Taxation when markets are not competitive: Evidence from a loan tax

Felipe Brugués

Rebecca De Simone[†]

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Abstract

We explore how lender market structure affects the efficiency and equity of financial taxation, an important revenue source and policy tool for governments worldwide. Using a natural experiment—the unexpected introduction of a loan transaction tax in Ecuador—we employ pass-through estimates, a quantitative model, and a comprehensive commercial loan dataset to investigate this issue. Our model broadens the scope of traditional bank competition theories by allowing for a range of competitive behaviors, including joint profit maximization, credit rationing, and Bertrand-Nash competition. Contrary to the common assumption of fully competitive differentiated lending markets, we find little evidence to support pure Bertrand-Nash competition or credit rationing. Instead, our results are more consistent with joint profit maximization among banks. While we find that loan taxes are indeed greatly distortive, neglecting the possibility of uncompetitive lending inflates estimated tax deadweight loss by approximately 80 to 120%. This distortion occurs because non-competitive banks internalize a portion of the tax burden. Conversely, subsidies are less effective in non-competitive settings. Findings suggest policymakers consider the interplay between market structure and tax-and-subsidy strategies.

[†]The authors are from the Business School of Instituto Tecnológico Autónomo de México and the London Business School, respectively. They can be reached at felipe.brugues@itam.mx and rdesmone@london.edu.
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Understanding the relationship between lender competition and the welfare effects of financial taxes and subsidies is crucial for policymakers. However, classic public finance theories, often cited in policy recommendations, usually assume perfect competition, neglecting that tax effectiveness could depend on the market's competitive structure (Weyl and Fabinger, 2013; Pless and van Benthem, 2019).[1] This assumption underscores opposition to financial taxes because they are considered highly distortive. For example, the IMF routinely advises governments not to tax capital. However, optimal taxation is challenging to implement in many low- and middle-income countries where governments instead focus the tax burden on large firms, banks, and similar sectors where it is easier to enforce tax payment (Besley and Persson, 2009). Moreover, capital taxes are a popular policy tool for governments that raise sufficient tax revenue elsewhere.

So, is a blanket proscription justified when markets are not competitive? The empirical evidence is thin. This paper exploits a natural experiment to empirically investigate how the market structure in commercial lending influences the effectiveness and incidence of financial transaction taxes. Specifically, we use the unanticipated introduction in 2014 of a loan-transaction tax in Ecuador to fund a public cancer hospital (Sociedad de Lucha Contra el Cáncer, or SOLCA).

Ecuador designed the SOLCA tax as a one-time charge of 0.5% of the value of credit at the point of loan approval.[2] Crucially, the tax was unanticipated in the press and amongst lobbyists and swiftly enacted—it was proposed in September and was in effect in October 2014. Thus, the SOLCA tax introduction serves as (1) a representative type of capital tax employed in more than 40 countries, and (2) a quasi-exogenous shock to the marginal cost of lending, uncorrelated with any concurrent changes in credit demand.[3]

We leverage comprehensive administrative data from 2010 to 2017 that allow us to measure loan-level contract terms for new commercial credit and detailed firm-level information for

[1] See Slemrod (1990) and Auerbach (2002) for excellent overviews of the classical paradigm in public finance.

[2] Specifically, the tax was 0.5% for credit with maturity greater than one year and 0.5%*(maturity in months/12) for credit with maturity below one year during our sample period. See Section 1 for details.

[3] Countries that impose financial transaction taxes beyond Ecuador include Argentina, Brazil, Peru, Columbia, Venezuela, Bolivia, Egypt, South Africa, Hungary, Spain, Sweden, and Malaysia. In 2020, the CEPR estimated more than 40 countries use a type of financial transaction tax. See https://cepr.net/report/financial-transactions-taxes-around-the-world/ [accessed 8 August 2023]. Moreover, financial transaction taxes are frequently proposed, including in the Inclusive Prosperity Act proposed by Senator Bernie Sanders in 2019 and COM/2013/71 proposed by the European Commission in 2013, which is still on the table as of 2023.

commercial borrowers. By relying on the unexpected nature of the introduction of the tax, we obtain pass-through estimates through event-studies specifications. On average, borrowers shoulder between 30 to 50% of the loan tax, with banks absorbing the remainder by reducing the loan interest rate.[4]

While the reduced-form results provide credible pass-through estimates, past theoretical results (Weyl and Fabinger, 2013) show these are not sufficient to fully characterize distortions and incidence without making an assumption on the competitive mode of conduct in the market, such as Bertrand-Nash competition, credit rationing (Cournot), or joint maximization. To account for this issue, we introduce a flexible discrete-continuous structural model of commercial lending that nests various forms of market competition used in the literature (e.g., Crawford et al., 2018; Benetton, 2021) and can be estimated using traditional methodologies (Train, 1986). This approach relaxes the need to make an *a priori* assumption on the competitive conduct in the market. While flexible, it introduces an additional difficulty. Namely, the known result that competitive conduct and supply-side parameters are not separately identified with price and quantity data alone (Bresnahan, 1982). Our key innovation is the insight that the pass-through estimates themselves serve as quasi-experimental variation in the marginal cost of lending that are sufficient to identify the general competition parameter.

Our model transparently maps the estimated pass-through rate and demand parameters into inference about the form of competition. We find that lenders are not competing. The estimated conduct parameter that captures how lenders value other lenders' profits is statistically indistinguishable from that representing a perfectly collusive model in which lenders form agreements (perhaps tacitly) about prices and act as a single profit-maximizing monopolist in the market. We can rule out that banks are Bertrand-Nash or Cournot (credit rationing) competing with 95% confidence.

Why might banks collude? The easy answer is that, as in other sectors, banks prefer higher markups. But specific to banking, policymakers balance macroprudential goals, which favor

[4]Note that this reduced-form, incomplete pass-through on its own is indicative of imperfect competition. If lenders priced purely based on lending's marginal cost, they wouldn't feasibly decrease interest rates in response to the new tax. However, reduced-form pass-through alone cannot confirm collusion in a model-free way. The same observed pass-through is consistent with differing values of the conduct parameter capturing lender collusion when demand elasticities are not held constant.

market concentration in lending, against the potential drawbacks related to credit cost and distribution (Keeley, 1990; Hellmann et al., 2000; Beck et al., 2013). We also provide evidence supporting collusion specifically in our setting. Markets with lower competition as measured by standard competition proxies also have less competitive passthrough and collusion parameters (conduct). Moreover, banks that are members of a banking association that anecdotally helps lenders coordinate indeed have less competitive passthrough and conduct.

We then use our model to quantify how important competition in commercial lending is to the welfare effects of the bank tax. Not accounting for lender collusion would vastly overstate the welfare costs of bank transaction taxes and the welfare gains from subsidies. If we incorrectly assume no bank collusion when setting interest rates, we estimate the Ecuadorian loan tax's deadweight loss to be 96 cents per dollar. Instead, we estimate a significantly smaller loss of 36 cents per dollar by allowing the model to depart from differentiated Bertrand-Nash price competition, the most common conduct used in the literature. Thus, the tax would be less distortive than originally believed. In terms of incidence, we also find that borrowers would shoulder a more significant portion of the tax in a competitive setting. In contrast, the incidence falls on banks in the joint maximization environment. Hence, the policymaker's evaluation of the implications of such taxation would be greatly affected both on size and incidence, depending on the market structure assumption.[5]

While our study focuses on the 2014 SOLCA tax in Ecuador, its implications extend beyond this specific context due to the global prevalence of uncompetitive banking sectors and the widespread use of financial taxes. What is more, financial taxes are ubiquitous around the world, which implies that our results offer valuable insights to inform the effectiveness of capital taxes more generally, as well as taxes and subsidies designed for policy objectives, like carbon taxes, which can vary significantly based on sectoral competition. Indeed, at the most basic economic level, the SOLCA tax serves as a quasi-exogenous shock to the marginal cost of lending. Thus, our methodology readily applies to other marginal cost shocks, such as studying

[5] Let us say explicitly that policymakers would consider many factors, including the relative cost-benefit of collusion in lending markets itself. In related work (Brugués and De Simone, 2023), we quantify the *costs* of collusion among lenders in terms of both the extensive and intensive margin of credit in the economy. This does not negate the fact that the impact of the tax itself depends on lender competition, i.e., holding conduct constant.

the effect of interest rate pass-through when lending markets are not competitive.[6]

Our study advances the literature in several ways. First, we offer one of the first empirical pieces of evidence of how market structure mediates the effects of financial transaction taxes, and the first in the economically important commercial lending sector. Our study builds upon an extensive literature focusing on the welfare and distributional effects of the pass-through of taxes (and regulatory costs equivalent to taxes) in product markets (Nakamura and Zerom, 2010; Fabra and Reguant, 2014; Ganapati et al., 2020), as well as the theoretical literature linking such effects to competitive environments (Weyl and Fabinger, 2013). However, the distributional effects of taxes in lending markets and how this depends on the market structure of the banking industry are less studied. Reduced-form evidence from high-income countries supports that pass-throughs vary by market concentration (Scharfstein and Sunderam, 2016; Drechsler et al., 2017; Benetton and Fantino, 2021). While suggestive, these do not illuminate the source of bank pricing power. Our paper adopts a distinct public finance lens, investigating how bank concentration mediates the welfare effects of financial tax policy.

Specifically, we underscore the significance of competition, estimating its direct effects on lending markets by leveraging the SOLCA loan transaction tax introduction in Ecuador. Our methodology, reminiscent of Atkin and Donaldson (2015) in international trade and Bergquist and Dinerstein (2020), offers a novel approach underrepresented in the lending literature. There are also a few related papers outside the lending context. Ganapati et al. (2020) study the welfare effects of energy input costs for US manufacturers when accounting for imperfect competition. Like us, they find that the incidence of cost shocks on consumers is lower under collusion than when firms compete. Miravete et al. (2018) study the tradeoff between tax rates and revenue when markets are not competitive using the setting of retail sales of alcohol in Pennsylvania. As in our study, they find that the government's revenue gain is significantly lower than expected under standard differentiated price competition. Our study demonstrates

[6]A substantial literature documents the pass-through 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; Eisenschmidt et al., 2023; Li et al., 2013). Our results can extrapolate to this question to the extent interest rate changes act through similar cost-shifter mechanisms as a tax. The advantage of using the SOLCA tax as a setting to estimate the magnitude of the impact rather than interest rate changes is that the tax is a cleaner shock. For example, it is more credible that the tax did not impact welfare both directly and through large feedback effects, such as changing the investment opportunity set. This is less credible in the interest rate setting.

how market competition affects the incidence and effectiveness of the SOLCA tax as a case study applicable more generally to a wide range of capital taxes and fees.

Second, we contribute a methodological innovation by using the pass-through of the SOLCA tax to estimate a free bank conduct parameter and quantify the degree to which banks collude and what market features facilitate collusion. This strategy allows us to empirically test the competition model of lending directly. A substantial portion of the credit literature—Crawford et al. (2018) and Cox et al. (2020) in commercial lending but also in deposits (Egan et al. (2017)), mortgages (Robles-Garcia (2021); Benetton (2021)), auto lending (Yannelis and Zhang (2021)), and consumer lending (Cuesta and Sepúlveda (2021))—focuses on non-collusive models and the role of lending market frictions. We provide a fresh perspective by generalizing bank conduct so that we can estimate how markups reflect pricing power from the demand-side factors emphasized in these papers and how much they reflect lender collusion. Our approach is in the spirit of Atkin and Donaldson (2015), who use observable pass-through to determine the division of surplus between consumers and intermediaries stemming from international trade, and of Bergquist and Dinerstein (2020), who use experimentally estimated pass-throughs in agricultural markets to test for collusion of intermediaries. To our knowledge, this approach is novel in the lending literature.

The rest of the paper is organized as follows. Section 1 describes the SOLCA tax, the Ecuadorian credit market, and our data sources. Section 2 presents our baseline model of commercial lending, with Section 2.1 describing how we identify the conduct parameter using pass-through from the SOLCA tax. Section 3 presents the empirical pass-through estimates. Section 4 describes how we estimate the model. Section 5 presents the estimation results, model validation exercises, and counterfactual simulations. Section 7 concludes.

1 Description of SOLCA Tax and Dataset

1.1 Loan Transaction Tax

Like many developing countries, particularly in Latin America, Ecuador employs bank levies as a revenue source (Kirilenko and Summers, 2003). Starting in 1964, Ecuador utilized a bank levy to raise funds to fund cancer treatment (Sociedad de Lucha contra el Cáncer or SOLCA tax). This tax applied to financial operations at rates between 0.25 to 1 percent of the value of the transaction or loan. In 2008, the Ecuadorian government eliminated all taxes on financial transactions, including the SOLCA tax, opting instead to fund cancer treatment and research through the regular budget.

However, in September 2014, the Ecuadorian National Assembly ratified a new law called the "Código Orgánico Monetario y Financiero" that standardized banking, finance, and insurance regulations. A last-minute amendment reintroduced the SOLCA tax to address funding gaps for cancer treatment.[7] This reintroduction was unexpected by both borrowers and financial institutions in Ecuador.[8] The government implemented the new SOLCA tax by the end of October 2014, a mere month after the law's passage.

The tax, collected by banks at loan grant and remitted to the tax authority, is levied on borrowers for each new loan. It applies to commercial, credit card, auto, and mortgage loans. Throughout our sample period, 2010-2017, only loans from private banks were subject to the SOLCA tax; the law exempted loans from state-owned banks. However, since state-owned banks do not primarily compete in conventional commercial credit, the tax effectively applied to all commercial loans. The tax amount varies with loan maturity: loans with a one-year or longer term incur the full 0.5% tax, while shorter-term loans are taxed proportionally.[9]

In summary, the re-introduction of the SOLCA tax was unanticipated and implemented swiftly. It applies to the universe of conventional (non-micro) commercial loans. Next, we describe the data that allow us to pin down the impact of the tax on commercial loan terms.

1.2 Datasets

We construct a comprehensive and detailed dataset from administrative databases collected by Ecuador's bank regulator, the Superintendencia de Bancos, and its business bureau, the

[7]The law also regulated mobile money payments and strengthened anti-money laundering measures.

[8]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 29^{th} of July 2014, in *El Universo*; and "El Código Monetario pasó con reformas de última hora," by Mónica Orozco, published the 25^{th} of July 2014 in *El Comerico*.

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

Superintendencia de Compañías. The data are quarterly and span the period between January 2010 and December 2017.

The primary data are the universe of new and outstanding commercial bank loans from banks operating in Ecuador between 2010 and 2017. This encompasses loans from 27 private commercial banks and six state-owned banks. These state-owned banks predominantly offer microloans to small businesses and retail mortgages.

While the dataset is not a credit registry—it doesn't allow banks to view other banks' loan information—it provides similar types of information. Variables include loan amount, type, interest rate, term-to-maturity, and internal bank risk assessments at the time of loan issuance. Additionally, it includes quarterly snapshots on outstanding loans, including repayment performance data and loan drawdown.

For our analysis, we focus only on regular commercial loans issued to registered corporations. This excludes microloans and loans to sole proprietorships. State-owned banks are also excluded from our main analyses.[10] This specialization matches our firm data 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.

We use a unique firm identifier to merge the loan dataset with annual, firm-level data from the Superintendencia de Compañías, Ecuador's business bureau. This dataset provides balance sheets, income statements, and wage information.

1.3 Descriptive Statistics

We now describe the Ecuadorian commercial loan market and our main loan- and firm-level variables. Table 1 displays bank-province-year level credit statistics. The average (median) bank issues $59M ($1.4M) in corporate loans annually. A few banks dominate the commercial loan market. The average bank lends to 83 corporations in a year, but 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. Thus, the competitive structure of Ecuador's commercial loan sector is broadly representative of corporate lending elsewhere.

[10]We use data from state-owned banks for counterfactual analyses only, to check if the terms of loans not affected by the SOLCA tax changed at the same time.

[Place Table 1 here.]

To see this from another angle, Table 2 presents descriptive statistics on market access and lending by market concentration, as measured by the Herfindahl–Hirschman Index (HHI) based on commercial lending share over 2010 to 2017. Sensibly, highly concentrated markets feature fewer branches and fewer competing banks. Branches in highly-concentrated markets are smaller, cater to fewer clients, offer fewer loans in total as well as per client, and offer slightly shorter maturities and charge higher interest rates.

[Place Table 2 here.]

Next, Table 3 provides summary statistics on the merged commercial loan dataset spanning the years 2010 to 2017. The top panel summarizes the data at the firm-year level. We have 457,623 firm-year observations, corresponding to 31,903 unique corporations. Of these, 97,796 firm-year observations relate to active firm-year borrowers, whereas 359,827 observations pertain to non-borrowing firm-years. The average borrowing firm is roughly twelve years post-incorporation and possesses, on average, $2M in assets. However, it's worth noting that the firm size distribution is highly skewed—the median firm holds only $400,000 in total assets. Total sales demonstrate a similar skew, with average (median) sales of $2.6M ($620,000). The average (median) borrowing firm is highly leveraged, displaying a total debt-to-assets ratio of 0.66 (0.71). In contrast, non-borrowing firms are generally younger, with a mean age of around ten years since incorporation, and are smaller, with mean (median) assets of $460,000 ($50,000) and mean (median) sales of $430,000 ($30,000). These 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 active borrowers in a given year. The bottom panel describes the loan-level data for the universe of commercial (non-micro) loans granted to corporations between 2010 and 2017. On average, firms maintain 1.38 (1) banking relationships within a given borrowing year. The average (median) duration of these borrower-lender relationships is 2.31 (2) years. Most clients repeatedly borrow from the same bank, as indicated by the average client borrowing 9 (2) times in a year. Each loan is for on average \$100,000 (median \$10,000) and usually possesses a six (three) month term-to-maturity. The loans carry an average (median) annualized nominal interest rate of 9.20% (8.95%).

The banks in our sample only write down the value of about two percent of the loans. Actual default is a rare occurrence in our sample, happening less than 1% of the time; in the total sample, which includes sole proprietorships and micro-loans, the default rate is 3%. The general impression is of a small pool of safe firms able to access formal bank loans, albeit at relatively high interest rates and with short maturities. This trend is common worldwide among countries at various stages of economic development, particularly those outside major capital markets like the United States and the United Kingdom. We provide additional evidence that the Ecuadorian commercial loan market is representative in Appendix Appendix H, where we report correlations between average equilibrium interest rates and market characteristics at the aggregated bank-province-year level. The general patterns we observe between market access and loan pricing align with those documented in the existing literature.

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.

2 Model of Commercial Lending with Endogenous Collusion

We have already outlined the state of the Ecuadorian commercial lending market at the time of the re-introduction of the SOLCA tax and established that commercial credit in Ecuador is comparable to commercial credit in other economies. This serves as the institutional framework upon which we build our analyses.

In this section, we introduce the theoretical framework—a quantitative model of commercial lending. The model enables us to directly characterize bank competition and its impacts. For a complete exposition of the model's main features, please refer to Appendix A.

Our model is most applicable to small-to-medium-sized, single establishment firms and to private, traditional deposit-funded banks. We assume that borrowers and lenders are risk neutral, borrowers have the freedom to choose from any bank in their local market, and the returns on borrowers' investments can be parameterized.

First, firm i in period t decides whether to borrow from one of the banks k actively lending in market m.[11] The (indirect) profit function for borrower i choosing bank k in market m at time t is defined as follows:

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

Here, $\overline{\Pi}_{ikmt}$ represents the indirect profit function of the optimized values of loan usage, L_{ikmt}, which is equivalent to an indirect utility function in the consumer framework. X_{it} denotes observable characteristics of the firm, such as assets or revenue. r_{ikmt} is the interest rate.[12] X_{ikmt} represents 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 (by the bank and the econometrician) borrower characteristics, like shareholders' net worth and management's entrepreneurial ability. ξ_{kmt} captures unobserved bank characteristics that affect all firms borrowing from bank k. ε_{ikmt} is an idiosyncratic taste shock. Finally, β collects the demand parameters common to all borrowers in market m. If the firm chooses not to borrow, it gets the value of its outside option, $\Pi_{i0} = \varepsilon_{i0mt}$, normalized to zero indirect profit. Firms select bank k that gives them their highest expected indirect profit, such that demand probability is $s_{ikmt} = Prob(\Pi_{ikmt} \geq \Pi_{ik'mt}, \forall k' \in m)$.

Then, given the set K_{im} of banks in local market m in period t available for firm i, the total expected demand is pinned down by $Q_{ikmt}(r) = s_{ikmt}(r)L_{ikmt}(r)$. This relationship-level expected demand is given by the product of firm i's demand probability from bank k, s_{ikt} and its expected loan use L_{ikt} given posted interest rates $r = \{r_{i1mt}, ..., r_{1Kmt}\}$. Continuous-loan demand

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

[12] Unlike Benetton (2021), we allow the price to vary by borrower-bank pair.

is determined by Hotelling's lemma, such that input demand is given by $L_{ikmt} = -\partial\Pi_{ikmt}/\partial r_{ikmt}$.

On the supply side, we allow for different forms of competition among banks 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). Specifically, $\upsilon_m = 0$ corresponds to Bertrand-Nash, $\upsilon_m = 1$ to joint-maximization, and other values indicate intermediate degrees of competition, including those corresponding to Cournot competition, which we pin down in Section 5.5. Intuitively, the parameter captures the degree of correlation in price co-movements.

Banks choose borrower-specific interest rates to maximize their period-t profits.[13] Specifically, bank k offers interest rate r_{ikmt} to firm i to maximize bank profits B_{ikmt}, subject to the market conduct:

$$\max_{r_{ikmt}} B_{ikmt} = (1 - d_{ikmt}) r_{ikmt} Q_{ikmt}(r) - mc_{ikmt} Q_{ikmt}(r) \qquad (2)$$
$$\text{s.t. } \upsilon_m = \frac{\partial r_{ikmt}}{\partial r_{ijmt}} \text{ for } j \neq k,$$

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

$$(1 - d_{ikmt}) Q_{ikmt} + ((1 - d_{ikmt}) r_{ikmt} - mc_{ikmt}) \Big(\frac{\partial Q_{ikmt}}{\partial r_{ikmt}} + \upsilon_m \sum_{j \neq k} \frac{\partial Q_{ikmt}}{\partial r_{ijmt}} \Big) = 0. \qquad (3)$$

Rearranging Equation 3 yields:

$$r_{ikmt} = \frac{mc_{ikmt}}{1 - d_{ikmt}} - \frac{Q_{ikmt}}{\underbrace{\frac{\partial Q_{ikmt}}{\partial r_{ikmt}}}_{\text{Bertrand-Nash}} + \underbrace{\upsilon_m \sum_{j \neq k} \frac{\partial Q_{ikmt}}{\partial r_{ijmt}}}_{\text{Alternative Conduct}}}, \qquad (4)$$

which we express in terms of price elasticities:

$$r_{ikmt} = \frac{mc_{ikmt}}{1 - d_{ikmt}} - \frac{1}{\frac{\epsilon_{kk}}{r_{ikmt}} + \upsilon_m \sum_{j \neq k} \frac{\epsilon_{kj}}{r_{ijmt}}}. \qquad (5)$$

[13] That is, the banks compete on price. Yet, by including the conduct parameter we also allow for banks to compete in credit rationing, i.e., quantities following Cournot.

Much like a regular pricing equation, the model includes a marginal cost term and a markup. In our case, the markup comprises two components: 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 thus nests the Bertrand-Nash pricing behavior of Crawford et al. (2018) and Benetton (2021), but also allows for deviations due to collusive conduct among banks. For $\upsilon_m > 0$, the bank takes into account the joint losses from competition when setting loan rates. The higher the value υ_m, the more closely bank behavior aligns with full joint-maximization (monopoly), and the higher the profit-maximizing price r_{ikmt}. Our model also adjusts prices upward to account for expected risk from non-repayment, plausibly capturing adverse selection in risk.[14] [15]

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

[14]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 those in both these papers, 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, collusion, etc.

[15]Our model does not endogenize the default decision, in contrast to Crawford et al. (2018), as base default rates are low in our setting and previous evidence in developing countries shows moral hazard might have second-order effects (Castellanos et al., 2023).

2.1 Identification of the conduct parameter

Our model alone does not allow separate identification of the supply parameters. To understand why, 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.[16] By inverting Equation 5, we obtain:

$$mc_{ikmt} = r_{ikmt}(1 - d_{ikmt}) + \frac{1 - d_{ikmt}}{\frac{\epsilon_{kk}}{r_{ikmt}} + \sum_{j \neq k} \frac{\epsilon_{kj}}{r_{ijmt}}}. \tag{6}$$

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 $\upsilon_m \in [0, 1]$.

To overcome this difficulty, we follow insights from the public finance literature (Weyl and Fabinger, 2013), which demonstrate that the pass-through of taxes and marginal costs to final prices are tightly linked to competition conduct. By incorporating reduced-form pass-through estimates derived from the SOLCA tax, we introduce an additional identifying equation that enables us to separate marginal costs from conduct parameters.[17] The reason we can recover conduct with information on pass-through estimates is that, given estimates of demand elasticities (or curvatures), the relationship between conduct and pass-through is monotonic. Therefore, for a given observation of pass-through, and holding demand elasticities constant, only one conduct value could rationalize any given pass-through.

To express the pass-through rate as a function of bank conduct υ_m, we express Equation 3 into terms of semi-elasticities and apply the implicit function theorem, yielding

$$\begin{aligned} \rho_{ikmt}(\upsilon_m) \equiv & \frac{\delta r_{ikmt}}{\delta mc_{ikmt}} \\ = & \frac{(\widetilde{\varepsilon}_{kk} + \upsilon_m \sum_{j \neq k} \widetilde{\varepsilon}_{kj})/(1 - d_{ikmt})}{(\widetilde{\varepsilon}_{kk} + \upsilon_m \sum_{j \neq k} \widetilde{\varepsilon}_{kj}) + (r_{ikmt} - mc_{ikmt}/(1 - d_{ikmt}))\left(\frac{\partial \widetilde{\varepsilon}_{kk}}{\partial r_{ikmt}} + \upsilon_m \sum_{j \neq k} \frac{\partial \widetilde{\varepsilon}_{kj}}{\partial r_{ikmt}}\right)} \end{aligned} \tag{7}$$

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

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

As a result, Equations 6 and 7 together form a system of two equations in two unknowns (mc_{ikmt}, υ_m), thereby allowing the identification of supply parameters.

In practice, we only observe pass-throughs 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). By taking the expected value of these pass-through rates for different markets, we introduce an additional moment for each market to uniquely identify the conduct parameter υ_m for that market. Thus, the empirical analogue of those market moments can be used to estimate conduct in practice. Figure 1 provides an overview of how we connect our theoretical framework to the available data and the quasi-experimental variation supplied by the SOLCA tax.

[Place Figure 1 here.]

3 Estimating the SOLCA tax pass-through

In this section, we describe how we measure the pass-through of the SOLCA bank transaction tax on contracted nominal interest rates. This is the empirical variation we use to identify our model, described in Section 2 above. We first 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. Next, we describe how we directly estimate tax pass-through and interpret the pooled pass-through estimates. As a sanity check on our estimates, we perform reduced-form heterogeneity analysis describing how market-level pass-through varies with proxies for market competitiveness. Finally, we report the pass-through of the SOLCA tax at the regional level, which we will use later on to calibrate market-level conduct.

3.1 Checking Identification Assumptions

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.

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

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.[18] 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 A7). 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 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 pass-through of the tax to borrowers because banks bore some of the burden by lowering loan interest rates.[19] If, instead, δ_k is positive, there is more-than-complete pass-through, 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 pass-through of the tax to borrowers—the borrowers pay the entire tax, and the bank

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

[19] 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.

does not adjust the interest rate. If we assume a constant marginal cost, either incomplete or more-than-complete pass-through is evidence of imperfect competition in the commercial bank lending market.[20]

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 2 presents the evolution around the introduction of the tax of the coefficients from modeling Equation 8, i.e., from testing the effect of the tax on nominal interest rates of loans granted by private commercial lenders.

[Place Figure 2 here.]

The two panels are for regular loans. These are primarily borrowed by corporations regulated by the Ecuadorian Business Bureau ("SA" firms, for Sociedad Anónima, or RUC firms, for the name of their unique firm identifier).[21]

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 pass-through is (0.5-0.2) / 0.5 = 0.6, i.e., the lender and borrower approximately split the tax burden.[22] Estimated effects are similar if we use pair (bank-firm) fixed effects instead of separate bank and firm fixed effects, as shown

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

[21]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.

[22]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.

in the right panel of Figure 2.[23] 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 pass-through 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 pass-through estimate. Therefore, we 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 strikingly different. Figure 3 shows cyclical levels of nominal interest rates, none 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 anticipation of the SOLCA tax, supporting the institutional fact that the tax was a surprise and that other factors were not impacting interest rates of loans not subject to the SOLCA tax just after it was introduced.

[Place Figure 3 here.]

The SOLCA tax could affect loan contract terms other than interest rates. Figure 4 reports event study analyses where the outcome is loan term-to-maturity (left panel) or amount borrowed (right panel). The left panel of Figure 4 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

[23] 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.

implemented, both amount and especially maturity revert towards their pre-tax levels.

Note that there is a significant drop in the amount borrowed in the quarter before the SOLCA tax was released relative to the average amount borrowed two quarters before. In the quarter after the tax is introduced, the amount borrowed reverts back to its long-term prior trend. It is not clear what caused this reduction and there is no equivalent difference in either interest rates or maturity in this quarter. However, if anything, this decrease supports our assertion that the tax was unanticipated, as presumably if borrowers and lenders knew that a loan tax was going to be implemented they would have strong incentives to *increase* borrowing before the law was passed.

[Place Figure 4 here.]

Note that the theory of tax incidence under imperfectly competitive markets (Weyl and Fabinger, 2013; Pless and van Benthem, 2019) links price pass-through 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 Appendix Table A7, 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 pass-through. We, therefore, include contemporaneous maturity and loan amount in all regressions.

3.2 Estimating the Tax pass-through Directly

The event study specification described by Equation 8 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 pass-through. We therefore directly measure the pass-through 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:

$$rTax_{lfbt} = \rho tax_{lfbt} + \sum_{k=1}^{20} \beta_a^k 1\{A \in j\} + \sum_{k=1}^{20} \beta_m^k 1\{M \in z\} + \alpha_d DP_{lfbt} + \alpha_f + \alpha_b + \varepsilon_{lfbt}, \quad (9)$$

where $rTax$ is the tax-inclusive interest rate and tax is the tax amount in percent.[24] 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.[25] 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.[26] The time window is from eight quarters before the introduction of the tax to three quarters afterward. In this specification, ρ is the pass-through rate. Complete pass-through corresponds to $\rho = 1$, $\rho < 1$ indicates incomplete pass-through, and $\rho > 1$ corresponds to more-than-complete pass-through.

Model (1) of Table 4 reports the direct pass-through of the tax to tax-inclusive interest rates 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 pass-through 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).

[24]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).

[25]Notice a slight abuse of notation: while interest rates compound annually, the tax is only collected once, at the beginning of the credit. Hence, we are not directly comparing identical measures. Yet, most credit in our sample have term-to-maturity less than 1 year, so in practice, this abuse of notation has little effect. Indeed, in results not shown here we obtain almost identical estimates by restricting to contracts with term-to-maturity equal or less than 1 year.

[26]Indeed, in specifications with log-linear controls, pass-throughs are consistently lower than with the semi-parametric controls.

[Place Table 4 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 pass-through 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.

3.3 Heterogeneity by Market Competitiveness

We now turn to provide evidence that pass-through may be indicative of differences in market power and conduct across markets. The intuition is based on the insight from Weyl and Fabinger (2013) and others that pass-through is higher under Bertrand-Nash competition than under joint maximization, if demand is log-concave.[27] We therefore test if observed pass-through from the SOLCA tax is higher (lower) where we observe more (less) competitive conditions. This exercise also allows our setting to be compared to the results of the large number of papers that test the reduced-form relationship between bank competition proxies and interest rates. We find that our results are entirely consistent with existing evidence (Scharfstein and Sunderam, 2016; Di Maggio et al., 2017; Drechsler et al., 2017; Benetton and Fantino, 2021; Wang et al., 2022; Eisenschmidt et al., 2023; Li et al., 2013), further supporting the representativeness of the Ecuadorian commercial loan market.

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

$$\begin{aligned} rTax_{lfbt} =& \rho tax_{lfbt} + \delta_h tax_{lfbt} \times X_{lfbt} + \sum_{k=1}^{20} \beta_a^k 1\{A \in j\} + \\ & \sum_{k=1}^{20} \beta_m^k 1\{M \in z\} + \alpha_d DP_{lfbt} + \alpha_{fb} + \varepsilon_{lfbt}, \end{aligned} \quad (10)$$

where Xt_{lfbt} is some market or firm characteristic, such as number of lenders by firm, or number of lenders in the market, etc. Coefficient δ_h captures the heterogeneity in the treatment

[27]When demand is log-concave, pass-throughs are incomplete, like in our setting.

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. The variable # *Lenders* is the continuous count of unique bank relationships the firm has engaged in. The 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 were 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. *Multimarket Contact* measures the average number of other markets (provinces) in which banks in the market interact.[28] Lastly, *Market Share Nonmembers* is the market share (defined on loan share) of banks in the given market that are not members of the Asociación de Bancos del Ecuador (ASOBANCA). To facilitate comparison and have standard units, we standardize all continuous variables.

Table 5 presents the results. In all models, coefficients are standardized such that the main effect is the pass-through for the average borrower. In Models (1), (2), and (3), we study pass-through heterogeneity in terms of the availability of lenders in the market. For all three definitions, a higher number of lenders is interpreted as higher competition. In all models, we find that markets with more lenders have pass-throughs that approach Bertrand-Nash, i.e., where the pass-through is closer to the competitive benchmark of full passthrough ($\rho = 1$). Instead, if we measure competition using province (Model (4)) or city (Model (5)) HHI, we find that pass-throughs move away from Bertrand-Nash. In other words, whether HHI is defined at the province or city level, if the market is more concentrated, as indicated by a higher HHI, then estimated pass-throughs are lower. In in Model (6) we demonstrate that areas with higher multi-market contact, or the number of other markets where the same set of banks offer commercial loans, have pass-throughs in line with less competitive conduct.

[Place Table 5 here.]

Finally, it is beyond the scope of this paper to fully demonstrate the exact mechanisms of

[28] This is in the spirit of Ciliberto and Williams (2014) and Hatfield and Wallen (2022), which show that multimarket contact may facilitate tacit collusion and reduce competition.

how banks collude when pricing loans. However, in Model (7), we present suggestive evidence that, along with the multi-market contact result in Model (6), hints that frequent contact between banks may be part of the answer. ASOBANCA, a prominent bank lobbying group in Ecuador that organizes regular meetings and events between banks and whose website lists a primary purpose as promoting cooperation and communication between members. It is therefore a plausible mechanism for explicit or implicit collusion.[29] In Model (7), we show that the SOLCA tax pass-through for ASOBANCA members is more competitive the higher the market share of non-members in a given market. This is consistent with the general finding in game theory that collusion becomes more difficult to sustain as the number and importance of competitors in a market increases (Horstmann et al., 2018).

Overall, these results are consistent with the hypothesis that banks collude implicitly and/or explicitly and that pass-through can capture heterogeneity in competition across markets. Indeed, all measures of competition show consistent results. However, this is suggestive rather than conclusive evidence that markets are not competitive. It may be that conduct is very close to Bertrand-Nash, yet markets differ widely in their demand determinants. For example, 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.

3.4 Pass-throughs by Region

While in practice, one could estimate pass-throughs 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 pass-through for the provinces Azuay, Guayas, and Pichincha, which

[29] The banking association, known as Asociación de Bancos del Ecuador "ASOBANCA", was investigated and charged in 2016 by the anti-trust regulator for disloyal competition and coordination in terms of the introduction of the new electronic payment system approved in the 2014 financial law. It is important to highlight that the claim was finally dismissed by the Constitutional Court in 2022. See Link to decision [accessed 30 August 2023]. Similarly, in 2022, the Bank Regulator has expressed concerns over policy recommendations ASOBANCA has offered to the Legislature, in that such policy recommendations have anti-competitive effects. See [Comment by Regulator [accessed 30 August 2023].

are the largest, and aggregate across provinces for the regions Costa and Sierra/Oriente. Table 6 presents the direct tax pass-throughs by region. Although noisy for the smaller regions, we consistently find point estimates that indicate incomplete pass-through. We will use these point estimates to estimate conduct at the regional level.

[Place Table 6 here.]

4 Estimating the Model

In this section, we lay out our model estimation strategy for the structural demand and supply model.

4.1 Demand

We follow Train (1986) and Benetton (2021) in writing the (indirect) profit function $\overline{\Pi}_{ik}$ using the parametric form:[30]

$$\overline{\Pi}_{ikmt} = \exp(\mu)\exp(\xi_{kmt} + \psi_i - \alpha_m r_{ikmt} + \beta_{m1} X_{it} + \beta_{m2} X_{ikmt}) + \gamma_N N_{ikmt}, \tag{11}$$

where N_{ikmt} is the branch network in the local market. Plugging in predicted prices from Appendix Equation A17, we obtain the following indirect profit function:

$$\begin{aligned}
\Pi_{ikmt} &= \exp(\mu)\exp\Big(\underbrace{\xi_{kmt} - \alpha_m \tilde{r}_{kmt}}_{\tilde{\xi}_{kmt}} + \underbrace{(\beta_{m1} - \alpha_m \tilde{\gamma}_{x1})}_{\tilde{\beta}_{m1}} X_{it} + \underbrace{(\beta_{m2} - \alpha_m \tilde{\gamma}_{x2})}_{\tilde{\beta}_{m2}} X_{ikmt} \\
&\quad - \alpha_m \tilde{\gamma}_2 ln(L_{ikmt}) - \alpha_m \tilde{\gamma}_3 ln(M_{ikmt}) - \alpha_m \tilde{\omega}_i^r + \underbrace{\psi_i - \alpha_m \tilde{\tau}_{ikmt}}_{\tilde{\psi}_{ikmt}}\Big) \\
&\quad + \gamma_N N_{ikmt} + \varepsilon_{ikmt} && (12) \\
&= \exp(\mu)\exp\Big(\tilde{\xi}_{kmt} + \tilde{\beta}_{m1} X_{it} + \tilde{\beta}_{m2} X_{ikmt} - \alpha_m \tilde{\gamma}_2 ln(L_{ikmt}) - \alpha_m \tilde{\gamma}_3 ln(M_{ikmt}) && (13) \\
&\quad - \alpha_m \tilde{\omega}_i^r + \tilde{\psi}_{ikmt}\Big) + \gamma_N N_{ikmt} + \varepsilon_{ikmt}
\end{aligned}$$

We assume the idiosyncratic taste shocks ε_{ikmt} are i.i.d. Type-I Extreme Value, and that the

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

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. Notice that we deal with the same major empirical challenge common in the literature. Namely, we observe the terms of only granted loans while our demand model requires prices from all available banks to all potential borrowers. To address this long-standing problem in the literature, we predict the prices of unobserved, counterfactual loans following the strategy of Adams et al. (2009), Crawford et al. (2018), Ioannidou et al. (2022). Details are reported in Appendix D.

Before we describe our instrumental variable strategy to identify α_m, we describe our maximum likelihood demand estimation procedure. First, we derive the maximum likelihood function. The conditional probability that the firm i chooses bank j is given by

$$s_{ikmt}(\psi_i) = \frac{\exp(\Pi_{ikmt})}{\sum_j \exp(\Pi_{ijmt})}, \tag{14}$$

while the unconditional probability is given by

$$S_{ikmt} = \int s_{ikmt}(\psi_i))dF(\psi_i). \tag{15}$$

Given actual bank choices, we can use Hotelling's lemma to obtain the loan demand function L_{ikmt}:[31]

$$\ln(L_{ikmt}) = \ln(\exp \mu\alpha_m) + \xi_{kmt} - \alpha_m r_{ikmt} + \beta_{m1} X_{it} + \beta_{m2} X_{ikmt} + \psi_i \tag{16}$$

[31] Here, we took the derivative of Equation 11 with respect to the interest rate.

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

$$\ln(L_{ikmt}) = \ln(\exp \mu\alpha_m) + \tilde{\xi}_{kmt} - \alpha_m(r_{ikmt} - \tilde{r}_{kmt}) + \beta_{m1}X_{it} + \beta_{m2}X_{ikmt} + \psi_i. \tag{17}$$

From Equation 17 and the normality assumption for ψ_i, the probability of the conditional loan demand is

$$f(ln(L_{ikmt})|k, k \neq 0) = \tag{18}$$
$$\frac{1}{\sqrt{2\pi\sigma^2}} \times \exp\left[-\frac{\Big(\ln(L_{ikmt}) - \ln(\exp\mu\alpha_m) - \tilde{\xi}_{kmt} + \alpha_m(r_{ikmt} - \tilde{r}_{kmt}) - \beta_{m1}X_{it} - \beta_{m2}X_{ikmt}\Big)^2}{2\sigma^2}\right].$$

Note that as branch network enters linearly in the indirect utility, it does not appear in input demand. Hence, this assumption implies an exclusion restriction: branch density affects likelihood of borrowing but not intensity.[32]

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

$$\ln(\mathcal{L}) = \sum_{t=0}^{T}\sum_{m=0}^{M}\sum_{j=0}^{J_m}\sum_{k=0}^{K_m} 1_{ikmt}[\ln(S_{ikmt}) + \ln(f(\ln(L_{ikmt})|k, k \neq 0))], \tag{19}$$

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.

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 1,000 bootstrap samples for each region to obtain standard errors for all coefficients.[33]

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

[33]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

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:

$$\tilde{\xi}_{kmt} = -\alpha_m \tilde{r}_{kmt} + \beta_b X_{kmt} + \epsilon_{kmt}. \tag{20}$$

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, with a model R-squared of 0.43. Moreover, as we report in Table A6, market-specific F-statistics are high, and over-identification tests cannot reject the null of valid and exogenous instruments.

4.1.1 Demand Elasticities

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

$$\epsilon^{L}_{ikmt} = \frac{\partial L_{ikmt}}{\partial r_{ikmt}} \frac{r_{ikmt}}{L_{ikmt}} = \frac{\partial ln(L_{ikmt})}{\partial r_{ikmt}} r_{ikmt} = -\alpha_m r_{ikmt} \tag{21}$$

and

$$\begin{aligned}
\epsilon^{s}_{ikmt} &= \frac{\partial s_{ikmt}}{\partial r_{ikmt}} \frac{r_{ikmt}}{s_{ikmt}} \\
&= -\alpha_m \exp \mu \exp(\xi_{kmt} + \psi_i - \alpha_m r_{ikmt} + \beta_{m1} X_{it} + \beta_{m2} X_{ikmt})(1 - s_{ikmt}) s_{ikmt} \times \frac{r_{ikmt}}{s_{ikmt}} \\
&= -\alpha_m \exp \mu \exp(\xi_{kmt} + \psi_i - \alpha_m r_{ikmt} + \beta_{m1} X_{it} + \beta_{m2} X_{ikmt})(1 - s_{ikmt}) r_{ikmt}
\end{aligned} \tag{22}$$

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.

The elasticity for total demand is given by:

$$\epsilon^{Q}_{ikmt} = \frac{\partial Q_{ikmt}}{\partial r_{ikmt}} \frac{r_{ikmt}}{Q_{ikmt}} = \frac{\partial s_{ikmt} L_{ikmt}}{\partial r_{ikmt}} \frac{r_{ikmt}}{s_{ikmt} L_{ikmt}}$$
$$= \frac{\partial s_{ikmt}}{\partial r_{ikmt}} \frac{r_{ikmt}}{s_{ikmt}} + \frac{\partial L_{ikmt}}{\partial r_{ikmt}} \frac{r_{ikmt}}{L_{ikmt}} = \epsilon^{s}_{ikmt} + \epsilon^{L}_{ikmt}. \tag{23}$$

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

$$\epsilon^{L,j}_{ikmt} = 0 \tag{24}$$

and

$$\epsilon^{s,j}_{ikmt} = \frac{\partial s_{ikmt}}{\partial r_{jkmt}} \frac{r_{jkmt}}{s_{ikmt}} = \alpha_m \exp \mu \exp(\xi_{jmt} + \psi_i - \alpha_m r_{ijmt} + \beta_{m1} X_{it} + \beta_{m2} X_{ijmt}) s_{ijmt} s_{ikmt} \times \frac{r_{ijmt}}{s_{ikmt}}$$
$$= \alpha_m \exp \mu \exp(\xi_{jmt} + \psi_i - \alpha_m r_{ijmt} + \beta_{m1} X_{it} + \beta_{m2} X_{ijmt}) s_{ijmt} r_{jkmt} \tag{25}$$

4.2 Supply

The supply side parameters (mc_{ik}, υ_m) are estimated using optimal pricing formulae through the inverted Equation 6 and the pass-through Equation 7 as the targeting moment.

5 Estimation Results

In this section, we present our estimates of the model parameters and assess model fit. We then describe how we calibrate the conduct parameter describing the extent of lender collusion. Finally, we test the calibrated conduct parameter against benchmarks corresponding to Bertrand-Nash competition, Cournot competition, and joint maximization/collusion.

5.1 Demand Parameters

Table 7 collects the demand parameter estimates, reported as the mean and standard deviation of the point estimates with each market (region). Standard deviations are bootstrapped by estimating each region-level parameter on 1,000 bootstrap samples and then taking the standard deviation across bootstrap sample and within region.

[Place Table 7 here.]

Generally speaking, the signs of the estimates are as expected, but there is 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 8. We find that a 1% increase in price leads to a 4.63% decrease in loan use (continuous) and a 6.01% decrease in market share.[34] 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 elastic, 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 pass-throughs.

[Place Table 8 here.]

The remaining demand parameters presented in Table 7 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) 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 indicating investment and such inputs are complements; and (5), firms with higher leverage are less likely to borrow.

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

[34]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).

(exclusion). In Appendix F we report the demand estimates pooled across regions and we reproduce 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. This is strong evidence that our instruments are relevant.

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

5.2 Model Fit

In Table 9, we present descriptive statistics on the fit of the model. We focus on market shares (discrete choice), loan use (continuous choice), prices, and default rates. The table shows that the model fits the mean data well, with a perfect fit for market shares, loan use, and default rates. Our model under-predicts prices by a small margin. Naturally, across all measures, our model predicts less variation than in the data.

[Place Table 9 here.]

5.3 Supply-Side Parameters

As a first exercise to show the importance of the assumptions on competitive conduct υ_m, we simulate the model assuming a conduct parameter $\upsilon_m = 0$, i.e., Bertrand-Nash competition.[35] 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

[35] In Brugués and De Simone (2023), we use our model to quantify intensive and extensive margin impacts of pricing power from collusion above and beyond demand-size sources of market power; provide a decomposition of markups into a portion from lender conduct, borrower preferences, and borrower risk; and examine the impact of proposed competition reforms in the banking sector.

model-implied marginal costs and markups under these two scenarios. Results are reported in Table 10.

[Place Table 10 here.]

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 6) to back out prices by setting $\upsilon_m = 0$ and using only the own-price elasticities of demand. We find average (median) marginal costs of 8.82 (9.3) 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 2.43 (2.30) percentage points or 21.6% (20.04%) 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 to 4.87 (3.10) 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 first order condition 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 6.38 (4.79) percentage points or 56.71 (42.67) 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. This difference may also help explain why markups in the literature tend to be somewhat low.[36]

[36]For instance, Benetton (2021) finds markups of 18% the average interest rate, while Crawford et al. (2018) reports markups of only 5%.

5.4 Testing Conduct at the National-level

Next, we present a simple exercise to highlight the identification intuition for conduct υ_m. We first use the estimated supply and demand parameters for each mode of conduct to simulate pass-throughs of the introduction of the 0.5% tax rate. The goal of this section is to obtain distributions of pass-throughs consistent with each conduct while at the same time flexibly accounting for demand heterogeneity. We then can compare these simulated distributions with the pass-through distribution from the actual data and show that, even after controlling for demand heterogeneity, pass-throughs can serve as an identification moment by providing a strong test.

To obtain model-consistent pass-throughs, 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 pass-throughs 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. Next, 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 3) 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 pass-throughs 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 pass-throughs are centered slightly above one under Bertrand-Nash, despite the significant demand heterogeneity documented above. Contrasting this distribution with the empirical point estimate for pass-through of 0.54 and the upper 95% interval at 0.64, we reject that that conduct is Bertrand-Nash in the actual data. Note that our discrete-continuous demand model is flexible enough that we can obtain pass-through estimates both above and below one under Bertrand-Nash, which, as documented by Miravete et al. (2023), many discrete-choice models are not able to accommodate.

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

[Place Figure 5 here.]

5.5 Testing for Cournot

Pure Bertrand-Nash competition and full joint-maximization correspond to conduct parameters—an υ_m of zero and one, respectively—that do not vary across markets. In contrast, the conduct parameter for Cournot (quantity competition/credit rationing) depends on market-level elasticities as well as the number of competitors. We obtain the market-level estimate υ_m for Cournot in two steps. First, we compute market-level estimates of the markup for Bertrand-Nash and Cournot following Magnolfi et al. (2022), who show that both markups can be written as a function of market shares and the Jacobians of the demand system. Then, we find the parameter υ_m which maps the Bertrand-Nash markup to the Cournot markup, given estimates of the market-level cross-price semi-elasticities $\tilde{\epsilon}_{kj}$. We calculate that the conduct parameter corresponding to Cournot competition for Azuay is 0.2042, for Costa it is 0.4357, in Guayas we calculate 0.0609, in Pichincha 0.1993, and in the Sierra and Oriente region it is 0.2858.

5.6 Calibrating Conduct for each Market

Next, we calibrate the conduct parameter in each market. To keep the exercise computationally feasible, we implement the following simulated method of moments procedure for each region, separately. First, we randomly pick 2,500 firms from the region. Second, we run a minimum distance calibration of the conduct parameter $\widehat{\theta}$ that matches the empirical pass-through we estimated in our data with the pass-through simulated by the model. We use a grid search with a grid size of 0.01. Table 11 reports the results. Column (1) presents the best-fit conduct estimate. Column (2) is the bootstrapped standard error, calculated with 1,000 bootstrap samples at each grid point.

[Place Table 11 here.]

We observe that the calibrated model returns a precisely non-zero conduct parameter for each region. We also see that estimated conduct varies significantly across regions, ranging from a low of 033 in Guayas up to a high of 0.91 in Costa.

How robust are these calibrations to our modeling choices? Figure 6 reports for each region the lowest feasible conduct parameter estimates (y-axis) by degree of match, where zero in the match order (x-axis) represents the conduct that minimizes the squared distance between simulated and observed pass-through in the model and 50 indicates the 50^{th} best match. This analysis tests how stable our match is. Note that this is a conservative estimate because we are choosing the lowest feasible conduct, thus intentionally biasing our analyses towards conduct consistent with Bertrand-Nash competition.

The black dot at zero in the x-axis corresponds to our best estimate of the conduct parameter, and the grey area represents confidence intervals based on the bootstrapped standard errors. The dotted line at one on the y-axis corresponds to complete joint maximization, the dashed line at zero to pure Bertrand-Nash competition, and the dot-dash line to the conduct corresponding to Cournot/quantity competition in each region. So, for example, in the region Azuay, reported in the top left panel, our best estimate of conduct is 0.77, but conduct could be as low as 0.49 or as high as 1.05. We therefore reject that banks Bertrand-Nash compete in Azuay but fail to reject that they joint maximize when setting commercial loan prices.

[Place Figure 6 here.]

In all regions, we observe stability in the first ten-to-twenty best-fitting models. We can reject pure Bertrand-Nash and Cournot competition at the 95% confidence level in the ten best-fitting model estimates for all regions. In Guayas and Pichincha we can reject joint maximization in the best-fitting models. We fail to reject full joint maximization in three of the five regions. These patterns are consistent with the simulation results reported in Section 5.4. It is clear that banks are not Bertrand-Nash competitive, and results are most consistent with some degree of joint maximization.

While these results might appear counter to the aggregate level estimates where we fail to reject joint maximization, applying the same grid methodology at the national-level helps clarify the results. Figure 7 presents the average pass-throughs by conduct level. The figure shows that using aggregate pass-throughs, we are able to reject a large range of conduct parameters below 0.5. The figure also shows that we are not able to reject values above 0.5, and that we cannot reject joint-maximization, offering a similar takeaway to the result in Figure 5.[37]

[Place Figure 7 here.]

Reviewing our evidence to this point, banks have an incentive to collude, they have the opportunity to do so, through lending associations, multi-market contact and so forth, and regulators have an incentive to allow them to for macro stability reasons. Next, we will show that this collusion matters for the effectiveness and efficiency of fiscal policy.

5.7 Testing the Identification Assumption for Conduct

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

$$\rho = \frac{1}{1 + \frac{\theta}{\epsilon_{ms}}}, \tag{26}$$

where θ is the conduct parameter (e.g., $\theta = 1$ under joint maximization and $\theta = 0$ under Bertrand-Nash) and ϵ_{ms} is the curvature of demand. Under this simple model, pass-through is

[37]The point estimates differ relative to Figure 5 as we only use a random subsample of 2,500 borrowers rather than the full set of borrowers from the estimated model. We use the reduced sample due to the computational intensity of calculating Nash equilibrium prices for each borrower and each grid.

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

We have already presented reduced-form evidence in Section 3.3 that pass-through is strongly related with proxies for bank collusion when setting interest rates. Yet, interpretation in our setting is not so straightforward as these reduced-form evidence suggest. Demand curvature may be different across markets, so pass-throughs may differ even if conduct is identical. With our estimated model in hand, we can now directly test the relationship between conduct and pass-through.

We report the results for each region separately in Figure 8. The y-axis plots simulated pass-through and the x-axis the corresponding conduct parameter. We confirm that in all regions, pass-through decreases (non-linearly) with conduct. In addition, the relationship is mostly monotonic. As shown above in Figure 7, the relationship between pass-through and conduct is also decreasing and monotonic at the national-level.

[Place Figure 8 here.]

6 Tax Incidence, Tax Revenue, and Conduct

Financial taxes and levies are pervasive, including on loans across South America (Argentina, Brazil, Peru, Columbia, Venezuela, Bolivia, Ecuador), Africa (Egypt, South Africa), Europe (Hungary, Spain, Sweden), and Asia (Malaysia). Stamp duties on mortgage loans are also widely used, including in the United Kingdom, India, and Spain, and bank levies are common, especially in Europe. Moreover, while generally considered distortionary (Restrepo, 2019), financial transaction taxes are frequently proposed, including in the Inclusive Prosperity Act proposed by Senator Bernie Sanders in 2019 and COM/2013/71 proposed by the European Commission in 2013, which is still on the table as of 2023. However, the literature has not reached consensus on who bears the burden of financial taxes. Theoretically, the answer is not obvious. It should depend on demand and supply parameters, including supply conduct. Nevertheless, empirical work on such taxes implicitly or explicitly assumes a conduct of zero (i.e., Bertrand-Nash competition).

We fill this gap by studying how bank conduct affects who bears the burden of financial taxes through the lens of our model. To do so we calibrate the incidence, or who bears the burden of the tax. We also calibrate the efficiency cost of the tax, as proxied by its marginal excess burden, or the deadweight loss from raising a marginal dollar of tax revenue. We then examine how the effect depends on the market structure of commercial lending, as summarized by lender conduct.

To calculate the incidence and marginal excess burden of a loan tax, we must calibrate the effect of the tax on borrower surplus, lender surplus and on tax revenue. Specifically, we follow the public finance literature in defining the incidence of a unit tax t as $I = \frac{dCS/dt}{dPS/dt}$, where CS is borrower surplus and PS is the bank's surplus (Weyl and Fabinger, 2013; Kroft et al., 2020). Marginal excess burden is the sum of marginal borrower surplus, marginal bank surplus, and marginal tax revenue. We then scale this sum by marginal tax revenue so that it represents the change in welfare as a percentage of the additional tax revenue.

Borrower surplus for firm i after borrowing from bank k in market m at time t is simply the indirect utility level. Thus, the change in borrower surplus from a change in unit tax is:

$$\frac{dCS_{ikmt}}{dt} = \frac{d\overline{\Pi}_{ikmt}}{dt} = \frac{d\overline{\Pi}_{ikmt}}{dr}\rho_m = -L_{ikmt}\rho_m. \tag{27}$$

Through Hotelling's lemma, we obtain that the change in borrower surplus will be proportional to loan size adjusted by pass-through.

Next, for bank profits $B_{ikmt} = (1 - d_{ikmt})(r_{ikmt} - t)Q_{ikmt}(r) - mc_{ikmt}Q_{ikmt}(r)$, for tax-inclusive price r, the effect on bank surplus is given by:

$$\left.\frac{dPS_{ikmt}}{dt}\right|_{t=0} = \frac{dB_{ikmt}}{dt} = (1 - d_{ikmt})Q_{ikmt}(\rho_m - 1) + ((1 - d_{ikmt})(r_{ikmt} - t) - mc_{ikmt})\frac{\partial Q_{ikmt}}{\partial r_{ikmt}}\rho_m \tag{28}$$

$$= (1 - d_{ikmt})Q_{ikmt}(\rho_m - 1) - \frac{\partial Q_{ikmt}}{\partial r_{ikmt}}\rho_m \frac{Q_{ikmt}}{\frac{\partial Q_{ikmt}}{\partial r_{ikmt}} + \upsilon_m \sum_{j\neq k} \frac{\partial Q_{ikmt}}{\partial r_{ijmt}}} \tag{29}$$

$$= -Q_{ikmt}\left[(1 - d_{ikmt})(1 - \rho_m) + \frac{\rho_m}{1 + \upsilon_m \sum_{j\neq k} \frac{\tilde{\epsilon}_{jk}}{\tilde{\epsilon}_{kk}}}\right], \tag{30}$$

where the second equality follows from the bank's first-order condition.

Finally, tax revenue is defined as $R_{ikmt} = tQ_{ikmt}$ and the marginal tax revenue is given by:

$$\left.\frac{dR_{ikmt}}{dt}\right|_{t=0} = Q_{ikmt}\left[1 + t\rho_m\tilde{\epsilon}_{kk}\right] = Q_{ikmt}. \tag{31}$$

We calibrate these equations using the counterfactual estimates from our model simulated under conducts υ_m equal to zero (Bertrand-Nash), one (joint maximization), and the *calibrated conduct* value obtained by matching simulated market pass-through to empirical market pass-through. For Bertrand-Nash and joint maximization, we also explore the differences that arise from relying on model-consistent pass-through estimates instead of the empirical ones for parameter ρ_m.

Table 12 presents the results. Model (1) presents "ex-ante" estimates in the sense of not conditioning on the borrowing firm's choice of bank. Model (B) presents "ex-post" estimates that do condition on the borrower's observed choice of bank. For the ex-post estimates, both bank surplus and tax revenue are scaled by the choice probability, which in our setting is proportional to lender market share. We note that the results for *calibrated conduct* serve as benchmark, assuming these are the true effects.

[Place Table 12 here.]

Panel A presents our empirical benchmark, where we estimate incidence and excess burden using calibrated conduct and the empirical pass-through. This is our best estimate of the actual welfare impact of the SOLCA tax in commercial lending markets. For Panel B, we counterfactually set conduct either equal to pure Bertrand-Nash competition ($\upsilon_m \equiv 0$) or to full joint maximization ($\upsilon_m \equiv 1$). We then simulate the tax pass-through using the model conditional on these conduct assumptions. This is our measure of how the expected welfare impact of the tax depends on the assumption about lender collusion.

First, consider the measured incidence in Panel A. We find that prior to choosing a bank, unconditional incidence falls on average (median) on the borrower (equally shared). Once a bank is chosen, the conditional incidence falls primarily on the banks, with a mean (median) incidence of 0.37 (0.35).

From Panel B it is clear that the conduct assumption greatly affects the estimates relative to the benchmark presented in Panel A that utilizes empirical pass-through estimates for ρ_m. Regardless of whether we focus on the ex-ante or ex-post measure, the burden of taxation is estimated to fall much more on the borrower if one assumes Bertrand Nash competition ($\upsilon_m \equiv 0$) rather than using calibrated conduct estimated on the data. However, incidence under the assumption of joint-maximization ($\upsilon_m \equiv 1$) is closer to our benchmark results using calibrated conduct.

This matches our expectation, as we have shown that calibrated conduct is closer to joint-maximization for many markets and that simulated pass-throughs under the assumption of joint-maximization mirrored closely those observed empirically. These results also match the theoretical discussion by Weyl and Fabinger (2013) on the effects of conduct on incidence. But from a policy perspective, noting this distinction is important, as the policymaker may weigh borrower surplus differently than bank surplus and thus the desired distributive effects of taxation will be affected by the prevalent lender conduct in the market.

Next, consider the benchmark marginal excess burden, which we define as the sum of marginal borrower surplus, marginal bank surplus, and marginal tax revenue, scaled by marginal tax revenue. It represents the additional welfare loss per unit of revenue raised by the tax. Our first takeaway is that our estimates of the marginal excess burden of the SOLCA tax, in Panel A, is on average (median) 41% (50%) of marginal tax revenue for the benchmark using calibrated conduct. Thus, the bank loan tax is indeed distortionary in the data, as expected.

But our second key takeaway is that the predictions of excess burden are much higher if we assume pure Bertrand-Nash competition than if we assume full joint maximization. Specifically, in Panel B, we find that the excess burden prediction from the simulation assuming joint-maximization is similar to that estimated under the benchmark model using calibrated conduct. However, assuming Bertrand-Nash conduct greatly overstates the losses, yielding an average (median) 92% (96%) of welfare loss per marginal dollar raised. Thus, naively assuming Bertrand-Nash would overstate excess burden by around 100%.[38]

Thus, we estimate that excess burden is large, indicating that this type of taxation is clearly distortionary. But realized welfare losses are dramatically less than would be expected under a classical framework that assumes no lender collusion. This empirical finding is novel from an academic perspective—our empirical results match the theoretical predictions of Kroft et al. (2020) on the effects of conduct for excess burden. But they are also of real import to policymakers making hard tax and budget tradeoffs in far from first-best environments where optimal taxation is infeasible.

Comparing our results to other estimates of marginal excess burden per dollar raised, we find that loan transaction taxes are more distortionary than tax on retail products based on US evidence (Kroft et al., 2020), but close to the effect of income taxes on the top one percent in the US (Saez et al., 2012). This general conclusion is in line with previous macro-studies looking at the effect of bank taxes on economic growth (Restrepo, 2019).

While we have shown that the conduct assumption hugely impacts the expected welfare impact of the SOLCA tax, another novel implication is that how distortionary the transaction cost actually is depends on the competition structure of the commercial loan market. In particular, the counterfactual experiments through the lens of our model suggest that consumers bear a much higher burden of the tax under Bertrand-Nash competition and the deadweight loss is greater per unit of revenue raised. Intuitively, the higher markups above marginal cost that banks can achieve under joint maximization also gives them more freedom to absorb shocks while still operating profitably.

The final takeaway relates to the use of simulated vs. empirical pass-throughs. Consider Panel C where we use empirical pass-through ρ_m but counterfactually set conduct υ_m to be either

[38]This is similar to the effect of naively assuming away tax salience in the US (Kroft et al., 2020).

zero or one, i.e., assuming that banks either pure Bertrand-Nash compete or fully joint maximize, respectively. Reassuringly, if one relies on empirical pass-throughs, estimates both for incidence and excess burden are relatively consistent across the various conduct assumptions. This is important because it implies that, from a policy perspective, it may be feasible to obtain robust predictions without the need for testing conduct beforehand, even if exact magnitudes cannot be pinned down without a model that incorporates flexible conduct. Recall that this is not obvious, as in general keeping pass-through constant, incidence and excess burden change with conduct (Weyl and Fabinger, 2013). Here, the key driver bringing incidence and excess burden close across conduct models boils down to the relative importance of substitution patterns (cross elasticities vs. own elasticities). In our empirical setting, cross-elasticities are much smaller than the elastic discrete-continuous demand. Thus, our finding may be generalizable to other markets with similar features.

6.1 Government Subsidies

As we have already studied the effects of government *taxes*, we can easily obtain estimates for the effects of government *subsidies*. Such a policy could absorb a fraction of each dollar lent, paid directly to banks, reducing the marginal cost of lending. Indeed, this exercise is simply the mirror. Following Table 12, such a policy would be expansionary: deadweight-loss would be reduced by an average (median) 41 (50) cents per dollar spent in subsidy. Banks will be the main beneficiaries of such a policy, as banks pass along only a fraction of each dollar of subsidy.

7 Conclusion

In this paper, we investigate the impact of bank competition on the welfare consequences of financial taxes 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 parameter describing bank conduct. We estimate the model and its results using data from all commercial credit transactions in Ecuador. We reject that banks Bertrand-Nash or Cournot compete, but we fail to reject the joint profit maximization model.

These results already have several important implications for policymakers and the literature. First, we show that lender collusion significantly affects the welfare outcomes of financial taxation. When accounting for collusion, the estimated deadweight loss from the SOLCA tax was significantly less than what would be calculated under the assumption of perfect competition. This implies that as a second-best option, financial taxes are not as distortive as commonly supposed when markets are not perfectly competitive. The findings have broader applicability to various types of capital taxes and financial levies common in many countries. They could also inform the design of other policy tools, like carbon taxes or interest rate pass-through, where variation in sectoral competition could affect the welfare impact of the policy. Conversely, we find that subsidies are less effective in non-competitive settings.

Second, we find that 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 becuase models that assume banks compete when they do not will overestimate marginal costs. Also, 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.

Overall, our findings suggest that it is important to account for potential lender collusion when studying the impact on borrowers of competition in lending markets. And academics and policymakers should consider how welfare depends on market structure when designing tax-and-subsidy strategies.

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8 Tables and Figures

Identified by SOLCA tax quasi-experiment

Calculated from demand model (identified by instruments)

Calculated from demand model (identified by instruments)

$$\rho_{ikmt} \equiv \frac{\delta r_{ikmt}}{\delta mc_{ikmt}}$$

$$= \Big[\big(\widetilde{\varepsilon}_{kk} + \upsilon_m \sum_{j\neq k} \widetilde{\varepsilon}_{kj}\big)/(1 - d_{ikmt})\Big] \Big/ \Big[\big(\widetilde{\varepsilon}_{kk} + \upsilon_m \sum_{j\neq k} \widetilde{\varepsilon}_{kj}\big) + \big(r_{ikmt} - mc_{ikmt}/(1 - d_{ikmt})\big)\Big(\frac{\partial \widetilde{\varepsilon}_{kk}}{\partial r_{ikmt}} + \upsilon_m \sum_{j\neq k} \frac{\partial \widetilde{\varepsilon}_{kj}}{\partial r_{ikmt}}\Big)\Big]$$

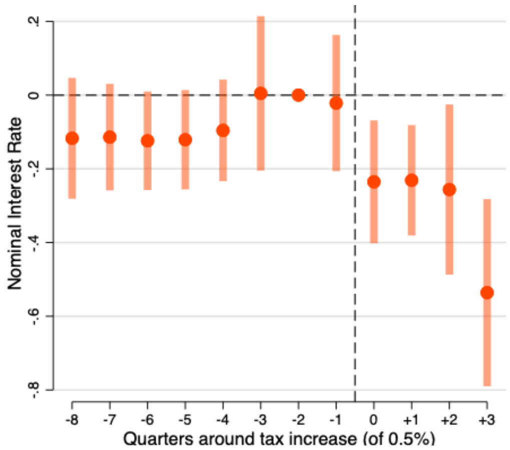
Observed or estimated in data

Where:

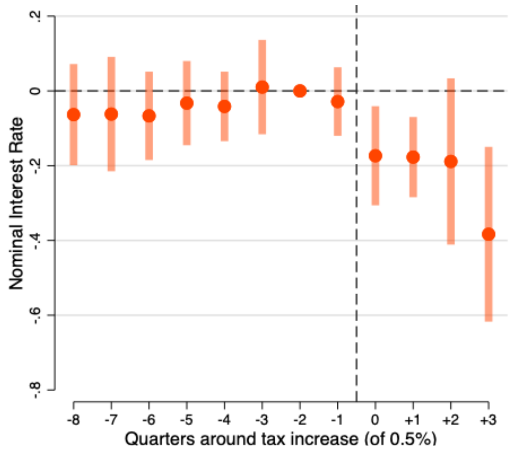
$$mc_{ikmt} = r_{ikmt}(1 - d_{ikmt}) + \frac{1 - d_{ikmt}}{\frac{\epsilon_{kk}}{r_{ikmt}} + \upsilon_m \sum_{j\neq k} \frac{\epsilon_{kj}}{r_{ijmt}}}$$

FIGURE 1: MODEL OF COMMERCIAL CREDIT

The figure describes the main identifying equations for the model and how each component is identified.



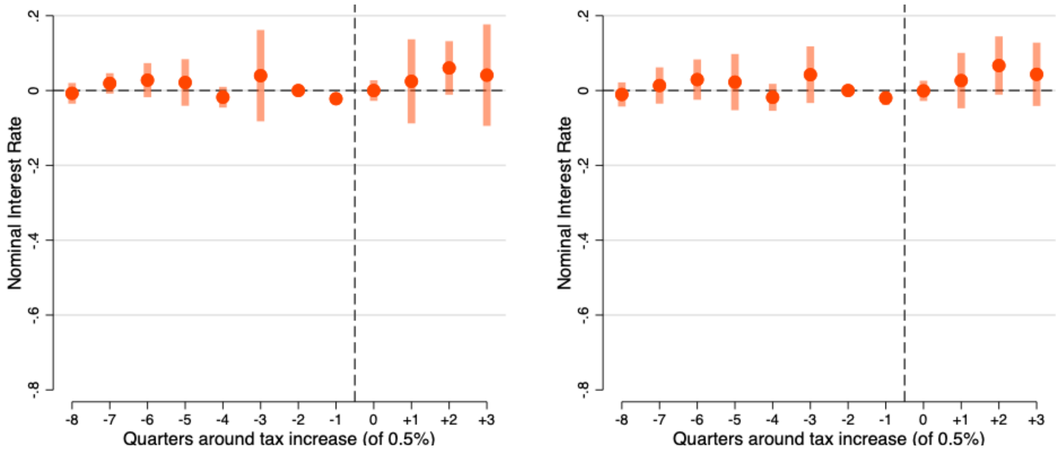
(a) Regular loans; bank & firm FE



(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 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 $\times$ 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.

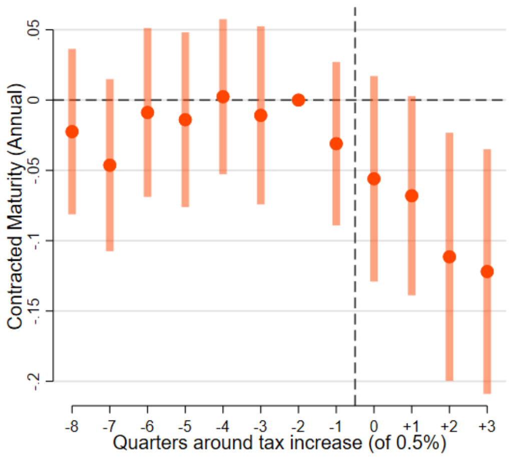


(a) Regular loans; bank & firm FE

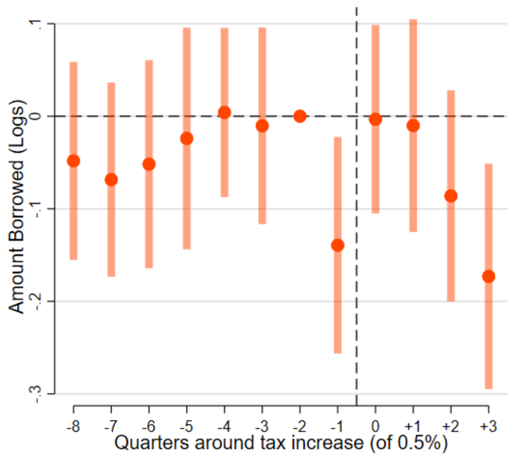
(b) Regular loans, bank-firm pair FE

FIGURE 3: 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 4: 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.

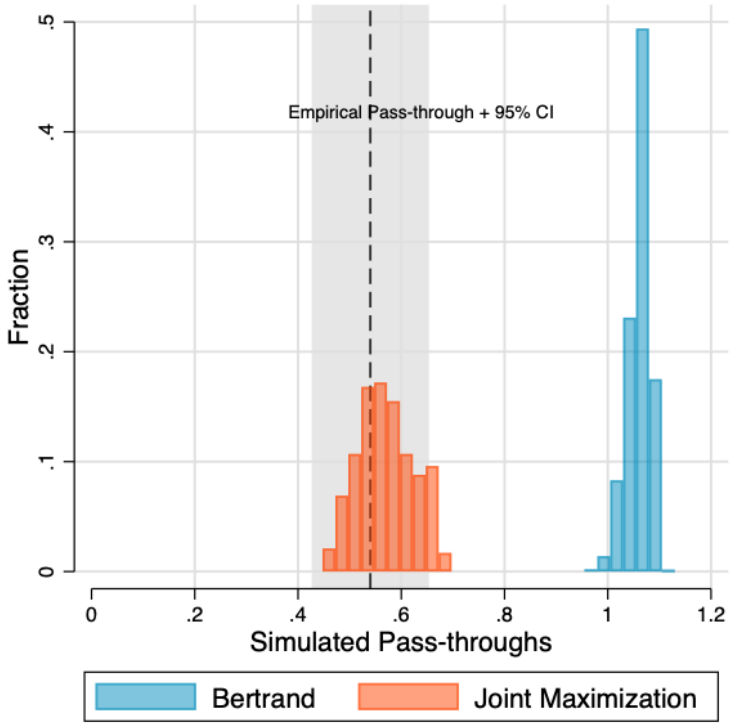
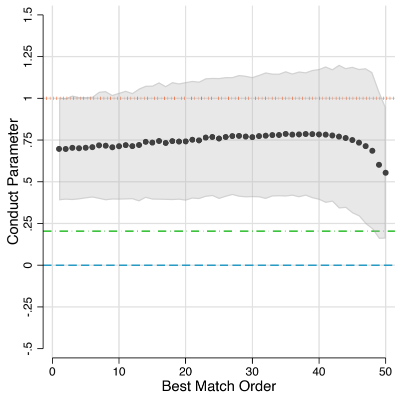
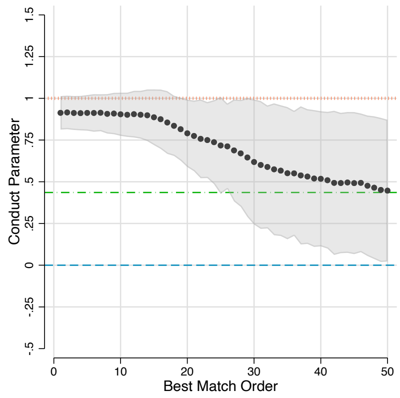


FIGURE 5: DISTRIBUTION OF SIMULATED PASS-THROUGHS BY CONDUCT

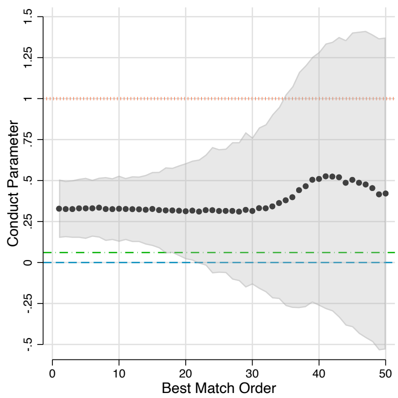
The figure reports the distribution of nation-wide bootstrapped average simulated Nash-equilibrium pass-throughs of a tax introduction of 0.5% by mode of conduct (Bertrand-Nash in blue and Joint Maximization in Orange). Bootstrap estimates come from 1,000 bootstrapped samples of borrowers-level estimates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



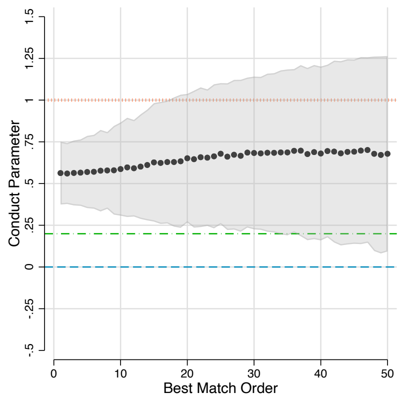
(a) Azuay



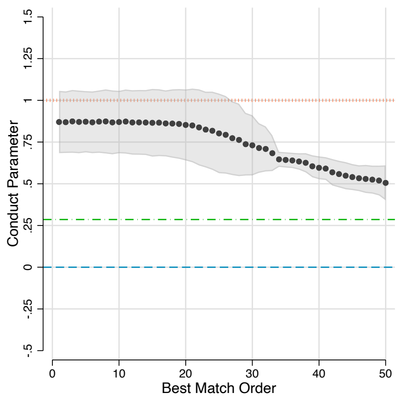
(b) Costa



(c) Guayas



(d) Pichincha



(e) Sierra & Oriente

FIGURE 6: REGIONAL CONDUCT BY MATCH ORDER

The figure reports conduct parameter estimates by lending region against the matches between empirical and model-estimated tax pass-through. The best fit is match order one. The model is separately estimated by region on a random sample of 2,500 firms using a simulated method of moments model. The bootstrapped standard errors are estimated using 1,000 bootstrap samples. The dotted line at conduct one corresponds to joint maximization; the dashed line at conduct zero corresponds to Bertrand-Nash competition, and the intermediate conduct corresponds to Cournot competition in each region.

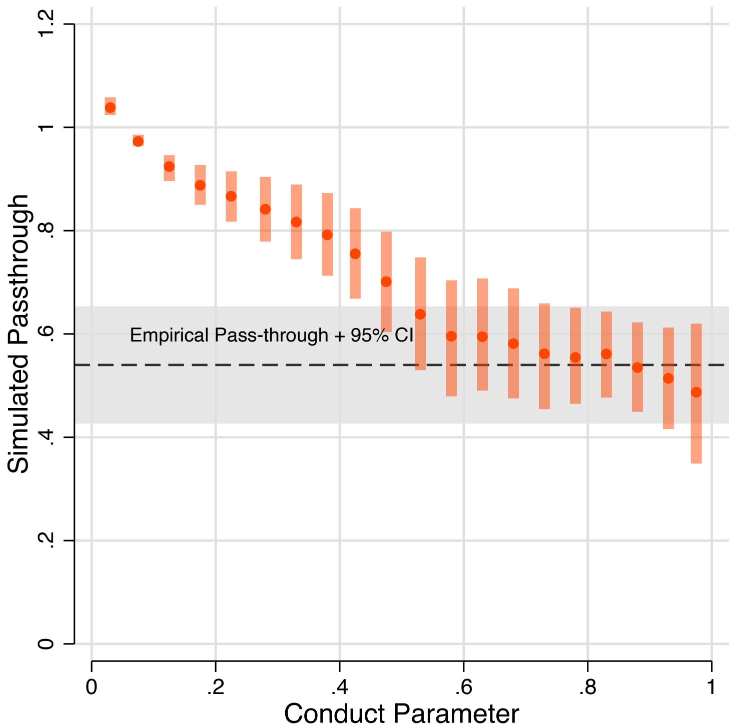
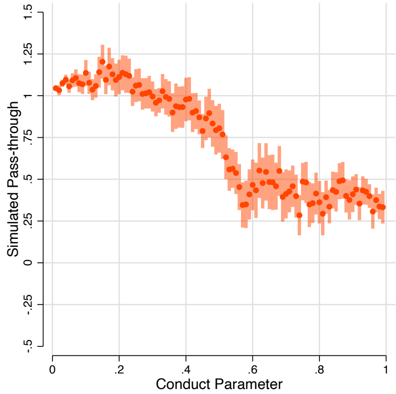
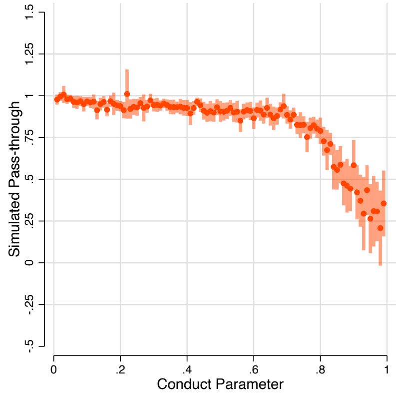


FIGURE 7: AVERAGE NATION-WIDE SIMULATED PASS-THROUGHS BY CONDUCT GRID

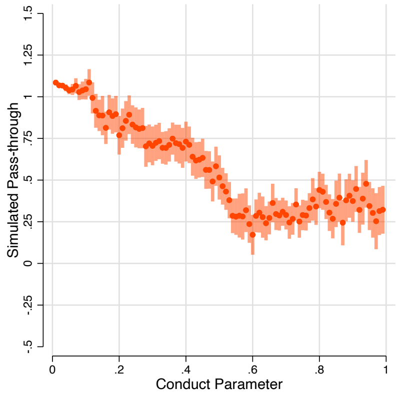
The figure reports the average nation-wide simulated Nash-equilibrium pass-throughs of a tax introduction of 0.5% over a grid of conducts between 0 and 1. Each region samples 2,500 borrowers. Confidence intervals are clustered at the region-conduct grid level. The dashed line shows the estimated empirical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



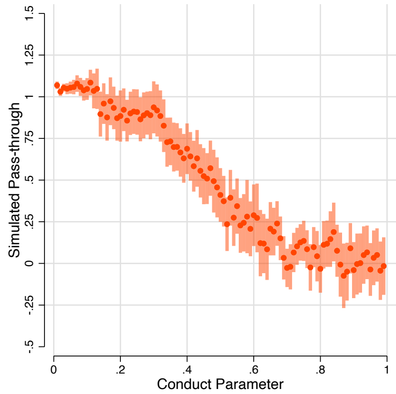
(a) Azuay



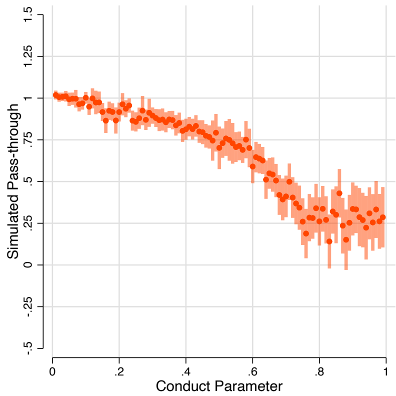
(b) Costa



(c) Guayas



(d) Pichincha



(e) Sierra & Oriente

FIGURE 8: RELATIONSHIP BETWEEN OBSERVED PASS-THROUGH AND MODELED CONDUCT

The figure reports the relationship between empirical pass-through (y-axis) and conduct parameter (x-axis) by lending region. The model is separately estimated by region on a random sample of 2,500 firms using a simulated method of moments model that matches empirical to model-estimated tax pass-through. The bootstrapped standard errors are estimated using 1,000 bootstrap samples.

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: AGGREGATE PASS-THROUGH ESTIMATES

The table reports aggregate pass-through 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 pass-through null hypothesis ($\rho = 1$).

	Outcome: Tax-inclusive interest rate			
	(1)	(2)	(3)	(4)
Pass-through (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 5: HETEROGENEITY IN DIRECT TAX PASS-THROUGH

The table reports heterogeneity in aggregate pass-through estimates to the tax-inclusive interest rates of commercial loans around the introduction of the 2014 SOLCA tax in Ecuador. Data are at the loan-level for 2010 to 2017, excluding October 2014. The main independent variable is the tax rate, measured as 0.5 adjusted proportionally by term-to-maturities if maturity is less than 1 year. The dependent variable is the tax-inclusive interest rate, which is the sum of the nominal, annualized interest rate plus the tax rate. Both are in percentage points. Regressions control for twenty buckets of term-to-maturity, and twenty buckets of loan amount, predicted default probability, and bank × firm (pair) FE. Interacted variables are: *# 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. *Market Share Nonmembers* is the market share (defined on loan share) of banks in the given market that are not members of the Asociación de Bancos del Ecuador. 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 pass-through null hypothesis ($\rho = 1$). For the interaction term, testing is against the no-effect null hypothesis.

	Outcome: Tax-inclusive interest rate						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Pass-through (ρ)	0.565**	0.676	0.441***	0.550**	0.603**	0.529**	0.517***
	(0.212)	(0.209)	(0.207)	(0.195)	(0.200)	(0.203)	(0.187)
Interacted with	*# Lenders*	*# Av. City Active Lenders*	*# Potential Lenders*	*HHI Province*	*HHI City*	*Multimarket Contact*	Mkt. Share Nonmember
	0.136	0.583***	0.459***	-0.565***	-0.413***	-0.226**	0.186*
	(0.125)	(0.177)	(0.117)	(0.113)	(0.086)	(0.092)	(0.104)
Pair FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Amount Bucket	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Maturity Bucket	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Default Risk Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	347,471	347,471	347,471	347,471	347,463	347,471	345,700
R-squared	0.777	0.777	0.777	0.777	0.777	0.777	0.772

TABLE 6: PASS-THROUGH PER REGION

The table reports pass-through estimates by lending region to the interest rates of commercial loans around the introduction of the 2014 SOLCA tax in Ecuador. Data are at the loan-level 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 $\times$ firm (pair) FE. The model is separately estimated by region. Robust standard errors are clustered at the bank-quarter level.

	Pass-through (ρ)	**S.E.**	**Observations**	**P-value** (**Pass-through = 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 7: DEMAND PARAMETERS

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

Region	Variable	Mean	Std. Dev.
Azuay	Price	−0.245***	(0.055)
Azuay	Sigma	1.602***	(0.032)
Azuay	Scaling Factor	−0.027	(0.337)
Azuay	Log(Branches)	0.869	(1.951)
Azuay	Age Firm	0.376***	(0.007)
Azuay	Age Relationship	0.183***	(0.037)
Azuay	Assets	0.109	(0.136)
Azuay	Debt	−0.025	(0.063)
Azuay	Expenditures	0.165***	(0.045)
Azuay	Revenue	0.003	(0.043)
Azuay	Wages	0.123***	(0.028)
Costa	Price	−0.048**	(0.021)
Costa	Sigma	1.421***	(0.034)
Costa	Scaling Factor	−0.046	(0.403)
Costa	Log(Branches)	0.827	(1.166)
Costa	Age Firm	0.204***	(0.007)
Costa	Age Relationship	0.148***	(0.033)
Costa	Assets	0.019	(0.060)
Costa	Debt	−0.005	(0.030)
Costa	Expenditures	0.060*	(0.036)
Costa	Revenue	0.023	(0.035)
Costa	Wages	0.063**	(0.026)
Guayas	Price	−0.434***	(0.158)
Guayas	Sigma	−0.069	(0.065)
Guayas	Scaling Factor	−0.016	(0.350)
Guayas	Log(Branches)	0.732	(1.306)
Guayas	Age Firm	0.215***	(0.009)
Guayas	Age Relationship	0.036	(0.042)
Guayas	Assets	0.022	(0.124)
Guayas	Debt	−0.007	(0.070)
Guayas	Expenditures	0.062**	(0.028)
Guayas	Revenue	0.021	(0.031)
Guayas	Wages	0.016	(0.029)

Continued on next page

TABLE 7 – 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	(0.321)
Pichincha	Log(Branches)	0.735	(1.377)
Pichincha	Age Firm	0.205***	(0.007)
Pichincha	Age Relationship	0.157***	(0.030)
Pichincha	Assets	0.051	(0.107)
Pichincha	Debt	−0.010	(0.053)
Pichincha	Expenditures	0.207***	(0.039)
Pichincha	Revenue	0.002	(0.037)
Pichincha	Wages	−0.003	(0.032)
Sierra	Price	−0.091***	(0.012)
Sierra	Sigma	1.168***	(0.038)
Sierra	Scaling Factor	−0.033	(0.545)
Sierra	Log(Branches)	0.865	(1.321)
Sierra	Age Firm	0.225***	(0.008)
Sierra	Age Relationship	0.152***	(0.040)
Sierra	Assets	−0.009	(0.095)
Sierra	Debt	−0.026	(0.043)
Sierra	Expenditures	0.395***	(0.044)
Sierra	Revenue	0.012	(0.037)
Sierra	Wages	0.078**	(0.034)

TABLE 8: 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 9: 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 10: MOVE TO COMPETITION

This table presents the estimated borrower-bank-loan specific (Panel A) marginal costs under two modes of conduct (when banks are forced to Bertrand Nash compete: Not allowing banks to collude ($\upsilon_m \equiv 0$); and assuming banks joint maximize: Allowing banks to collude ($\upsilon_m \equiv 1$). Panel B presents predicted prices. Panel C shows the markups under Bertrand and Joint Maximization.

	Mean	**Median**
	Panel A: Marginal Costs	
Marginal Cost - Not allowing banks to collude ($\upsilon_m \equiv 0$)	8.82	9.30
Marginal Cost - Allowing banks to collude ($\upsilon_m \equiv 1$)	4.87	3.10
% Change in Marginal Cost	-50.57	-55.75
	Panel B: Prices	
Prices - Predicted	11.25	11.56
	Panel C: Markups	
Markup - Not allowing banks to collude ($\upsilon_m \equiv 0$)	2.43	2.30
Markup - Allowing banks to collude ($\upsilon_m \equiv 1$)	6.38	4.79

TABLE 11: CONDUCT PER REGION

The table reports conduct parameters estimates by lending region. The model is separately estimated by region on a random sample of 2,500 firms using a simulated method of moments model that matches empirical to model-estimated tax pass-through. The bootstrapped standard error is based on 1,000 bootstrap samples.

	Mean	Standard Error
Azuay	0.70	0.12
Costa	0.91	0.04
Guayas	0.33	0.07
Pichincha	0.56	0.07
Sierra & Oriente	0.67	0.06

TABLE 12: TAX INCIDENCE

This table presents simulated estimates of tax incidence and marginal excess burden through the lens of the model separately by lender conduct—either calibrated, Bertrand-Nash or joint maximization. For Bertrand-Nash and joint maximization we explore results using model-consistent and empirical pass-through estimates. Model (1) presents ex-ante estimates, before the decision of which bank to choose from. Instead, Model (2) presents ex-post estimates, conditional on the observed choice of bank. In practice, the difference between Models (1) and (2) is that Model (1) adjusts bank surplus and tax revenue by the choice probability (market share s_{ikmt}). *Marginal excess burden* is defined as the sum of marginal borrower surplus, marginal bank surplus, and marginal tax revenue.

	Mean	**Median**	**Mean**	**Median**
	Unconditional (1)		**Conditional (2)**	
Panel A: The empirical benchmark				
Calibrated Conduct | Empirical Pass-through				
Incidence	2.76	0.95	0.37	0.35
Excess Burden over Marginal Tax Revenue			-0.41	-0.50
Panel B: Counterfactual Simulations				
Joint-Maximization | Simulated Pass-through				
Incidence	3.51	1.05	0.48	0.41
Excess Burden over Marginal Tax Revenue			-0.36	-0.40
Bertrand-Nash | Simulated Pass-through				
Incidence	6.34	1.93	0.88	0.97
Excess Burden over Marginal Tax Revenue			-0.92	-0.97
Panel C: Counterfactual Conduct, Empirical Pass-through				
Joint-Maximization | Empirical Pass-through				
Incidence	3.64	1.02	0.49	0.35
Excess Burden over Marginal Tax Revenue			-0.35	-0.34
Bertrand-Nash | Empirical Pass-through				
Incidence	3.55	1.14	0.52	0.51
Excess Burden over Marginal Tax Revenue			-0.51	-0.50

Appendix A A Model of Commercial Lending with General Competitive Conduct

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

Appendix A.1 Setup

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

Appendix A.2 Credit Demand

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

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

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

where $\overline{\Pi}_{ikmt}$ is the indirect profit function of the optimized values of loan usage, L_{ikmt}. It is equivalent to an indirect utility function in the consumer framework. X_{it} are observable characteristics of the firm, for example, its assets or revenue. r_{ikmt} is the interest rate.[1] X_{ikmt} are time-varying characteristics of the bank-firm pair such as the age of the relationship. N_{kmt} is time-varying branch availability offered by the bank in market m. ψ_i captures unobserved (both by the bank and the econometrician) borrower characteristics, such as the shareholders' net worth and 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:

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

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

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

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

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

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

for ψ_i having a distribution F.

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

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

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

lemma:[3]

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

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

The demand model is defined jointly by Equations A4 and A5, 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).[4] 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 con-

[3] Benetton (2021) uses Roy's identity, which states that product demand is given by the derivative of the indirect utility with respect to the price of the good, adjusted by the derivative of the indirect utility with respect to the budget that is available for purchase. This adjustment normalizes for the utility value of a dollar. As firms do not necessarily have a binding constraint, especially when making investments, we 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.

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

duct:

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

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:

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

Rearranging Equation A7 yields:

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

which we write using price elasticities:

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

Much like a regular pricing equation, the model splits the price equation into a marginal cost term and a markup. In our case, the markup is composed of two terms: the usual own-price elasticity markup ($\epsilon_{kk} = \partial Q_{ikmt} / \partial r_{ikmt} r_{ikmt} / Q_{ikmt}$) plus a term that captures the importance of the cross-price elasticities ($\epsilon_{kj} = \partial Q_{ikmt} / \partial r_{ikmt} r_{ijmt} / Q_{ikmt}$). The model, therefore, nests the Bertrand-Nash pricing behavior of Crawford et al. (2018), Benetton (2021) and others, but allows for deviations of alternative conduct. For $\upsilon_m > 0$, the bank considers the joint losses from competition. The higher the value υ_m, the 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:

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

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 $A_k \equiv -[\sum_j \frac{\partial Q_{kmt}}{\partial r_{jmt}}]/[\frac{\partial Q_{kmt}}{\partial r_{kmt}}]$. Thus, the diversion ratio is the extent to which borrowers switch to borrowing from another bank in response to a change in loan price. We can then express the markup formula as

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

We 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 borrower's identity. For example, some borrowers may be easier to monitor so that the bank will have a lower marginal cost of lending to them. Second, we allow the marginal cost to be bank-dependent, capturing differences in efficiency across banks. Third, we allow for differences across markets, permitting geographical dispersion such as that related to the density of the bank's local branches. Fourth, we 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.

Appendix A.3 Discussion of identification of the conduct parameter

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

First, we establish that our model alone does not allow separate identification of the supply parameters. Suppose that the econometrician has identified the demand and default parameters, either through traditional estimation approaches or because the econometrician has direct measurements of these objects using an experimental design.[5] By inverting Equation A9, we obtain:

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

This equation indicates that, 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.

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

Thus, relying on demand shifter instruments is unlikely to satisfy the exclusion restriction. For instance, borrower observable characteristics like firm growth rates, assets, or even the age of the CEO will be correlated with changes in the borrower-specific marginal cost.

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

To obtain an expression for pass-through as a function of conduct υ_m, express Equation A7 in terms of semi-elasticities:

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

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

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

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

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

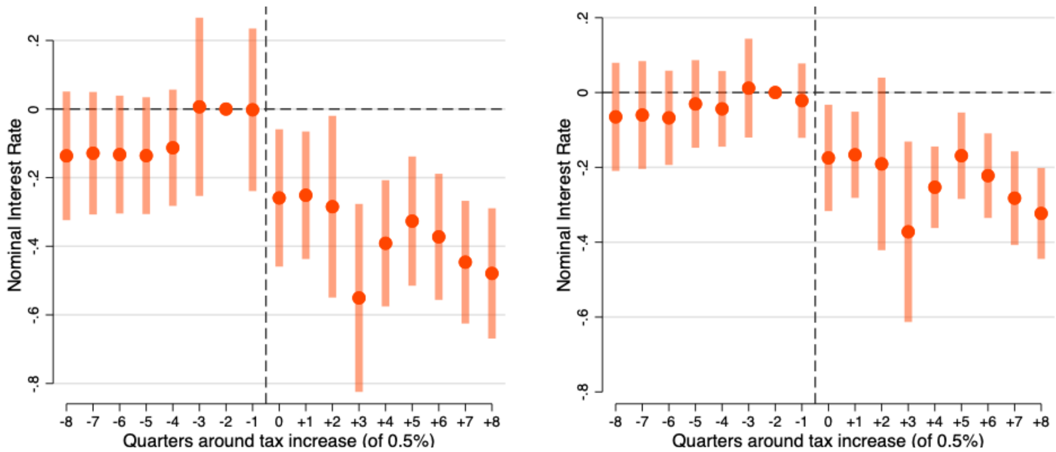
[6] While to our knowledge, this approach is novel in the lending literature, papers in the development (Bergquist and Dinerstein, 2020) and trade (Atkin and Donaldson, 2015) literatures have used pass-through to identify the modes of competition in agricultural and consumer goods markets.

general bank competition model is:

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

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

Appendix B Robustness of passthrough estimates

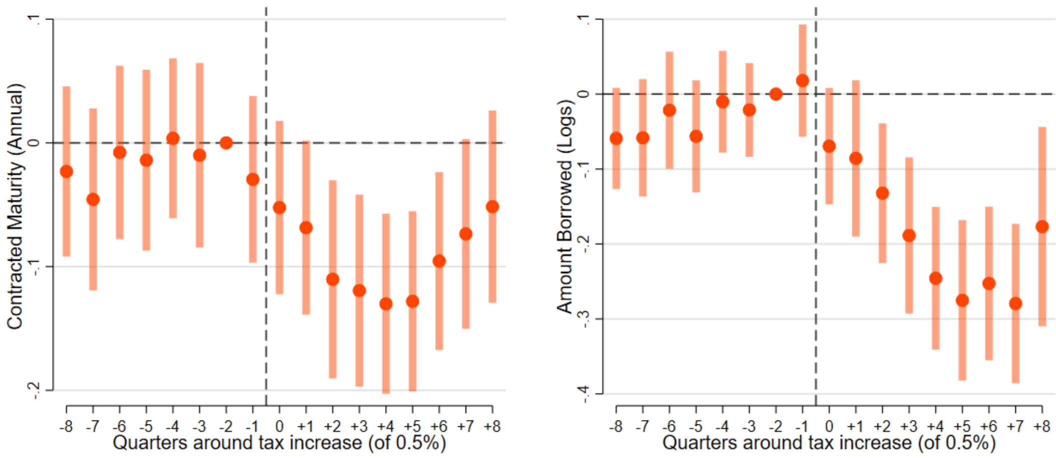


(a) Regular loans; bank & firm FE

(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 C Loan default prediction

We predict default at the loan level by regressing the event of a loan becoming 90 days or more behind payment on lagged firm-level 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

VARIABLES	(1) 1(Default)	(2) 1(Default)	(3) 1(Default)	(4) 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 D Price Prediction

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

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

$$r_{ikmt} = \gamma_0 + \gamma_x X_{ikmt} + \gamma_2 ln(L_{ikmt}) + \gamma_3 ln(M_{ikmt}) + \lambda_{kmt} + \omega_i^r + \tau_{ikmt}, \tag{A16}$$

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.[7] 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.[8]

Table A2 reports the price regressions. By comparing Model (1) with Model (2) and Model

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

[8]Table A2 and Appendix Table A3 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 A16 with firm fixed effects as our preferred specification.

(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.[9]

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

TABLE A2: PRICE PREDICTION REGRESSIONS

The table reports estimates of Equation **??**, 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

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, ranking firm revenue and performance and past repayment decisions as the primary factors determining lending terms. These are all hard data directly observable in our data.

Second, in Appendix C, we test the extent to which the variation in prices we cannot explain predicts firms' subsequent default. Specifically, we regress loan default on the same set of controls and the residuals from the regressions reported in Table A2. 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 E for further information and diagnostics on our matching model.

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

$$\begin{aligned} r_{ikmt} &= \tilde{r}_{ikmt} + \tilde{\tau}_{ikmt}, \\ &= \tilde{r}_{kmt} + \tilde{\gamma}_x X_{ikmt} + \tilde{\gamma}_2 ln(L_{ikmt}) + \tilde{\gamma}_3 ln(M_{ikmt}) + \tilde{\omega}_i^r + \tilde{\tau}_{ikmt} \end{aligned} \tag{A17}$$

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 A3. As shown in the figure, our model predicts well the areas with greater mass as well as the support of the distribution of observed prices. Moreover, our model predicts similar prices for non-chosen options for borrowers but higher prices (around 8%) for non-borrowers.

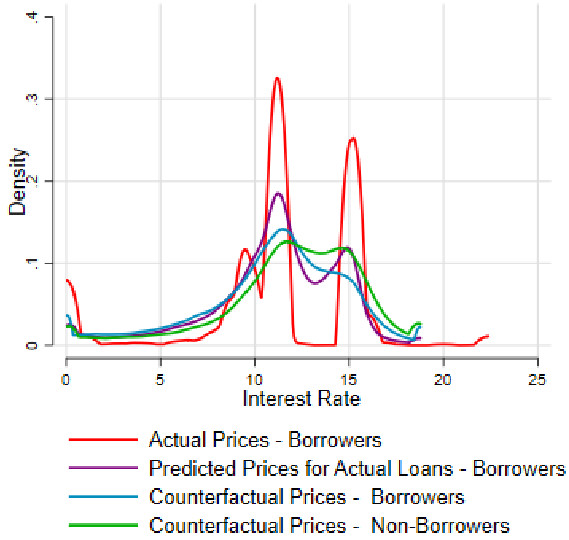


FIGURE A3: DISTRIBUTION OF PREDICTED PRICES

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

TABLE A3: 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 A2. The same set of controls are used as in the corresponding Model in Table A2. 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 E Firm matching model

TABLE A4: PROPENSITY SCORE MATCHING - BIAS

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

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

Appendix F Demand Estimates

TABLE A5: DEMAND PARAMETERS

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

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

TABLE A6: OVER-IDENTIFICATION TESTS FOR INSTRUMENTED PRICE PARAMETER

The table shows the region-level estimated price parameter, from the demand-side estimation of the indirect profit function in Equation 11. $\widehat{Price}$ are the estimates of the instrumented price parameter. *t-statistic* is the associated t-statistic for a test against the null of zero. *F-statistic* is the Cragg-Donald Wald F statistic for the first-stage against the null that the excluded instruments are irrelevant in the first-stage regression. Finally, *P-value over-identification* is the p-value for a Sargen-Hansen test of over-identifying restrictions with the null hypotheses that the error term is uncorrelated with the instruments.

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

Appendix G Simulations and Counterfactual Exercises

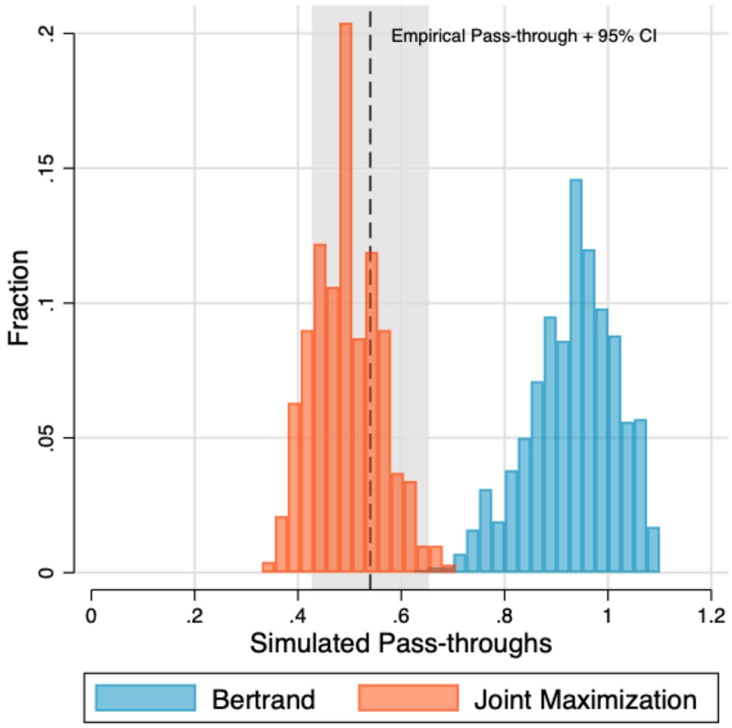


FIGURE A4: DISTRIBUTION OF SIMULATED PASSTHROUGHS FOR CHOSEN BANKS BY CONDUCT

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 H 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).[10] The Superintendencia de Bancos y Seguros (SB; Superintendent of Banks and Insurance Companies) is the regulator for the sector.[11]

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.[12] 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.

Appendix H.1 Market characteristics' relationship to interest rates

We test the representativeness of Ecuadorian commercial lending by checking the correlations between average equilibrium interest rates and market characteristics at the aggregated bank-province-year level. Table A7 reports the results. Model 1 employs year fixed effects (FE), Model 2 utilizes province and year FE, and Model 3 runs estimates with both year and bank FE.

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

[11]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.

[12]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.

TABLE A7: 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

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

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