	Revenue	0.021	(0.032)
Guayas	Wages	0.016	(0.029)

Continued on next page

TABLE 9 – continued from previous page

Region	Variable	Mean	Standard Deviation
Pichincha	Price	−0.386***	(0.101)
Pichincha	Sigma	1.156***	(0.057)
Pichincha	Scaling Factor	−0.014	(0.308)
Pichincha	Log(Branches)	0.735	(1.543)
Pichincha	Age Firm	0.205***	(0.007)
Pichincha	Age Relationship	0.157***	(0.029)
Pichincha	Assets	0.051	(0.104)
Pichincha	Debt	−0.010	(0.055)
Pichincha	Expenditures	0.207***	(0.039)
Pichincha	Revenue	0.002	(0.038)
Pichincha	Wages	−0.003	(0.033)
Sierra	Price	−0.091***	(0.012)
Sierra	Sigma	1.168***	(0.038)
Sierra	Scaling Factor	−0.033	(0.540)
Sierra	Log(Branches)	0.865	(1.596)
Sierra	Age Firm	0.225***	(0.008)
Sierra	Age Relationship	0.152***	(0.040)
Sierra	Assets	−0.009	(0.094)
Sierra	Debt	−0.026	(0.044)
Sierra	Expenditures	0.395***	(0.043)
Sierra	Revenue	0.012	(0.037)
Sierra	Wages	0.078**	(0.034)

TABLE 10: LOAN DEMAND, OWN-PRODUCT AND CROSS-PRODUCT DEMAND ELASTICITIES

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

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

TABLE 11: DESCRIPTION OF MODEL FIT

The table presents measures of model fit regarding market shares, loan use, prices, and default rates. Differences in observations are because loan use, prices, and default are only measured for actual, realized loans.

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

TABLE 12: MOVE TO COMPETITION

This table presents the estimated borrower-bank-loan specific (panel A) marginal costs under two modes of conduct (Bertrand Nash: Not Accounting for Conduct; and Joint Maximization: Accounting for Conduct). Panel B presents predicted prices and contrast them with equilibrium prices after shutting down conduct $\upsilon_m = 0$. Panel C shows the markups under Bertrand and Joint Maximization, as well as the equilibrium markups after shutting down conduct. Lastly, Panel D shows the intensive and extensive margin effects from shutting down conduct to zero.

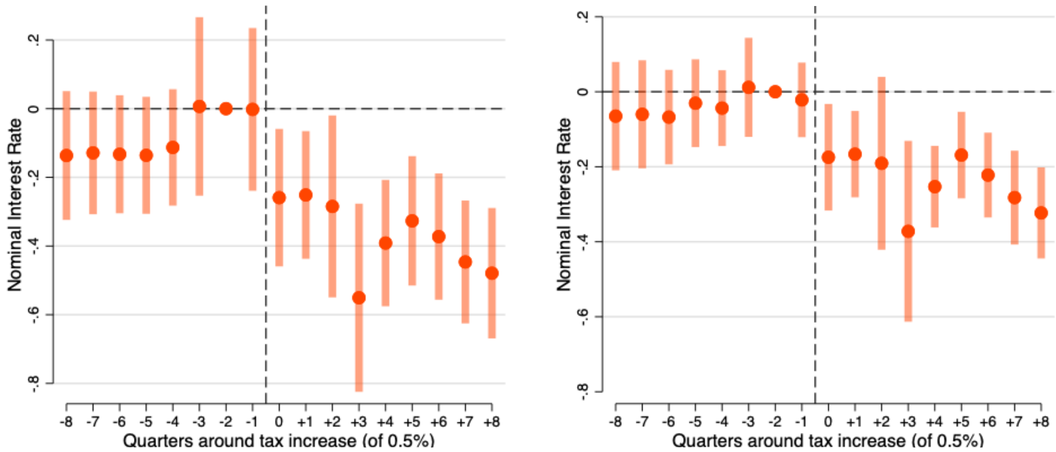
	Mean	**Median**
	Panel A: Marginal Costs	
Marginal Cost - Not Accounting for Conduct	9.07	9.55
Marginal Cost - Accounting for Conduct	5.01	3.18
% Change in Marginal Cost	-50.57	-55.75
	Panel B: Prices	
Prices - Predicted	11.25	11.56
Prices - Move to Bertrand-Nash	9.43	10.34
% Change in Equilibrium Prices	-17.18	-5.36
	Panel C: Markups	
Markup - Not Accounting for Conduct	2.19	2.12
Markup - Accounting for Conduct	6.24	4.56
Markup - Move to Bertrand-Nash	4.42	2.27
% Share of Markup due to Conduct	26.27	20.64
	Panel D: Intensive & Extensive Margin	
% Change in Continuous Loan Use - Move to Bertrand-Nash	21.39	20.29
Market Share Outside Option - Predicted Prices	0.033	
Market Share Outside Option - Move to Bertrand-Nash	0.029	

TABLE 13: SIMULATED VS. ACTUAL PASSTHROUGH BY REGION

The table shows the region-level empirical and simulated passthrough. The empirical passthrough are estimates of the passthrough by lending region to the interest rates of commercial loans around the introduction of the 2014 SOLCA tax in Ecuador. Data are at the loan-level for 2010 to 2017, excluding October 2014. The main independent variable is the tax rate, measured as 0.5 adjusted proportionally by term-to-maturities if maturity is less than 1 year. The dependent variable is the tax-inclusive interest rate, which is the sum of the nominal, annualized interest rate plus the tax rate. Both are in percentage points. Regressions control for twenty buckets of term-to-maturity, and twenty buckets of loan amount, predicted default probability, and bank × firm (pair) FE. To produce the simulated passthrough we use the estimated supply and demand parameters from our model to simulate passthroughs of the introduction of the 0.5% tax rate for each mode of conduct (Bertrand-Nash and joint maximization), while flexibly accounting for demand heterogeneity. The tax shock is modeled as a 0.5 percentage point linear increase in the bank-borrower-specific marginal costs of lending. Then, for each borrower, we use their estimated demand functions to solve for the Nash equilibrium of prices implied by the system of equations of first-order conditions (Equation 7) for all banks in their choice set, under the assumption that $\upsilon_m = 0$ under Bertrand-Nash and $\upsilon_m = 1$ under joint maximization. Columns (2) and (3) describe the results of following this rpocess for 1,000 bootstrap simulations, where we sampled borrowers with replacement.

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

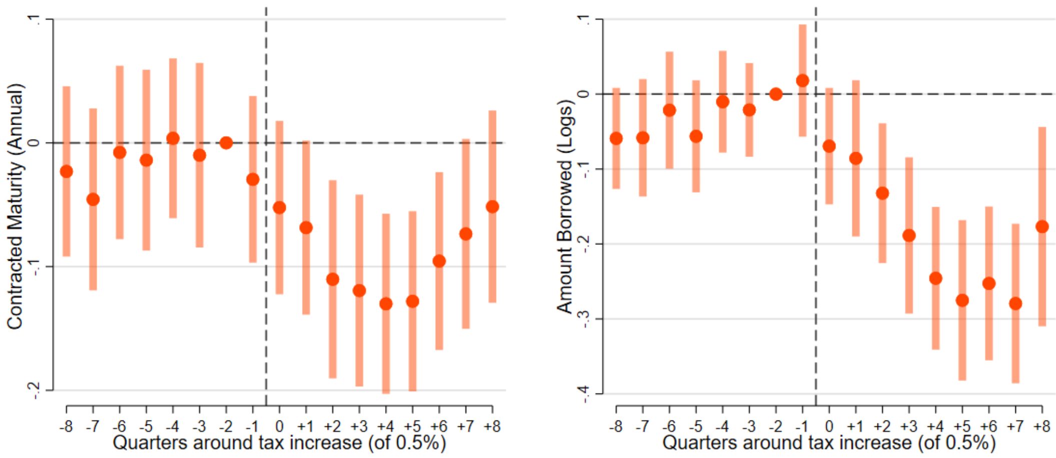
Appendix A Robustness of passthrough estimates



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

FIGURE A1: DYNAMIC ANALYSIS OF THE INTRODUCTION OF THE SOLCA TAX ON NOMINAL INTEREST RATES OF NEW COMMERCIAL DEBT LENT BY PRIVATE BANKS

The figure reports the period-by-period difference in average nominal interest rates from private banks around treatment assignment relative to event-time period $t = -2$ (normalized to zero), using firm FE plus bank FE (Panel (a)) and firm × bank FE (Panel (b)). Data are loan-level on commercial loans granted by private banks to Ecuadorian corporations. The figure tests for both treatment effects and looks for evidence of significant differences in outcomes before treatment assignment (pre-trends). Standard errors 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 A2: DYNAMIC ANALYSIS OF THE INTRODUCTION OF THE SOLCA TAX ON MATURITY AND AMOUNT OF NEW COMMERCIAL DEBT LENT BY PRIVATE BANKS

The figure reports the period-by-period difference in average term-to-maturity (Panel (a)) or the log of amount borrowed (Panel (b)) for new loans around treatment assignment relative to event-time period $t = -2$ (normalized to zero). Both specifications control for bank FE and firm FE. Data are loan-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-quarter level.

Appendix B 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 default predictors, 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 micro credit, and if a firm has only one lender relationship, and firm, province-year and sector-year fixed effects. Table A1 portrays the 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 A1: COMMERCIAL LOAN DEFAULT MODEL

	(1)	(2)	(3)	(4)
VARIABLES	1(Default)	1(Default)	1(Default)	1(Default)
Firm Age at Grant	-0.00757***	-0.00695***	-0.00875***	-0.00828***
	(0.000856)	(0.000930)	(0.000992)	(0.00102)
Term-to-Maturity (Months)	-0.0470***	-0.0580***	-0.0619***	-0.0623***
	(0.00766)	(0.00801)	(0.00837)	(0.00851)
log(Amount borrowed)	-0.0148***	-0.0248***	-0.0241***	-0.0271***
	(0.00460)	(0.00500)	(0.00518)	(0.00530)
Nominal Interest Rate	0.0289***	0.0269***	0.0251***	0.0244***
	(0.00227)	(0.00235)	(0.00262)	(0.00266)
log(Total Wages)	-0.0170***	-0.0158***	-0.0129***	-0.0177***
	(0.00425)	(0.00437)	(0.00452)	(0.00461)
log(Total Assets)	-0.00455	-0.00385	0.00277	0.00534
	(0.00758)	(0.00784)	(0.00815)	(0.00835)
log(Total Revenue)	-0.0323***	-0.0320***	-0.0334***	-0.0324***
	(0.00415)	(0.00428)	(0.00443)	(0.00453)
log(Total Debt)	-0.0545***	-0.0502***	-0.0566***	-0.0537***
	(0.00700)	(0.00719)	(0.00745)	(0.00761)
Leverage Ratio	0.0643**	0.0571**	0.112***	0.121***
	(0.0272)	(0.0280)	(0.0283)	(0.0288)
Tangibility Ratio	0.424***	0.412***	0.394***	0.316***
	(0.0374)	(0.0385)	(0.0397)	(0.0423)
Total Bank Relationships	-0.00873	-0.0192**	-0.0245***	-0.0133
	(0.00777)	(0.00818)	(0.00867)	(0.00884)
Age of Relationship at Grant	-0.145***	-0.135***	-0.155***	-0.152***
	(0.00653)	(0.00670)	(0.00743)	(0.00760)
1(Below A Rating) = 1	2.017***	2.103***	2.160***	2.189***
	(0.0266)	(0.0282)	(0.0293)	(0.0299)
1(Microcredit) = 1	0.144**	0.141**	0.0941	0.0805
	(0.0650)	(0.0672)	(0.0700)	(0.0714)
1(Only 1 Bank) = 1	0.133***	0.167***	0.154***	0.163***
	(0.0303)	(0.0313)	(0.0323)	(0.0329)
Constant	-1.772***	-1.485***	-2.275***	-2.275***
	(0.0739)	(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

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Appendix C Price prediction

TABLE A2: 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 8. The same set of controls are used as in the corresponding Model in Table 8. 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.

Appendix C.1 Firm matching model

TABLE A3: 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 reports the

Appendix D Demand Estimates

TABLE A4: DEMAND PARAMETERS

The table presents the mean and standard deviation of estimated parameters across markets (provinces). The coefficient for *Price* comes from an instrumental variable approach that corrects for price endogeneity and measurement error in predicted prices for non-observed offers. The standard deviation is calculated as the standard error of the parameter values obtained by estimating the model on 200 bootstrap samples.

Variable	**(1)** **Mean**	**(2)** **Standard Deviation**
Price	-0.24	0.08
Sigma	0.81	0.04
Scaling factor	1.06	0.39
Log(Branches)	2.26	2.76
Age Firm	-0.03	0.01
Age Relationship	0.39	0.04
Assets	0.24	0.11
Debt	-0.01	0.05
Expenditures	0.06	0.04
Revenues	-0.02	0.04
Wages	0.01	0.03

TABLE A5: 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 22. $\widehat{Price}$ are the estimates of the instrumented price parameter. *t-statistic* is the associated t-statistic for a test against the null of zero. *F-statistic* is the Cragg-Donald Wald F statistic for the first-stage against the null that the excluded instruments are irrelevant in the first-stage regression. Finally, *P-value over-identification* is the p-value for a Sargen-Hansen test of over-identifying restrictions with the null hypotheses that the error term is uncorrelated with the instruments.

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

Appendix E Simulations and Counterfactual Exercises

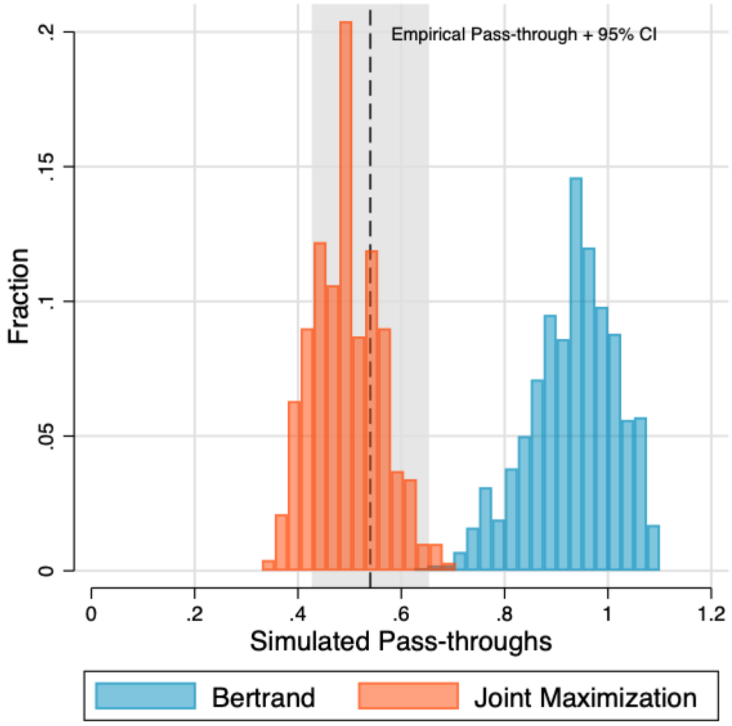


FIGURE A3: DISTRIBUTION OF SIMULATED PASSTHROUGHS FOR CHOSEN BANKS BY CONDUCT

The figure reports the distribution of nation-wide bootstrapped average simulated Nash-equilibrium passthroughs of a tax introduction of 0.5% by mode of conduct (Bertrand-Nash in blue and Joint Maximization in Orange). *Only simulated passthroughs for the bank the firms actually chose to borrower from are included.* Bootstrap estimates come from 1,000 bootstrapped samples of borrowers-level estimates of passthrough under each model. The dashed line shows the estimated empirical passthroughs regressions (using data with actual loans) presented in the reduced-form section of the paper, and the shaded area shows the 95% confidence interval.

Appendix F Ecuadorian Banking Sector

Overall, Ecuador is typical of similar middle-income, bank-dependent economies studies in the literature. 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)). Overall, the Ecuadorian financial sector is typical of banking systems in the Latin American region and of middle-income economies broadly.

[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 rates place constraints on bank market power and affect the distribution of credit and this is reflected in our model.