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

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Abstract

We examine how market structure impacts the effectiveness of financial taxes and subsidies using pass-through estimates from Ecuador's unexpected introduction of a loan tax in 2014. Utilizing a comprehensive commercial loan dataset and a quantitative model that generalizes bank competition theories—including Bertrand-Nash competition, credit rationing, and joint maximization—we reject standard competition models and find that distortions from the loan tax depend significantly on market competitiveness. Ignoring market structure inflates estimated deadweight loss by 80% because non-competitive banks absorb some tax burden. Conversely, subsidies are less effective in less competitive markets. Findings suggest policymakers consider market structure in tax-and-subsidy strategies.

JEL Classification Codes: Banks (G21); Government Regulation of Banks (G28); Taxation and Subsidies (H2); Market Structure, Firm Strategy, and Market Performance (L1)

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Policymakers target taxes and subsidies on the banking sector because of its essential role in aggregating wealth and allocating it across the real economy. These policies are widely discussed in public forums and in the academic literature. Yet the discussion often overlooks the potential impact of the banking sector's competitive structure on the effectiveness of taxes and subsidies (Weyl and Fabinger (2013); Pless and van Benthem (2019)), even though banking is not well described by the competitive benchmark in the classical paradigm of public finance (Slemrod (1990); Auerbach (2002)).[1] This paper fills this gap by empirically investigating how bank competitive conduct mediates the welfare effects of financial tax and credit policies.

Our study makes two important contributions. We are the first to test competitive conduct in a market with selection.[2] We reject the traditional benchmark modes of competition—differentiated price competition (Bertrand-Nash) and credit rationing (Cournot). Second, we estimate the impact of incorrect assumptions about competition, finding that these errors lead to significant mismeasurement of the incidence and welfare effects of financial taxes and subsidies. Overall, both in practice for policymakers and when modeling credit markets, the assumptions about how lenders compete are consequential.

We focus on the setting of an unanticipated introduction in 2014 of a loan 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.[3] Crucially, the tax was unanticipated and swiftly enacted—it was proposed in September and was in effect by October 2014. Thus, the SOLCA tax introduction serves as (1) a representative example of a capital tax employed worldwide,[4] and (2) a quasi-exogenous shock to the marginal cost of lending, uncorrelated with any concurrent changes in credit demand.

We gather a comprehensive administrative dataset covering 2010 to 2017 that combines

[1]There is recent reduced-form evidence that tax pass-throughs vary by market concentration in lending markets (Drechsler et al. (2017); Benetton and Fantino (2021)). Yet the standard assumption in the structural lending literature remains that lenders do not consider their competitor's profits when pricing loans (Egan et al. (2017); Crawford et al. (2018); Robles-Garcia (2021); Benetton et al. (2024); Cuesta and Sepúlveda (2024); Cox et al. (2023); Yannelis and Zhang (2023)). More broadly, empirical evidence of competition in banking and its effects includes Ciliberto and Williams (2014); Cornaggia et al. (2015); Hatfield and Wallen (2023); Brugués and De Simone (2023); and Jiang et al. (2023).

[2]We do not model asymmetric information directly, rather, it is captured in borrower-specific, time-varying marginal costs. This captures "aggregate" selection induced by changes in interest rates. Additionally, we allow for common-knowledge heterogeneity in default rates that depend on borrower characteristics, as in Benetton et al. (2024). As demand for credit also depends on those same characteristics, our model can capture the correlation between default risk and willingness to pay, effectively capturing selection patterns (Einav et al., 2021).

[3]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.

[4]The Centre for Economic Policy Research estimates that more than 40 countries used a financial transaction tax in 2020 (https://cepr.net/report/financial-transactions-taxes-around-the-world/, accessed November 1, 2024). And such taxes are frequently proposed.

the terms of individual loans for new commercial credit and detailed firm-level information for commercial borrowers, who primarily rely on bank credit for financing.[5] We rely on the unexpected introduction of the tax to obtain pass-through estimates using an event study. On average, borrowers shoulder approximately 35% to 50% of the loan tax on the average loan while the bank absorbs the remainder by reducing equilibrium loan interest rates. We do not observe any anticipatory movement in interest rates, while the incomplete tax pass-through persists through eight quarters after the tax was implemented. We also do not observe any response in the interest rates of loans from government banks, which were not subject to the tax. Moreover, we compare within active firm-bank pairs so that changes in the composition of borrower risk are unlikely to drive the results.

The literature has argued that persistent incomplete pass-through is *prima facie* evidence of imperfect competition (e.g., Drechsler et al., 2017; Benetton and Fantino, 2021; Eisenschmidt et al., 2023). The intuition is that if lenders priced purely based on the marginal cost of lending, they could not profitably decrease interest rates long term in response to the new tax. However, reduced-form evidence alone is insufficient to fully characterize welfare since the same observed pass-through is consistent with multiple market structures if the analysis does not hold other demand and supply parameters constant (Weyl and Fabinger, 2013). Our approach avoids the need to make an *a priori* assumption on the competitive conduct in the market and instead allows us to estimate conduct from the data. Specifically, we introduce a free conduct parameter into a flexible discrete-continuous structural model of commercial lending that captures the equilibrium competitive behavior of banks in the same market. Crucially, our model allows the common competitive structures in the literature as special cases—Bertrand-Nash competition (the literature's benchmark), credit rationing (Cournot), and joint maximization—and can be estimated using traditional methodologies (Train, 1986).

While flexible, our approach introduces an additional difficulty: it is not possible to separately estimate competitive conduct and supply-side parameters using only price and quantity data without proper demand or markup shifters (Bresnahan, 1982; Berry and Haile, 2014). But in markets with selection, it is challenging to distinguish risk-adjusted costs from demand (Einav et al., 2021). In particular, variables that shift demand are likely also to shift the underlying marginal cost of lending. Therefore, traditional conduct testing methods based on demand demographics and product characteristics instruments (Backus et al., 2024; Duarte et al., 2024) are likely invalid in selection markets. Our key innovation is the insight that the tax

[5] Data from the World Bank Enterprise Survey 2017 reveals 60% of Ecuadorian firms have bank credit, comparable to the Latin American average (53% of firms). Other prominent sources of financing in Ecuador include internal financing (covering 54% of investments) and supplier trade credit (used by 64% of firms).

pass-through estimates themselves serve as quasi-experimental variation in lending markups 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 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 cartel in the market. We can rule out that banks are Bertrand-Nash or Cournot (credit rationing) competing with at least 95% confidence. We test the robustness of the results by transparently validating the identification conditions relating pass-through to conduct and find that our method is powered to effectively test the benchmark models in the literature. Furthermore, to reduce concerns that conduct might have been affected from the introduction of the tax, we show estimates are not meaningfully affected if we estimate demand using data from before the tax is introduced.

We also explore the robustness of the conduct result by concentrating on the conduct testing framework (Backus et al., 2024; Duarte et al., 2024; Dearing et al., 2024) and applying it to the internalization parameter approach of Miller and Weinberg (2017), which allows for partial cartels. We find that a partial cartel of the top four largest banks or of banks in a banking association with open anti-trust cases offer a better fit than Bertrand-Nash, and that the tests favor strong internalization parameters for a given cartel definition. In terms of the best fitting cartel, the tests favor a top four bank cartel, though a full banking cartel in line with our conduct approach is also consistent with the data.

Why might banks collude? The easy answer is that, as in other sectors, banks prefer higher markups. But specific to banking, policymakers often favor market concentration and lender cooperation in lending to reduce fragility in the banking system.[6] Besides the structural testing results, we also provide reduced-form evidence supporting collusion in our setting. Markets with lower competition, measured by a variety of competition proxies from the literature, have less complete pass-through and less competitive conduct parameters. Moreover, loans from members of a banking association with multiple outstanding anti-trust cases have less complete pass-throughs. However, our aim is not to describe the exact form of existing cartels, but to show that the standard benchmark models (differentiated Bertrand-Nash or credit rationing) are rejected in this setting, and to explore the consequences for public finance questions.

Specifically, we use our model to quantify how important competition in commercial lending is to the welfare effects of the bank tax from an ex-ante perspective, where the policymaker

[6]This "competition-fragility" hypothesis proposes that competition reduces bank profit margins and charter values, encouraging banks to increase risk (e.g., Beck et al. (2013); Jiang et al. (2023)), though this hypothesis is contested.

does not know the empirical tax pass-through. Not accounting for lender collusion would vastly overstate the welfare costs of taxes (and, conversely, the welfare gains from subsidies). Assuming Bertrand-Nash price competition when setting interest rates, we estimate the SOLCA tax's deadweight loss to be 92 cents per dollar. Instead, while still distortive, we estimate a significantly smaller loss of 41 cents per dollar when allowing the model to depart from differentiated Bertrand-Nash price competition, the most common conduct in the literature. Thus, the tax was less distortive than originally believed without accounting for lender equilibrium competition.

This is because the incidence of the tax depends critically on the competitive structure of the market. Under Bertrand-Nash competition, borrowers bear a higher burden of the tax, leading to a greater deadweight loss per unit of revenue raised. In contrast, in a joint maximization environment, the tax falls primarily on banks, reducing its distortionary effect on borrowing. Hence, the policymaker's evaluation of the efficiency and incidence implications of introducing a capital tax is greatly affected by the market structure assumption.[7] As in Miravete et al. (2018), we find that revenue-maximizing tax rates are higher under less competitive conduct, indicating that the Laffer curve shifts rightward under reduced competition. Moreover, we estimate that tax revenue would be approximately 10% lower if lenders Bertrand-Nash competed.

The focus of our study is on the 2014 SOLCA tax in Ecuador, but its implications go beyond this specific context due to the global prevalence of uncompetitive banking sectors and the widespread use of capital taxes.[8] Moreover, at the most basic economic level, the SOLCA tax is a quasi-exogenous shock to lending markups in our setting. Thus, our methodology readily applies to other markup shocks (keeping demand constant), such as studying the effect of monetary policy pass-through when lending markets are not competitive.

The final important implication of our model estimates is that in our setting we find that estimates for both incidence and excess burden are consistent across the various conduct assumptions if one relies on empirical pass-throughs to capture competition behavior among banks.[9] This is because consumer surplus and government marginal revenue mostly depend on pass-through rates, while producer surplus depends on pass-through and demand elasticities. In our setting, the relevant empirical cross-price elasticities are much smaller than the own-price

[7] We study how lender collusion influences the effect of the SOLCA tax, *assuming* that lender conduct remains constant. Of course, there is distortion from collusion in lending markets independent of fiscal policy. We address this separate question in related research, Brugués and De Simone (2023), where we utilize our model to quantify the impacts on both the intensive and extensive margins from lender collusion.

[8] We provide evidence that the Ecuadorian commercial loan market is representative in Section 1 and in Appendix Appendix A, where we report correlations between average equilibrium interest rates and market characteristics at the aggregated bank-province-year level. We also compare our estimates to those in the public finance and banking literatures throughout.

[9] Exact welfare magnitudes cannot be pinned down without a model that incorporates flexible conduct.

elasticity. As a result, the influence of conduct on final producer surplus is relatively small. This implies that, from a policy perspective, it may be feasible in Ecuador and countries with similar loan demand features to robustly evaluate ex-post the welfare effect of financial taxes without the need to model and test conduct beforehand.[10] This insight further enhances the practical usefulness of our findings to policymakers, including outside of our specific setting.

Our study advances the literature in several ways. First, our paper connects to an extensive literature on pass-through (Nakamura and Zerom, 2010; Weyl and Fabinger, 2013; Fabra and Reguant, 2014). Within this literature, a few papers empirically study how incidence varies with regulatory and demand-based drivers of market power (Cabral et al., 2018; Ganapati et al., 2020; Conlon and Rao, 2023; O'Connell and Smith, 2024). Closest to our study, Cabral et al. (2018) study pass-through in health insurance, also a selection market. They create a framework to decompose pass-throughs into selection, risk, and demand-based market-power, and find that pass-through is mostly explained by demand-side market power. However, they do not test different modes of insurer conduct. Our study is the first to study supply-side drivers of pass-through accounting for selection and risk. Moreover, to our knowledge, this study is the first to investigate how market structure mediates the incidence and welfare effects of taxes in a market with selection.

Within the lending literature, there are few studies of the distributional effects of taxes and how this depends on intermediary market structure. Existing papers provide reduced-form evidence from high-income countries.[11] Specifically, there is evidence that supports that deposit (Drechsler et al., 2017) and lending (Benetton and Fantino, 2021) pass-throughs vary by lender concentration. Relative to this literature, this paper quantifies the welfare impacts of lender collusion on fiscal policy, establishes the mechanism of this effect and how it varies across the firm-size distribution, and illuminates the source of bank pricing power. To do so, our paper adopts a public finance lens, novel to this literature, and a unique quasi-experiment and comprehensive dataset.

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. Following this strategy we are the first to empirically test the competition model of lending directly, rather than assuming away collusion. A substantial portion of the credit literature—Crawford et al. (2018) and Cox et al. (2023) in commercial lending and also in deposits (Egan et al., 2017), mortgages (Robles-Garcia, 2021;

[10] This is not obvious as, keeping pass-through constant, incidence and excess burden generally change with conduct (Weyl and Fabinger, 2013).

[11] In a companion paper, Brugués and De Simone (2023), we quantify the welfare impacts of lender collusion.

Benetton, 2021), auto lending (Yannelis and Zhang, 2023), and consumer lending (Cuesta and Sepúlveda, 2024)—focuses on Bertrand-Nash models and the role of lending market frictions in explaining observed prices.[12] 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 competition.

This contribution relates to an extensive industrial organization literature that models and estimates firm conduct, following the pioneering work of Bresnahan (1982). Notable recent examples (Nevo, 2001; Miller and Weinberg, 2017; Backus et al., 2024; Calder-Wang and Kim, 2024) follow his lead in using exclusion restrictions from plausibly exogenous shifters of markups to test alternative conduct models. This literature relies on instruments on product characteristics or demand demographics instruments that shift demand without affecting marginal costs (Berry and Haile (2014); Backus et al. (2024); Duarte et al. (2024); Dearing et al. (2024)). However, in markets with selection and other pair-specific frictions, such instruments also correlate with marginal costs, violating the exclusion restriction.[13] Instead, we use a tax as an exogenous shifter and propose the targeting of pass-throughs as a moment to estimate lender conduct.[14] Our methodology thus extends the classic industry-wide papers from Sumner (1981) and Sullivan (1985) and 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. Our approach offers an elegant, and, to the best of our knowledge, novel approach to studying an industry that involves selection, like lending.

Lastly, our paper relates to a fast-growing financial literature on monetary policy pass-through to loan and deposit rates (Di Maggio et al., 2017; Drechsler et al., 2017; Benetton and Fantino, 2021; Wang et al., 2022; Eisenschmidt et al., 2023; Li et al., 2023). For loans, Benetton and Fantino (2021) find more complete pass-through of monetary policy to interest rates in competitive markets (measured by HHI). Wang et al. (2022) also find that pass-through

[12] Hatfield and Wallen (2023) consider the impact of bank collusion in the deposit market through multi-market contact but do not take a modeling approach that allows quantification of otherwise unobservable bank conduct. Ciliberto and Williams (2014) also considers the effect of collusion through multi-market contact in the airline industry but do not allow for a fully flexible conduct parameter. Our approach allows us to flexibly consider multiple traditional models of bank competition and estimate the conduct parameter without taking an ex-ante stand on the mode of conduct in the data.

[13] E.g., firm growth rates, assets, and the age of the CEO correlate with borrower-specific marginal cost changes.

[14] Delipalla and O'Donnell (2001) were the first to use tax changes to test conduct in the cigarette industry while Rojas (2008) also use pass-through from a large increase in excise tax on beer to compare prices to those implied by various pricing models. Contemporaneously, Dearing et al. (2024) show theoretically and empirically that pass-throughs are the economic determinants of instrument relevance for conduct testing.

in loans is incomplete. For deposits, Drechsler et al. (2017) find that the pass-through of a federal funds rate increase to deposit rates is incomplete, with a widening spread between the federal funds rate and deposit rates. This spread is greater in less competitive markets. Hatfield and Wallen (2023) also find lower pass-throughs in less competitive deposit markets, where competition is measured by multi-market contact among lenders. The imposition of a small loan tax provides a cleaner setting than an interest rate change, which impacts welfare directly and through large feedback effects. Nevertheless, our methodology can readily apply to these settings by modeling deposit or loan demand flexibly and using the interest rate pass-through estimates to infer the mode of competition among lenders. For example, our findings suggests that expansionary monetary policy in Ecuador would have a more diluted effect on lending than expected assuming no collusion, with banks appropriating a significant portion of the implied loan subsidy.

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 2.3 describing how we identify the conduct parameter using pass-through from the SOLCA tax. Section 3 presents empirical pass-through estimates. Section 4 describes how we estimate the demand model and present estimates and model fit. Section 5 presents the estimation strategy and estimates for the supply model. Section 6 offers model validation exercises and counterfactual simulations, while Section 7 presents welfare analysis of the SOLCA tax and how it depends on lender competitive conduct. Section 8 concludes.

1 Description of the SOLCA Tax and Dataset

1.1 Loan Tax

Like many developing countries, particularly in Latin America, Ecuador employs financial transaction taxes as a revenue source (Kirilenko and Summers, 2003). From 1964, Ecuador utilized a bank levy to raise funds to fund free cancer treatment centers run by the Sociedad de Lucha contra el Cáncer (SOLCA). These taxes applied to all 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, opting instead to fund SOLCA through the regular budget.

In September 2014, the Ecuadorian National Assembly passed the legislative framework governing the country's financial and monetary system, the "Código Orgánico Monetario y

Financiero."[15] to consolidate existing regulations in one framework and to pass new regulation of mobile money payments and strengthen anti-money laundering measures. A last-minute amendment reintroduced a SOLCA tax to address funding gaps for cancer treatment. This reintroduction was unexpected by both borrowers and financial institutions in Ecuador.[16] 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 through 2017, only loans from private banks were subject to the SOLCA tax; the law exempted loans from government banks. However, since government banks do not significantly compete in conventional commercial credit, the tax applied to most commercial loans.[17] 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.[18] In summary, the re-introduction of the SOLCA tax was unanticipated and implemented swiftly. It applies to the universe of conventional 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 dataset by combining administrative databases collected by Ecuador's bank regulator, the Superintendencia de Bancos (Superbancos), and its business bureau, the Superintendencia de Compañías (Supercias). 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 government banks. Two of these government banks offer microloans to small businesses, in addition to retail mortgages. While the dataset is not a credit registry—it

[15] In civil law countries like Ecuador, such codes are comprehensive legal statutes that centralize and standardize regulation for all institutions and activities related to finance and monetary policy, akin to a "financial constitution." The code delineates regulatory authority, outlines obligations and operational rules for banks, insurance companies, and other financial entities, and specifies consumer protection standards.

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

[17] See Appendix A for a description of public and private commercial lending, the extent to which these markets were segmented, and how the tax affected this segmentation.

[18] 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.

does not 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 analyses, we focus only on regular commercial loans issued to corporations regulated by Ecuador's business bureau ("SA" firms, for "Sociedad Anónima").[19] This excludes microloans and loans to sole proprietorships. These filters match the coverage of our firm-level data and allow 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 Supercias, 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 variables. Table 1 displays bank-province-year level credit statistics. The average (median) bank issues \$57M (\$1.4M) in corporate loans in each province-year. The average bank lends to 83 corporations in a given province-year, but there are also banks with very few commercial clients, as the median bank has 12 firm clients a province-year. In total, banks offer 487 (24) loans in an average (median) province-year. These patterns in the competitive structure of Ecuador's commercial loan sector are representative of corporate lending elsewhere, as it is common to observe a few dominant national banks lending alongside smaller banks specializing regionally or in particular loan segments.

[Place Table 1 here.]

To test if the Ecuadorian commercial market relates to bank competition similarly to what has been documented in the banking literature, 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.

[19]In Ecuador, business structures include stock corporations (SA) and limited liability companies (SL). The key difference is that shares in stock corporations can be freely traded, while quotas in limited liability companies require unanimous consent to transfer.

[Place Table 2 here.]

Next, Table 3 describes the merged commercial loan dataset spanning the years 2010 to 2017. The top panel summarizes the data at the firm-year level. All measurements expressed in currency are in 2010 U.S. dollars. 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, $2 million in assets. As is common elsewhere, the firm size distribution is highly skewed—the median firm holds $400,000 in total assets. Total sales demonstrate a similar skew, with average (median) sales of $2.6 million ($620,000). The average (median) borrowing firm is highly leveraged, displaying an average (median) debt-to-assets ratio of 0.66 (0.71). On average (at median), firms maintain 1.38 (1) banking relationships within a given borrowing year. Most clients repeatedly borrow, as indicated by the average client borrowing 9 (2) times in a year.

[Place Table 3 here.]

In contrast, panel (b) reports that 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).[20] Panel (c) describes the loan-level data for the universe of commercial (non-micro) loans granted to corporations between 2010 and 2017. The average (median) duration of borrower-lender relationships is 2.31 (2) years. Each loan is for on average (median) of $100,000 ($10,000) and the average (median) term-to-maturity is six (three) months. The average (median) annualized nominal interest rate is 9.20% (8.95%). Finally, panel (d) reports bank-year level deposit rates, a proxy for the marginal cost of funds, of around 4%.

The banks in our sample only write down the value of about two percent of the loans that they issue. Actual default is a rare occurrence in our sample, happening less than one percent of the time. In the total sample, which includes sole proprietorships and micro-loans, the default rate is three percent. The combination of low default rates, high lending rates, and a moderate level of marginal cost based on the deposit rate proxy is indicative of lender market power. We provide additional evidence that the Ecuadorian commercial loan market is representative in Appendix A, where we report correlations between average equilibrium interest rates and

[20]Non-borrowing firms may have leverage from sources other than traditional banks. For instance, micro-loans from micro-lending institutions and trade-credit.

market characteristics at the aggregated bank-province-year level. As with the competitive structure of the commercial loan market, the general patterns we observe between market access and loan pricing align with those documented in the existing banking literature.

The main takeaways are that (1) Ecuador is highly representative of other bank-dependent economies, especially in that (2) 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 Commercial Lending Model with Flexible Market Conduct

We have outlined the state of the Ecuadorian commercial lending market at the time of the re-introduction of the SOLCA tax in 2014 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 B. 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.[21]

First, firm i in period t decides whether to borrow from one of the banks k actively lending in market m.[22] 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 at the optimized values of loan usage, L_{ikmt}. It is equivalent to an indirect utility function in the consumer framework. X_{it} denotes observable characteristics of the firm, such as its assets and revenue. r_{ikmt} is the interest rate.[23] X_{ikmt} represents time-varying characteristics of the bank-firm pair, such as the age of the relationship. N_{kmt} is the 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'

[21] We later relax the assumption that the borrowers can borrow from any bank that has lent in the market.

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

[23] Different from Benetton (2021), we allow the price to vary by borrower-bank pair.

net worth and management 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 the demand probability is $s_{ikmt} = Prob(\Pi_{ikmt} \geq \Pi_{ik'mt}, \forall k' \in m)$.

Then, given the set K_{imt} of banks in local market m in the 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 the product of firm i's probability of demanding a loan from bank k, s_{ikmt}, and its expected loan use, L_{ikmt}, given posted interest rates $r = \{r_{i1mt}, ..., r_{1Kmt}\}$. Continuous loan demand is determined by Hotelling's lemma such that input demand is given by $L_{ikmt} = -\partial\Pi_{ikmt}/\partial r_{ikmt}$.

On the supply side, we allow for different forms of competition among banks by introducing the market conduct parameter $\upsilon_m = \frac{\partial r_{ijmt}}{\partial r_{ikmt}}$ $(j \neq k)$. υ_m measures the degree of competition (joint profit maximization) in the market (Weyl and Fabinger, 2013; Kroft et al., 2024). 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 5.1. Intuitively, the parameter captures the degree of correlation in price co-movements.[24]

Banks choose borrower-specific interest rates to maximize their period-t profits. It is important to emphasize that, although we model banks as competing on price, by including the conduct parameter we also allow for banks to compete via credit rationing (quantity/Cournot competition). Specifically, bank k offers interest rate r_{ikmt} to firm i to maximize bank profits B_{ikmt}, subject to the market conduct and one-time tax τ_{ikmt}:

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

Here, d_{ikmt} represents banks' expectations of the firm's default probability at the time of loan issuance. Before the introduction of the tax $\tau_{ikmt} = 0$, and after the introduction of the tax $\tau_{ikmt} \in (0, 0.5]$, depending on the contracted maturity of the loan. The related first-order conditions for

[24]This approach has been criticized in Corts (1999). Nevertheless, it is appropriate for our setting and question, as discussed in Section 6.2, where we also show our conclusions are robust to instead implementing the internalization matrix approach of Miller and Weinberg (2017).

each r_{ikmt} are then given by:

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

Rearranging Equation 3 we derive:

$$r_{ikmt} = \frac{mc_{ikmt}}{1-d_{ikmt}} - \frac{Q_{ikmt}}{\frac{\partial Q_{ikmt}}{\partial r_{ikmt}} + \upsilon_m \sum_{j\neq k} \frac{\partial Q_{ikmt}}{\partial r_{ijmt}}}, \tag{4}$$

which we express in terms of price elasticities:

$$r_{ikmt} = \frac{mc_{ikmt}}{1-d_{ikmt}} - \frac{1}{\underbrace{\frac{\epsilon_{kk}}{r_{ikmt}}}_{\text{Bertrand-Nash}} + \underbrace{\upsilon_m \sum_{j\neq k} \frac{\epsilon_{kj}}{r_{ijmt}}}_{\text{Alternative Conduct}}}. \tag{5}$$

The pricing equation includes a marginal cost term and a markup. The markup comprises two components. First, there is the usual own-price elasticity markup that is retained under pure Bertrand-Nash competition ($\epsilon_{kk} = \partial Q_{ikmt}/\partial r_{ikmt} r_{ikmt}/Q_{ikmt}$). The second term in the markup ($\epsilon_{kj} = \partial Q_{ikmt}/\partial r_{ikmt} r_{ijmt}/Q_{ikmt}$) captures the importance of the cross-price elasticities and clarifies the role of alternative conduct: when $\upsilon_m > 0$, the bank takes into account the joint losses from competition when setting loan rates. The higher the value of υ_m, the more closely bank behavior aligns with full joint-maximization (full cartel), and the higher the profit-maximizing price, r_{ikmt}. The model thus nests the Bertrand-Nash pricing behavior of Crawford et al. (2018), Benetton (2021), and others, but also allows for deviations due to collusive conduct among banks. Our model also adjusts prices upward to account for expected risk from non-repayment, plausibly capturing selection in risk (Einav et al., 2021; Benetton et al., 2024).[25]

2.1 Assumption on Marginal Costs

Our approach allows flexible demand, by capturing both the discrete and continuous elements of demand, and is general enough to test alternative modes of conduct. However, in common with the vast majority of papers in the literature (Backus et al., 2024; Duarte et al., 2024;

[25] 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 closely follows Benetton (2021). An alternative model would adopt 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. Instead of assuming the specific mode of competition, we follow a more general approach that nests several types of competition.

Dearing et al., 2024), we assume that the marginal cost is constant within each loan-year, which may affect our simulated tax pass-throughs and bias our testing framework.

To address this, we make our marginal cost assumption as general as possible. We allow marginal cost to be (1) borrower specific, accounting for, e.g., heterogeneous monitoring costs; (2) bank specific, capturing differences in efficiency across banks; (3) market specific, permitting geographical dispersion such as that related to the density of the bank's local branches. Moreover, we account for pair-specific productivity differences by indexing marginal costs at the pair level, controlling for such factors as bank lending specialization. And, although marginal costs are constant for a given borrower, the pool of borrowers is allowed to affect the firm's total cost function, allowing them to be decreasing, increasing, or constant, depending on the selection patterns of borrowing firms in the data, as in Cabral et al. (2018). Finally, all these factors vary over time.

Moreover, given that we empirically find incomplete pass-through of the SOLCA tax to interest rates, the biggest concern would arise if our marginal cost assumption biased our simulated pass-through away from complete pass-through, i.e., towards finding that banks collude. This would occur if marginal costs of lending are increasing in the quantity demanded by the borrower, as, all else equal, increasing marginal costs would imply more incomplete pass-throughs (Weyl and Fabinger, 2013). To address this concern, we propose a marginal cost curvature testing framework, relying on pair-level estimates of marginal costs and a demand shifter. The testing framework and the results are reported in Appendix C. We find little evidence of increasing marginal costs, either when pooling data from all banks or when estimating the cost curvature at the bank level. If anything, marginal costs appear to be decreasing at the loan level, meaning that, conditional on the loan being realized, larger loans have lower marginal costs.[26] Such decreasing marginal costs would bias our estimates under our constancy of marginal cost assumption in favor of *more* competitive conduct and *against* collusion.

2.2 Accounting for Selection

Given the importance of information frictions in banking, it is worth discussing the role of selection and moral hazard in our model. Our model does not directly endogenize the default decision, in contrast to Crawford et al. (2018). In our setting, base default rates are low (see Appendix A),[27] and previous evidence in developing countries shows moral hazard has second-order effects (Castellanos et al., 2023). However, we do account for selection in two ways. First,

[26]Though the effects are statistically significant, they appear to be economically small: an increase in loan size by $1 million relates to a decrease in marginal costs of $9.

[27]In Crawford et al. (2018), default rates are on average 6%, whereas in our full sample is close to 0%.

we allow for maximum flexibility in marginal costs, which vary at the borrower-pair-year level. Although both parties know this information, this captures the "aggregate" positive or negative selection induced by changes in interest rates, as in Cabral et al. (2018). Additionally, we allow for common-knowledge heterogeneity in default rates that depend on borrower characteristics, as in Benetton et al. (2024). As demand for credit also depends on those same characteristics, our model can capture the correlation between default risk and willingness to pay, capturing selection patterns based on observables (Einav et al., 2021).

2.3 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.[28] By inverting Equation 5, we obtain:

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

This equation demonstrates why observing prices, quantities, demand, and default parameters alone is insufficient to identify pair-specific marginal costs. The reason is that conduct, υ_m, is also unobserved. Without information on υ_m, we can only bound marginal costs using the fact that $\upsilon_m \in [0, 1]$.

To overcome this difficulty, we follow insights from the public finance literature that the pass-through of taxes and marginal costs to final prices are tightly linked to competition conduct (Weyl and Fabinger, 2013). By incorporating the reduced-form pass-through estimates of the SOLCA tax, we introduce an additional identifying equation that enables us to separate marginal costs from conduct parameters. The reason we can recover conduct with information on pass-through estimates is that, given estimates of demand, 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 rationalizes a given pass-through.

To express the pass-through rate as a function of bank conduct υ_m, we express Equation 3

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

into terms of semi-elasticities and apply the implicit function theorem, yielding:

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

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. Notice that under a pair-level constant marginal cost assumption, the pass-through function depends on demand elasticities, demand curvature, interest rates, marginal costs, and default rates.

In practice, we observe pass-throughs at a more aggregate level, such as at 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. The empirical analogue of these market moments can then be used to estimate conduct empirically. Figure 1 summarizes 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 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 did not anticipate the introduction of the tax ("parallel trends"). 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 analyses 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 to calibrate market-level conduct.

3.1 Checking Pass-through Identification Assumptions

If the reduced-form pass-through estimates are biased, then using them as a target in simulations might bias best-fit conduct estimates (Dearing et al., 2024; MacKay et al., 2014). The identification assumption is that, absent the introduction of the SOLCA tax, interest rates would have remained unchanged over time for the same borrower-bank pair, controlling for borrower- and relationship-specific unobservables, contemporaneous loan terms, and time-varying borrower risk (default probability). We rigorously test this assumption by (1) looking for evidence that loan interest rates only respond after the SOLCA tax and (2) only for loans subject to the SOLCA tax; (3) that the SOLCA tax was unexpected by borrowers and banks; (4) showing the pass-through is robust to empirical specification; and (5) testing for contemporaneous marginal cost shocks in aggregate lending, from a oil price and deposit rate fluctuations. First, event studies transparently show the evolution of interest rates over time. Consider the following model for loan l contracted by firm i from bank k at time t:

$$r_{likt} = \sum_{j=-8}^{3} \delta_j 1\{t \in j\} + \beta_a ln(A_{likt}) + \beta_m ln(M_{likt}) + \alpha_i + \alpha_k + \eta DP_{likt} + \varepsilon_{likt}, \tag{8}$$

where r is the pre-tax interest rate, A is the amount borrowed, M is the maturity in years, α_i are firm fixed effects, α_k are bank fixed effects, DP is the predicted default probability, and ε are time-varying unobservables.[29] Firm (bank) fixed effects control for time-invariant unobservable firm (bank) characteristics. In alternative specifications, we incorporate firm-by-bank fixed effects to account for stable, relationship-specific unobservable factors, such as the quality of the bank-borrower match. This specification also controls for compositional effects of borrower risk, as the effects are estimated within already active firm-bank pairs. Finally, periods j are quarters around 2014 quarter 4, 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 Appendix Table A1). Moreover, as shown below, the tax negatively affected the contracted maturity and amount. Thus, their exclusion would lead to an upward bias in the estimated coefficients δ_j, i.e., a bias towards complete pass-through. 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_j to

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

zero. Standard errors are clustered at the bank-quarter level to account for potential correlation of errors within bank prices in a given quarter.

The coefficient of interest, δ_j, identifies the average percent change in nominal interest rates on new loans from introducing the tax relative to two quarters ahead of the introduction (normalized to zero). If $\widehat{\delta_j}$ is negative, then prices (and markups) decreased in response to the introduction of the SOLCA tax. This would indicate incomplete pass-through of the tax to borrowers because banks bore some of the burden by lowering loan interest rates in equilibrium.[30] If, instead, $\widehat{\delta_j}$ is positive, there is more-than-complete pass-through, as the firm bears the full cost of the tax and pays a higher interest rate. Lastly, if $\widehat{\delta_j}$ is zero, there is complete pass-through of the tax to borrowers—the borrowers pay the entire tax and the bank does not adjust the interest rate. If we assume a constant marginal cost, either incomplete or more-than-complete pass-through is evidence of imperfect competition in the commercial bank lending market.[31]

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. This specification allows us to test for pre-trends visually. Pre-tax average nominal interest rates remained flat for eight quarters before the SOLCA tax. We can not statistically distinguish pre-event coefficients from the normalized period (-2). Immediately after the introduction of the tax, nominal interest rates decreased 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 0.6, i.e., the lender and borrower approximately split the tax burden.[32] Estimated effects are similar if we use pair (bank-firm) fixed effects instead of separate bank and firm fixed effects, as shown in the right panel of Figure 2.[33] This specification provides further evidence that compositional effects of borrower risk do not drive the effects since the effects are within already active firm-bank pairs.

[Place Figure 2 here.]

One might worry that regulatory and economic changes concurrent with the tax bias the estimates toward incomplete pass-through. As a falsification test, we run our baseline event

[30] Recall that the law mandates that the firm pay the tax, which is collected and remitted to the Tax Authority by the bank at loan grant. However, which party bears the tax burden need not be the same as the statutory burden. In this case, to the extent the bank lowers interest rates in equilibrium, they are bearing some of the cost of the tax.

[31] If we assume constant demand curvature, incomplete pass-through implies that the demand curve is log-concave while over-complete pass-through can indicate that it is log-convex.

[32] Calculated as (0.5-0.2) / 0.5 = 0.6. 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.

[33] 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.

study, Equation 8, on a sample of loans lent by government banks, which did not carry the SOLCA tax but were subject to similar unobserved factors affecting the entire banking industry. Moreover, regulation enforces limited substitutability between the regular commercial market and public loans because the latter are granted on subsidized terms, limiting the indirect impact of the SOLCA tax on public loan terms through general equilibrium competitive forces (Appendix A). Thus, government bank commercial loans serve as an excellent placebo sample even though the loans provided by private and government banks have different characteristics, and these banks serve different types of firms. Figure 3 shows cyclical levels of nominal interest rates, none significantly different from the event period -2 at conventional levels before or after the introduction of the tax, even though the coefficients are estimated more precisely than in our private loan sample. Nor do we visually see any anticipation of or response to the introduction of the SOLCA tax.

[Place Figure 3 here.]

We report additional robustness tests in Appendix E. We use a post-period of three quarters in the main analyses because as the time window increases, there will be increasingly more confounders that will affect prices, thereby plausibly contaminating the pass-through estimate. However, one might worry that we are not capturing an equilibrium response of interest rates but rather a temporary disturbance from the tax. In panels (a) and (b) of Figure E1, we extend the time horizon to eight quarters after the introduction of the tax and document persistent pass-through incompleteness.

Even in the short term, however, two main confounders could affect our estimates. First, in mid-2014 oil prices collapsed (Appendix Figure E2, panel (a)). Since Ecuador is an oil-dependent economy, this shock could plausibly affect interest rates, and we might be incorrectly attributing some of this effect to the tax. However, our event-study estimates remain quantitatively similar and statistically significant after controlling for a third-degree polynomial of oil prices (Appendix Figure E2, panel (b)). Second, as a response to the oil shock and contemporaneous bank regulation, marginal costs for banks can be affected through changes in deposit rates (a measure of the cost of funds for banks). Indeed, measures of average yearly bank rates show that deposit rates increased in 2014 (Appendix Figure E3, panel (a)).[34] If taken as contemporaneous, unobserved cost shocks, increasing deposit rates would bias our pass-through estimates, as the total cost shock (deposit rates plus loan tax) would be more extensive than can be accounted for by the SOLCA tax introduction alone. Reassuringly, panel

[34] We calculate bank-year deposit rates by obtaining nationwide deposit rates for different deposit maturities (products) reported by the Ecuadorian Central Bank at the year level and then weight these by bank-year shares of deposit products.

(b) of Appendix Figure E3 reports that the pass-through of taxes to spreads (pre-tax nominal interest rates minus average bank-year deposit rates) is even more incomplete than our baseline estimates, though the confidence intervals are wider. Taken together, these tests alleviate concerns that contemporaneous time shocks contaminate our pass-through estimates.

Another possible source of bias in our pass-through estimates is contemporaneous changes in aggregate credit, which could also affect bank-product marginal costs if banks do not have constant returns to scale. We test if this is driving the result by exploring aggregate commercial credit volume around the introduction of the tax in Appendix Figure E4. Although the estimates are negative, indicating a decrease in total credit, we find no significant difference in total commercial credit through the first three quarters after the introduction of the SOLCA tax relative to two periods prior.[35] Thus, at least for early periods of the tax, our estimates capture the effect of the tax on prices rather than potential changes in the marginal costs of banks.[36]

Finally, the theory of tax incidence under imperfectly competitive markets links price pass-through to market conduct (Weyl and Fabinger, 2013; Pless and van Benthem, 2019). 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, Appendix Table A1 presents correlations between the nominal interest rate on new debt and other contract features and market characteristics. We find a robust negative relationship between both amount and maturity and interest rates.

Therefore, we now turn to testing for the effect of introducing the SOLCA tax on 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 because the tax schedule features a kink at the one-year maturity. The right-hand panel shows 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 gradual, aiding in the interpretation that interest rates are indeed a primary channel in which banks compete. Appendix Figure E5 looks over a longer post period. This reveals that, unlike the average interest rate that did not revert up to eight quarters after the SOLCA tax was implemented, both amount and especially maturity revert towards their pre-tax levels within eight quarters after SOLCA tax implementation.

[35]This result also holds in a before/after pooled comparison.

[36]To square the muted response in total credit with relatively elastic demand for credit, notice that pass-through estimates from the specification with bank and firm fixed effects are much lower than those coming from the specification with borrower-lender pair fixed effects, indicating that new borrowers have more incomplete pass-throughs and thus a smaller increase in their prices from the tax.

[Place Figure 4 here.]

Since we find a negative effect of the SOLCA tax on loan 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. Specifically, we control semi-parametrically for maturity and amount in our main analyses rather than log-linearly, as this specification offers more conservative estimates due to its flexibility in capturing non-linear relationships.

3.2 Estimating 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 i from bank k at time t:

$$rTax_{likt} = \rho tax_{likt} + \sum_{j=1}^{20} \beta_a^j 1\{A \in h\} + \sum_{j=1}^{20} \beta_m^j 1\{M \in z\} + \alpha_d DP_{likt} + \alpha_i + \alpha_k + \varepsilon_{likt}, \qquad (9)$$

where $rTax$ is the tax-inclusive, annualized interest rate and tax is the tax amount in percent.[37] 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.[38] Control variables include: flexible controls for the amount (A) and maturity (M) of the loan using 20 buckets; the loan maturity, M, with its 20 corresponding buckets; firm fixed effects α_i; bank fixed effects α_k; the predicted default probability DP; and time-varying unobservables captured by ε. As mentioned above, we control semi-parametrically for maturity and amount rather than log-linearly as it

[37] Papers that run this type of empirical specification to recover pass-throughs include Atkin and Donaldson (2015); Pless and van Benthem (2019); Stolper (2024); and Genakos and Pagliero (2022).

[38] There is a slight abuse of notation since interest rates compound annually, but taxes are collected only once at the start of the credit. However, most loans in our sample have a term-to-maturity of less than one year, making this distinction minimal. Unreported results show nearly identical estimates when focusing on loans with a maturity of one year or less.

will offer more conservative estimates. The estimation window is from eight quarters before the introduction of the tax through three quarters afterward.

Column (1) of Table 4 reports the estimated direct pass-through, $\widehat{\rho}$, of the tax to tax-inclusive interest rates on commercial loans granted by private banks. Hypothesis testing is conducted against the complete pass-through null hypothesis ($\rho_o = 1$). If $\widehat{\rho} < 1$ it indicates incomplete pass-through and $\widehat{\rho} > 1$ corresponds to more-than-complete pass-through. We find that there is, on average, incomplete pass-through of the tax in aggregate. In particular, the borrower pays approximately 35% of the SOLCA bank tax on the average loan while the bank shoulders the rest by reducing the interest rate. Column (2) adds the probability of loan default as a control. The estimated coefficient remains statistically indistinguishable from that of column (1).

[Place Table 4 here.]

Columns (3) and (4) differ from columns (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 established lending relationships with new loans both before and after the SOLCA tax was introduced. 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. Comparing the model specifications, a higher pass-through within relationships that are already established might indicate that these relationships have lower demand elasticity, all else equal, while firms that switch banks have more elastic demand (Weyl and Fabinger, 2013; Ganapati et al., 2020). Moreover, the fact that we find incomplete pass-through within pre-established relationships is also evidence that credit terms are not fixed long-term, and thus, a period-by-period model of pricing is accurate, even in long-term relationships.

As above, we perform robustness checks on the pass-through estimates controlling for potential time-varying confounders. In Appendix Table E1, we run the same pass-through regressions as above, focusing on the pair fixed effect model and still find incomplete pass-through estimates between 0.4 to 0.7 under specifications controlling for oil or quarterly GDP growth and in specifications that identify off within-period heterogeneity in the tax impact via year-quarter, which exploit the tax differences across borrowers within the same quarter-year. These results again provide support that contemporaneous shocks do not drive the incomplete pass-through estimates.

3.3 Heterogeneity by Market Competitiveness

We now provide evidence that pass-through is indicative of differences in market power and conduct across markets. We test if observed pass-through from the SOLCA tax is higher (lower) where we observe more (less) competitive conditions. The hypothesized positive relationship between tax pass-through and competitive market structure 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.[39]

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

$$\begin{aligned} rTax_{likt} =& \rho tax_{likt} + \delta_h tax_{likt} \times X_{likt} + \sum_{j=1}^{20} \beta_a^j 1\{A \in h\} + \sum_{j=1}^{20} \beta_m^j 1\{M \in z\} + \\ & \alpha_d DP_{likt} + \alpha_{ik} + \varepsilon_{likt}, \end{aligned} \tag{10}$$

where Xt_{likt} 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 effect. All interacted variables are standardized such that the main effect is the pass-through for the average borrower. We use the same time windows as in the event-studies, namely, eight quarters before and three quarters after the policy.

Table 5 presents the results. In column (1), we study pass-through heterogeneity in terms of the availability of lenders in the market, where the variable # *Potential Lenders* is the maximum number of active lenders that have historically lent in the market up to October 2014. We find that markets with more potential lenders have pass-throughs that approach Bertrand-Nash, i.e., where the pass-through is closer to the competitive benchmark of full pass-through ($\rho = 1$).

[Place Table 5 here.]

Turning to column (2), if the market is more concentrated, as indicated by a higher value of $HHI\ City$, the average yearly Herfindahl-Hirschman index (HHI) based on commercial lending share in the firm's city, then estimated pass-throughs are lower, i.e., further from the Bertrand-Nash benchmark of complete pass-through. Moreover, in column (3), we see that areas with higher $Multi{-}Market\ Contact$, or a higher number of other markets (provinces) where the same banks offer commercial loans, have pass-throughs in line with less competitive conduct.[40]

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

[40] This test is in the spirit of Ciliberto and Williams (2014) and Hatfield and Wallen (2023), which show that multi-market contact may facilitate tacit collusion and reduce competition.

It is beyond the scope of this paper to fully demonstrate the exact mechanisms of how banks collude when pricing loans. However, in column (4), we present suggestive evidence that, along with the multi-market contact result in column (3), hints that frequent contact between banks may be part of the answer. The Asociación de Bancos del Ecuador (ASOBANCA) is 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.[41] In column (4), we report that the SOLCA tax pass-through for ASOBANCA members is less competitive the higher the market share of members in the market. Appendix Figure E6 clearly portrays that the incomplete pass-through is driven by the least competitive markets, and confirms again the lack pre-trends, even across markets.

Overall, 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, competition proxies produce consistent results. Moreover, this exercise allows our setting to be compared to the results of the many 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 (Di Maggio et al., 2017; Drechsler et al., 2017; Benetton and Fantino, 2021; Wang et al., 2022; Eisenschmidt et al., 2023; Li et al., 2023), further supporting the representativeness of the Ecuadorian commercial loan market.

However, this is suggestive rather than conclusive evidence that markets are not competitive. It may be that conduct is 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 controls for contract terms may capture some of this cross-market heterogeneity in demand, it might be insufficient if demand curves are non-linear. This is why a model is needed to estimate conduct and test whether the data departs from a Bertrand-Nash (no collusion) benchmark.

[41] ASOBANCA was investigated and charged in 2016 by the anti-trust regulator for coordination during the introduction of a new electronic payment system approved in the 2014 financial law. The charge was finally dismissed by the Constitutional Court in 2022. See Link to decision [accessed 30 August 2023]. Similarly, in 2022, the Bank Regulator expressed concerns over policy recommendations ASOBANCA made to the Legislature, claiming that they would have anti-competitive effects. See Comment by Regulator [accessed 30 August 2023].

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. We estimate pass-through for the provinces Azuay, Guayas, and Pichincha, which have the most economic activity, and aggregate across provinces for the remaining coastal (Costa) and interior (Sierra/Oriente) regions. 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 market-level conduct.

[Place Table 6 here.]

4 Estimating the Model: Demand

In this section, we describe our estimation strategy for the demand parameters in the model described in Section 2. We then present and interpret our estimates of the demand model parameters at the regional level. Finally, we assess model fit.

4.1 Estimation Strategy

We follow Train (1986) and Benetton (2021) in writing the (indirect) profit function $\overline{\Pi}_{ik}$ using the parametric form:[42]

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

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

[42]Note that they transform the dollar units into utility units through the inclusion of income in the utility function because they use indirect utility rather than indirect profit.

A key empirical challenge is that we observe the terms of granted loans while our demand model requires a menu of prices from all available banks to all potential borrowers in each market. To address this long-standing problem in the literature, we predict the prices of unobserved, counterfactual loans following the strategy of Adams et al. (2009), Crawford et al. (2018), and Ioannidou et al. (2022). Details are reported in Appendix F. Plugging in predicted prices from estimating Appendix Equation F2, we obtain the following indirect profit function:

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

In the last equality, we use a log-linear approximation of the function $\tau(M_{ikmt})$.[43] We assume the idiosyncratic taste shocks ε_{ikmt} are i.i.d. Type-I Extreme Value and that the borrower's unobservable characteristic heterogeneity, $\tilde{\psi}_{ikmt} = \psi_i - \alpha_m \tilde{\tau}_{ikmt}$, follows a normal distribution with mean zero and variance σ_b^2. Notice that, in principle, we could estimate the demand price parameter α_m from any of the variables $\tilde{\gamma}_2 L_{ikmt}$, and $\tilde{\omega}_i^r$. Yet, due to the noise created by the estimated parameters—following a traditional measurement error on the independent variable argument—the coefficient on α_m would be biased. For that reason, we follow the conventional route and estimate α_m from $\tilde{\xi}_{kmt}$ through a second-stage instrumental variable approach that relies on exogenous variation in average prices at the bank-market-year level that addresses concerns of measurement error and endogeneity.

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

$$
s_{ikmt}(\psi_i) = \frac{\exp(\Pi_{ikmt})}{1 + \sum_j \exp(\Pi_{ijmt})}, \qquad (14)
$$

where the indirect profit from not borrowing has been normalized to 0. The unconditional

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

probability is given by

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

Given actual bank choices, we obtain the loan demand function, L_{ikmt}, by Hotelling's lemma:[44]

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

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 assuming normality for ψ_i, the probability of the conditional loan demand is:

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

Note that as branch network enters linearly in the indirect utility, it does not appear in input demand. Hence, this assumption implies an exclusion restriction: branch density affects the likelihood of borrowing but not its intensity.[45]

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 $\tilde{\beta}$ and β from the indirect profit function. In the first iteration ($r = 1$) we set coefficients to a guess from estimating a Logit model. In the subsequent iterations, we obtain the coefficients through

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

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

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.[46]

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

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

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

The identification assumptions of our instrumental variable strategy are that none of the instruments are weak (relevance) and that all impact demand only through their effect on price (exclusion). In Appendix G, 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. In aggregate, the instruments relate well with the bank-market interest rates, with a model R-squared of 0.43. Moreover, market-specific F-statistics, reported in Table G2, are high. This is strong evidence that our instruments are relevant.

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

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

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

4.2 Estimated Demand Parameters

Table 7 collects the aggregate demand parameter estimates, reported as the mean and standard deviation of the point estimates aggregated across regions. Standard deviations are bootstrapped by estimating each region-level parameter on 1,000 bootstrap samples, averaging them, and then taking the standard deviation across bootstrap samples.

[Place Table 7 here.]

The signs of the estimates are as expected. First, 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 and report them in Section 4.3

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 the 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. Reported estimates at the regional level are available in Internet Appendix Table G1. These more granular estimates demonstrate the same patterns, while estimates and their direction continue to be sensible.

4.3 Estimating Demand Elasticities

The equations for the discrete-continuous model of loan demand (intensive margin) elasticity and product share (extensive margin) demand elasticity are given in Appendix H. We report estimated own- and cross-demand elasticities in Table 8. *Continuous* is the intensive margin elasticity and *Discrete* is the discrete-choice elasticity, both with respect to interest rates. We find that a one percent increase in price leads to an average (median) 4.63% (4.5%) decrease in loan use (continuous) and a 6.01% (0.55%) decrease in market share.[47] Next, *Total* is the

[47]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 (2021) and Benetton et al. (2024).

sum of continuous and discrete. Note 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. Critically, our model is flexible enough to capture this borrower heterogeneity. This is vital since this demand heterogeneity may help explain differences in pass-throughs (Miravete et al., 2023). Finally, *Cross* elasticity is the discrete bank substitution elasticity with respect to interest rates. We find that a one percent increase in interest rates increases competitors' market shares by 0.17% (0.01%). We validate these structural elasticities with reduced-form instrumental variable approach in Appendix Figure H1. Reassuringly, the median structural elasticities match the reduced-form estimates well.

[Place Table 8 here.]

4.4 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.[48] 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 Estimating the Model: Supply

After estimating demand, this section focuses on testing against the three benchmark competition models—Bertrand-Nash, Cournot/quantity, and joint maximization. We do this by comparing model-simulated and empirical tax pass-through estimates. Through this approach, we are able to robustly reject Bertrand-Nash and Cournot competition among lenders but we fail to reject some degree of joint maximization. Then, we calibrate the competitive conduct parameter, which will be used as an input into our tax welfare analyses.

5.1 Testing Competitive Conduct Against Competition Modes

In this sub-section, we test conduct versus well-defined conduct values corresponding to the leading models of competition in the banking market. Pure Bertrand-Nash competition and

[48] In Appendix D, we discuss our empirical strategy to estimate default rates.

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.[49] For the aggregate market, we obtain a Cournot parameter close to 0.2

We simulate tax pass-throughs for conduct parameters $\upsilon_m \in [0, 1]$ at grid increments of 0.01, given marginal costs consistent with that parameter obtained through inverted pricing Equation 6, as well as demand and default functions. Then to obtain the pass-throughs for each conduct $\upsilon_m \in [0, 1]$, we follow the next steps.

First, we randomly pick 2,500 firms from the region.[50]. We simulate the tax introduction, given estimated demand, the default functions, and pair-level constant marginal costs. Following the established relationship between tax and marginal cost pass-throughs documented by the public finance literature (Gruber, 2005; Weyl and Fabinger, 2013), we model the introduction of the tax as a 0.5 percentage point linear increase in the marginal costs for each pair.[51] 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. Second, we compute the Nash equilibrium of all prices for all banks in the choice set of a given borrower and obtain pair-level *simulated* pass-through estimates.

Figure 5 presents nationwide average simulated pass-throughs by conduct level. The y-axis plots simulated pass-through, and the x-axis plots the corresponding conduct parameter. We indicate the areas for Bertrand-Nash, Cournot, and joint maximization with horizontal lines. We also plot the empirical pass-through estimate obtained above with its corresponding confidence interval horizontally.

The figure has several takeaways. First, it shows that pass-through as a testing objective is generally well-powered to test conduct, as pass-throughs non-monotonically change with conduct. Indeed, the figure shows that we can reject an extensive range of conduct parameters below 0.5, including Bertrand-Nash and Cournot. Second, the figure shows that for joint

[49] 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 one can write both markups as a function of the 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 is 0.2042 for Azuay, 0.4357 for Costa, 0.0609 for Guayas, 0.1993 for Pichincha, and 0.2858 for the Sierra and Oriente region. These Cournot values lie above the Bertrand-Nash conduct value of zero and below the full joint-maximization value of one and are in line with the number of borrowers in each market.

[50] We use at most 2,500 firms per market due to computation constraints: for each firm, we estimate Nash-equilibrium prices over a grid of 100 conduct parameters.

[51] The literature has shown that economic incidence does not depend on the statutory incidence. It is possible to show in our setting that incidence is equal regardless of whether the tax is levied on borrowers or as a cost shock to banks.

maximization, the simulated pass-through estimate overlaps the empirical pass-through, and thus, we fail to reject joint maximization. Third, the figure clearly emphasizes the limitations of testing power in our dataset. For conduct values above 0.5, simulated pass-throughs show less responsiveness to conduct, making our approach less effective at distinguishing between values above 0.5. Hence, while our method fails to reject joint maximization, it would also fail to reject other competitive conducts with values above 0.5.

[Place Figure 5 here.]

Conduct values other than key models, such as those tested here, are often hard to interpret (Corts, 1999). Appendix Figure I1 reports a complementary exercise where we compare the distribution of actual and simulated pass-throughs for just the edge conduct cases of zero and one, which are well-defined. The takeaway is similar.[52] Note that this is a sharp test because our discrete-continuous demand model is flexible enough that we can obtain pass-through estimates both above and below one under Bertrand-Nash, which, as documented by Miravete et al. (2023), many discrete-choice models are not able to accommodate.[53] Importantly, the identification strength of pass-through and conduct is not observed only in nationwide results. Indeed, Appendix Figure I5 confirms that pass-through decreases in all regions (non-linearly, but mostly monotonically) with conduct.

Besides providing a clear identification test, Figure 5 and its regional counterparts clarify the bias in pass-through estimates that would be consistent with our findings. For instance, Table I3 presents pass-through estimates focusing only on the two months after the introduction of the tax, to exclude potential aggregate shocks that might affect our estimates. In this specification, as shown in past literature (Genakos and Pagliero, 2022), the short-term pass-through is generally closer to complete pass-through. We obtain pass-through estimates of 0.143 for Azuay, 0.563 for Costa, 0.816 for Guayas, 0.667 for Pichincha, and 0.831 for Sierra. Although closer to complete, our framework would still reject Bertrand-Nash at the aggregate level and in *all* markets and only fail to reject credit-rationing (Cournot) in one of the five markets.

[52]Point estimates differ relative to Figure I1 as for this figure we only use a random subsample of 2,500 borrowers rather than the complete set of borrowers from Appendix Figure I1. We use the reduced sample due to the computational intensity of calculating Nash equilibrium prices for each borrower and each grid.

[53]Given that the objective of our paper is to rely on empirically estimated pass-throughs to calibrate/test conduct, rather than relying on a model to predict unobserved pass-throughs, allowing for further flexibility a la Berry et al. (1995) would be counterproductive. If we were to do so, we would mechanically bias model-predicted pass-throughs towards complete or more-than-complete pass-throughs (as shown in Miravete et al. (2023)). Thus, implementing such an approach would bias us in favor of finding anti-competitive conduct.

5.2 Calibrating Best-Fit Conduct

Next, we calibrate best-fit conduct at the regional level. Though intermediate values of conduct are often hard to interpret (Corts, 1999), these are useful in benchmarking the miscalculation errors in incidence and welfare losses from incorrectly assuming wrong models of conduct (Kroft et al., 2024).

We start with the simulated tax pass-through estimates that we obtained for conduct testing above in Section 5.1 and match it to reduced-form regional tax pass-through estimates to find best-fit conduct. Specifically, 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. Note that this procedure returns conservative conduct estimates because we choose the lowest feasible conduct in case of ties in fit. We are thus intentionally biasing our analyses towards conduct consistent with Bertrand-Nash competition. Also, our simulation method allows for varying elasticity and curvature estimates, which are re-calculated during the Nash-equilibrium price search process. Moreover, as we obtain the simulated pass-throughs within a given bank-borrower pair, they correspond to the reduced-form estimates estimated with pair-level fixed effects as these aggregate pair-level pass-throughs.

Table 10 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. The calibrated model returns a precisely non-zero conduct parameter for each region. The estimated conduct varies significantly across regions, with Guayas showing a low of 0.33, indicating more competitive behavior among banks, to a high of 0.91 in the Costa region, suggesting near-collusive conduct. This underscores the importance of considering the distribution of market power within the country.

[Place Table 10 here.]

Finally, also note that our calibrating target is the conservative estimate from the pair fixed-effects model (aggregate pass-through of 0.53 rather than 0.36). Instead, if we used the lower moment, estimates across the board would be consistent primarily with joint maximization. We do not use those estimates as the main moments for two reasons: (1) we prefer the more conservative results as a benchmark, and (2) the thought experiment of estimating within pair pass-throughs in the models matches the empirical benchmark of pair fixed effects.

6 Assessing the Validity of Estimated Competitive Conduct

This section further assesses how robust our conduct estimates are to our modeling choices. We first show that tests of the three benchmark competition modes are robust to using conduct estimates that depart from the best-fit estimated conduct in our baseline SMM. Next, we show that our results are robust to modeling collusion as a profit internalization matrix, following Miller and Weinberg (2017), and we test for partial cartels within that framework. Finally, we demonstrate the importance of free parametrization of conduct in lending models for supply-side parameters.

6.1 Stability of Estimated Conduct

Figure 6 tests the stability and robustness of our conduct estimates and our ability to test against our three benchmark competition modes. The figure plots the lowest feasible conduct parameter estimates (y-axis) against the degree of match (x-axis). We report the top 50 conduct estimates for each region in order of the degree of match to the data. Specifically, the black dot at zero in the x-axis corresponds to our best estimate of the conduct parameter—the conduct that minimizes the squared distance between simulated and observed pass-through in the model. The black dot corresponding to 50 on the x-axis indicates the 50^{th} best match.

[Place Figure 6 here.]

The gray area in each panel of Figure 6 represents confidence intervals based on the bootstrapped standard errors. The orange dotted line at one on the y-axis corresponds to complete joint maximization, the blue dashed line at zero to pure Bertrand-Nash competition, and the green 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 0.7, but conduct could be as low as 0.46 or as high as 0.94. We therefore reject that banks Bertrand-Nash or Cournot compete in Azuay but fail to reject that they joint maximize when setting commercial loan prices.

We observe stability in the first ten to twenty best-fitting models in all regions. We can reject pure Bertrand-Nash and Cournot competition with a 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. Overall, banks are not Bertrand-Nash competitive, and results are consistent with some degree of joint maximization.

6.2 Testing Partial Cartels

A potential shortcoming of our framework is that the interpretation of conduct parameters is difficult (Corts, 1999), except for exceptional cases, such as those considered in this paper (Bertrand-Nash, Cournot, joint maximization). Thus, our framework does not allow us to test for partial cartels, which may be of special interest to the policymaker. To address this concern, we implement the internalization parameter approach of Miller and Weinberg (2017), which permits partial cartels as well as different degrees of internalization interests within the cartel. Moreover, to further address concerns related to indirect inference and potential bias in the targeting moment (MacKay et al., 2014; Dearing et al., 2024), we present robustness results of this alternative framework to test for best-fitting models following the conduct testing literature developed by Backus et al. (2024); Duarte et al. (2024); Dearing et al. (2024) by exploiting the introduction of the tax as a testing instrument.

Under the internalization framework, the optimal pricing equation for or banks $k = 1, 2, .., K$, borrower i, market m, and time k is given by:

$$(1 - d_{imt}) \circ r_{imt} = mc_{imt} - \left[\Upsilon_{mt} \circ \frac{\partial Q_{imt}}{\partial r_{imt}}\right]^{-1} (1 - d_{imt}) \circ Q_{imt}. \tag{21}$$

where $\circ$ is element-by-element matrix multiplication. The matrix of partial derivatives is defined as:

$$\frac{\partial Q_{imt}}{\partial r_{imt}} = \begin{bmatrix} \frac{\partial Q_{i1mt}}{\partial r_{i1mt}} & \frac{\partial Q_{i2mt}}{\partial r_{i1mt}} & \dots & \frac{\partial Q_{iKmt}}{\partial r_{i1mt}} \\ \frac{\partial Q_{i1mt}}{\partial r_{i2mt}} & \frac{\partial Q_{i2mt}}{\partial r_{i2mt}} & \dots & \frac{\partial Q_{iKmt}}{\partial r_{i2mt}} \\ \dots & \dots & \dots & \dots \\ \frac{\partial Q_{i1mt}}{\partial r_{iKmt}} & \frac{\partial Q_{i2mt}}{\partial r_{iKmt}} & \dots & \frac{\partial Q_{iKmt}}{\partial r_{iKmt}} \end{bmatrix}, \tag{22}$$

and the profit-internalization matrix is defined for all banks available at market m at time t as:

$$\Upsilon_{mt} = \begin{bmatrix} 1 & \upsilon_{12} & \dots & \upsilon_{1K} \\ \upsilon_{21} & 1 & \dots & \upsilon_{2K} \\ \dots & \dots & \dots & \dots \\ \upsilon_{K1} & \upsilon_{K2} & \dots & 1 \end{bmatrix}. \tag{23}$$

where υ_{kj} represents the profit weight (internalization parameter) describing how much the profits of j matter for bank k. When $\upsilon_{kj} = 0$ for all $j \neq k$, we are in the Bertrand-Nash world: each firm maximizes profits subject to its residual demand. When $\upsilon_{kj} = 1$ for all $j \neq k$, banks are maximizing industry-wide profits. For other values, we can have asymmetric internalization of profits, allowing for partial cartels and different conduct values (such as Cournot). Note that given the small size of our study country and since we only have one tax change, we set $\upsilon_{kjmt} = \upsilon_{kj}$, i.e., for each pair of banks we hold the internalization constant fixed across markets and time. Appendix J further describes how we model conduct in the form of an internalization matrix and reports implementation details, including the details of the testing framework.

We now re-test if we can reject the Bertrand-Nash competition benchmark ($\upsilon_{kj} = 0 \mid \forall k, j$) of the naive policymaker. Table 11 reports the results of our tests of Bertrand-Nash as the null model against various cartels posed as alternative models. A positive T-test (column 3) value implies that the cartel models are preferred to Bertrand-Nash, and a high F-test (column 4) suggests the instruments are relevant. Panel (a) tests Bertrand-Nash against an alternative with internalization parameters υ_{kj} set to one for all members of the ASOBANCA banking association ($\upsilon_{kj} = \kappa \mid \forall k\&j \in \{BA\}$), the defendant in several extant antitrust lawsuits and a significant driver of pass-through heterogeneity in Section 3.3. Panel (b) tests against a cartel composed of the top four largest banks by assets in the country ($\upsilon_{kj} = \kappa \mid \forall k\&j \in \{BA\&Top4\}$); and Panel (c) tests against a cartel composing the entire banking system ($\upsilon_{kj} = 1 \mid \forall k, j$), in line with our joint-maximization model in the conduct parameter approach.

[Place Table 11 here.]

We see in Table 11 that *all* the cartel models fit the data better than Bertrand-Nash, consistent with our conduct parameter approach. All the instruments are relevant except for low internalization parameters κ in the full cartel model in panel (c). Thus, we again reject the standard benchmark of Bertrand-Nash competition.

Next, we explore evidence of best-fitting partial cartels. Specifically, Appendix Table J1 tests which internalization parameter κ better fits the data *within* a specific cartel model, while Appendix Table J2 reports tests across cartel models, keeping the internalization parameter κ constant across models. Overall, the tests offer support for strong cartels with internalization parameters $\kappa = 1$. Although the purpose of this paper is not to pinpoint the exact composition of a banking cartel, the evidence favors a banking association cartel comprising the top four largest banks. However, a full banking cartel is also consistent with the data. Given these results, which agree with those of our main conduct parameter approach, we continue with the counterfactual analysis through the conduct approach due to its simplicity for calculating tax incidence and tax deadweight loss.

6.3 Importance of Conduct Assumption for Supply-Side Parameters

In this exercise, we simulate the model assuming Bertrand-Nash competition ($\upsilon_m = 0$). Next, we separately perform this exercise assuming joint profit maximization ($\upsilon_m = 1$) as if there were a full cartel in each market. We then compare the model-implied marginal costs and markups under these two scenarios. This exercise thus also serves to demonstrate the importance of the assumptions on competitive conduct in the literature. Results are reported in Table 12.

[Place Table 12 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 using only the own-price elasticities of demand. Panel (a) reports 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. Panel (c) reports the corresponding average (median) markup—the gap between prices and marginal costs—is 2.43 (2.30) percentage points with corresponding Lerner Indices of 0.23 (0.21).

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—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. Note that our model-free proxy for the marginal cost of funds for the average bank using deposit interest rates, reported in Table 3 at around 4%, is much closer to the marginal cost estimated under joint maximization. This non-targeted moment supports our model-based evidence that assuming Bertrand-Nash competition overestimates lender marginal costs.

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 with Lerner Indices of 0.61 (0.68) 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.[54]

In summary, our model delivers reasonable competitive conduct estimates consistent with reduced-form evidence and observed pass-through. Using these estimates, we can reject that banks Bertrand-Nash or Cournot compete at conventional confidence levels. Instead, our estimates are most consistent with some degree of joint maximization. Thus, banks have an incentive to collude; they can do so, e.g., through lending associations and multi-market contact, and regulators have incentives to allow them to do so for macro stability reasons. Assuming otherwise leads to significant mismeasurement of marginal costs and markups. Next, we show that this collusion matters for the effectiveness and efficiency of fiscal policy.

7 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), capital 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 2024.[55] However, the literature has not agreed on who bears the burden of financial taxes. Theoretically, the answer is not obvious as it depends on demand and supply parameters, including supply conduct. Nevertheless, empirical work on such taxes implicitly or explicitly assumes zero conduct (Bertrand-Nash competition).

We fill this gap by studying how bank conduct affects the incidence, or who bears the burden of financial taxes, through the lens of our model. 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

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

[55] See https://www.sanders.senate.gov/wp-content/uploads/inclusive-prosperity-fact-sheet-2019.pdf and https://www.eumonitor.eu/9353000/1/j9vvik7m1c3gyxp/vj75tbvif1yr, respectively, last accessed November 1, 2024.

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 bank surplus (Weyl and Fabinger, 2013; Kroft et al., 2024). 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 marginal dollar of 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:

$$\frac{dCS_{ikmt}}{dt} = \frac{d\overline{\Pi}_{ikmt}}{dt} = \frac{d\overline{\Pi}_{ikmt}}{dr}\rho_m = -L_{ikmt}\rho_m. \tag{24}$$

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:

$$\left.\frac{dPS_{ikmt}}{dt}\right|_{t=0} = \frac{dB_{ikmt}}{dt} = (1 - d_{ikmt})Q_{ikmt}(\rho_m - 1) + ((1 - d_{ikmt})(r_{ikmt} - t) - mc_{ikmt})\frac{\partial Q_{ikmt}}{\partial r_{ikmt}}\rho_m \tag{25}$$

$$= (1 - d_{ikmt})Q_{ikmt}(\rho_m - 1) - \frac{\partial Q_{ikmt}}{\partial r_{ikmt}}\rho_m \frac{Q_{ikmt}}{\frac{\partial Q_{ikmt}}{\partial r_{ikmt}} + \upsilon_m \sum_{j \neq k} \frac{\partial Q_{ikmt}}{\partial r_{ijmt}}} \tag{26}$$

$$= -Q_{ikmt}\left[(1 - d_{ikmt})(1 - \rho_m) + \frac{\rho_m}{1 + \upsilon_m \sum_{j \neq k} \frac{\tilde{\epsilon}_{jk}}{\tilde{\epsilon}_{kk}}}\right], \tag{27}$$

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:

$$\left.\frac{dR_{ikmt}}{dt}\right|_{t=0} = Q_{ikmt}\left[1 + t\rho_m\tilde{\epsilon}_{kk}\right] = Q_{ikmt}. \tag{28}$$

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* values 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 the parameter ρ_m.

Table 13 presents the results. Column (1) ("Unconditional") presents "ex-ante" estimates in the sense of not conditioning on the borrowing firm's choice of bank. Column (2) ("Conditional") 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. 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.[56] First, consider the measured incidence. 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).

[Place Table 13 here.]

In panel (b) of Table 13 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. We see 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 falls much more on the borrower if one assumes Bertrand Nash competition ($\upsilon_m \equiv 0$) rather than using calibrated conduct estimated on the data. 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 closely mirror those observed empirically. These results also match the theoretical discussion by Weyl and Fabinger (2013) on the effects of conduct on incidence.[57] But from a policy perspective, noting this distinction is important. The policymaker may weigh borrower surplus differently than bank surplus. Our results imply that the desired distributive effects of taxation will be affected by the prevalent lender conduct in the market.

[56] A reader might be concerned that the introduction of the tax and future changes coming from the regulatory environment might affect the competitive and demand structure of the market. In Internet Appendix Table I1, we explore the robustness of results by focusing on the period before the introduction of the tax, which is not yet affected by the policy. The results are qualitatively and quantitatively similar to those presented in the main text.

[57] Ganapati et al. (2020) and O'Connell and Smith (2024) also find that the incidence of cost shocks on consumers is lower under collusion than when firms compete, in the contexts of energy input costs for U.S. manufacturers and U.S. sin taxes, respectively. Here, we show this matters not only for demand-based market power but also supply-side, conduct-based market power.

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 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.

Another 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%.[58]

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.[59] This empirical finding is novel from an academic perspective—our empirical results match the theoretical predictions of Kroft et al. (2024) 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 taxes are more distortionary than tax on retail products based on US evidence (Kroft et al., 2024), 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 show the conduct assumption hugely impacts the expected welfare impact of the SOLCA tax, another novel implication is that how distortionary the transaction cost is depends on the competition structure of the commercial loan market. In particular, the counterfactual experiments suggest that borrowers 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

[58]This is similar to the effect of naively assuming away tax salience in the US (Kroft et al., 2024).

[59]The market structure in commercial lending is here taken as given. In related work, Brugués and De Simone (2023), we show that lower lender competition is itself distortionary as it leads to smaller loan sizes and higher prices. Comparing the two, low competition in lending markets is much more distortionary than tax distortion when lenders compete hard. The additional deadweight loss from taxation under Bertrand-Nash, compared to joint-maximization, is around 9% of the deadweight loss from joint maximization.

markups above marginal cost that banks can achieve under joint maximization also give them more freedom to absorb shocks while still operating profitably.

The final takeaway relates to the use of simulated versus empirical pass-throughs. Consider panel (c) where we use empirical pass-through ρ_m but counterfactually set conduct υ_m to be either zero or one, i.e., assume 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 measurements of incidence and welfare without the need for testing conduct beforehand, even if exact magnitudes cannot be pinned down without a model that incorporates flexible conduct. This is not obvious as, keeping pass-through constant, incidence and excess burden generally change with conduct (Weyl and Fabinger, 2013). Here, the key driver bringing incidence and excess burden close across conduct models is 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. Our finding may be generalizable to other markets with similar features. Of course, all of this is feasible *ex-post*, i.e., after the tax has been implemented. From an *ex-ante* perspective, where a policymaker wants to predict incidence and welfare prior the execution of the policy, the assumption of conduct is of first-order importance.

7.1 Heterogeneity in Incidence and Welfare Effects

From a policy perspective, the distributional effects of taxation are first-order concerns (Saez and Zucman, 2023). We exploit access to micro-level data on borrowers to offer insights into the distributive incidence and welfare costs of the financial tax.

[Place Figure 7 here.]

Figure 7 shows the results. In the best-fit (calibrated) model, incidence (panel (a)) decreases in firm size (as measured by assets), indicating that banks absorb more of the tax burden when borrowers are larger. While the result is similar under joint maximization, a naive policymaker would have predicted the opposite relationship. Namely, under Bertrand-Nash, a policymaker would have predicted that banks absorb more of the burden for smaller borrowers.

Similarly, the best-fit model shows a slight positive slope for deadweight loss (panel (b)), indicating that distortions are slightly smaller for larger borrowers. As with incidence, a naive policymaker that assumed Bertrand-Nash competition would have predicted the opposite, i.e., that larger firms face larger distortions. Moreover, the joint-maximization model matches the best-fit model across the borrower-size distribution well for the two measures, both in terms of levels and slope. However, while heterogeneity exists, the differences across the size distribution are small. An increase move from the 25th percentile in terms of assets to the 75th one is related to a 2% relative increase in deadweight loss and a 4% relative decrease in incidence.

7.2 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 of the simulations presented in Table 13. Our estimates suggest that such a policy would be expansionary: deadweight loss would be reduced by an average (median) of 41 (50) cents per dollar spent in subsidy. Moreover, banks will be the main beneficiaries of such a policy, as banks pass along only a fraction of each dollar of subsidy. Thus, subsidizing lending is less effective in non-competitive settings than when banks Bertrand-Nash compete.

7.3 Revenue Maximizing Tax Rates

From Equation 28 for marginal tax revenue, we can estimate the level t at which the marginal revenue enters the "prohibitive" zone, where the marginal tax revenue is negative. For any quantity level Q_{ikmt}, this critical value in percentage terms will be equal to:

$$t^* = \frac{-1}{\rho_m \widetilde{\epsilon}_{kk}}.$$

Calibrating for mean (median) values of own-demand, total semi-elasticity $\widetilde{\epsilon}_{kk}$ of -1.13 (-0.64) and empirical pass-through ρ_m of 0.54, yields a revenue maximizing tax rate of 1.6% (2.89%).[60] The values will be similar for model-consistent estimates in joint maximization with a revenue-maximizing tax rate of 1.76% (3.13%), while in Bertrand-Nash the revenue-maximizing tax rate is 0.83% (1.47%).[61] Thus, in all models, revenue maximizing rates are larger for *this segment* of borrowers. Moreover, in line with Miravete et al. (2018), market power shifts the Laffer curve rightward, indicating greater possible tax rates the less competitive the market. The intuition for this is that output distortions are lower as a response to the tax rate from the reduced pass-through from market power.

[60] Semi-elasticities are obtained by dividing elasticities by the interest rate in percentage terms.
[61] We use pass-through $\rho_m = 0.5$ for joint-maximization and $\rho_m = 1.06$ for Bertrand-Nash.

7.4 Tax Revenue

Using total volume of loans from private banks, including not only commercial loans but also mortgages, micro- and consumption loans, and calibrating a tax rate of 0.5%, we measure total tax revenue raised per year in 2015-2017 to be equal to 117 million USD, which is close to the reported tax revenue figure by SRI in 2017 of 96 million USD.

Relying on our intensive margin elasticities and pass-through rates from commercial credit, we estimate the decrease in tax revenue raised if credit was more competitive (Bertrand-Nash). Namely, the tax rate is around 5% of the interest rates in commercial credit,[62] the intensive margin elasticity is equal to -4.5, and the Bertrand-Nash pass-through is equal to 1.06 instead of 0.54. The difference in pass-through to final prices (0.52) implies a decrease in total credit of around 10%, given that interest rates would further increase by around 2.5%. Thus, tax revenue if the commercial lending market was Bertrand-Nash competitive would be around 10% lower.

8 Conclusion

We investigate the impact of bank competition on the welfare consequences of financial taxes and credit policy using the introduction of a surprise loan tax in Ecuador and a structural model of commercial lending. Overall, our findings suggest that it is important to account for lender collusion when proposing a tax or subsidy in credit markets, or when studying the impact of one ex post. First, we show that lender collusion significantly affects the welfare outcomes of financial taxation and credit policy. 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. Conversely, we find that subsidies are less effective in non-competitive settings. Moreover, 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 because models that assume banks compete when they do not will overestimate marginal costs and underestimate markups.

[62] They are a smaller share in other types of credit.

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9 Tables and Figures

Identified by SOLCA tax quasi-experiment

Calculated from demand model (identified by instruments)

Calculated from demand model (identified by instruments)

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

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

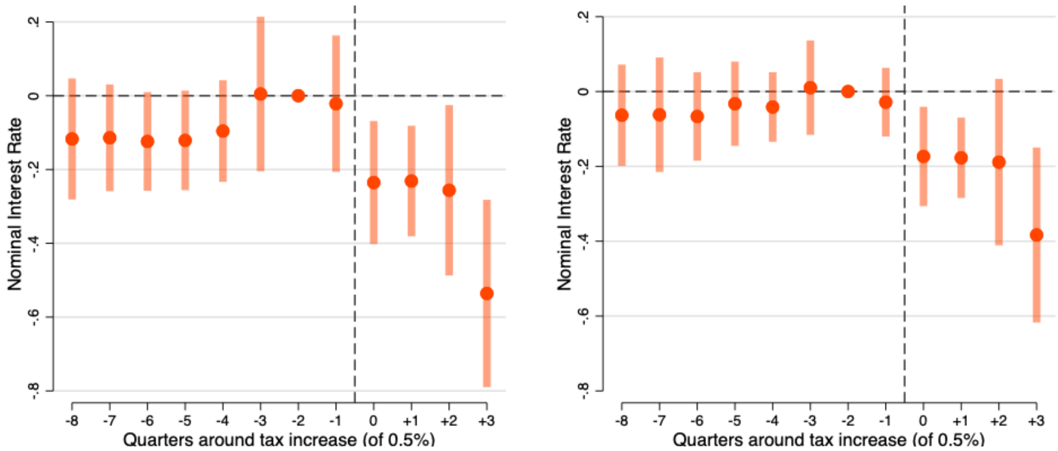
Observed or estimated in data

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

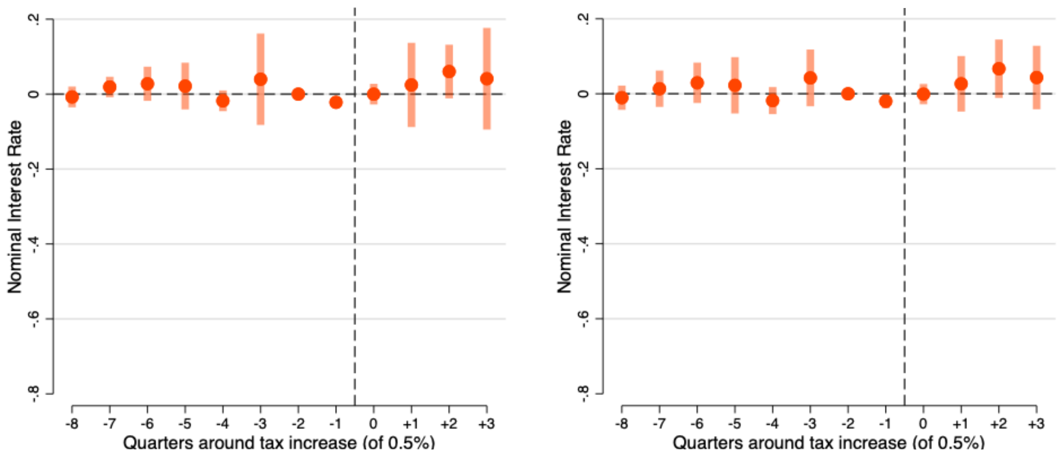
The figure describes the main identifying equations for the model and how each component is identified.



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

FIGURE 2: EFFECT OF THE TAX ON PRE-TAX NOMINAL INTEREST RATES OF NEW COMMERCIAL CREDIT BY PRIVATE BANKS

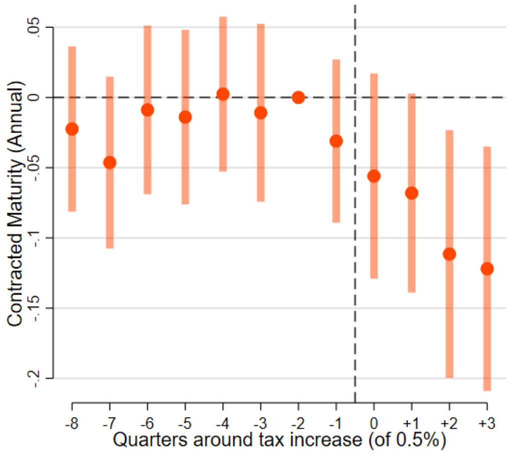
The figure reports the period-by-period difference in average pre-tax nominal interest rates on new commercial loans from private banks around treatment assignment relative to event-time period $t = -2$ (normalized to zero), using firm and bank fixed effects (Panel (a)) or firm $\times$ bank fixed effects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



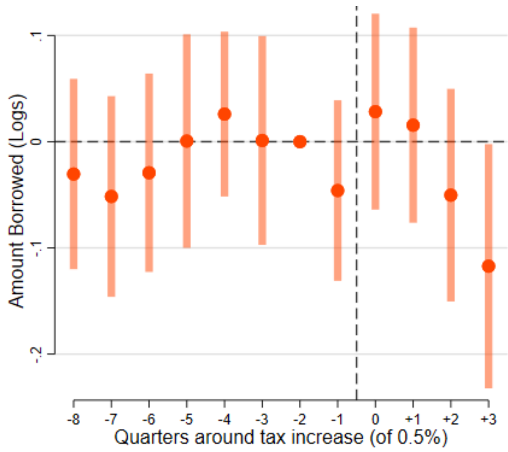
(a) Regular loans; bank & firm FE (b) Regular loans; bank-firm pair FE

FIGURE 3: EFFECT OF THE TAX ON PRE-TAX NOMINAL INTEREST RATES OF NEW COMMERCIAL CREDIT BY STATE-OWNED BANKS

The figure reports the period-by-period difference in average pre-tax nominal interest rates on new commercial loans from public banks around treatment assignment relative to event-time period $t = -2$ (normalized to zero), using firm and bank fixed effects (Panel (a)) or firm $\times$ bank fixed effects (Panel (b)). Data are loan-level. The figure tests for both treatment effects and for evidence of significant differences in outcomes before treatment assignment (pre-trends). Standard error bars are shown at the 95% confidence level and are clustered at the bank-quarter level.



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



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

FIGURE 4: EFFECT OF THE TAX ON MATURITY AND AMOUNT OF NEW COMMERCIAL CREDIT BY PRIVATE BANKS

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

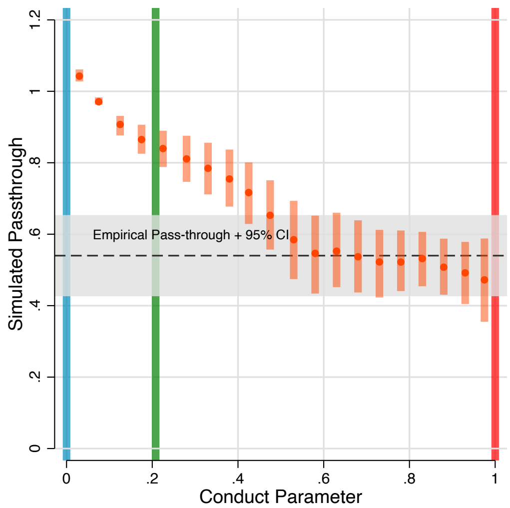
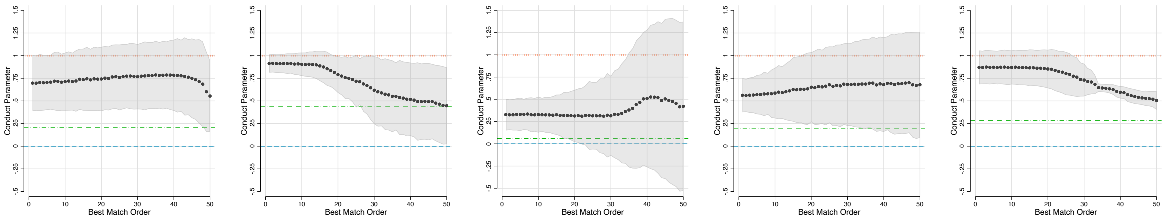


FIGURE 5: AVERAGE SIMULATED PASS-THROUGHS BY CONDUCT GRID

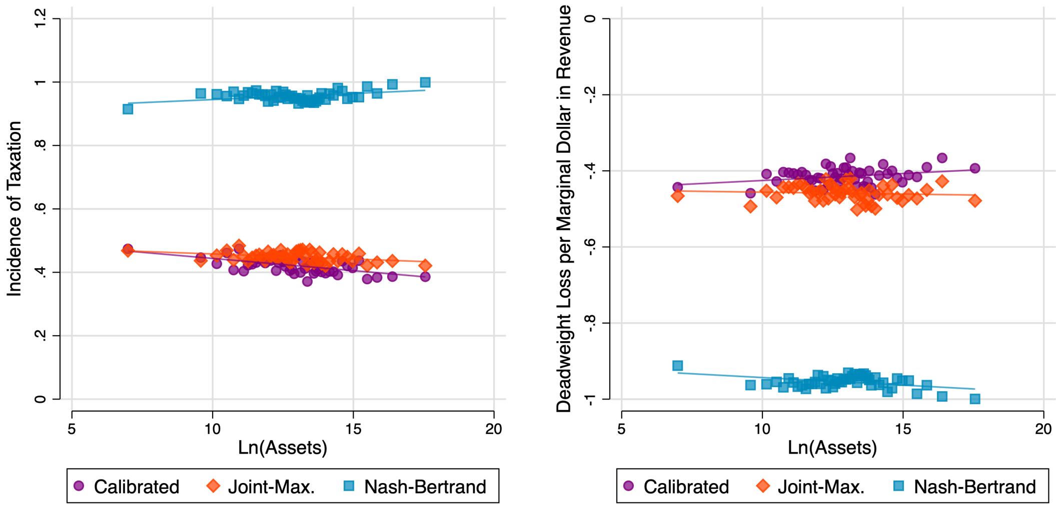
The figure reports the average nation-wide simulated Nash-equilibrium pass-throughs of the introduction of a tax of 0.5% over a grid of competitive conducts between 0 and 1. We estimate on a random sample of 2,500 borrowers from each region. Confidence intervals are clustered at the region-conduct grid 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. The blue vertical bar represents Bertrand-Nash conduct, the green vertical bar represents the average across all market-specific Cournot/credit rationing conducts, while the red vertical bar represents joint-maximization.



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

FIGURE 6: REGIONAL CONDUCT PARAMETER BY MATCH ORDER

The figure reports the competitive conduct parameter estimates by lending region against the ordered best-ranked matches between empirical and model-estimated tax pass-throughs. 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 full joint maximization and the dashed line at conduct zero to pure Bertrand-Nash competition. The intermediate conduct represented by the dot-dash line reporesents the competitive conduct value that corresponds to Cournot competition in each region. Note Region Sierra includes provinces from Oriente as well.



(a) Incidence (b) Deadweight Loss

FIGURE 7: HETEROGENEITY IN INCIDENCE AND DEADWEIGHT LOSS BY FIRM SIZE (ASSETS)

The figure reports binscatter plots on the incidence and deadweight loss estimates by firm size (ln assets) by model.

TABLE 1: AGGREGATE-LEVEL CREDIT CHARACTERISTICS

The table describes the commercial loan market in aggregate. Data are at the bank-province-year level for the period 2010 to 2017. Data are for both private and state-owned banks. Bank-province-years with no new loans are excluded. *Total Volume* is the sum of the dollar value of all loans extended in each province-year. *# Clients* is the count of unique clients and *# Loans* is the count of loans extended in each province-year.

Variable	**Mean**	**Median**
Total Volume	57,322,751	1,400,573
# Clients	83.47	12.00
# Loans	487.38	24.00
Observations	1,976	1,976

TABLE 2: CREDIT 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. State-owned banks and bank-province-years for private banks where no new loans were granted are excluded. Data are cut above and below the median HHI value (2,253.35), 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 of competing branches active in the province. *Panel B* presents credit information. *Total Volume* is the sum of the dollar value of all loans extended in each province-year. *# Clients* is the count of unique clients and *# Loans* is the count of loans extended in each province-year. *Av. Loan* is the average loan size. *Av. Maturity* is the 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.

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	981	995
	Panel B: Credit Information	
Total Volume (M USD)	105	0.013
# Clients	141.53	25.37
# Loans	937.30	93.01
Av. Loan (K USD)	182.43	99.33
Av. Maturity	1.09	0.92
Av. Interest Rate (%)	9.99	11.01
# Loans per Client	114.79	12.97
Observations	981	995

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

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

TABLE 4: AGGREGATE PASS-THROUGH ESTIMATES

The table reports aggregate pass-through estimates to the tax-inclusive interest rates of commercial loans around the introduction of the 2014 SOLCA tax in Ecuador. Data are at the loan-level for 2010 to 2017, excluding October 2014. The main independent variable is the tax rate, measured as 0.5 adjusted proportionally by term-to-maturities if maturity is less than 1 year. The dependent variable is the tax-inclusive interest rate, which is the sum of the nominal, annualized interest rate plus the tax rate. Both are in percentage points. Regressions control for twenty buckets of term-to-maturity, and twenty buckets of loan amount. Models (2) and (4) control for predicted default probability. Models (1) and (2) control for bank and firm fixed effects, whereas (3) and (4) control for bank × firm (pair) fixed effects. 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 (ρ = 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 Fixed Effect	Yes	Yes	No	No
Firm Fixed Effect	Yes	Yes	No	No
Pair Fixed Effect	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) fixed effects. Interacted variables are: *# Potential Lenders* is the maximum number of active lenders as of October 2014; *HHI City* is the Herfindahl-Hirschman Index per year per city prior to October 2014; *Multimarket Contact* is the average number, across all bank pairs active in the province, of other provinces in which banks jointly operate in. *Market Share ASOBANCA members* is the market share (defined on loan share) of banks in the given market that are members of the Asociación de Bancos del Ecuador (ASOBANCA), run on the subsample of loans in markets were at least one ASOBANCA member lends. In all models, interacted variables are standardized such that the main effect is the pass-through for the average borrower. 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)
Pass-through (ρ)	0.441***	0.603**	0.529**	0.512***
	(0.207)	(0.200)	(0.203)	(0.187)
Interacted with:	*# Potential* Lenders	*City HHI*	*Multimarket* Contact	Mkt. Share ASOBANCA members
	0.459***	-0.413***	-0.226**	-0.183*
	(0.117)	(0.086)	(0.092)	(0.104)
Pair Fixed Effect	Yes	Yes	Yes	Yes
Amount Bucket	Yes	Yes	Yes	Yes
Maturity Bucket	Yes	Yes	Yes	Yes
Default Risk Control	Yes	Yes	Yes	Yes
Observations	347,471	347,471	347,471	345,700
R-squared	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 × firm (pair) fixed effects. The model is separately estimated by region. Robust standard errors are clustered at the bank-quarter level.

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

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

TABLE 8: LOAN DEMAND, OWN-PRODUCT AND CROSS-PRODUCT DEMAND ELASTICITIES

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

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

TABLE 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. Market shares and loan use come from the structural demand model, discussed in section 4. Estimation methodology for default is available in Appendix D and for prices in Appendix F.

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

TABLE 10: CONDUCT PER REGION

The table reports competitive conduct parameter estimates by lending region. The model is separately estimated on a random sample of 2,500 firms from each region 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 11: BERTRAND-NASH AND CARTEL MODEL TESTING USING INTERNALIZATION PARAMETERS

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

Panel A. Bertrand-Nash versus κ-Partial Banking Association Cartel			
Null Model	**Alternative Model**	**T-test**	**F-stat First Stage**
(1)	(2)	(3)	(4)
0.0	0.2	16.5	18.4
0.0	0.4	11.6	26.7
0.0	0.8	10.2	38.4
0.0	1.0	3.0	45.0
Panel B. Bertrand-Nash versus κ-Partial Top 4 Cartel			
Null Model	**Alternative Model**	**T-test**	**F-stat First Stage**
(1)	(2)	(3)	(4)
0.0	0.2	35.6	42.7
0.0	0.4	27.2	72.0
0.0	0.8	11.5	106.7
0.0	1.0	8.0	106.8
Panel C. Bertrand-Nash versus κ-Full Cartel			
Null Model	**Alternative Model**	**T-test**	**F-stat First Stage**
(1)	(2)	(3)	(4)
0.0	0.2	9.4	1.6
0.0	0.4	9.5	2.8
0.0	0.8	8.7	12.7
0.0	1.0	4.2	10.5

TABLE 12: MOVE TO COMPETITION

This table presents the estimated borrower-bank-loan specific (Panel A) marginal costs under two modes of counterfactual competitive conduct: (1) banks are forced to Bertrand-Nash compete, i.e., banks cannot collude ($\upsilon_m \equiv 0$); and (2) banks joint maximize, i.e., banks are allowed to collude ($\upsilon_m \equiv 1$). Panel B presents predicted prices. Panel C shows the markups under Bertrand and Joint Maximization conducts.

	Mean	**Median**
	Panel A: Marginal Costs	
Marginal Cost - Bertrand-Nash ($\upsilon_m \equiv 0$)	8.82	9.30
Marginal Cost - Joint-Maximization ($\upsilon_m \equiv 1$)	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 - Bertrand-Nash ($\upsilon_m \equiv 0$)	2.43	2.30
Lerner Index - Bertrand-Nash ($\upsilon_m \equiv 0$)	0.23	0.19
Markup - Joint-Maximization ($\upsilon_m \equiv 1$)	6.38	4.79
Lerner Index - Joint-Maximization ($\upsilon_m \equiv 1$)	0.61	0.68

TABLE 13: TAX INCIDENCE

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

	Mean	**Median**	**Mean**	**Median**
	Unconditional (1)		**Conditional (2)**	
Panel A: The empirical benchmark				
Calibrated Conduct | Empirical Pass-through				
Incidence	2.76	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

Internet Appendix

Appendix A The Ecuadorian Banking Sector

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

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

Appendix A.1 Market characteristics' relationship to interest rates

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

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

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

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

TABLE A1: INTEREST RATE AND MARKET CHARACTERISTICS

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

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

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

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

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

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

Here, we benchmark against default in related papers:

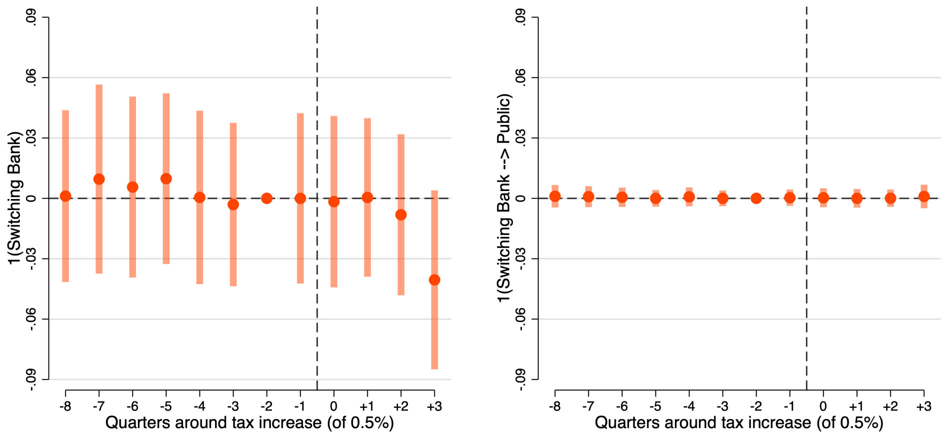
- Crawford et al. (2018) report a default rate of 6% in a sample of Italian small business lines of credit (with maturity 6 months to a year) between 1988 and 1998, which included a financial crisis in 1992.
- Default rates are close to 10% for credit of 13 months maturity

Appendix A.3 Commercial lending of private and public banks

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

While theoretically salient, however, the existence of the public commercial loan market does not appear to be first order in practice in this setting. This is suggested by Figure 3, where we see no reaction in interest rates to the introduction of the SOLCA tax. And recall that in Figure 3 in Appendix E, we see that there was also no significant effect on loan maturity or amount borrowed in loans lent by public banks.

Moreover, we see no evidence that there was significant switching of firms around the introduction of the tax, either between any banks or from borrowing taxed private-sector loans to borrowing untaxed public-sector loans. To test this, we first define the variable *Switch*, which takes the value one if the loan borrowed in period t is from a different bank, public or private, than the last loan borrowed. The left-hand panel of Figure A1 reports the evolution in the probability of switching lenders around the introduction of the SOLCA tax relative to the probability two quarters before the tax was introduced. We see no significant difference either leading up to the tax or immediately after its introduction. If anything, there is a decrease in the probability of switching lenders three quarters after the introduction of the tax, though it is not significant at conventional confidence levels. This may reflect the macroeconomic shock from falling oil prices that sent Ecuador into recession in the first quarter of 2015 (see Appendix I for



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

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

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

further information on this recession and its potential to affect our results). of In the right-hand panel of Figure A1 we similarly see no evidence of a change in the probability of switching to borrowing from a public bank. Overall, we see no evidence that the existence of a public source of commercial loans that were not subject to the SOLCA tax had a significant impact on the pass-through of the tax or on lender competition in the private commercial loan market. This is due to the enforced separation between the two markets necessitated to reserve the subsidized interest rates of public commercial loans for micro businesses.

Appendix B A Model of Commercial Lending with General Competitive Conduct

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

Appendix B.1 Setup

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

Appendix B.2 Credit Demand

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

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

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

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

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

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

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

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

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

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

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

for ψ_i, which has a distribution F.

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

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

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

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

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

Putting everything together, the demand model is defined jointly by Equations B4 and B5, which describe the discrete bank choice and the continuous loan demand, respectively. Then the total expected demand, given rates of all banks in market m, is $Q_{ik}(r) = s_{ik}(r)L_{ik}(r)$. This expected demand is given by the product of the model's demand probability and the expected loan use by i from a loan from bank k.

Appendix B.3 Credit Supply

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

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

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

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

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

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

degree of correlation in price co-movements in equilibrium.

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

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

Rearranging Equation B7 yields:

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

which we write using price elasticities:

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

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

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

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

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

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

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

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

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

Appendix B.4 Discussion of identification of the conduct parameter

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

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

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

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

Traditional approaches in the literature (e.g., Bresnahan, 1982; Berry and Haile, 2014;

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

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

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

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

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

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

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

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

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

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

our general bank competition model is:

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

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

Appendix C Testing Marginal Cost Assumptions

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

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

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

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

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

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

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

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

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

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

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

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

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

TABLE C1: TEST OF MARGINAL COST ASSUMPTIONS

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

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

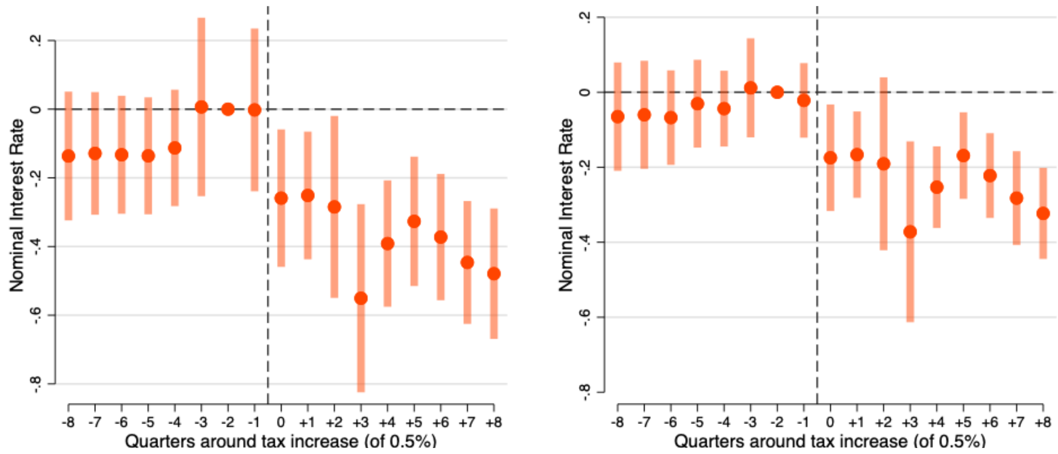
Appendix D Loan Default Prediction

We predict default at the loan level by regressing the event of a loan becoming 90 days or more behind payment on lagged firm-level covariates that predict default in the literature, including firm age at the grant of the loan, the loan's term-to-maturity and the amount that was borrowed, the nominal interest rate on the loan, total firm wages, assets, revenue, and debt, tangibility (property plant and equipment scaled by total assets), the total number of bank relationships and their age at the grant of the loan, if bank internal ratings on any of the firm's bank debt has ever been rated as risky or a doubtful collection (less than an A rating), if the loan is classified as a microcredit, and an indicator that takes the value one if a firm has only one lender relationship, and firm, province-year and sector-year fixed effects. Table D1 reports the estimated default models. Column (4) is our preferred specification that we use to construct the regression control *Pr(Loan Default)*, which is defined as the difference between the observed propensity to default on a loan and the residuals of this predictive regression.

TABLE D1: COMMERCIAL LOAN DEFAULT MODEL

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

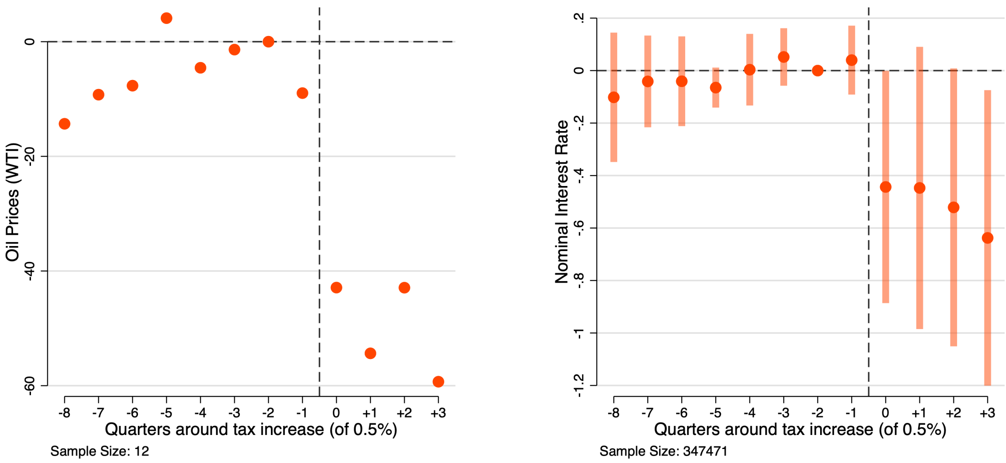
Appendix E Robustness of pass-through estimates



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

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

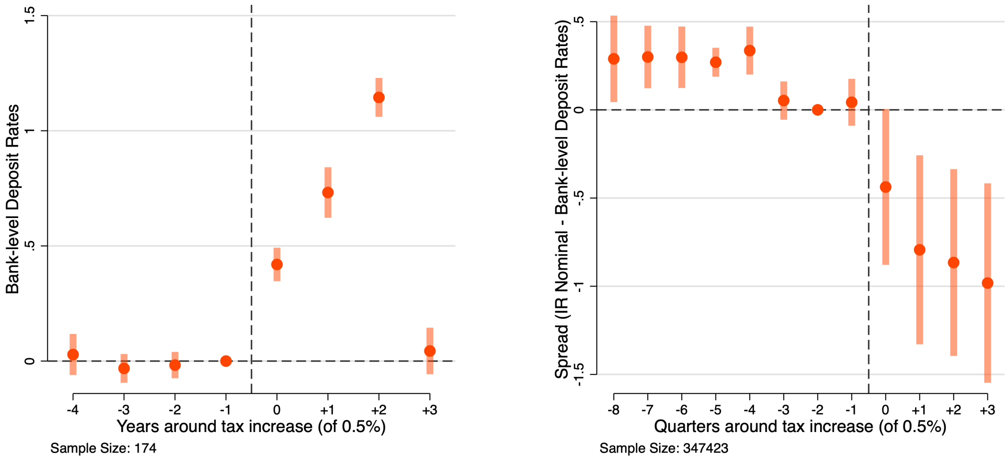
Replicating Figure 2 in an eight quarter estimation window around the SOLCA tax implementation. It reports the period-by-period difference in average pre-tax nominal interest rates on new commercial loans from private banks around treatment assignment relative to event-time period $t = -2$ (normalized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



(a) Oil Prices (b) Interest Rates cont. Oil

FIGURE E2: ROBUSTNESS CONTROLLING FOR OIL PRICES

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



(a) Deposit Rates (b) Spread

FIGURE E3: ROBUSTNESS ON SPREADS

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

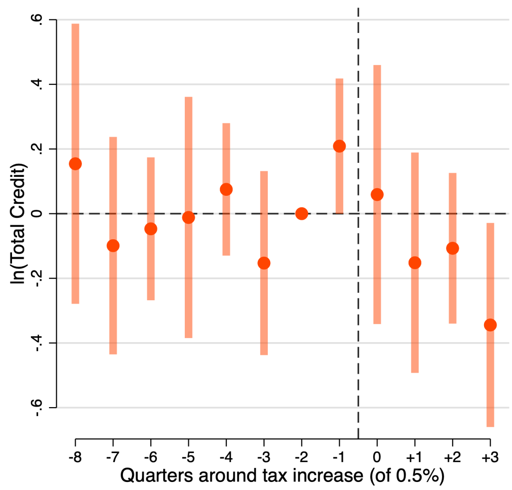
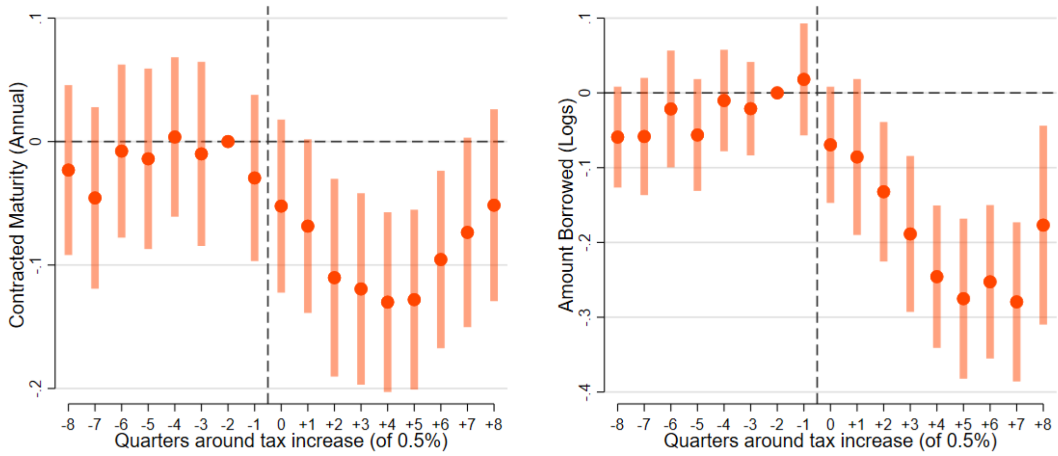


FIGURE E4: DYNAMIC ANALYSIS OF THE INTRODUCTION OF THE SOLCA TAX ON TOTAL COMMERCIAL CREDIT LENT BY PRIVATE BANKS

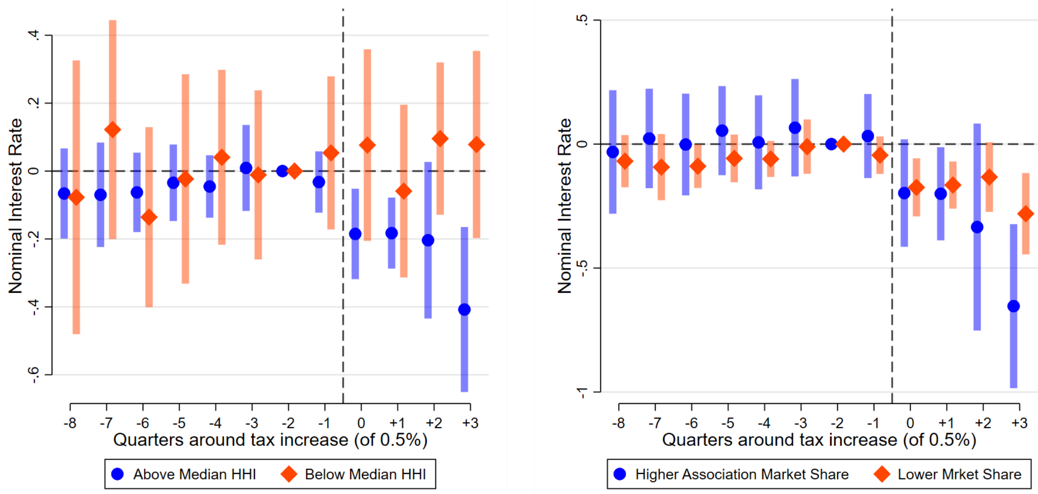
The figure reports the period-by-period difference in total commercial lending from private banks around treatment assignment relative to event-time period $t = -2$ (normalized to zero), using bank fixed effects. Data are bank-quarter level on commercial loans granted by private banks to Ecuadorian corporations.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



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

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

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



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

FIGURE E6: SOLCA TAX PASS-THROUGH BY MARKET CONCENTRATION

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

TABLE E1: ROBUSTNESS OF PASS-THROUGH ESTIMATES

The table reports aggregate pass-through estimates to the tax-inclusive interest rates of commercial loans around the introduction of the 2014 SOLCA tax in Ecuador. Data are at the loan-level for 2010 to 2017, excluding October 2014. The main independent variable is the tax rate, measured as 0.5 adjusted proportionally by term-to-maturities if maturity is less than 1 year. The dependent variable is the tax-inclusive interest rate, which is the sum of the nominal, annualized interest rate plus the tax rate. Both are in percentage points. Regressions control for twenty buckets of term-to-maturity, twenty buckets of loan amount, and the loan's predicted default probability. Column (1) additionally controls for a third-degree polynomial of quarterly prices of WTI crude oil. Column (2) controls for a third-degree polynomial of province quarterly GDP growth. Column (3) includes quarter fixed effects. Robust standard errors clustered at the bank-quarter level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The table bottom of the table reports testing against the full pass-through null hypothesis ($\rho_o = 1$).

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

Appendix F Price Prediction

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

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

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

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

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

Table F1 reports the price regressions. Comparing column (1) with column (2) and column (3) with column (4), demonstrates that the fit of the regression (R-squared) increases only marginally when we use separate bank, year and province fixed effects versus dummies for the interaction of the three variables. The largest improvement in the fit occurs when we include firm fixed effects, strongly supporting the hypothesis that banks use fixed firm attributes unobservable to the econometrician as a key determinant of loan pricing. In this specification, we can explain approximately 65% of the variation in observed commercial loan prices.[3]

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

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

[2]Table F1 and Appendix Table F2 fully replicate Tables 2 and 3 of Crawford et al. (2018) using our dataset. It motivates our decision to use the pricing model used in Equation F1 with firm fixed effects as our preferred specification.

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

TABLE F1: PRICE PREDICTION REGRESSIONS

The table reports estimates of Equation F1, an OLS regression of the nominal interest rate on commercial bank loans (in percentage points) on a series of controls and dummies. An observation is at the loan level. See Table 3 for variable definitions. Standard errors are clustered at the bank-province-year level and reported in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

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

Second, in Appendix D, we test the extent to which the variation in prices we cannot explain predicts firms' subsequent default. Specifically, we regress loan default on the same set of controls and the residuals from the regressions reported in Table F1. Results are reported in Table F2. We fail to reject the null hypothesis that the residuals have no significant statistical correlation with default once we include firm fixed effects. Instead, the relationship is consistently positive even with firm fixed effects, but not economically large. Indeed, once we account for firm fixed effects, the relationship between prices and default is precisely estimated as zero.

TABLE F2: THE ABILITY OF PRICING RESIDUALS TO PREDICT DEFAULT

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

Notes. The table reports estimates from an OLS regression of a indicator variable that takes the value of one if the firm defaults on a commercial bank loan and zero otherwise on the residuals of the pricing regressions reported in Table F1. The same set of controls are used as in the corresponding Model in Table F1. The observation is at the loan level. Residuals are divided by 100 to aid interpretation of the reported coefficients. Standard errors are clustered at the bank-province-year level and reported in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

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

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

where $\tilde{\tau}_{ikmt}$ will be unobserved for non-chosen banks and non-borrowing firms, and $\tilde{r}_{kmt} = \tilde{\gamma}_0 + \tilde{\lambda}_{kmt}$. We present the resulting distribution of prices for borrowers' actual choices and non-chosen banks, as well as non-borrowers' prices, in Figure F1. As shown in the figure, our model predicts well the areas with greater mass as well as the support of the distribution of observed prices. Moreover, our model predicts similar prices for non-chosen options for borrowers but higher prices (around 8%) for non-borrowers.

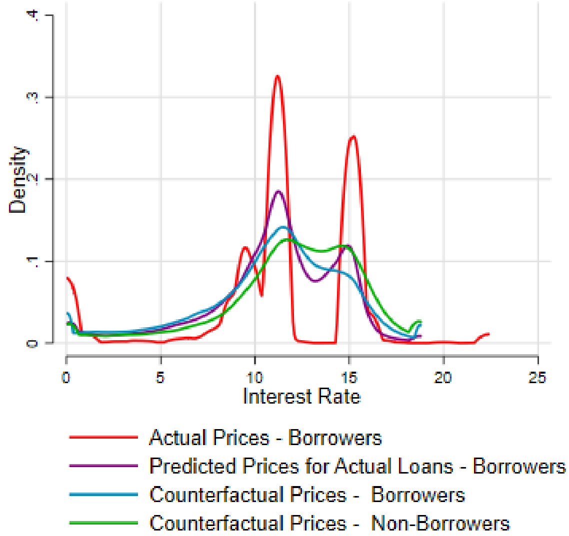


FIGURE F1: DISTRIBUTION OF PREDICTED PRICES

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

Appendix F.1 Firm matching model

We employ a propensity score matching approach to predict prices for firms that do not borrow in our sample. In this we follow the strategy taken in the literature to solve this empirical challenge, including in Adams et al. (2009) and Crawford et al. (2018). Specifically, we match borrowing firms to non-borrowing firms that are similar in their observable characteristics and then assign a borrowing firm's fixed effect, $\tilde{\omega}_i^r$, to the matched non-borrowing firm. We follow the same procedure to predict the loan size and term-to-maturity. Table F3 reports diagnostics on our matching model.

TABLE F3: PROPENSITY SCORE MATCHING - BIAS

	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 G Demand Estimates by Region

TABLE G1: DEMAND PARAMETERS

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

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

Continued on next page

TABLE G1 – continued from previous page

Region	Variable	Mean	Standard Deviation
Guayas	Age Firm	0.215***	(0.009)
Guayas	Age Relationship	0.036	(0.042)
Guayas	Assets	0.022	(0.124)
Guayas	Debt	−0.007	(0.070)
Guayas	Expenditures	0.062**	(0.028)
Guayas	Revenue	0.021	(0.031)
Guayas	Wages	0.016	(0.029)
Pichincha	Price	−0.386***	(0.101)
Pichincha	Sigma	1.156***	(0.057)
Pichincha	Scaling Factor	−0.014	(0.321)
Pichincha	Log(Branches)	0.735	(1.377)
Pichincha	Age Firm	0.205***	(0.007)
Pichincha	Age Relationship	0.157***	(0.030)
Pichincha	Assets	0.051	(0.107)
Pichincha	Debt	−0.010	(0.053)
Pichincha	Expenditures	0.207***	(0.039)
Pichincha	Revenue	0.002	(0.037)
Pichincha	Wages	−0.003	(0.032)
Sierra	Price	−0.091***	(0.012)
Sierra	Sigma	1.168***	(0.038)
Sierra	Scaling Factor	−0.033	(0.545)
Sierra	Log(Branches)	0.865	(1.321)
Sierra	Age Firm	0.225***	(0.008)
Sierra	Age Relationship	0.152***	(0.040)
Sierra	Assets	−0.009	(0.095)
Sierra	Debt	−0.026	(0.043)
Sierra	Expenditures	0.395***	(0.044)
Sierra	Revenue	0.012	(0.037)
Sierra	Wages	0.078**	(0.034)

TABLE G2: OVER-IDENTIFICATION TESTS FOR INSTRUMENTED PRICE PARAMETER

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

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

Appendix H Estimating Demand Elasticities

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

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

and

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

The elasticity for total demand is given by:

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

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

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

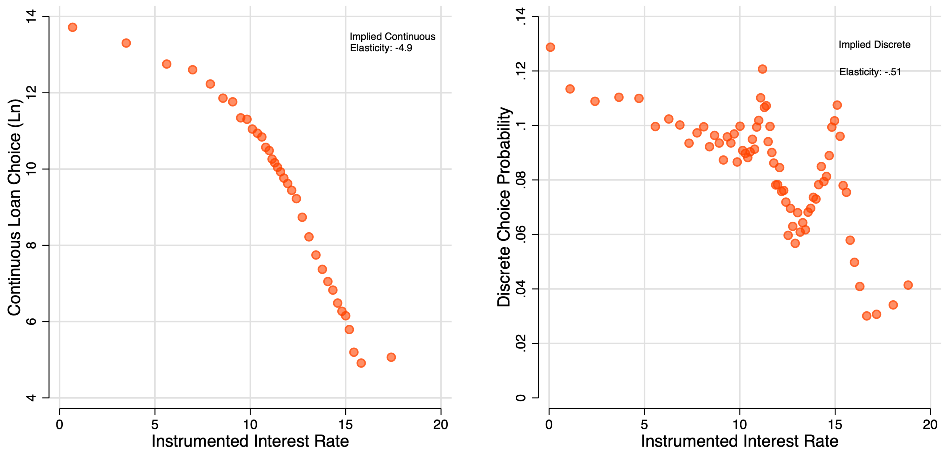
and

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

Appendix H.1 Reduced-Form Elasticities

We validate the estimated structural elasticities reported in Table 8 using a reduced-form instrumental variable approach. Specifically, we regress demand on instrumented loan interest rates, controlling for bank, province, and year fixed-effects. Instruments include delinquency rates in microcredit, housing and consumption, and interest rates in consumption, micro-lending, commercial credit in other regions.

We report the relationship between the instrumented interest rate and continuous demand (ln(loan value)) in panel (a) of Figure H1, while panel (b) presents the relationship with discrete-choice demand (choice probability). The corresponding implied elasticities are reported in the upper right corner of each panel. Reassuringly, the median structural elasticities match the reduced-form estimates for elasticities that we calculate using an instrumental variable approach in regression form.



(a) Continuous (b) Discrete

FIGURE H1: REDUCED-FORM ELASTICITIES

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

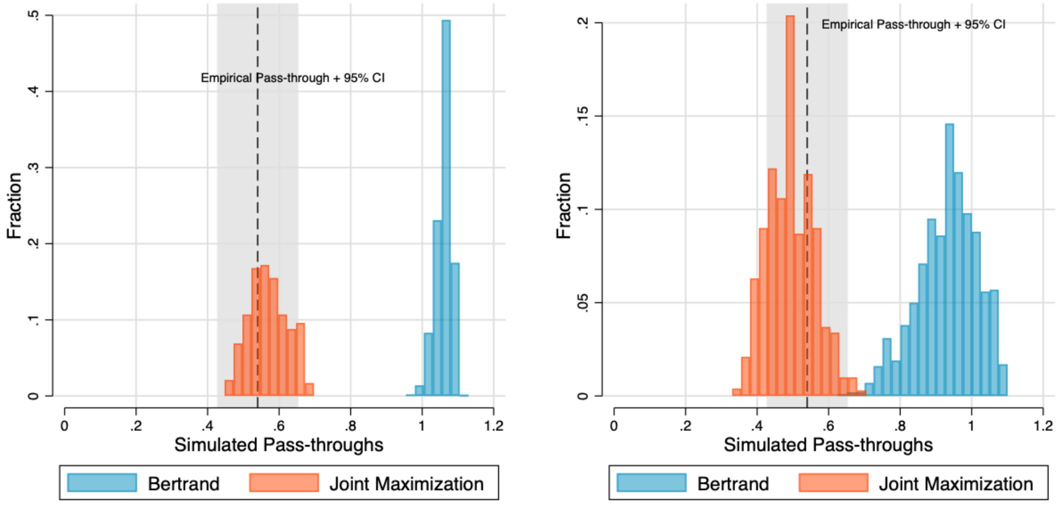
Appendix I Additional Simulations and Counterfactuals

Appendix I.1 Robustness to Modeling Lender-Borrower Relationships

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

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

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



(a) All loans (b) Chosen loans

FIGURE I1: DISTRIBUTION OF SIMULATED PASS-THROUGHS BY CONDUCT

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

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

Appendix I.2 Sensitivity Tests to the Invariant Conduct Assumption

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

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

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

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

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

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

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

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

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

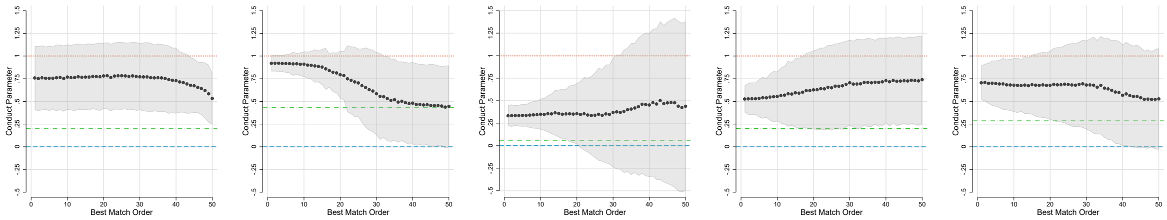
Third, Appendix Table I2 presents the corresponding values for the calibrated conduct parameter estimated over the full sample (Columns 1 and 2 and reproduced from Table 10) and over the pre-SOLCA tax sample (Columns 3 and 4). We again see that the conduct estimates from the two samples are statistically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

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

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

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

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



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

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

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

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

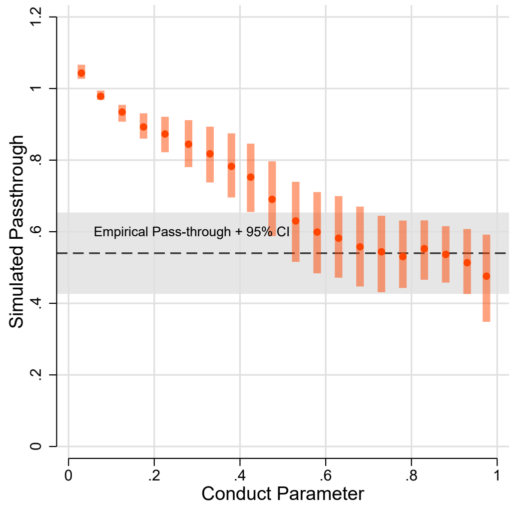


FIGURE I3: AVERAGE NATION-WIDE SIMULATED PASS-THROUGHS BY CONDUCT GRID; PRE-SOLCA TAX SUBSAMPLE

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

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

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

TABLE I3: PASS-THROUGH ESTIMATES: SHORT-TERM

The table reports aggregate pass-through estimates to the tax-inclusive interest rates of commercial loans around the introduction of the 2014 SOLCA tax in Ecuador. Data are at the loan-level for 2010 to 2017, excluding October 2014. The sample is restricted to include only November and December 2014. The main independent variable is the tax rate, measured as 0.5 adjusted proportionally by term-to-maturities if maturity is less than 1 year. The dependent variable is the tax-inclusive interest rate, which is the sum of the nominal, annualized interest rate plus the tax rate. Both are in percentage points. Regressions control for twenty buckets of term-to-maturity, twenty buckets of loan amount, predicted default probability, and bank-firm FE. Model (1) pools all regional markets. Models (2)-(6) report estimates by regional market. Robust standard errors clustered at the bank-quarter level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Testing is conducted against the full pass-through null hypothesis ($\rho = 1$).

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

Appendix I.3 Testing the Identification Assumption for Conduct

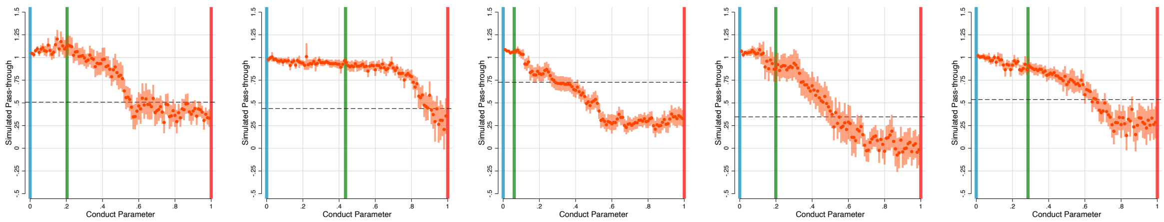
Our model identification assumes a direct relationship between pass-through and the conduct parameter. Specifically, we assume that pass-through is non-constant as competitive conduct, or the degree of joint maximization among banks competing in the same market, increases. For ease of interpretation,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

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

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

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

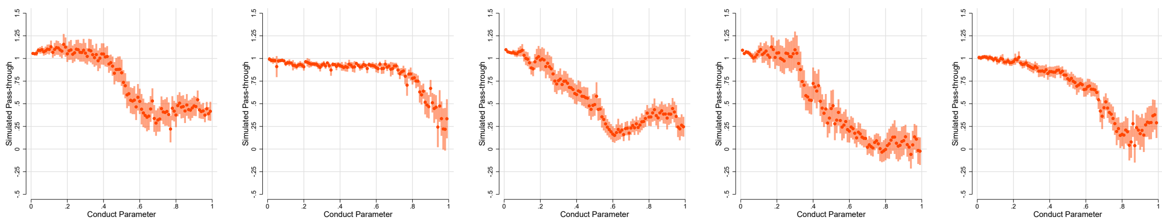
With our estimated model in hand, we can directly test the relationship between conduct and pass-through. Figure I4 replicates Figure 5 in the main paper for each region separately. The exercise is to simulate the pass-through of a 0.5% loan tax like the SOLCA tax over the entire support of the conduct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



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

FIGURE I4: SIMULATED PASS-THROUGH AND COMPETITIVE CONDUCT

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



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

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

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

Appendix J Testing Partial Cartels

Appendix J.1 The Corts' Critique

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

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

Appendix J.2 Modeling Partial Cartels

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

Appendix J.3 Testing Framework

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

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

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

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

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

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

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

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

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

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

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

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

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

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

Appendix J.4 Testing Results

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

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

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

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

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

TABLE J1: WITHIN CARTEL MODEL TESTING USING INTERNALIZATION PARAMETERS

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

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

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

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

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

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

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

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

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

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