Estimating The Information Component in Switching Costs: A Structural Approach*

Santiago Truffa[†]
Sheisha Kulkarni[‡]
Gonzalo Iberti[§]

July 2025

Abstract

We exploit a regulatory reform in Chile as a natural experiment to quantify the role of information frictions in consumer credit markets. The 2012 policy mandated simplified and standardized disclosure of loan terms in contracts and quotes, directly targeting the informational component of switching costs. Using administrative, loan-level data covering the universe of bank-originated credit, we document a significant increase in price sensitivity in borrower switching behavior following the reform. We use this change to structurally estimate a reduction of approximately 10% in information frictions. Embedding this estimate into a dynamic structural model that incorporates borrower search and bank pricing responses, we simulate long-run market equilibrium effects. We find that improved consumer search efficiency lowers average interest rates by 180 basis points and raises long-term borrower welfare by 15%. Importantly, the effects are heterogeneous across local markets and depend on features such as bank concentration and cost structures. In less competitive areas, consumers experience smaller gains, while more competitive regions exhibit stronger interest rate reductions and welfare improvements. These results highlight the potential for disclosure policy to reshape market outcomes through its effect on consumer behavior and firm competition.

*We are grateful to Jose Antonio Espin-Sanchez, Ernesto Dal Bo, Oleg Gredil, John Morgan, Gonzalo Maturana and Beau Page as well as the seminar participants at SBIF, CFPB and CU Boulder Conference on Consumer Financial Decision Making for their helpful comments. This research has received financial support from the Alfred P. Sloan Foundation through the NBER Household Finance small grant program

[†]ESE Business School, Universidad de los Andes. E-mail: struffa.ese@uandes.cl

[‡]University of Virginia–McIntire School of Commerce. E-mail:sk7nn@virginia.edu

[§]Universidad Adolfo Ibanez. E-mail: gonzalo.iberti@uai.cl

1 Introduction

When consumers consider switching banks, they often face a complex decision landscape defined by opaque and non-standardized credit products. The fundamental characteristics of loan contracts are frequently buried in fine print and presented in idiosyncratic formats across lenders, making it difficult for borrowers to assess and compare offers. This friction undermines the functioning of competitive credit markets and can result in inefficient matching between consumers and lenders. In this paper, we investigate the role of information frictions in household financial decisions by combining the clean identification strategy of reduced-form methods with the policy relevance and interpretability of structural modeling.

We exploit a natural experiment in Chile, where a 2012 legislative reform mandated standardized and simplified loan disclosure forms across all regulated banks. The policy was designed to improve market transparency, reduce search and comparison costs, and ultimately facilitate switching by allowing consumers to easily identify relevant loan features, such as fees and effective interest rates. This reform provides a unique opportunity to isolate and measure the impact of reduced informational frictions on consumer behavior, loan pricing, and market equilibrium.

Our empirical strategy leverages rich administrative microdata from the Chilean banking regulator, which includes the universe of consumer loan originations across all banks, with detailed information on borrower-bank matches, loan terms, and bank characteristics. Unlike most prior work that relies on aggregated or a subset of the financial system (—e.g., Bertrand and Morse (2011); Bertrand et al. (2010), Kim et al. (2003)), our matched panel structure allows us to observe the full market and trace how consumers respond to relative price changes before and after the policy.

To estimate the effect of the policy on information frictions, we use reduced-form regressions comparing price sensitivity in switching behavior pre- and post-reform. These estimates identify a key friction parameter, which we feed into a dynamic structural model to assess equilibrium and welfare outcomes. Our model embeds a Berry (1994)-style demand system with an Artuç et al. (2010)-type model of dynamic consumer choice. Banks are strategic players that optimally set interest rates given their market power and cost of funds, while consumers face search frictions and make rational switching decisions over time.

The reduced-form results indicate a significant increase in consumer price sensitivity following the disclosure reform, consistent with a 10% reduction in information frictions. When embedded into the structural model, these estimates imply a long-run reduction in average interest rates of 180 basis points and a 15% increase in consumer surplus. The model also predicts a narrowing dispersion of interest rates, suggesting intensified competition and improved matching efficiency.

Importantly, our framework allows us to quantify the strategic supply-side response of banks. Lower-cost banks lose market share as consumers shift toward lenders with more favorable interest rates. In response, banks adjust pricing dynamically, with less competitive banks lowering rates to retain customers, while others exploit increased market power to raise prices. The model captures these transitional dynamics, providing a richer understanding of how disclosure policies can re-shape market equilibrium over time.

This paper builds upon our companion study Kulkarni et al. (2025), which uses the same policy shock and dataset to cleanly identify reduced-form local average treatment effects of disclosure standardization, showing that borrowers exposed to simplified disclosures make better-informed decisions. In contrast, this paper uses a structural framework to extrapolate beyond the treated subpopulation and study the full general equilibrium consequences of the reform. By recovering policy-relevant fundamentals—such as price elasticities and friction parameters—we can simulate counterfactual disclosure regimes, compute aggregate welfare gains, and evaluate heterogeneous effects across market segments.

Our contribution also relates to the growing structural household finance literature that aims to understand how consumers navigate complex financial environments. While early work focused on static demand estimation Einav et al. (2012), recent models incorporate institutional features of credit markets, heterogeneity in borrower sophistication, and supply-side responses Benetton (2021); Guiso et al. (2022). Estimating dynamic models that capture both demand and supply remains computationally challenging. We circumvent this by using quasi-experimental variation to identify key parameters externally, thereby achieving a tractable yet policy-relevant model.

Overall, our results underscore the value of disclosure standardization in enhancing market efficiency and consumer welfare. More broadly, our framework highlights how reduced-form identification can inform the discipline of structural models, offering credible counterfactuals, and guiding the design of future financial market regulations.

The rest of the paper is organized as follows. Section II discusses the relevant literature and our contributions. Sections III and IV describe the policy change and the data, respectively. Section V explains our theoretical model. Section VI estimates the parameters of our model and uses the model to simulate welfare. Section VII concludes.

2 Literature review

Search costs affect the ability of consumers to switch between institutions. Evidence suggests that consumers are not always efficient when choosing among different contracts, or they leave money on the table by switching providers less than they should (Handel (2013), Illanes (2016), Brown and Goolsbee (2009), and Luco (2013)). Price dispersion increases with search costs Hong and Shum (2006): if similar products are priced at widely varying amounts, consumers could have been better off, or attained a more efficient price by merely purchasing the product from a different lender. This is especially true for financial products, for example Standard & Poors index funds Hortaçsu and Syverson (2004), money market funds Christoffersen and Musto (2002), mutual funds Bergstresser et al. (2009), retail municipal bonds Green et al. (2007), car loans Palmer (2015), and mortgages (Woodward and Hall (2012), Baye and Morgan (2001), Baye and Morgan (2006)).

One prominent explanation for why price dispersion persists in equilibrium, particularly in financial markets, is that consumers must expend costly effort to acquire information on prices (see Farrell and Klemperer (2007) for a thorough review). There is also an added benefit to sellers if high search costs exist in a product market. Gabaix and Laibson (2006) and Ellison and Wolitzky (2012) show that firms may wish to strategically generate search costs, leading to a reduction in consumer welfare Grubb (2015). Furthermore, these search costs may not be overcome by educational initiatives, which may further confuse consumers Carlin (2010). Experimental research suggests that when senders have worse information, they are more likely to disguise it in more complex disclosure to receivers when they can benefit from doing so Jin et al. (2018). However, it is not clear if these search costs are necessarily harmful to consumers in equilibrium. Indeed Chioveanu and Zhou (2013) predict that policies that aim to make prices more comparable may end up hurting consumers in equilibrium.

This paper builds directly on the analysis presented in Kulkarni et al. (2025), which exploits a policy-induced standardization of consumer credit contracts in Chile to identify local average treatment effects on borrower behavior. That work leverages quasi-experimental variation to estimate the causal impact of standardized contract disclosure on borrowing and default, using a reduced-form approach. While that analysis identifies behavioral responses to information simplification, it is inherently partial-equilibrium and does not allow for counterfactual exercises involving market structure or long-run dynamics.

Structural models are becoming a cornerstone of modern household finance research, allowing economists to simulate counterfactual scenarios and evaluate policy changes in ways that reduced-form studies cannot. More recent work has extended structural approaches to specific household finance settings: for instance, Einav et al. (2012) develop a structural model of subprime auto lending to show how loan contract terms like down-payments and interest rates screen borrowers and influence default outcomes.

One frontier in this literature is building structural models that include both household demand and the supply side in a unified equilibrium framework Benetton (2021). Traditionally, many household finance models took prices (interest rates, etc.) as given or exogenous. However, in reality, outcomes like interest rates, credit availability, or fees are determined through the interaction of consumers and competing lenders – an equilibrium of supply and demand. Incorporating this is challenging: it requires solving for equilibrium strategies of lenders (banks, credit card companies, etc.) while accounting for households' dynamic behavior. Essentially, one must solve a dynamic game or equilibrium where households optimize given expectations of future prices, and lenders set prices or contract terms anticipating household behavior. Technically, this is much harder than a single-agent optimization, as it involves finding a fixed-point (prices such that demand and supply align). Computational complexity grows quickly – especially if we allow for many heterogeneous consumers and strategic firms, each with their own state variables. As a result, fully dynamic models with rich demand and supply are still relatively rare, and researchers often have to make simplifying assumptions to keep things tractable.

Studying consumer switching behavior in credit markets inherently requires a dynamic perspective. Once a household decides to switch financial institutions, its economic environment and decision set are permanently altered—entering a new state of the world. Static models fail to capture this core feature. In contrast, dynamic structural models allow households to form forward-looking expectations, such as anticipating future interest rate changes or credit conditions, and incorporate these into current choices. This temporal interdependence enhances realism but significantly increases model complexity. Researchers must track evolving state variables, such as a household's bank affiliation, prevailing market shares, and the evolution of interest rates or product availability over time. As a result, these models often become high-dimensional, particularly when trying to incorporate feedback effects between demand and supply.

Many applied structural models in household finance—such as life-cycle saving or mortgage default models—focus on consumer dynamics in isolation, treating prices as exogenous or non-strategic. General equilibrium models that incorporate strategic supply-side behavior over time are more rare and technically demanding. A notable exception is Campbell et al. (2020), which embeds overlapping generations of households and a forward-looking financial intermediary in a dynamic equilibrium framework, illustrating the analytical power of such models to capture the macroeconomic and welfare consequences of financial contract design.

In our setting, we explicitly combine the demand and supply sides of the credit market in a dynamic framework. Households are modeled as forward-looking agents who re-evaluate and potentially re-optimize their banking relationships each period. On the supply side, while banks also respond strategically to changing market shares and consumer behavior, we adopt a simplifying assumption: banks optimize interest rates in a static manner each period (as in Berry (1994)), taking current market conditions as given. This approach enables tractability in solving the dynamic equilibrium, while still allowing for rich consumer dynamics and endogenous market structure. Extending the model to allow for fully dynamic strategic behavior by banks—such as investment in customer acquisition or reputation—remains an important avenue for future research.

Another advantage of structural approaches is the ability to study heterogeneous effects of policies across different markets or consumer segments. A given intervention – say an informational treatment like ours– can have different welfare consequences across communities or borrower types, depending on local market conditions. In the realm of financial advice and product complexity, recent work Reuter and Schoar (2024) emphasizes both demand-side and supply-side frictions: households may not seek out the best financial products due to search costs or lack of literacy, while brokers might have incentives to steer clients to high-fee products. A structural perspective in this context can ask how changing the "market design" of advice (for example, banning commissions or improving transparency) would equilibrate – possibly improving welfare for unsophisticated investors, but also possibly reducing the availability of advice in some areas if brokers exit. Indeed, Guiso et al. (2022) find that simply outlawing banks' ability to steer clients in the mortgage market doesn't unambiguously raise welfare – because what appears as "steering" also sometimes helps match unsophisticated borrowers with suitable products .

We contribute to the empirical literature by explicitly estimating the informational friction component of search costs. Contrary to the findings of Chioveanu and Zhou (2013), we find that policies that make prices more comparable actually improve consumer welfare. Additionally, we contribute to other research findings that have measured switching costs generally in the banking sector, as search costs are only one component of switching costs. They provide a structural approach that uses changes in the market shares of banks to estimate switching costs. Degryse et al. (2011) study borrowers from a Belgian bank and Shy (2002) uses a similar methodology to estimate depositor switching costs for four banks in Finland. As a byproduct of our estimation strategy, we also provide an alternative structural model for estimating information frictions from comprehensive micro-data rather than the aggregate market shares used by previous papers Kim et al. (2003).

Our paper offers a methodological contribution of creating a closed-solution model of the financial system with consumers. By combining the Artuç et al. (2010) and Berry (1994) models, we are able to simulate both consumer search changes and bank responses. By estimating these parameters through reduced-form methods, we contribute to a growing literature started by Fu and Gregory (2017) and Galiani et al. (2015) that combines reduced-form identification of parameters within larger structural models.

Contrary to other markets that have been singled out for their high search costs, regulators have been willing to provide legislation to protect consumers in financial transactions. For example, the Truth in Lending Act passed in the United States in 1968 provides consumers with an interest rate that incorporates all the costs of the loan. In 2009, the CARD Act was passed, which outlined to consumers the implications of paying the minimum and other sized payments towards their credit card bill. Agarwal et al. (2015) find that consumers increase the size of their payments, though not at an economically large rate. Increasing the saliency of rates to consumers as done by Ferman (2015), Bertrand and Morse (2011) and Bertrand et al. (2010) show that consumers do not appreciably change their interest rate elasticities if interest rates are shown more prominently. We are able to extend previous research beyond how disclosure affects the extensive margin of a subset of lenders to broader consumer choices within the financial system. Because we see consumer behavior across the financial system, we are able to provide estimates of consumer welfare based solely on changes in disclosure.

3 Transparency shock: Law 20.555

After the 2008 financial crisis, much emphasis was placed on international agencies and national governments to design policies that provided more protection to financial consumers. Reforming the National Consumer Service so that it could intervene in consumer credit markets, represented one of the fundamental campaign promises made by President Sebastian Pinera. In 2009 alone, the National Consumer Service received approximately 328,000 queries and 170,000 claims. Of the latter, 27 percent corresponded to the financial services and insurance sector. The government attributed part of the problem to the fact that

> financial service providers have not always prioritized their duty to adequately inform consumers so that they can freely decide with whom they should contract. Financial institutions are not providing transparent information to allow consumers to effectively evaluate and compare the costs associated with a credit, like interest rate, commissions and exit costs associated with the termination of the contract.

In response, the Chilean government introduced law 20.555 in March 2012 that aimed to protect consumers in credit markets by regulating and standardizing how relevant information should be presented to consumers. This law built on the introduction of APR (called

CAE) that was introduced in 2011 in law 20.448.[1] While law 20.448 regulated all fees and features associated with particular credit products, other credit products could continue to obscure important information in the fine print. Law 20.555 not only mandated that the CAE had to be displayed on both contracts and quotes for credit, it created a summary page (Figure 1) that lenders had to provide to consumers. This summary page standardized disclosure related to the total cost of credit, fees, insurance, and contingent fees associated with the credit product across lenders. This additional disclosure was created explicitly to reduce informational frictions between borrowers and lenders. As the Ministry of Finance stated in the law,

> We have noted the existence of informational asymmetries in the financial services market for individuals, where the current attributions of the National Consumer Service (SERNAC) have not been sufficient to resolve them. Therefore, we consider it essential to strengthen the consumer protection of financial services, through the allocation of greater powers and competencies to SERNAC, improving the delivery of information and carrying out studies that reduce information asymmetries.

In addition to the standardization of loan contracts, the law strengthened consumer financial protection through the allocation of more competencies to the National Consumer Service. This gave the National Consumer Service more resources and powers that would enable the agency to more effectively monitor financial institutions and enforce their compliance with the new and existing laws that protected financial consumers.

4 Data and stylized facts

We use rich administrative data reported by banks to the Comisión para el Mercado Financiero (CMF), Chile's financial regulator. For regulatory compliance, all supervised financial institutions are required to submit granular information on their loan portfolios at a high frequency. In our case, the primary data sources are collected bi-weekly or monthly and include detailed records on credit originations, loan performance, and borrower characteristics. This enables us to observe the full universe of loans in the Chilean banking system, tracking each loan from origination through its life cycle.

Our empirical analysis focuses on non-collateralized consumer loans, which constitute a widely used and relatively homogeneous credit product. These loans—commonly used for durable consumption, travel, or other personal expenditures—are typically unsecured, offered

[1]The implications of this regulation are explained in a companion paper.

by a broad range of lenders, and characterized by standard terms such as fixed maturity, fixed or variable interest rates, and no requirement of collateral. Unlike mortgage or auto loans, consumer loans are easy to compare across providers, and consumers can readily switch banks. This makes them a natural setting to study how informational frictions affect credit market outcomes.

We observe the full population of these loans between 2009 and 2015. Our final sample includes approximately 95 percent of non-collateralized loans under 1,500 UF (roughly USD 60,000 USD), representing the vast majority of the consumer credit market in Chile.[2] The construction of the panel draws from four key regulatory datasets: Loan Origination Records, which records all new credit operations reported by each lender. For each loan, we observe the origination date, loan amount, maturity, currency, interest rate, rate type, and an anonymized borrower ID. The Loan Performance Reports, with monthly file captures the evolution of the lender's credit portfolio at the loan level. It includes delinquency status, loan classification (performing vs. non-performing), and provisioning levels, allowing us to construct borrower-level measures of credit risk over time. A file with Borrower Characteristics comprising borrower-level demographic and financial information, including reported income and geographic location (comuna). And finally, merged National Civil Registry Data, with demographic records from the national registry using the borrower's anonymized RUT (Chile's equivalent of a Social Security Number). This allows us to include borrower characteristics such as gender, age, nationality, and marital status.

To construct a unified panel, we conditionally merge loans across datasets. When loan identifiers are partially inconsistent across files, we match on a combination of characteristics—including borrower ID, loan size, maturity, interest rate, and origination date—to ensure accurate linkage. Only loans that either matched exactly by code or satisfied stringent conditional criteria were retained.

Because data reported to the CMF is collected for regulatory purposes and often subject to verification (e.g., through supporting documents like tax returns or income certifications), we consider it a high-quality administrative source for studying credit market behavior.

Table 1 presents descriptive statistics for approximately 7.6 million non-collateralized consumer loans in our six-year sample spanning from 2009 to 2015. The average nominal interest rate is approximately 24 percent, broadly consistent with consumer lending rates in other Latin American credit markets. The average loan amount is roughly USD 4,000, equivalent to approximately one-sixth of the average annual income of borrowers. The mean maturity is 27 months, underscoring the short-term nature and relatively small size of these

[2]The remaining 5 percent of loans could not be merged due to inconsistencies in loan identifiers across files.

consumer credit products. In terms of loan performance, approximately 25 percent of loans experience at least one missed payment, while fewer than 1 percent of loans exhibit serious delinquency, defined as arrears exceeding 90 days.

To capture exogenous variation in interest rates for identification purposes, we augment our data with information from the Central Bank of Chile and banks' regulatory filings. Specifically, we use daily series of the interbank rate in UF and pesos to control for prevailing monetary conditions and to construct measures of expected inflation. We further incorporate bank-level balance sheet data, from which we compute a cost-of-funding proxy based on the ratio of interest paid over financial liabilities and equity, allowing us to capture bank heterogeneity in funding costs.

Figure 2 shows the distribution of residualized interest rates, obtained from a regression of observed rates on a rich set of loan and borrower covariates. Even after conditioning on observables, we observe substantial price dispersion, consistent with the presence of search frictions and imperfect competition, as emphasized in prior work on consumer credit markets.

To examine the raw effects of the policy on switching behavior, Figure 3 plots gross switching flows across banks at the regional level, comparing a window of 100 days before and after the policy implementation. We find evidence of an anticipatory increase in switching activity prior to the policy's effective date, followed by a reversion post-implementation. However, Figure 4 indicates that banks with lower cost of funding gained market share following the policy, suggesting that the reform enhanced consumers' ability to compare offers and reallocate credit relationships toward more competitive lenders.

Taken together, these patterns are consistent with the interpretation that the standardization and simplification of loan disclosure documents reduced informational switching frictions, enabling consumers to more efficiently reoptimize their borrowing relationships in response to price differences.

5 Model

To assess the long-run market implications of the standardized disclosure policy, we develop a dynamic structural model that captures both consumer behavior under informational frictions and banks' strategic pricing decisions. The model embeds consumer search and switching dynamics within a general equilibrium framework in which banks internalize endogenously the effect of their pricing on market shares and profits.

On the demand side, consumers are forward-looking and solve a dynamic optimization problem under rational expectations. In each period, they require one unit of credit and choose a lending bank, weighing interest rates across the market. However, informational frictions limit their ability to observe all available offers. These frictions introduce persistent heterogeneity in the prices consumers face and generate a wedge between the optimal and realized borrowing choices.

On the supply side, banks are Bertrand competitors that set interest rates to maximize expected discounted profits. Each bank's pricing decision reflects a markup over its marginal cost of funds, which is heterogeneous and observable in the data. Crucially, banks recognize that current pricing affects their market shares, which in turn shape future profits through consumer switching and market power dynamics.

By jointly modeling consumer search and bank pricing, the framework allows us to evaluate how reduced information frictions shift market dynamics over time. The introduction of standardized product disclosure, in this setting, alters consumer responsiveness and compels banks to adjust pricing strategies, leading to new equilibrium outcomes in prices, market shares, and welfare.

5.1 Consumers

To model consumer behavior, we adapt the dynamic discrete choice framework from Artuç et al. (2010). Consumers exhibit inelastic demand for one unit of credit per period. In each period t, a borrower begins as a client of bank i and pays interest rate r_t^i on their loan. Consumers evaluate the market for alternative offers and receive a vector of idiosyncratic taste shocks $\varepsilon_t = \varepsilon_{t\,j=1}^{j\,J}$, where J is the total number of banks.

Consumers choose whether to retain their current loan or switch to a new bank. To capture frictions in this decision process, we introduce an information friction parameter C^{ij}, which denotes the (non-monetary) cost of evaluating and switching from current bank i to bank j. These frictions may reflect search or comprehension barriers related to contract comparison. By construction, $C^{ii} = 0$ for all i.

If a consumer switches to bank j, they begin period $t+1$ as a client of j. Borrowers discount future utility at rate $\beta \in (0,1)$ and are sensitive to interest rates via the parameter $\rho > 0$. Let B_t denote the allocation of borrowers across banks at time t.

The period-t utility of a consumer currently at bank i is:

$$U_t^i(\varepsilon_t) = -\rho r_t^i + \max_{j \in 1,\dots,J} \varepsilon_t^j - C^{ij} + \beta V^j(B_{t+1}) \,, \tag{1}$$

where $V^j(B_{t+1})$ is the expected continuation value from being matched to bank j in the next period:

$$V^j(B_{t+1}) = \mathbb{E}_\varepsilon[U_t^j(\varepsilon_t)]. \tag{2}$$

Taking expectations over the taste shocks, we obtain the value function of remaining with bank i:

$$V_t^i = -\rho r_t^i + \beta V_{t+1}^i + \Gamma_t^i, \tag{3}$$

where Γ_t^i denotes the option value from being able to switch banks, defined as:

$$\Gamma_t^i = \mathbb{E}\varepsilon \left[\max j \; \varepsilon_t^j - C^{ij} + \beta V_{t+1}^j\right] - \beta V_{t+1}^i. \tag{4}$$

Assuming the taste shocks ε_t^j are i.i.d. across time and banks and follow a Type-I extreme value distribution with scale parameter ν, the fraction of borrowers who switch from bank i to j is given by the standard logit formula:

$$m^{ij}t = \frac{\exp\left[(-C^{ij} + \beta V^j t + 1)/\nu\right]}{\sum_{k=1}^{J} \exp\left[(-C^{ik} + \beta V_{t+1}^k)/\nu\right]}. \tag{5}$$

We can then normalize this by the fraction of consumers who stay at their current bank i:

$$\frac{m^{ij}t}{m^{ii}t} = \exp \frac{-C^{ij} + \beta(V^j t + 1 - V^i t + 1)}{\nu}. \tag{6}$$

Taking logs and rearranging gives an expression for the differential value:

$$\log(m^{ij}t) - \log(m^{ii}t) = \frac{1}{\nu}\left[-C^{ij} + \beta(V^j t + 1 - V^i t + 1)\right]. \tag{7}$$

Similarly, the option value Γ_t^i can be expressed (under the log-sum formula) as:

$$\Gamma_t^i = \nu \log\left[\sum_k \exp\left(\frac{-C^{ik} + \beta V_{t+1}^k}{\nu}\right)\right] - \beta V_{t+1}^i. \tag{8}$$

Or, rearranged using the definition of m_t^{ii}:

$$\Gamma_t^i = -\nu \log(m_t^{ii}). \tag{9}$$

This implies that the consumer's value function at bank i can be written in terms of observables as:

$$V_t^i = -\rho r_t^i + \beta V_{t+1}^i - \nu \log(m_t^{ii}). \tag{10}$$

Taking the difference in values across banks i and j:

$$V_t^j - V_t^i = -\rho(r_t^j - r_t^i) + \beta(V_{t+1}^j - V_{t+1}^i) - \nu\left[\log(m_t^{jj}) - \log(m_t^{ii})\right]. \tag{11}$$

Substituting this into the switching share equation and simplifying yields the estimating equation:

$$\log(m^{ij}t) - \log(m^{ii}t) - \beta\left[\log(m^{ij}t+1) - \log(m^{ii}t+1)\right] = -\frac{1-\beta}{\nu}C^{ij} + \frac{\beta\rho}{\nu}(r_{t+1}^j - r_{t+1}^i) + \upsilon_{t+1}, \tag{12}$$

where υ_{t+1} captures transitory unobserved components.

This regression equation allows us to estimate the information frictions C^{ij} and the interest rate sensitivity parameter ρ from observed gross switching patterns and interest rate differentials across banks, using only observable data and the exogenous policy shift.

5.2 Banks

We model bank behavior as static Bertrand competition in regional loan markets. In each market, there are J banks competing to serve borrowers who demand one unit of credit. Banks are profit maximizers and face downward-sloping demand curves, where demand elasticity arises endogenously from consumer switching behavior.

Each bank j charges an interest rate r_j and faces a marginal cost of funding MC_j, which captures institutional heterogeneity such as funding structure, risk exposure, or operating efficiency. The interest rate charged by a bank is a markup over this marginal cost, where the markup depends on the bank's market power in a given market.

Let Q_j denote the quantity of loans issued by bank j in a given region. The bank chooses r_j to maximize profits:

$$\Pi_j = r_j(Q_j) \cdot Q_j - C_j(Q_j), \tag{13}$$

where $C_j(Q_j)$ is the total cost of issuing Q_j loans, and $r_j(Q_j)$ reflects the inverse demand the bank faces.

Taking first-order conditions with respect to Q_j, we obtain:

$$\frac{d\Pi_j}{dQ_j} = \frac{dr_j}{dQ_j}Q_j + r_j = MC_j. \tag{14}$$

Rewriting this using the price elasticity of demand, $\varepsilon_j = -\frac{dQ_j}{dr_j} \cdot \frac{r_j}{Q_j}$, the optimal pricing rule becomes:

$$r_j = \frac{MC_j}{1 - \frac{1}{\varepsilon_j}}. \tag{15}$$

This classic Lerner-type rule highlights how market power depends on both cost and the elasticity of demand faced by the bank.

A central feature of our framework is that demand elasticity ε_j is derived from our structural demand estimates. In particular, under our consumer model, we can express the elasticity as a closed-form function of observed market shares and estimated price sensitivity $\hat{\rho}$:

$$\hat{\varepsilon}_j = -\hat{\rho} \cdot r_j \cdot (1 - s_j), \tag{16}$$

where s_j is bank j's market share in the regional market.

We can then recover the implied marginal cost from the observed price and estimated elasticity:

$$\widehat{MC}_j = r_j \cdot \left(1 - \frac{1}{\hat{\varepsilon}_j}\right). \tag{17}$$

This expression allows us to back out a bank-level measure of funding costs using only observed interest rates and market shares, assuming the $\hat{\rho}$ parameter is identified in the consumer demand stage. We compute $\widehat{MC}_j$ at the regional level and take its average over time to obtain a stable estimate of each bank's cost of funds, denoted $\overline{MC}_j$.

This in turn allows us to simulate the endogenous pricing response of banks to changes in their market share due to policy-induced consumer switching. Solving for r_j as a function of s_j and $\overline{MC}_j$, we obtain:

$$r_j = \frac{1 + \hat{\rho}(1 - s_j)}{\hat{\rho}(1 - s_j)} \cdot \overline{MC}_j = \overline{MC}_j + \frac{1}{\hat{\rho}(1 - s_j)}. \tag{18}$$

This pricing equation shows that banks with greater market power (higher s_j) set higher markups, while those facing more elastic demand (due to reduced information frictions) charge lower rates. This channel is central to understanding how disclosure policies influence long-run equilibrium outcomes.

6 Estimation

Our estimation strategy proceeds in two distinct stages, reflecting the separation of consumer-side and bank-side primitives in our structural model. This modular approach facilitates identification and reduces computational complexity, while allowing us to incorporate credible exogenous variation from policy.

6.1 Step 1: Estimating Consumer Price Sensitivity via Gross Flows

We begin by estimating the sensitivity of consumer switching behavior to relative prices, which captures the degree of information frictions present in the market. To identify this relationship, we exploit gross switching flows—the total number of borrowers who switch from one bank to another—rather than net flows, which reflect only the change in a bank's overall market share.

Gross flows are particularly informative in our setting because they capture the full extent of consumer search and switching, even when changes in market share are minimal. This distinction is critical for detecting changes in behavior induced by improved disclosure: a fall in information frictions may result in higher consumer mobility, even if overall bank rankings remain unchanged.

To illustrate this point, Figure 5 presents a histogram of the ratio of gross to net switching flows across regional markets. On average, gross flows are approximately three times larger than net flows, underscoring the rich variation available in the former to estimate switching behavior.

We exploit variation in gross flows before and after the disclosure reform to estimate how the elasticity of consumer switching responds to price differences, and how this response is moderated by the informational environment. The policy shock provides exogenous variation in consumer search costs, allowing us to identify the sensitivity parameter $\hat{\rho}$ that governs consumer behavior in our model.

6.2 Step 2: Estimating Bank Market Power via Net Flows

In the second step, we turn to the supply side and estimate the extent of market power held by banks in each regional market. This requires measuring how consumer responses aggregate into net switching flows—i.e., the change in a bank's customer base over time.

We use net flows as a sufficient statistic for market power under our pricing model. These net changes in market share are the key determinant of each bank's ability to mark up interest rates above marginal cost. Using the pricing equation derived in the bank section, we estimate the elasticity of demand facing each bank as a function of its observed share, and use this to back out implied marginal costs.

This two-step approach is consistent with our structural framework, in which the pricing side of the model is fed by demand elasticities estimated from switching behavior. By separating these components, we are able to use different sources of variation—gross vs. net flows—to credibly identify consumer and bank primitives, respectively.

6.3 Estimating Consumer Preferences and Information Frictions

Our consumer-side estimation exploits the structural decision to switch lenders. Based on the dynamic programming problem of consumers with rational expectations, we derived the following Euler equation that governs switching behavior:

$$\log(m^{ij}t) - \log(m^{ii}t) - \beta(\log(m^{ij}t+1) - \log(m^{ii}t+1)) = -\frac{(1-\beta)}{\nu}C^{ij} + \frac{\beta\rho}{\nu}(r^{j}_{t+1} - r^{i}_{t+1}) + \upsilon_{t+1} \tag{19}$$

Here, m^{ij}_t is the share of consumers switching from bank j to i in region r and time t, and m^{ii}_t is the share staying with i. The left-hand side captures the change in switching behavior over time, while the right-hand side includes switching costs C^{ij} and differences in interest rates. The parameter ν captures the variance of idiosyncratic shocks, and ρ reflects interest rate (price) sensitivity.

To estimate this equation, we aggregate our data to the region-bank-month level and use instrumental variables to address the endogeneity of future interest rates. We rely on macro-level cost shifters, including the interbank rate (peso and UF), expected inflation, and the ratio of interest payments to equity, to isolate variation in lending rates.

From this estimation, we recover $\hat{\rho}$, the price sensitivity parameter, which informs our dynamic structural model. We also perform robustness checks by varying β (discount factor) across reasonable ranges.

6.4 Quantifying Information Frictions

To assess the effect of the disclosure policy, we estimate the switching cost C before and after its implementation. Restricting to a seven-month window on either side of the policy change, we attribute changes in C to the reduction in information frictions. Table 3 summarizes the estimates.

We find that switching costs declined by approximately 10 percent, consistent with improved consumer information and lower frictions. This reduction in C represents an average treatment effect; heterogeneous impacts across consumer types (e.g., by education) are addressed in future work.

6.5 Estimating Bank Pricing Behavior

We estimate bank-side parameters using a random utility framework 'a la Berry (1994). Consumer utility from choosing bank j is:

$$u_{ij} = \beta X_j - \rho r_j + \epsilon_j + \varepsilon_{ij} \tag{20}$$

where X_j are observable bank characteristics, r_j is the interest rate, ϵ_j is an unobserved bank fixed effect, and ε_{ij} is an i.i.d. Type I extreme value shock.

Defining $\delta_j = \beta X_j - \rho r_j + \epsilon_j$, we relate observed market shares s_j to mean utility via:

$$\hat{\delta}_j = \log(\hat{s}_j) - \log(\hat{s}_0) \tag{21}$$

We estimate the linear model $\hat{\delta}_j = \beta X_j - \rho r_j + \epsilon_j$ using instrumental variables for r_j. The same instruments as in the consumer estimation (inflation, interbank rates, cost of funding) are used here. From this, we recover $\hat{\rho}$ and construct implied elasticities:

$$\hat{\varepsilon}_j = -\hat{\rho} r_j (1 - s_j) \tag{22}$$

These elasticities allow us to back out marginal costs using the pricing rule:

$$MC_j = r_j(1 - 1/\varepsilon_j) \tag{23}$$

6.6 Steady-State Computation

With all structural parameters estimated, we simulate the model to study long-run equilibrium effects. Consumers choose among banks to minimize borrowing costs while incurring switching frictions. The Bellman equation characterizing the value of bank i to a consumer is:

$$V^i = \rho r^i + \beta V^i + \nu \log\left(\sum_{k=1}^{J} \exp\left(\frac{\bar{\varepsilon}^{ik}}{\nu}\right)\right) \tag{24}$$

where $\bar{\varepsilon}^{ij} = \beta(V^j - V^i) - C^{ij}$. We solve for the fixed point of this system, yielding steady-state values for V, B^i (bank shares), and r^i (interest rates). The key equilibrium condition for prices is:

$$r^i = \overline{MC}_i + \frac{1}{\hat{\rho}(1 - s^i)} \tag{25}$$

6.7 Welfare and Transition Dynamics

To evaluate welfare, we simulate transition dynamics following a 10 percent reduction in C^{ij}. Consumers reallocate across banks based on updated value functions. Interest rates respond endogenously via changes in market power:

$$V_t^i = \rho r_t^i + \beta V_{t+1}^i + \nu \log \left(\sum_k \exp(\bar{\varepsilon}_t^{ik}/\nu) \right) \tag{26}$$

We compute welfare gains using the envelope theorem:

$$\Delta W = \sum_{t=0}^{\infty} \sum_j \beta^t m_t^{ij} \rho \Delta r_t^i / \Delta C \tag{27}$$

This yields consumer welfare improvements under counterfactual transparency policies and dynamic bank responses.

6.7.1 Simulations and Results from the Model

With our structural model in place, we now simulate a counterfactual scenario in which switching frictions are exogenously reduced by 10%. This reduction captures the impact of increased transparency and standardization in loan disclosures as enacted by the policy.

Figure 8 illustrates the transitional dynamics of market shares and equilibrium interest rates for one representative economic region. Following the reduction in switching frictions, consumers increasingly reallocate toward banks offering lower interest rates. Consequently, banks with relatively high funding costs experience substantial losses in market share. In response, these banks strategically lower their rates to retain customers. Conversely, banks that gain market share due to lower costs of funding respond by raising their rates as they gain market power. These strategic responses highlight the dynamic feedback between consumer switching and firm behavior.

In the long-run equilibrium, we observe a 7.7% average reduction in interest rates. Given a baseline average interest rate of 24%, this corresponds to a decrease of approximately 180 basis points. Figure 7 reports the associated welfare changes: on average, consumers experience a welfare gain of 14% in steady state. The model also predicts a decline in the dispersion of interest rates across banks, suggesting that consumers are more effectively comparing offers across institutions.

Importantly, the welfare gains are not uniformly distributed. Most of the benefits accrue to consumers who actively switch lenders in response to price differences. These consumers exploit the reduced friction to seek out better rates and thus enjoy larger utility gains. In contrast, consumers who remain passive or are less sensitive to relative prices capture only a portion of the benefits. This leads to redistribution in consumer surplus, based on responsiveness to pricing incentives.

The adjustment in rates across the economy occurs solely through changes in bank markups. Since we assume marginal funding costs remain constant, the observed interest rate declines reflect diminished market power in more competitive settings. However, in markets where banks gain market share, we observe a partial offset as these institutions raise interest rates due to increased market power. Hence, while the policy intervention improves aggregate outcomes, the full potential welfare gains are dampened by endogenous firm behavior.

Finally, we document substantial heterogeneity in the long-run effects across local markets. Figure 9 displays the regional distribution of steady-state interest rate reductions. The range is sizable: in some areas, average rates decline by as little as 96 basis points, while in others, they fall by over 160 basis points. This dispersion reflects the role of local market structure—regions with more fragmented or competitive banking sectors experience larger benefits from the policy shock.

Overall, our simulations underscore the importance of modeling both consumer behavior and strategic bank responses. They also suggest that while transparency reforms can yield significant welfare improvements, the distribution and magnitude of these gains depend crucially on the competitive landscape in which they are implemented.

7 Conclusion

This paper quantifies the role of informational frictions in household credit markets by studying a nationwide policy in Chile that standardized loan disclosures. Exploiting a unique administrative dataset that captures the full universe of consumer loans and borrower-bank matches, we estimate a dynamic structural model in which consumers face switching costs and banks endogenously adjust prices in response to changes in market power.

We show that reducing the information component of switching frictions leads to economically significant improvements in market outcomes. Specifically, we find that average interest rates decline by 180 basis points in the long run, and that price dispersion shrinks as consumers become more responsive to differences in loan terms. Welfare gains are substantial, with average consumer surplus rising by 15 percent. These gains are not uniform: they accrue disproportionately to consumers who switch lenders and to those residing in regions with more competitive banking environments.

Our model allows us to move beyond average treatment effects and simulate the transitional dynamics and heterogeneity in policy impacts. We find that while increased transparency improves market efficiency, market power and strategic bank behavior can attenuate its full benefits. Banks with growing market shares tend to increase prices, partially offsetting the gains from improved search. As such, policy effectiveness depends critically on local market conditions and the responsiveness of supply.

By combining reduced-form identification with a tractable structural framework, our approach provides a blueprint for evaluating the long-run equilibrium effects of consumer protection policies in financial markets. More broadly, our findings suggest that even modest reductions in information frictions can generate large efficiency and welfare gains—but that these gains are shaped, and sometimes constrained, by the endogenous response of financial intermediaries.

References

Agarwal, S., Chomsisengphet, S., Mahoney, N., and Stroebel, J. (2015). Regulating consumer financial products: Evidence from credit cards. *Journal of Financial Economics*, 130(1):111–164.

Artuç, E., Chaudhuri, S., and McLaren, J. (2010). Trade shocks and labor adjustment: A structural empirical approach. *American Economic Review*, 100(3):1008–1045.

Baye, M. R. and Morgan, J. (2001). Information gatekeepers on the internet and the competitiveness of homogeneous product markets. *American Economic Review*, 91(3):454–474.

Baye, M. R. and Morgan, J. (2006). Information gatekeepers and price discrimination on the internet. *Economics Letters*, 90(1):1–6.

Benetton, M. (2021). Leverage regulation and market structure: A structural model of the u.k. mortgage market. *The Journal of Finance*, 76(6):2997–3053.

Bergstresser, D., Chalmers, J., and Tufano, P. (2009). Assessing the costs and benefits of brokers in the mutual fund industry. *Review of Financial Studies*, 22(10):4129–4156.

Berry, S. T. (1994). Estimating discrete-choice models of product differentiation. *RAND Journal of Economics*, 25(2):242–262.

Bertrand, M., Karlan, D., Mullainathan, S., Shafir, E., and Zinman, J. (2010). What's advertising content worth? evidence from a consumer credit marketing field experiment. *Quarterly Journal of Economics*, 125(1):263–306.

Bertrand, M. and Morse, A. (2011). Information disclosure, cognitive biases, and payday borrowing. *Journal of Finance*, 66(6):1865–1893.

Brown, J. R. and Goolsbee, A. (2009). How much is a dollar worth? tipping versus equilibrium coexistence on competing online auction sites. *Journal of Political Economy*, 117(6):1061–1097.

Campbell, J. Y., Clara, N., and Cocco, J. F. (2020). Structuring mortgages for macroeconomic stability. Working Paper 27676, National Bureau of Economic Research.

Carlin, B. I. (2010). Strategic price complexity in retail financial markets. *Journal of Financial Economics*, 91(3):278–287.

Chioveanu, I. and Zhou, J. (2013). Price competition with consumer confusion. *Management Science*, 59(11):2450–2469.

Christoffersen, S. E. K. and Musto, D. K. (2002). Why do money fund managers voluntarily waive their fees? *Journal of Finance*, 57(3):1117–1140.

Degryse, H., Masschelein, N., and Mitchell, J. (2011). Staying, dropping, or switching: The impacts of bank mergers on small firms. *Review of Financial Studies*, 24(4):1102–1140.

Einav, L., Jenkins, M., and Levin, J. (2012). Contract pricing in consumer credit markets. *Econometrica*, 80(4):1387–1432.

Ellison, G. and Wolitzky, A. (2012). A search cost model of obfuscation. *RAND Journal of Economics*, 43(3):417–441.

Farrell, J. and Klemperer, P. (2007). Coordination and lock-in: Competition with switching costs and network effects. In *Handbook of Industrial Organization*, volume 3, pages 1967–2072. Elsevier.

Ferman, B. (2015). Reading the fine print: Information disclosure in the brazilian credit card market. *Management Science*, 62(12):3534–3548.

Fu, C. and Gregory, J. (2017). Estimation of an equilibrium model with externalities: Combining the strengths of structural models and quasi-experiments. NBER Working Paper 23300, National Bureau of Economic Research.

Gabaix, X. and Laibson, D. (2006). Shrouded attributes, consumer myopia, and information suppression in competitive markets. *Quarterly Journal of Economics*, 121(2):505–540.

Galiani, S., Murphy, A., and Pantano, J. (2015). Estimating neighborhood choice models: Lessons from a housing assistance experiment. Working paper, American Economic Association.

Green, R. C., Hollifield, B., and Schürhoff, N. (2007). Financial intermediation and the costs of trading in an opaque market. *Review of Financial Studies*, 20(2):275–314.

Grubb, M. D. (2015). Consumer inattention and bill-shock regulation. *Review of Economic Studies*, 82(1):219–257.

Guiso, L., Lenzu, S., and Pozzi, A. (2022). The cost of steering in financial markets: Evidence from the mortgage market. *Journal of Financial Economics*, 143(3):1209–1226.

Handel, B. R. (2013). Adverse selection and inertia in health insurance markets: When nudging hurts. *American Economic Review*, 103(7):2643–2682.

Hong, H. and Shum, M. (2006). Using price distributions to estimate search costs. *RAND Journal of Economics*, 37(2):257–275.

Hortaçsu, A. and Syverson, C. (2004). Product differentiation, search costs, and competition in the mutual fund industry: A case study of s&p 500 index funds. *Quarterly Journal of Economics*, 119(2):403–456.

Illanes, G. (2016). Switching costs in pension plan choice. Working paper, Northwestern University.

Jin, G. Z., Luca, M., and Martin, D. (2018). Complex disclosure. NBER Working Paper 24675, National Bureau of Economic Research.

Kim, M., Kliger, D., and Vale, B. (2003). Estimating switching costs: The case of banking. *Journal of Financial Intermediation*, 12(1):25–56.

Kulkarni, S., Iberti, G., and Truffa, S. (2025). Removing the fine print: Standardized products, disclosure, and consumer outcomes. *Journal of Financial Economics*.

Luco, F. (2013). Switching costs and competition in retirement investment. Working paper, Texas A&M University.

Palmer, C. (2015). Why did so many subprime borrowers default during the crisis: Loose credit or plummeting prices? Working paper, MIT Sloan School of Management.

Reuter, J. and Schoar, A. (2024). Demand-side and supply-side constraints in the market for financial advice. Working Paper 32452, National Bureau of Economic Research.

Shy, O. (2002). A quick-and-easy method for estimating switching costs. *International Journal of Industrial Organization*, 20(1):71–87.

Woodward, S. E. and Hall, R. E. (2012). Diagnosing consumer confusion and sub-optimal shopping effort: Theory and mortgage-market evidence. *American Economic Review*, 102(7):3249–3276.

Table 1: Summary Statistics of Unique Consumer Loans

Statistic	N	Mean	St. Dev.	Min	Max
Maturity (months)	7,655,263	27.129	19.738	1	367
Annual interest rate (%)	7,655,263	24.317	13.698	0.000	75.120
Loan size (CLP)	7,655,263	2,704,592	3,869,648	1	170,837,440
Annual income (CLP)	7,655,263	12,633,395	4,380,763	0	4,042,936,038
Ever defaulted	7,655,263	0.260	0.439	0	1
Ever delinquent	7,655,263	0.007	0.082	0	1
Age (years)	7,655,263	44.243	13.658	18	116.071
Years married	7,655,263	12.527	14.913	0.1	70.3
Deceased (indicator)	7,655,263	0.002	0.049	0	1
Civil status (categorical)	7,655,263	1.519	0.752	1	7
Gender (1 = female, 2 = male)	7,655,263	1.417	0.496	0	2
Nationality (1 = Chilean)	7,655,263	1.026	0.233	0	3

Note: This table reports summary statistics for the universe of non-collateralized consumer loans originated between 2009 and 2015. Variables include loan contract features (maturity, interest rate, loan size), borrower demographics (age, gender, civil status), and credit performance (default and delinquency indicators). Loan size and income are reported in Chilean pesos (CLP).

Table 2: Estimation of Interest Rate Sensitivity Using Logarithmic Switching Flows

	Dependent Variable: Log Switching Flow (by Region)		
	$\beta = 0.90$	$\beta = 0.95$	$\beta = 0.97$
	(1)	(2)	(3)
Interest Rate Difference (res region)	0.28747*	0.25406*	0.24531*
	(0.0132)	(0.0140)	(0.0140)
Constant	-0.34907***	-0.21464***	-0.17906***
	(1.63e-08)	(9.77e-05)	(0.00080)
Observations	16,839	16,839	16,839

Note: This table reports estimates from the reduced-form dynamic switching regression using logarithmic transformations of switching flows across banks. The model is estimated for different values of the discount factor β. The dependent variable captures relative consumer transitions between bank pairs at the regional level. The coefficient on interest rate differentials identifies consumers' sensitivity to relative price offers. Standard errors are reported in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table 3: Estimation of Switching Cost Parameter Before and After Policy Reform

	Dependent Variable: Switching Regression by Region		
	Full Window (12 mo.) (1)	Pre-Policy (2)	Post-Policy (3)
Lender Fixed Effects	0.005	0.013**	0.001
	(0.004)	(0.006)	(0.004)
Region Fixed Effects	0.002	-0.004	0.004
	(0.003)	(0.004)	(0.006)
Interest Rate Difference (res)	0.022	0.036**	0.019
	(0.016)	(0.018)	(0.030)
Constant	-0.132***	-0.184***	-0.095***
	(0.033)	(0.050)	(0.036)
Observations	9,014	4,282	4,732

Note: This table estimates switching cost parameters around the introduction of the standardized disclosure policy. The dependent variable reflects switching patterns across banks at the regional level. Column (1) includes a 12-month window around the policy, while columns (2) and (3) estimate effects in pre- and post-policy 6-month windows, respectively. A reduction in the constant post-policy reflects a drop in average switching costs. Standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table 4: Determinants of Bank Market Shares: IV Regressions Using Borrower Characteristics

	Dependent Variable: log(Market Share)	
	IV Model (1)	IV Model + Region Fixed Effects (2)
Loan Maturity	-0.018***	-0.019***
	(0.0004)	(0.0004)
Loan Amount	0.00000***	0.00000***
	(0.000)	(0.000)
Fixed Rate Indicator	0.408***	0.372***
	(0.009)	(0.009)
Borrower Age	-0.00003***	-0.00003***
	(0.00000)	(0.00000)
Married Indicator	0.054***	0.045***
	(0.007)	(0.006)
Male Indicator	0.089***	0.132***
	(0.012)	(0.011)
Foreign Nationality Indicator	-0.237***	-0.153***
	(0.025)	(0.024)
Risk Score	-0.00000	
	(0.00000)	
Interest Rate	-0.035***	-0.040***
	(0.001)	(0.001)
Constant	-44.440***	-40.532***
	(0.967)	(0.924)
Observations	194,140	194,140

Note: This table presents IV estimates of borrower and loan characteristics on the logarithm of bank market share. Column (1) reports a baseline IV model. Column (2) includes local region fixed effects. The dependent variable reflects the log of market share by bank-month-region. Risk score and interest rates are instrumented using cost-shifter variables. Standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01.

SUMMARY CONSUMER CREDIT QUOTE SHEET OR CONTRACT

SERNAC SEAL (If applicable)
CAE: XX%

Name	–
Date	–
Period of quote validity	–

I. Principal Product	
Disbursement amount (pesos)	–
Credit term (months)	–
Value of quote (pesos)	–
Total cost of credit (pesos)	–
Annual Equivalent Rate	XX%

II. Expenses or Charges for the Credit	
Expenses or Charges	
Taxes	–
Notarial charges	–
Gross credit amount	–
Associated guarantees	Si/No - ¿Tipo de garantía?

Expenses or Charges for Voluntary Services	
Value: Reference fee	–
Insurance	
Monthly cost (pesos)	–
Total cost (pesos)	–
Coverage	–
Associated service provider name	XXX
Insurance	
Monthly cost (pesos)	–
Total cost (pesos)	–
Coverage	XXX
Associated service provider name	

III. Prepayment Conditions	
Prepaid charge (%)	–
Notice period for prepayments	

IV. Late Fees	
Interest on arrears (%)	–
Collection expenses (%)	–

Advisory
"The consumer credit of this summary sheet requires the contracting consumer <name> equity or future income sufficient to pay the total cost of $xx whose monthly payment is $xx, during the entire credit period."

Figure 1: English Translation of SERNAC Regulatory Disclosure

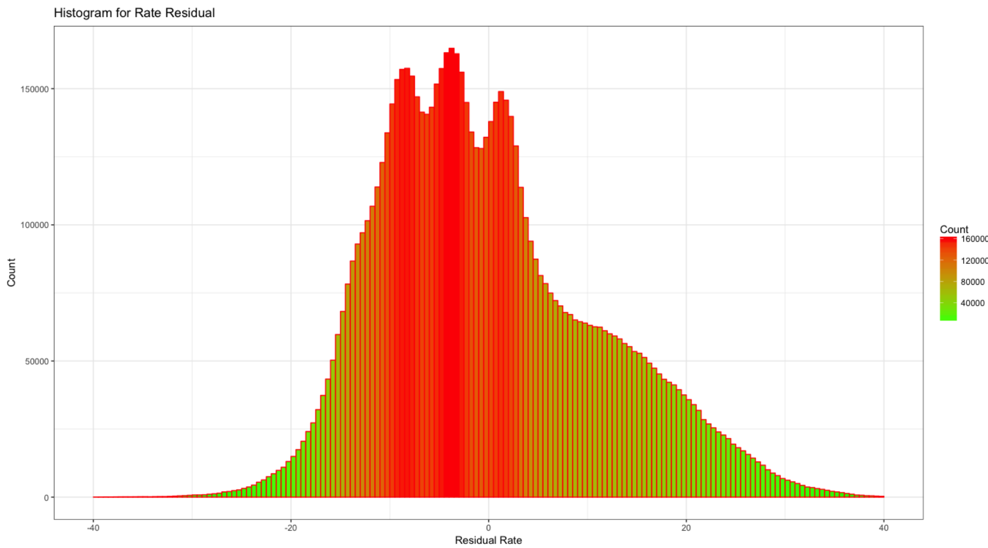

Figure 2: Price Dispersion

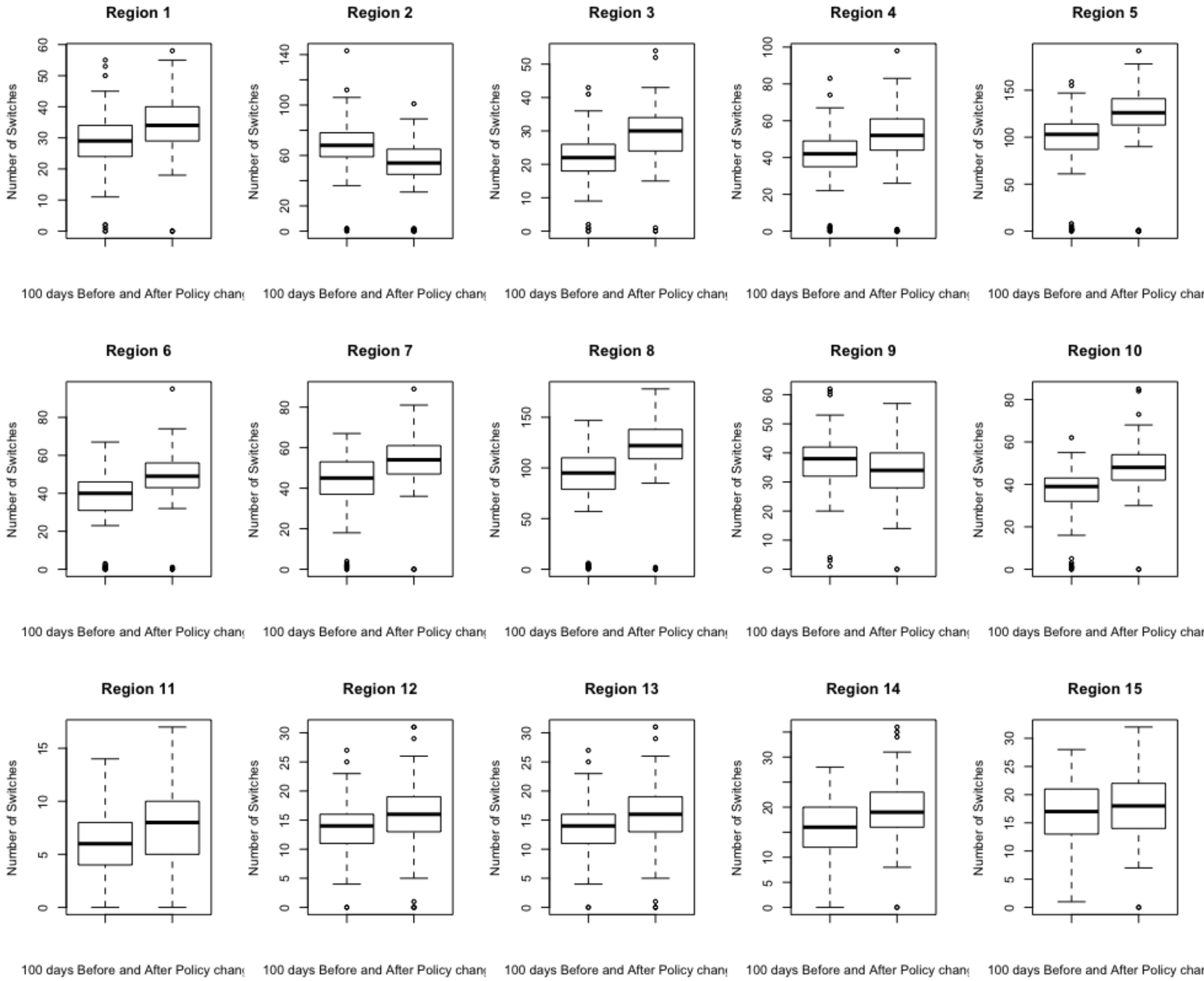

Figure 3: Total Switches by Region Before and After Policy Change

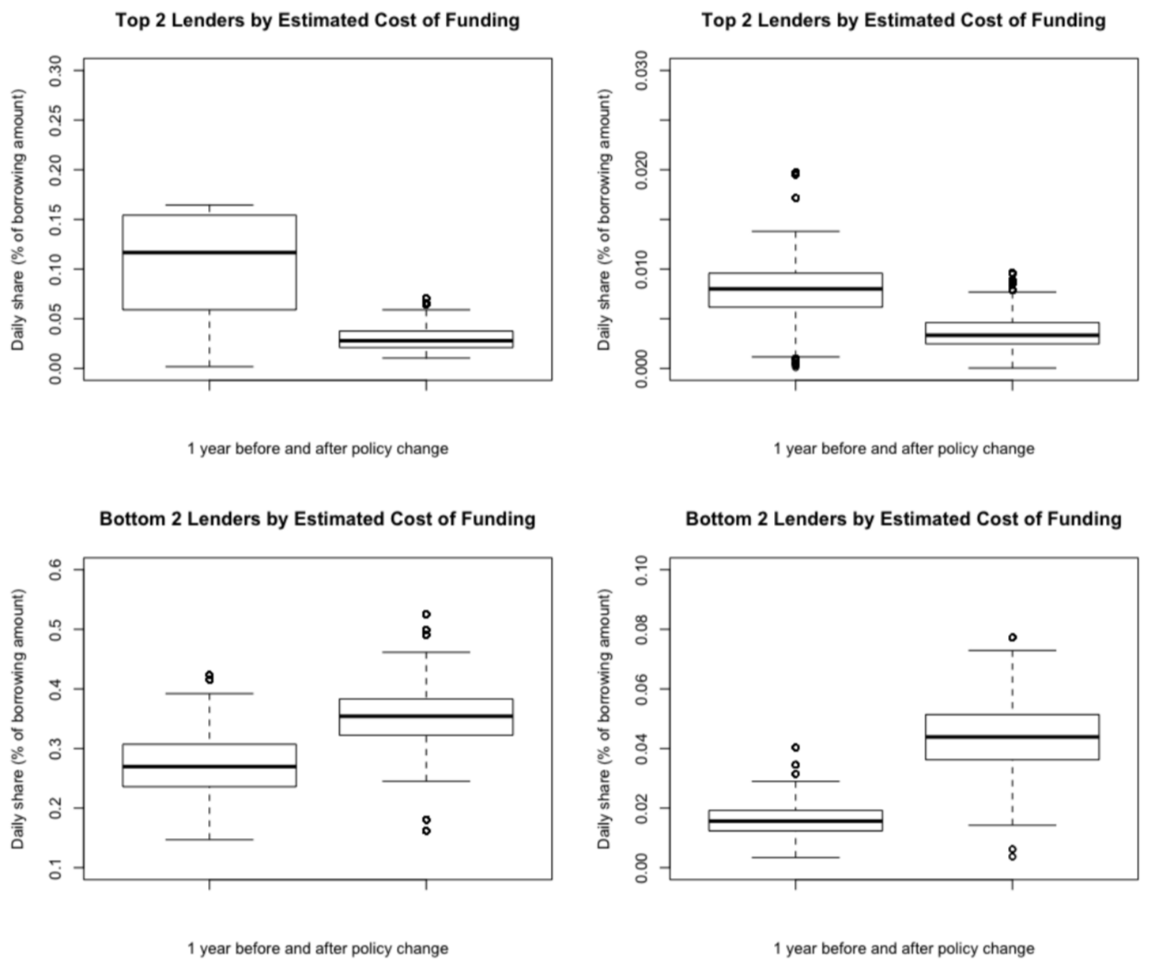

Figure 4: Daily shares for top 2 and bottom 2 lenders by cost of funding, Before and After Policy Change

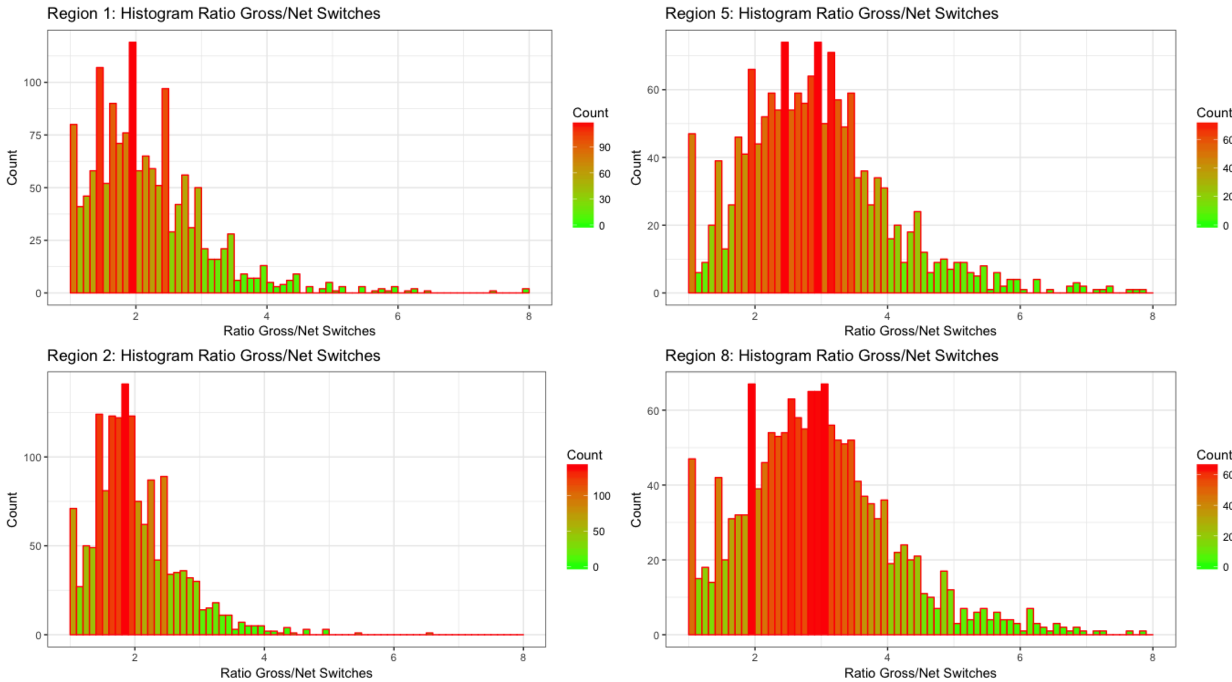

Figure 5: Gross vs Net Flows

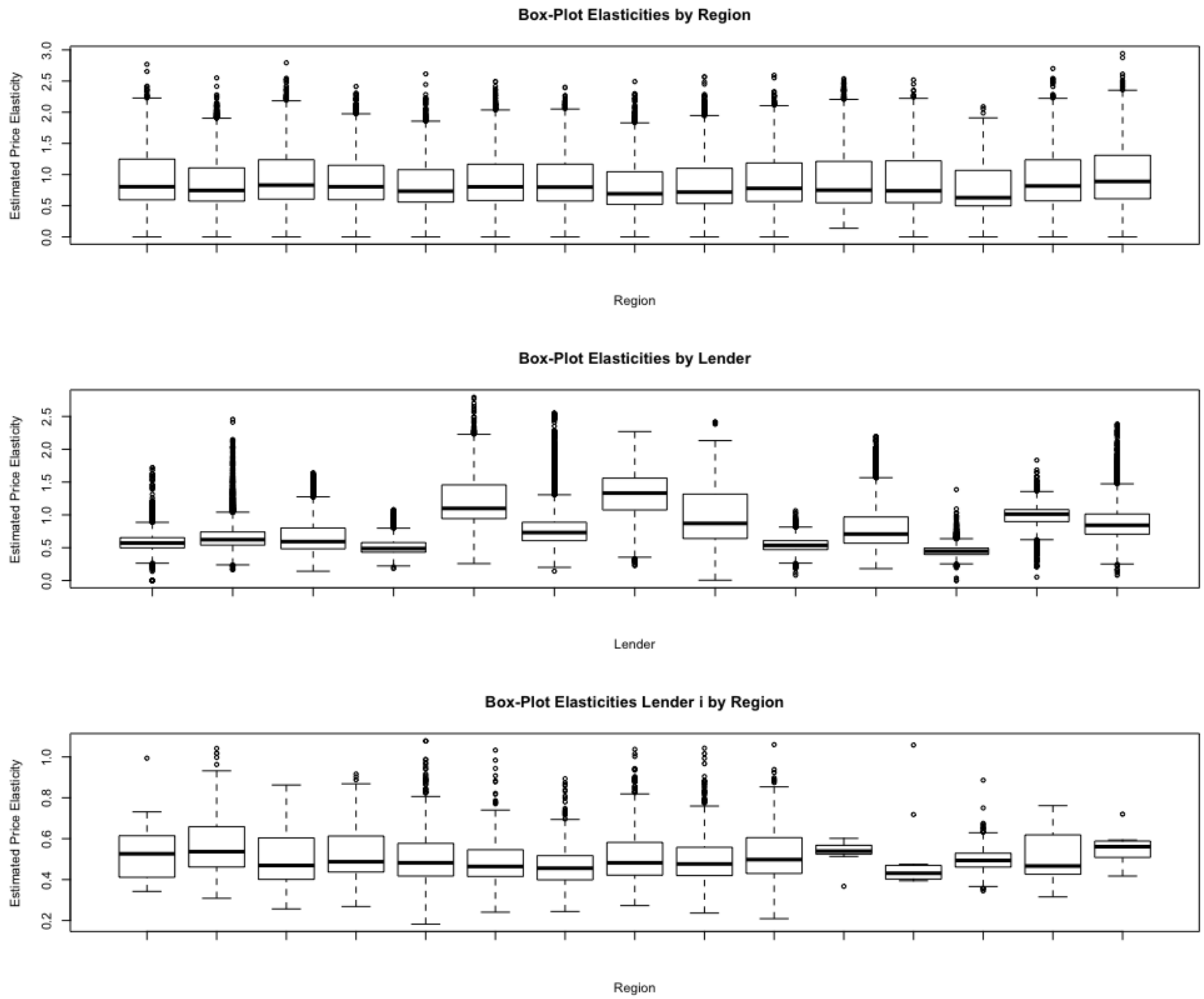

Figure 6: Predicted Elasticities by Region, Lender and LR

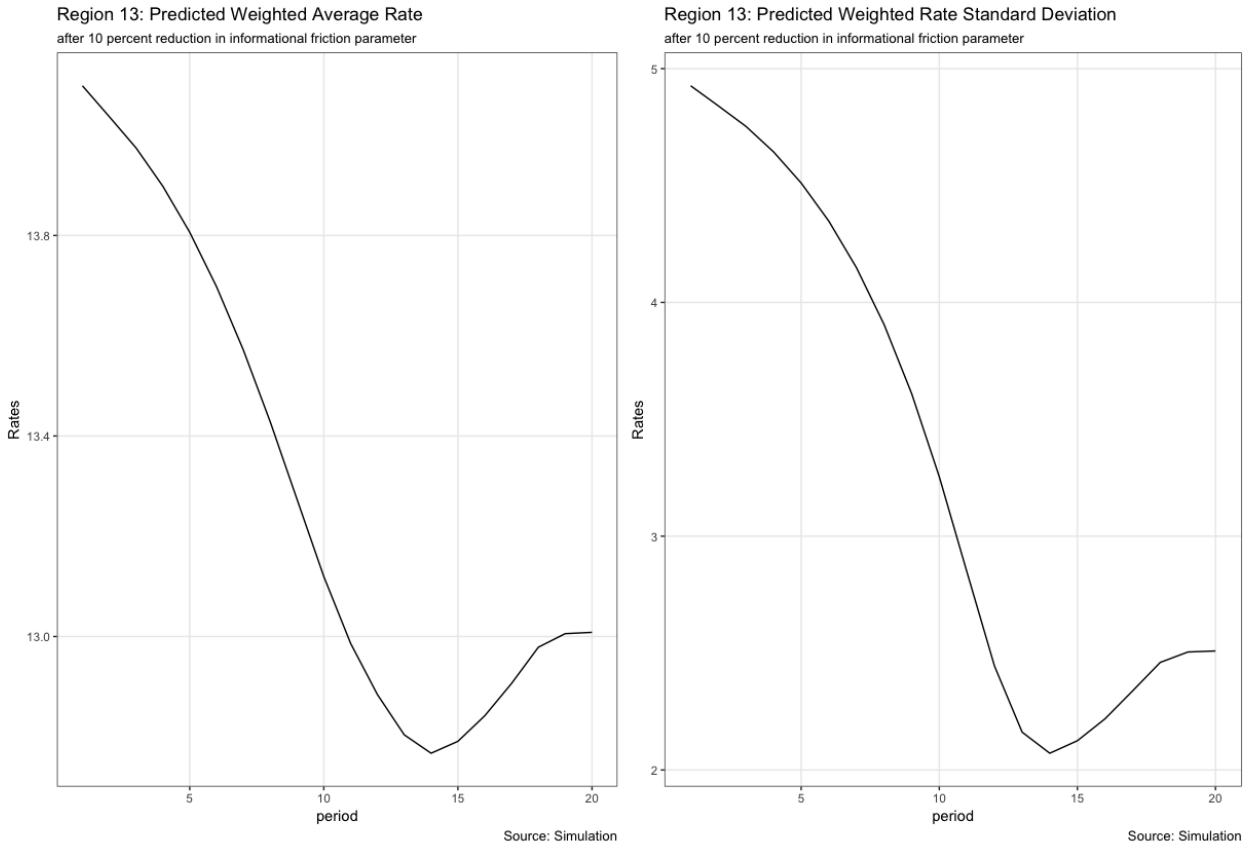

Figure 7: Simulations: Weighted Average Interest Rate and Standard Deviation

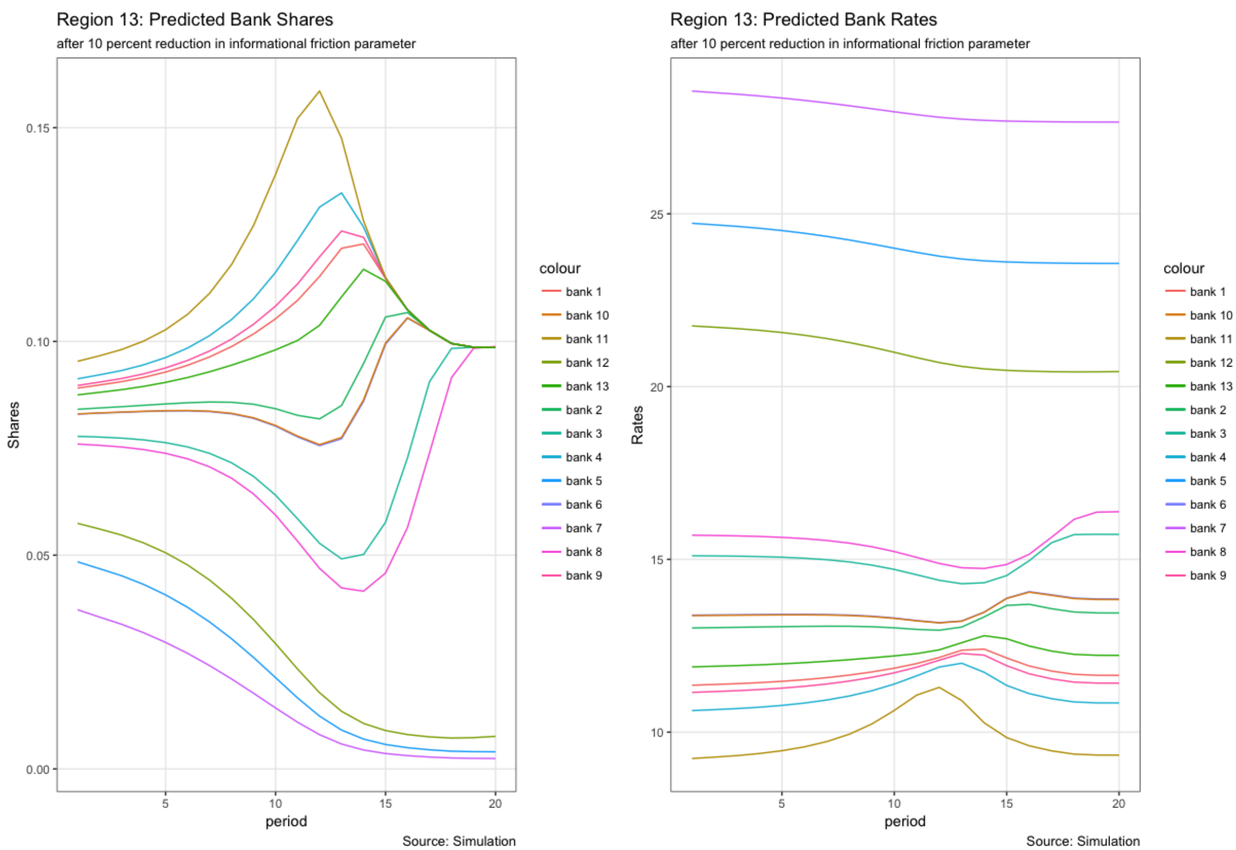

Figure 8: Simulations: Predicted Shares and Rates by Bank

	Simulated after 10 percent Drop in C		
	Weighted Average Rate (%)	Average Rate (%)	Consumer Welfare Change (%)
Region 1	-7.75	1.14	14.24
Region 2	-7.83	1.23	14.57
Region 3	-7.35	1.07	13.98
Region 4	-8.72	1.41	13.5
Region 5	-7.66	1.1	14.44
Region 6	-7.75	1.21	13.87
Region 7	-8.62	1.33	14.04
Region 8	-6.89	1.02	15.31
Region 9	-8.5	1.24	14.34
Region 10	-6.69	0.96	13.78
Region 11	-7.86	1.1	14.12
Region 12	-10.58	1.53	13.9
Region 13	-7.73	1.1	15.31
Region 14	-7.46	1.14	14.39
Region 15	-10.39	1.59	14.04
avg	-8.12	1.21	14.26

Parameters: C=16.05, nu = 3.4, rho = 0.04, beta = 0.95

Figure 9: Simulations: Summary of Results