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

Santiago Truffa †, Sheisha Kulkarni‡, Gonzalo Iberti §

June 2018

Abstract

We exploit a unique natural experiment to structurally estimate the information frictions associated with switching costs. Specifically, we study a Chilean policy that simplified and standardized the presentation of loan characteristics in contracts and quotes. Using administrative data from the banking regulator, we exploit how this policy change affected the price-sensitivity in consumer decisions to identify the reduction in information frictions. We then incorporate this estimate into a dynamic structural model to explore the link between reduced informational frictions and welfare in long-term market equilibrium. We find that, after the policy, information frictions fell around 10 percent, which translated into an interest reduction of 180 basis points. We estimate a welfare improvement for consumers of 15 percent in the long run.

*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

†Tulane University. E-mail: struffa@tulane.edu

‡UC Berkeley. E-mail:kulkarni@berkeley.edu

§SBIF. E-mail: giberti@sbif.cl

I Introduction

When a consumer considers whether to switch banks, they must often compare informationally opaque products. Loan characteristics of competing credit products may be difficult to distinguish since fundamental attributes are often hidden and displayed in a non-standard manner. For consumers to make optimal choices between alternatives, they need to overcome these informational frictions. Policies oriented to simplify and standardize loan contracts could deliver efficiency gains through better consumer choices. Although previous literature has identified switching costs in the banking sector, empirical and theoretical barriers make it difficult to disentangle the informational component of switching costs. We develop a framework that combines the advantages of reduced form estimation and structural modeling: we use a natural experiment to separately identify an information friction parameter, which we then incorporate into a dynamic structural model to asses changes in welfare and long-term market equilibrium.

We exploit a policy change in Chile that explicitly attempted to reduce the information friction component of switching costs for consumers. In 2012, legislation was passed to require loan quote and contract documents to be simplified and standardized across banks. This intervention explicitly reduced information frictions since the consumer no longer had to a) analyze fine print to find relevant fees that may be included in the cost of credit or b) standardize disclosure across lenders in order to compare the terms offered by different banks.

Two unique features of our data allow us to identify how this policy alters information frictions. First, we have administrative loan-level data from the Chilean banking regulator, which reports the matches between consumers and banks, instead of aggregate bank-level market shares [**KKM2003**]. Second, our data encompasses all the banks in the financial system, rather than a proper subset of the financial system (e.g. [**bertrand2011information**] and [**Bertrand˙etal:2010**]). Due to these features, we can observe the sensitivity of switching behaviour to relative prices before and after the policy change, which we exploit to measure information frictions.

Detailed micro-level data is not sufficient to empirically identify informational frictions; we also rely on a policy change that exogenously varies informational frictions without changing other components of switching costs. We exploit this change using reduced-form regressions to recover the fundamental informational parameter of our structural model. We then use this model to evaluate the consequences of informational frictions for welfare. We find that the introduction of standardized loan disclosure reduced informational frictions by 10%. According to our dynamic structural model, this leads to a reduction in average interest rates of 180 basis points as a result of consumers switching to banks that provide lower interest rates. Additionally, we observe a reduction in the standard deviation of rates, which suggests that search costs decreased for consumers. Overall, we estimate that consumers enjoyed an increase in welfare of 15% in the long-run.

To explore how consumer switching behavior affects the long-term equilibrium of the market, we developed a dynamic structural model that takes into consideration the strategic response of banks and the transitional dynamics these reactions generate. We do this by embedding a [**Berry94**] model of bank behavior within an [**Artuc2010**] model of consumer switching behavior. In the model, consumers have rational expectations and borrow one unit of money each period. Consumers search across banks for the best price, but not all consumers get the lowest price due to search frictions. Banks, on the other hand, are profit maximisers. Banks charge an interest rate each period that has a mark-up – a function of their endogenous market power – in addition to cost of funding.

We estimate each part of the model separately. We use gross switches between consumers and banks to identify the consumer information friction parameter. We then use market share data – that is, net switches – to identify our market power parameter as in [**Berry94**]. Thus, we use different sources of variation to independently identify each parameter.

This approach offers us two advantages. First, our fundamental parameters are identified: in particular, we estimate information frictions with a reduced form regression using exogenous variation provided by the policy change. Second, our model is computationally tractable: since we estimate our information friction and price sensitivity parameters separately, we can input these parameter estimates into a dynamic structural model without the computational burden of endogenously determining them from within the model.

In our simulations, we find that banks with a lower cost of funding see their market shares decrease, as consumers switch to banks that offer lower interest rates. Banks strategically react to consumer switching in two ways. First, banks that are losing market power reduce their interest rates to be more competitive, whereas banks that are gaining market power, increase interest rates. In the long run, a ten percent drop in switching frictions implies a long-term reduction of around 180 basis points in the average interest rate. This rate reduction means an average consumer welfare improvement of the order of 15 percent.

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.

II 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˙Morgan**], and [**Luco:2013**]). Price dispersion increases with search costs [**hong2006using**]: 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 [**Hortacsu**], money market funds [**Christoffersen**], mutual funds [**Bergstresser**], retail municipal bonds [**Green**], car loans [**Palmer**], and mortgages ([**Woodward**],[**Baye˙Morgan2001**], [**Baye˙Morgan2006**]).

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 [**Farrell2007**] for a thorough review). There is also an added benefit to sellers if high search costs exist in a product market. [**Gabaix2006**] and [**Ellison˙Wolitzky**] show that firms may wish to strategically generate search costs, leading to a reduction in consumer welfare [**Grubb2015**]. Furthermore, these search costs may not be overcome by educational initiatives, which may further confuse consumers [**carlin2010obfuscation**]. 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˙etal:2018**]. However, it is not clear if these search costs are necessarily harmful to consumers in equilibrium. Indeed [**Chioveanu**] predict that policies that aim to make prices more comparable may end up hurting consumers in equilibrium.

We contribute to the empirical literature by explicitly estimating the informational friction component of search costs. Contrary to the findings of [**Chioveanu**], we find that policies that make prices more comparable actually improve consumer welfare on the magnitude of 15 percent. 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**] study borrowers from a Belgian bank and [**Shy2002**] use 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 [**KKM2003**].

Our paper offers a methodological contribution of creating a closed model of the financial system with consumers. By combining the [**Artuc2010**] and [**Berry94**] 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 [**fu2017estimation**] and [**galiani2015estimating**] 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˙credit˙cards**] 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**], [**bertrand2011information**] and [**Bertrand˙etal: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.

III 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

> [f]inancial service providers have not always prioritized their duty to adequately inform consumers so that they can freely decide with whom they should con-

> tract. 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

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

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.

IV Data

We use administrative data reported to the Superintendica Banquero y Instituciones Financieros (SBIF), which is the Chilean banking regulator. All banks must periodically (in our case, bi-weekly) disclose to SBIF detailed information about new credit operations and the current state of their credit portfolio for regulatory purposes. This administrative dataset allows us to observe the entire banking system, for which we have detailed information for each loan at its origination date and its performance in time along with information about borrower characteristics.

Our analysis focus on consumer loans because they are simple and easy to compare vis-à-vis other financial products. These loans are non-collateralized loans, and many financial institutions offer them. Consumers may use these loans for durable purchases, vacations, and many other options. These consumer loans co-exist with a robust credit card industry, though not a market for borrowing against housing collateral. As these loans are common, simple, relatively homogenous, easy to compare, and easy to move between banks they should be the most sensitive to changes in the informational environment.

Our sample runs from 2009 until 2015 and covers 95 percent of non-collateralized loans under 1,500 UF ($60,000 USD). [2] Since this data is reported to banks by consumers in order

[2]The other 5 percent of loans were lost as they were not able to be merged across the various data files that housed borrower information. The data comes from 4 different files. First, we have data from file D32, which reports all loans that were originated on a given day. From D32 we get the day of the operation, the lender, the currency, loan size, maturity, type of rate and interest rate. D32 also identifies the borrower and a code identifying each loan. Secondly, we have data from file C12, which is a file where banks report monthly the state of their credit portfolio at the loan level. From C12 we can know whether a loan is late on a payment or has been delinquent. We also can observe how much the bank is provisioning for performing and non-performing operations giving us a measurement loan risk. Thirdly we get data from file D03, which contains borrower characteristics. File D03 has data on *comuna* where the borrower resides and self-reported annual income. As loan codes are not always consistent across files, we generate a conditional merge on loan and borrower characteristics. For loans with partial similarities in loan code, we check for the following

to obtain a loan, each institution can ask for supporting documents, such as taxes or proof of income in order to verify the information that is ultimately reported to the SBIF. Finally, we merge our loan files by RUT (the Chilean equivalent to a social security number) to data from the National Civil Registry that allow us to include borrower demographics such as age, gender, nationality and civil status to use as controls in our analysis.

Table 1 reports summary statistics for the 7.6 million loans in our six year sample. The average interest rate for the sample is 24 percent, which is consistent with rates for similar products in Latin America. The average loan size is approximately $4,000 USD, or 1/6th of the average annual income. The average maturity for these loans is 27 months, which suggests that the majority of the loans are relatively small and for short durations. Roughly one quarter of these loans miss at least one payment, while less than one percent of the loans will have payments missed for over three months.

We augment our data with variables from the Central Bank of Chile, to construct instruments for the interest rate that we will use in our estimation as costs shifters. We use the time series for the interbank rate in UF and pesos, which allows us to control for the daily level of interest rates and calculate expected inflation. We use annual bank balance sheet data to compute the ratio of interest paid over financial liabilities, to equity to to measure banks' relative cost of funding.

Figure 2 shows the histogram of the residual of interest rates on loan and consumer characteristics. Consistent with prior literature on search and switching costs in financial products, we find substantial price dispersion even when controlling for a variety of observable characteristics. To examine whether switching costs are reduced in the raw data, we plot a box plot with the total gross flows by region 100 days before and after the policy change in figure 3. We observe that more consumers decided to switch banks before the policy change. However, from figure 4 we observe that banks that have lower costs of financing

features to coincide: borrower ID, date of origination, interest rate, maturity and loan size. We incorporate to our sample all loans that had coinciding loan codes, or we were able to match on their characteristics across files.

gained market power after the policy change, suggesting that consumers were more likely to switch to banks that had a lower cost of funding.

V Model

To explore how this disclosure affected the long-term equilibrium of the market, we developed a dynamic structural model that takes into consideration the strategic response of banks and the transitional dynamics these reactions generate. In the model, consumers behave accordingly to a dynamic rational expectations model. Each period consumers require one unit of money to borrow. They search across different banks for the best price, however there are frictions to this search which explain why not all consumers get the lowest price available in the market. Banks are profit maximisers. Each period they charge an interest rate which is a markup over their cost of funding.

A Consumers

To model consumer behaviour we borrow a trade model from [**Artuc2010**]. Consumers have a inelastic demand for one unit of loan, every period. Each consumer starts a period t in some bank i where he pays an interest rate r_t^i for his loan. Borrowers search for credit opportunities. They receive a vector of *iid* utility shocks $\varepsilon^t = \{\varepsilon_j^t\}$, from each bank $j \epsilon \{1..J\}$. After observing these shocks, each consumer decides to either get a new loan at another bank, or stay on their current bank. For several reasons, borrowers will not always choose the best alternative. To allow for this possibility, we posit the existence of a wedge C^{ij} , which we call an information friction, that can be the interpreted as the costs of comparing offers from bank j given that the customer is currently a client in bank i. We assume $C^{ii} = 0$, i.e. there are no information frictions to getting a loan from a bank you are already a borrower at.

If a consumer decides to switch, then she starts next period $t + 1$ in bank j. There is going to be a common discount rate $\beta > 0$, and a rate sensitivity/preference parameter ρ (from before). Let B_t be the allocation of borrowers in period t.

The utility of a borrower who in period t is a client in bank i is given by:

$$U^i(\varepsilon_t) = -\rho r_t^i + max_{j\epsilon 1..J}\{\varepsilon_t^j - C^{ij} + \beta V(B_{t+1})]\}.$$

Where:

$$V^j(B_{t+1}) = E_\varepsilon[U^i(B_{t+1}, \varepsilon_t)],$$

is the average utility across idiosyncratic shocks. Taking expectation over idiosyncratic shocks:

$$V_i^i = -\rho r_t^i + E_\varepsilon \left[max_{j\epsilon 1..J}\{\varepsilon_t^j - C^{ij} + \beta[V^j(B_{t+1})]\right]$$

$$= -\rho r_t^i + \beta V_{t+1}^i + E_\varepsilon \left[max_{j\epsilon 1..J}\{\varepsilon_t^j - C^{ij} + \beta\{[V^j(B_{t+1}) - V_{t+1}^i)\}\}\right] \equiv -\rho r_t^i + \beta V_{t+1}^i + \Gamma_t^i$$

On average, the utility of currently being in bank i can be decomposed into the utility of being forever in bank i, given by $-\rho r_t^i + \beta V_{t+1}^i$, plus the option value of moving.[3]

We assume opportunity shocks to be *iid* across time and borrowers, and distributed extreme value type 1 with mean zero and variance parameter ν, then

$$f(\varepsilon) = \frac{e^{-\varepsilon/\nu-\gamma}}{\nu} exp\{-e^{-\varepsilon/\nu-\gamma}\}$$

and

$$F(\varepsilon) = exp\{-e^{-\varepsilon/\nu-\gamma}\}$$

[3]This characterization is consistent with our utility for banks in the long run. In the steady state of this model, the preference for a bank depends on a bank fixed effect (a composite of the preference for that bank's characteristics) plus an error term.

Under this parametric assumption, the fraction of moving borrowers from bank i to bank j is going to be given by:

$$m_t^{ij} = \frac{exp\{(-C^{ij} + \beta V_{t+1}^j)/\nu\}}{\sum_k exp\{(-C^{ik} + \beta V_{t+1}^k)/\nu\}}$$

normalizing by the fraction of borrowers who stayed in the same bank:

$$\frac{m_t^{ij}}{m_t^{ii}} = \frac{exp\{(-C^{ij} + \beta V_{t+1}^j)/\nu\}}{exp\{(\beta V_{t+1}^i)/\nu\}} = exp\{(-C^{ij} + \beta(V_{t+1}^j - V_{t+1}^i))/\nu\}$$

and thus:

$$\nu(log(m_t^{ij}) - log(m_t^{ii}) = -C^{ij} + \beta(V_{t+1}^j - V_{t+1}^i))$$

Now we can compute the option value of changing banks, under the same assumption of iid shocks:

$$\Gamma_t^i = E_\varepsilon \left[max_{j\epsilon 1..N}\{\varepsilon_t^j - C^{ij} + \beta[V^j(B_{t+1})]\right]$$

$$exp(\Gamma_t^i/\nu) = \sum_k exp\{(-C^{ik} + \beta(V_{t+1}^k - V_{t+1}^i))/\nu\}$$

using again the stayers for normalization

$$m_t^{ii} = \frac{exp\{(\beta V_{t+1}^i)/\nu\}}{\sum_k exp\{(-C^{ik} + \beta V_{t+1}^k)/\nu\}} \Rightarrow m_t^{ii} = \frac{1}{exp(\Gamma_t^i/\nu)}$$

So the the option value of staying in a bank is given by

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

Therefore we can now express everything in terms of observables. Taking differences across banks we get:

$$V_t^j - V_t^i - \rho r_t^j + \rho r_t^i + \beta(V_{t+1}^j - V_{t+1}^i) + \Gamma_t^j - \Gamma_t^i = 0$$

Which can be fully express in observables

$$\frac{\nu}{\beta}(log(m_t^{ij}) - log(m_t^{ii})) + \frac{C^{ij}}{\beta} - E_t\rho\{r_{t+1}^j - r_{t+1}^i\} - \nu(log(m_{t+1}^{ij}) - log(m_{t+1}^{ii})) - C^{ij} = 0$$

And this yields the following estimating equation:

$$log(m_t^{ij}) - log(m_t^{ii}) - \beta(log(m_{t+1}^{ij}) - log(m_{t+1}^{ii})) = \frac{-(1-\beta)}{\nu}C^{ij} + (\beta/\nu)(\rho r_{t+1}^j - \rho r_{t+1}^i) + \upsilon_{t+1}$$

We now have a single regression explaining consumer switches as a function of information frictions and relative differences in rates across banks.

B Banks

In each regional market, there are J banks. Banks are profit maximizers facing a downward-sloping demand curve. Each bank has a marginal cost of funding, which captures differences in financial expenditures and bank efficiency across banks. Banks charge an equilibrium interest rate which is a markup over their marginal cost. This rate can differ by region depending on the bank's market power. That market power will be a function of consumers sensitivity to prices (to be estimated) and the market share each banks enjoys in a given market, which is endogenously determined by consumers' switching behaviour. From the profit maximizing behaviour of banks for each period, we derive the following mark-up rule:

$$\Pi = r_j(Q)Q - C_j(Q)$$

Where $P(Q)$ is an inverse demand function banks observe and $C_j(Q)$ is the bank's cost of funding.

Since banks are profit maximizers, we get a first order condition:

$$\frac{\partial \Pi}{\partial Q} = 0 \Rightarrow \frac{\partial r_j}{\partial Q} Q + r_j = MC_j(Q)$$

Note that the price elasticity is given by $\epsilon = -\frac{\partial Q}{\partial r_j}\frac{r_j}{Q}$. Thus re-arranging terms we get:

$$r_j = MC_j/(1 - (1/\varepsilon_j))$$

where, r_j^I is the average interest rate that bank j charges and ε_j is the elasticity of demand of bank j. MC_j is the marginal cost of funding for bank j. These vary by region.

An important feature of this specification is that we have a close form solution to our elasticity which is an explicit function of the shares of consumers that a bank has in a given market. This will facilitate how we compute the dynamic equilibrium and thus simulate our model. Given our specification it can be shown that demand elasticity is given by:

$$\hat{\varepsilon}_j^I = -\hat{\rho} r_j(1 - s_j)$$

We can recover the marginal cost of funding for each bank from our markup formula:

$$MC_j^I = r_j^I(1 - 1/\epsilon_j^I)$$

Where, r_j^I is an average interest rate for lender that we observe in our data, and ϵ_j^I is the elasticity we recovered using market shares. We will approximate the marginal cost for each lender, by the average of observed marginal costs.

Finally, using our approximation of banks' funding costs, we predict how banks would strategically change their prices when consumer switching affects their (endogenous) market power in different markets.

$$r^I_j = \frac{1 + \hat{\rho}(1 - s^I_j)\bar{MC}_j}{\hat{\rho}(1 - s^I_j)} = \bar{MC}_j + \frac{1}{\hat{\rho}(1 - s^I_j)}$$

VI Estimation

We divide our estimation procedure into two parts. First, to recover the sensitivity of consumers to relative prices and how this sensitivity changes as the informational environment becomes more transparent, we use gross switching flows of clients between institutions. While net flows have traditionally been used to derive changes in market power, they are not ideal to identify changes in consumer behaviour. We use gross switching flows between banks to capture changes in consumer switching behaviour over time. Indeed, figure 5 shows a histogram for the ratio of gross to net flows for different regions in Chile. Gross flows are on average three times higher than net flows. Secondly, we estimate the market power of banks using data on net switching flows between banks. The net position of banks pins down their pricing behaviour.

A Estimating Equations: Consumers

Recall from the moidel section that we derived the following estimating equation:

$$log(m^{ij}_t) - log(m^{ii}_t) - \beta(log(m^{ij}_{t+1}) - log(m^{ii}_{t+1})) = \frac{-(1-\beta)}{\nu}C^{ij} + (\beta/\nu)(\rho r^j_{t+1} - \rho r^i_{t+1}) + \upsilon_{t+1}$$

For the above specification, we must aggregate our data at the region/bank/month level, so we can compute aggregate switches between institutions. In this expression, m^{ij}_t measures the flow (as a fraction) of consumers switching from bank j to bank i, m^{ii}_t is the fraction of consumers that decided to stay in bank i and r^j_{t+1} is the average interest rate charge by bank

j in a given region. On the left hand of the equations, we are computing how flows change in time, and in the right hand of the expression we have a relative prices. We must notice that we assume β fixed. We run the same specification for different values of this parameter.

Notice also how this specification suffers from endogeneity as flows in t+1 might be co-determined with rates in t+1. In order to estimate our preference parameters, we use instruments that affect equilibrium interest rates and yet should be orthogonal to consumers preferences between institutions. We use daily interbank interest rate, which measures macroeconomic effects that influence the cost of lending for all banks. As inflation is also an exogenous shifter of rates, we use current and expected inflation, which we infer using the peso and UF(inflation indexed)[4] interbank rates. Finally, we use the monthly ration between financial interest expenses and equity that we use as an instrument for cost of funding by institution. From our first stage regression, we recover $\hat{\rho}$.

Table 2 reports the first- and second-stage results for the above model. (The estimates imply the following parameter values. For beta = 0.9 , a volatility of 3.13 and informational friction parameter of 10.93. For beta = 0.95 , a volatility of 3.7 and informational friction parameter of 16.05. For beta = 0.97 , a volatility of 3.95 and informational friction parameter of 23.6.)

We can map the point estimates for the linear regression to an implicit C (switching cost) and ν (volatility). These estimates imply the following parameter values: for $\beta = 0.9$, a volatility of 3.13 and a switching cost parameter of 10.93, for $\beta = 0.95$, a volatility of 3.7 and switching cost parameter of 16.05, and for $\beta = 0.97$, a volatility of 3.95 and switching cost parameter of 23.6. This numerical estimate of switching costs includes a variety of factors such as direct costs of switching, inertia, and informational frictions. To isolate the influence of increased disclosure, we estimate C both before and after the policy came into effect.

[4]Loans in Chile are given in an inflation-indexed currency called UF whose exchange rate changes on a biweekly basis and is set by the Chilean government.

B Information Frictions Parameter

Now we would like to decompose what fraction of a switching cost are driven by information frictions. We will follow the same procedure as before, but we will evaluate how the switching cost C changes before and after the policy shock. Our identifying assumption here is that for a narrow time window around the policy change, any change in this parameter can be solely attributed to the change in transparency in the market induced by the government policy. For this reason, we consider switches within a seven month window before and after the policy change to estimate C. To calculate C from the regression tables, we use a β of 0.95. Table 3 reports the results for this regression.

Our point estimates suggest that there was a drop in switching costs of around 10 percent. Using the confidence interval for our point estimate on the constant, we see a drop between 8 and 15 percent in C. In our simulation we will use a drop in 10 percent as our main specification. However, as this is measures an average treatment effect, our computations mask the significant heterogeneity across different types of consumers. For example, consumers with more education were more responsive to this disclosure and received lower rates than consumers with less education. Further exploring different sources of heterogeneity across consumers and its distributive effects is part of our future research agenda.

C Banks

The model we have for banks has two special features. First, as we showed, there is a simple closed-form solution for elasticities and interest rates, which are a function of the endogenous share each bank has on a given market. Furthermore, given the specification of the model, the parameter we need to estimate to calculate market power, can be estimated from a simple logarithmic regression.

We use a random utility model such as in [**Berry94**]. In every region consumers need to choose between J banks. The long-term utility that a consumer i gets from banking in j is given by:

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

where X_j is a vector of bank observable characteristics, ϵ_j captures a bank level un-observable characteristics, and ε_{ij} is consumer level idiosyncratic error term which follows an extreme value distribution.

Let $\delta_j = \beta X_j - \rho r_j + \epsilon_j$ be the mean utility for bank j. Then $\delta = (\delta_1, .., \delta_J)$ is a vector of taste for banks which captures the fidelity to a given bank.

Let s_j be the aggregate market share for bank j, then $s_j = exp(\delta_j)/\sum_{j'=1}^{J} exp(\delta_{j'})$. Given shares, we can recover average taste for a bank, $\hat{\delta}_j = log(\hat{s}_j) - log(\hat{s}_0)$, from observed market shares. This yields the following estimating regression:

$$\hat{\delta}_j = log(\hat{s}_j) - log(\hat{s}_0) = \beta X_j - \rho r_j + \epsilon_j$$

We aggregate data to the bank/region level for each month. Once again, we might have an endogeneity problem as shares and interest rates can be co-determined. In order to estimate our preference parameters, we instrument our interest rate using cost shifters. In particular we use current and expected inflation, which we infer using the peso and UF(inflation indexed) interbank rates and the monthly ratio between financial interest expenses and equity that we use as an instrument for cost of funding by institution.

Our first and second stage estimation of our bank parameters is shown in table 4.

We estimate a sensitivity to interest rates of 0.04. This parameter value translates into a mean price elasticity of 0.77, that is banks on average face an inelastic demand.

The specification of the model allows us to have a different market power for each lender and for each market. Figure 6 shows predicted elasticities for different lenders in different markets. We observe that the same lender has higher elasticities in more competitive regions, and that within the same region, lenders have a wide spread of elasticities.

The advantage of modeling banks this way, is that we can not only easily recover elasticities using market share data, but also are able to feasibly compute a dynamic general equilibrium model because the closed-form solution depends on the fact the fundamental endogenous variables of the model, market shares.

D Steady State Results

In this section we incorporate our estimated parameters into our economy-wide model to compute consumer welfare and examine competitive responses by banks. The main purpose of this section is to evaluate what would be the equilibrium consequences in the long run from a 10 percent fall in information frictions. To do so we first must compute the steady state of the economy with the original parameters. Then we will shock this steady state, by decreasing the switching cost parameter in 10 percent. This will allows to isolate the effect of this treatment in the long run, and estimate its effects on equilibrium interest rates, market shares of banks and consumer welfare.

Recall we had with the following utility function for a consumer:

$$U^i(L_t,\varepsilon_t) = \rho r_t^i + max_{j\epsilon 1..J} E_\varepsilon\{\varepsilon_t^j - C^{ij} + \beta V^j(B_{t+1})\} = \rho r_t^i + \beta V^i(B_{t+1}) + max_{j\epsilon 1..J} E_\varepsilon\{\varepsilon_t^j + \bar{\varepsilon}_t^{ij}\}$$

where $\bar{\varepsilon}_t^{ij} \equiv \beta[V^j(B_{t+1}) - V^i(B_{t+1})] - C^{ij}$

Let $\bar{\varepsilon_t}^i = (\bar{\varepsilon}_t^{i1}, .., \bar{\varepsilon}_t^{iJ})$, and taking the expectation with respect to ε we get:

$$V^i(B_t) = \rho r_t^i + \beta[V^i(B_{t+1})] + \Phi(\bar{\varepsilon_t}^i)$$

where

$$\Phi(\bar{\varepsilon_t}^i) = \sum_{j=1}^{J} \int_{-\infty}^{\infty} (\varepsilon^j + \bar{\varepsilon_t}^{ij}) f(\varepsilon^j) \prod_{k\neq j} F(\varepsilon^j + \bar{\varepsilon}_t^{ij} - \bar{\varepsilon}_t^{ik}) d\varepsilon^j = E_\varepsilon[max_{j\epsilon 1..J}\{\varepsilon_t^j + \bar{\varepsilon}_t^{ij}\}]$$

To compute the steady state of this economy, let $V^i(B_t, s_t)$ represent the expected discounted utility of a consumer in bank i at time t

Worker optimization implies the following Bellman Equation:

$$U^i(L_t, \varepsilon_t) = \rho r_t^i + max_{j\epsilon 1..J} E_\varepsilon\{\varepsilon_t^j - C^{ij} + \beta V^j(B_{t+1})\} = \rho r_t^i + \beta V^i(B_{t+1}) + max_{j\epsilon 1..J} E_\varepsilon\{\varepsilon_t^j + \bar{\varepsilon}_t^{ij}\}$$

where $\bar{\varepsilon}_t^{ij} \equiv \beta[V^j(B_{t+1}) - V^i(B_{t+1})] - C^{ij}$

At any date t there is a threshold value $\bar{\varepsilon_t}^{ij}$ such that a consumer will stay in bank i if $\varepsilon_t^i > \bar{\varepsilon_t}^{ij}$ or would switch to bank j otherwise.

Let $\bar{\varepsilon_t}^i = (\bar{\varepsilon}_t^{i1}, .., \bar{\varepsilon}_t^{iJ})$, and taking the expectation with respect to ε we get:

$$V^i(B_t) = \rho r_t^i + \beta[V^i(B_{t+1})] + \Phi(\bar{\varepsilon_t}^i)$$

where

$$\Phi(\bar{\varepsilon_t}^i) = \sum_{j=1}^{J} \int_{-\infty}^{\infty} (\varepsilon^j + \bar{\varepsilon_t}^{ij}) f(\varepsilon^j) \prod_{k \neq j} F(\varepsilon^j + \bar{\varepsilon_t}^{ij} - \bar{}_t^{ik}) d\varepsilon^j = E_\varepsilon[max_{j\epsilon 1..J}\{\varepsilon_t^j + \bar{\varepsilon}_t^{ij}\}]$$

$\Phi(\bar{\varepsilon_t}^i)$ is the option value of a borrower in bank i. What make this computation feasible, is that given the properties of the extreme value distribution is can be shown that[5]:

$$\Phi(\bar{\varepsilon_t}^i) = \nu log[\sum_{k=1}^{J} exp(\bar{\varepsilon_t}^{ik}/\nu)]$$

Having a close form expression for this expectation allows us to numerically compute the equilibrium of this economy.

The properties of the extreme value distribution, also imply a very simple expression for the law of motion of consumers between banks, which is given by:

[5]For a derivation see Artuç et al., 2015.

$$B_{t+1}^i = \sum_{j=1}^{J} m_t^{ij} B_t^j$$

where

$$m_t^{ij} = \frac{exp(\bar{\varepsilon}_t^{ij}/\nu)}{\sum_{k=1}^{J} exp(\bar{\varepsilon}_t^{ik}/\nu)}$$

and m_t^{ij} is the fraction of workers in bank i that decide to move to j in period t.

The general strategy for computing the steady state is to recover the steady state values of $B^* = (B^{1*}, .., B^{J*})$ from the steady state values of $\bar{\varepsilon}^* = (\bar{\varepsilon}^{1*}, ..., \bar{\varepsilon}^{J*})$, which will then determine the steady state of interest rates $r^* = (r^{1*}, ..., r^{J*})$

More formally, from $V^i(B_t) = \rho r_t^i + \beta[V^i(B_{t+1})] + \Phi(\bar{\varepsilon}_t{}^i)$ write steady state values of V^* as a function of the steady state values of $\bar{\varepsilon}^*$

Secondly, substitute V^* in $\bar{\varepsilon}_t^{ij} \equiv \beta[V^j(B_{t+1}) - V^i(B_{t+1})] - C^{ij}$

Finally, to close the system we need the endogenous interest rate. Because we have a closed-form solution for interest rates, they depend only on the share of clients that each bank has on a given region.

$$r_{t+1}^i = \bar{MC}_i + \frac{1}{\hat{\rho}(1 - s_{t+1}^i)} = \bar{MC}_i + \frac{1}{\hat{\rho}(1 - \frac{B_{t+1}^i}{\sum_j B_{t+1}^j})}$$

This provides a system of non-linear equations that we solve numerically.

E Dynamic Equilibrium and Welfare Calculations

We start from the steady state equilibrium.

First we compute the value of V_0^* for all i

$$V_0^{*i} = \frac{1}{1-\beta}[\hat{\rho} r_0^{*i} + \nu log(\sum_{k=1}^{J} exp(\bar{\varepsilon}_0^{*ik}/\nu)]$$

Recursively we have the following expressions:

$$V_{t+1}^{i}=\frac{1}{\beta}[V_{t}^{i}-\hat{\rho}r_{t}^{i}-\nu log(\sum_{k=1}^{J}exp(\bar{\varepsilon}_{t}^{ik}/\nu)]$$

$$\bar{\varepsilon}_{t+1}^{ij}=\beta[V_{t+1}^{j}-V_{t+1}^{i}]-C^{ij}$$

Given that we already have a law of motion for consumers, and a closed-form solution for interest rates, then we can compute for each period, the equilibrium of this economy.

Finally, it is possible to approximate the full time welfare effects without computing value functions.To see this, recall the borrowers' Bellman equation, and consider what happens if we implement small changes to switching costs (for example via a transparency policy shock), which can effect the allocation of consumers across banks, and thus, equilibrium interest rates.

Employing the Envelope Theorem repeatedly, the effect of a change in switching costs for a worker in bank i can be written as:

$$\frac{\partial V^{i}}{\partial C}=\sum_{t=0}^{\infty}\sum_{j=1}^{J}\beta^{t}m_{t}^{ij}\rho\frac{\partial r^{i}}{\partial C}\sim\sum_{t=0}^{\infty}\sum_{j=1}^{J}\beta^{t}m_{t}^{ij}\rho\frac{\triangle r_{t}^{i}}{\triangle C}$$

Since we can calculate the trajectory of interest rates for each bank after a a small perturbation of C, and we can calculate the law of motion of consumers, we obtain an estimate of the welfare effects that this change induces.

E.1. Simulations and Results from the Model

Now that we have derived our economy-wide model, we shock the switching friction parameter by a baseline of a 10% reduction.[6] Figure 8 shows the dynamic changes in bank shares and equilibrium interest rates for one economic region after the policy shock. We find that banks with a higher cost of funding see their market shares dramatically decrease,

[6] We use different shocks and find that the size of the drop mostly determines the velocity of convergence and not the parameters the model converges to.

as consumer switch to banks that offer lower interest rates. Banks strategically react to consumer switching in two ways. First, banks that are losing market power, also reduce their interest rates to be more competitive, whereas banks where consumers are switching to, increase interest rates as they gain market power. In the long run, a ten percent drop in switching frictions translates into a 7.7 percent decrease in interest rates. For a level of 24 percent average, as we have in our economy, this would imply a long-term reduction of around 180 basis points. We evaluate how this rate reduction affects consumer welfare, and we find an improvement of the order of 14 percent (figure 7). We also observe convergence in interest rates, which suggests that consumers are comparing rates across lenders.

Overall, the benefits of interest rate reduction accrue mainly to clients that decided to switch banks. Thus, we find distributive effects between consumers that actively react to price differences and those choose to change banks and the inactive consumers that are not sensitive to relative prices. In the new steady state of our simulated economy, the change in interest rates come from changes in competitive power (mark-ups) as banks? funding remains unchanged. This implies that market power can reduce the economic gains from consumers re-allocating their loans across financial institutions, as banks that consumers switch to end up raising their rates due to their increased market power, implying that consumers that quickly use this information to switch capture the majority of the gains. As market conditions and market power attenuate these interventions, we find that the effects of transparency on credit outcomes vary from region to region. Figure 9 shows the long-term equilibrium effects we calculate for different regions. In some regions, interest rates dropped by 96 basis points, while in others they drop by 160 basis points. So while the overall rates may improve, these benefits are concentrated to consumers that switch banks and live in regions with more competitive banking sectors.

VII Conclusion

We exploit a policy change in Chile that reduced the informational friction component of switching costs for consumers. Using administrative loan-level data in combination with a dynamic structural model, we find that this introduction of a standardized loan contract reduces average interest rates by 180 basis points. Additionally, we observe a reduction across the standard deviation of average rates, which also suggests that search costs decreased for consumers. These rate decreases are attenuated for non-switchers and for consumers in regions that have less competitive banking sectors. As well, for consumers that switch to banks with growing market shares may experience an increase in rates as the bank compensates for increased demand with higher rates. Overall, we find that consumers enjoyed an increase in welfare of 15 percent.

Table 1: Summary Statistics Unique Loans

Statistic	N	Mean	St. Dev.	Min	Max
maturity	7,655,263	27.129	19.738	1	367
annual_rate	7,655,263	24.317	13.698	0.000	75.120
loan_size	7,655,263	2,704,592	3,869,648	1	170,837,440
annual_income	7,655,263	12,633,395	4,380,763	0	4,042,936,038
ever_default	7,655,263	0.260	0.439	0	1
ever_delinqued	7,655,263	0.007	0.082	0	1
age	7,655,263	44.243	13.658	18	116.071
years_married	7,655,263	12.527	14.913	0.1	70.3
death	7,655,263	0.002	0.049	0	1
civil_status	7,655,263	1.519	0.752	1	7
gender	7,655,263	1.417	0.496	0	2
nationality	7,655,263	1.026	0.233	0	3

Table 2: Logarithmic Regressions, Exploiting Shares

	Dependent variable:		
	reg_region		
	beta = 0.9	beta = 0.95	beta = 0.97
	(1)	(2)	(3)
drate_res_region	0.28747*	0.25406*	0.24531*
	(0.0132)	(0.014)	(0.014)
Constant	−0.34907***	−0.21464***	−0.17906***
	(1.63e-08)	(9.77e-05)	(0.000803)
Observations	16,839	16,839	16,839
R^2	−12.436	−12.436	−12.436
Adjusted R^2	−12.437	−12.437	−12.437
Residual Std. Error (df = 16837)	2.878	2.878	2.878
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 3: Obfuscation Parameter Estimation, Using Windows Before and After Policy

	Dependent variable:		
	reg_region		
	12 Month Period	Before	After
	(1)	(2)	(3)
lenderFE	0.005	0.013^{**}	0.001
	(0.004)	(0.006)	(0.004)
regionFE	0.002	-0.004	0.004
	(0.003)	(0.004)	(0.006)
drate_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
R^2	-0.085	-0.190	-0.073
Adjusted R^2	-0.086	-0.191	-0.074
Residual Std. Error	0.753 (df = 9010)	0.806 (df = 4278)	0.734 (df = 4728)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 4: Logarithmic regressions, exploiting shares

	Dependent variable:	
	log(share)	
	IV Model	IV Model+LR FE
	(1)	(2)
maturity	-0.018^{***}	-0.019^{***}
	(0.0004)	(0.0004)
amount	0.00000^{***}	0.00000^{***}
	(0.000)	(0.000)
rate_type	0.408^{***}	0.372^{***}
	(0.009)	(0.009)
age	-0.00003^{***}	-0.00003^{***}
	(0.00000)	(0.00000)
e_civil_lrd	0.054^{***}	0.045^{***}
	(0.007)	(0.006)
gender	0.089^{***}	0.132^{***}
	(0.012)	(0.011)
nationality	-0.237^{***}	-0.153^{***}
	(0.025)	(0.024)
risk		-0.00000
		(0.00000)
rate	-0.035^{***}	-0.040^{***}
	(0.001)	(0.001)
Constant	-44.440^{***}	-40.532^{***}
	(0.967)	(0.924)
Observations	194,140	194,140
R^2	0.090	0.169
Adjusted R^2	0.090	0.169
Residual Std. Error	1.369 (df = 194131)	1.308 (df = 194115)
Note:		*p<0.1; **p<0.05; ***p<0.01

Figure 1: English Translation of SERNAC Regulatory Disclosure

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	Sí/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	

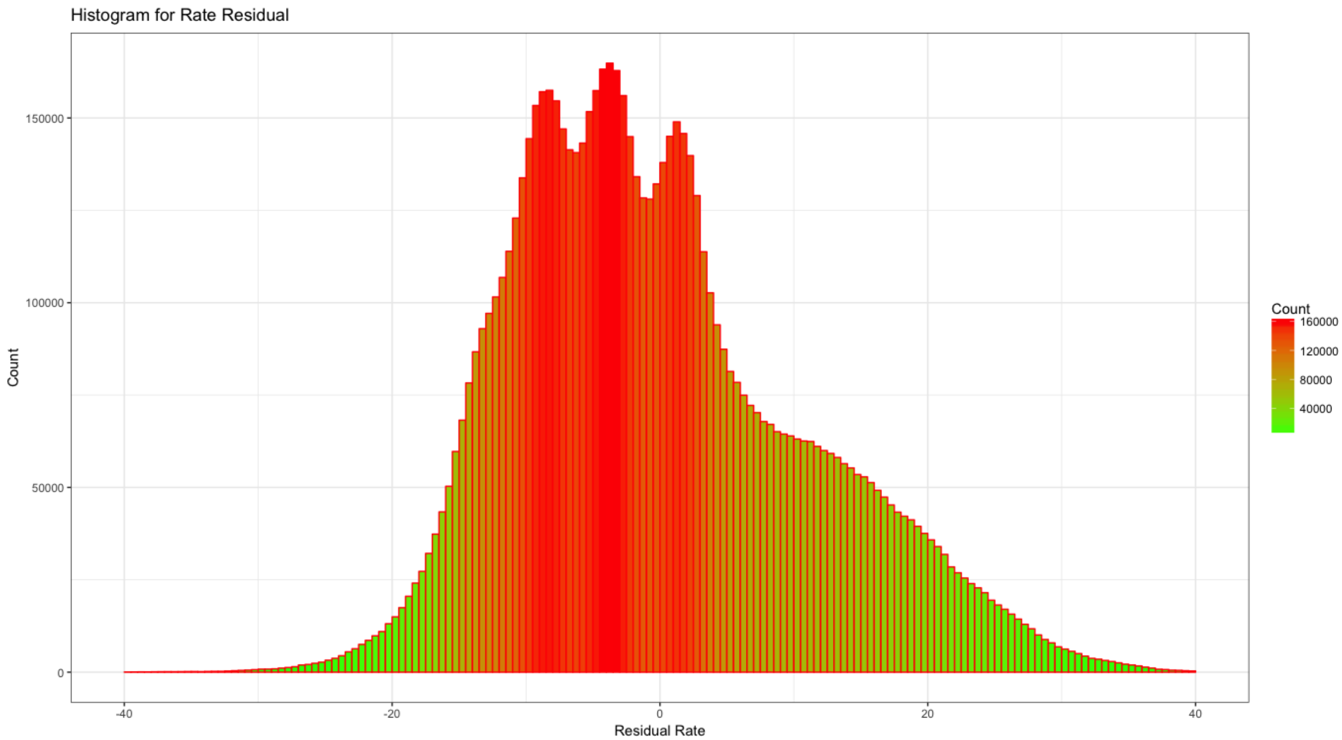
III. Prepayment Conditions	
Prepaid charge (%)	—
Notice period for prepayments	

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

Advisory

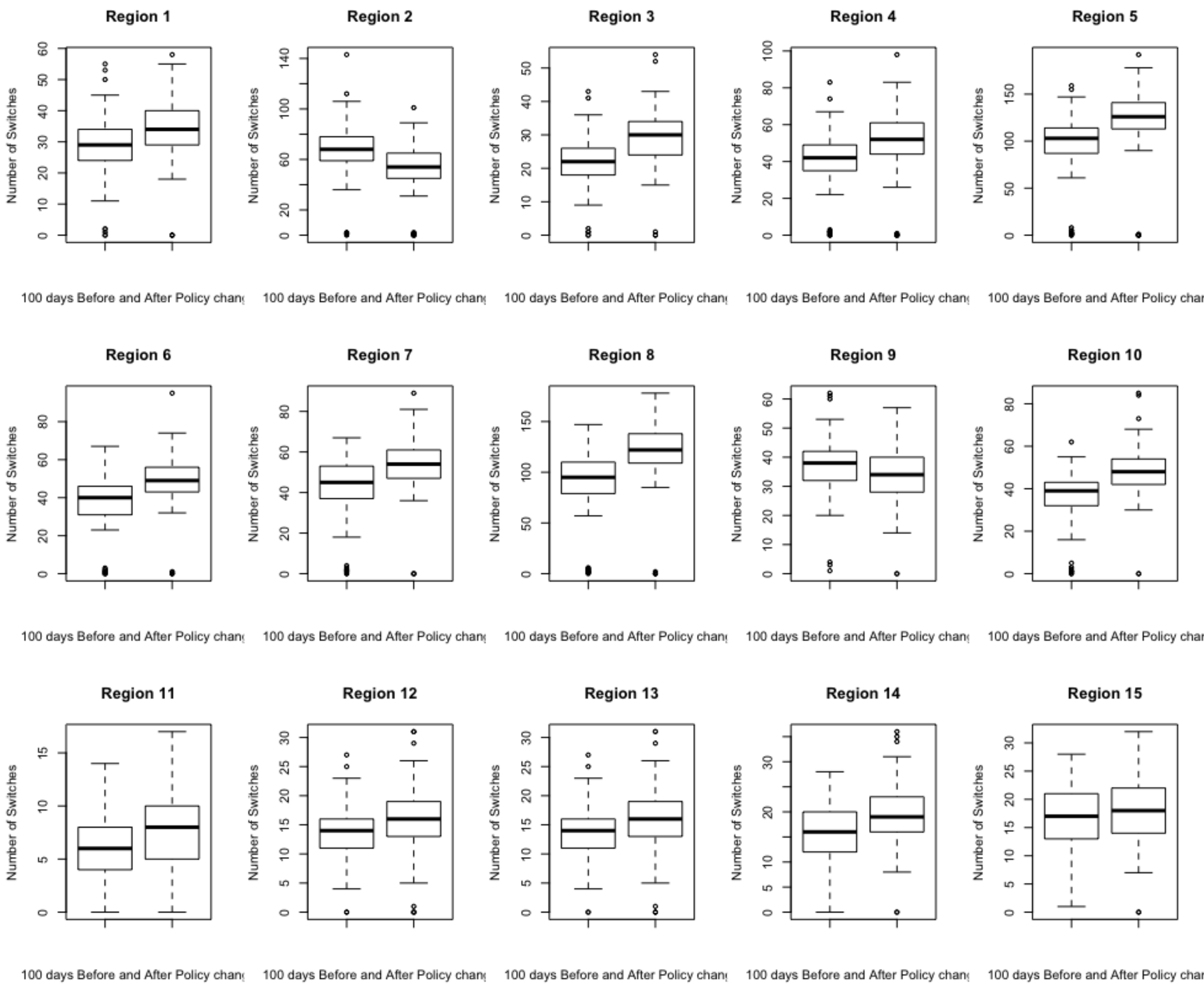
"The consumer credit of this summary sheet requires the contracting consumer <name> equity or future income sufficient to pay the total cost of $xx whose monthly payment is $xx, during the entire credit period."

Figure 2: Price Dispersion



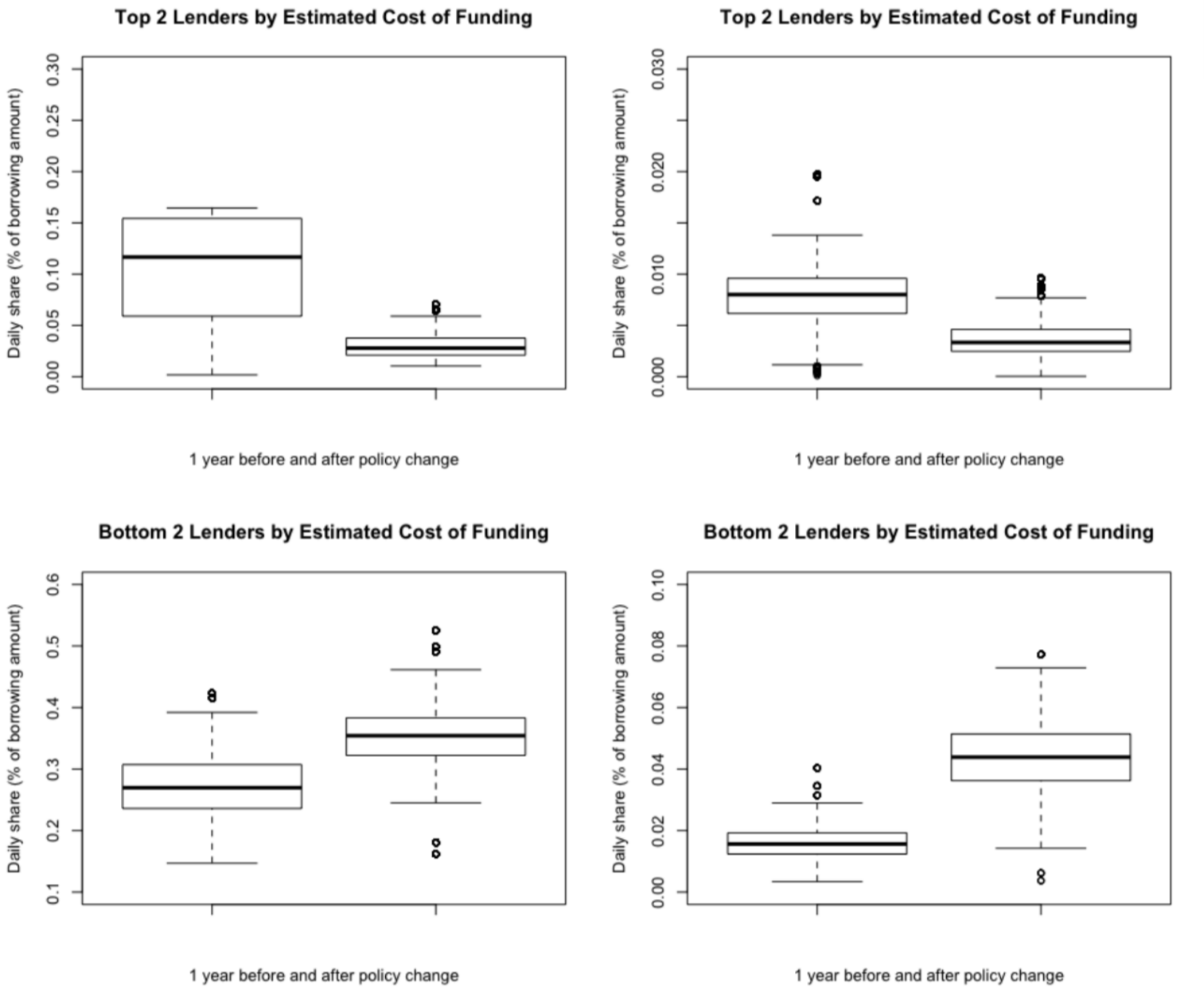
Un-explained rate dispersion

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



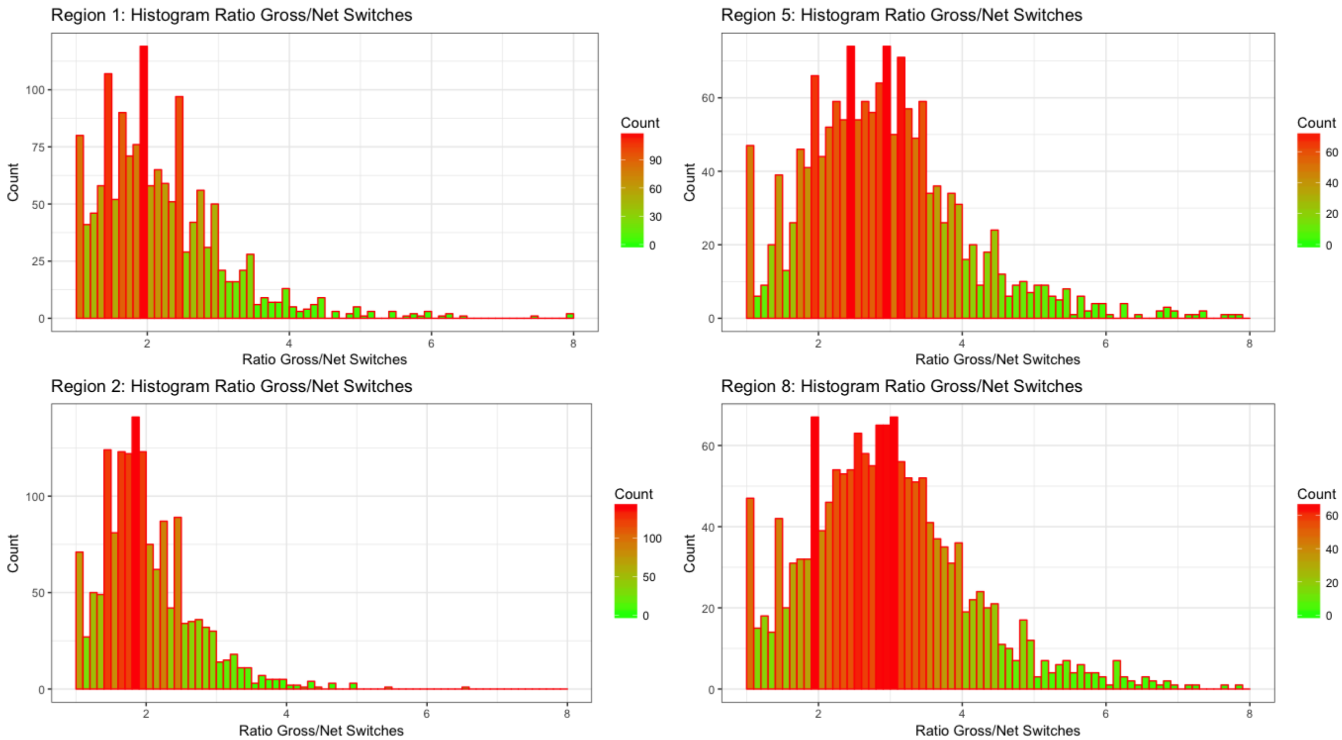
Box-plot captures predicted elasticities by Lender

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



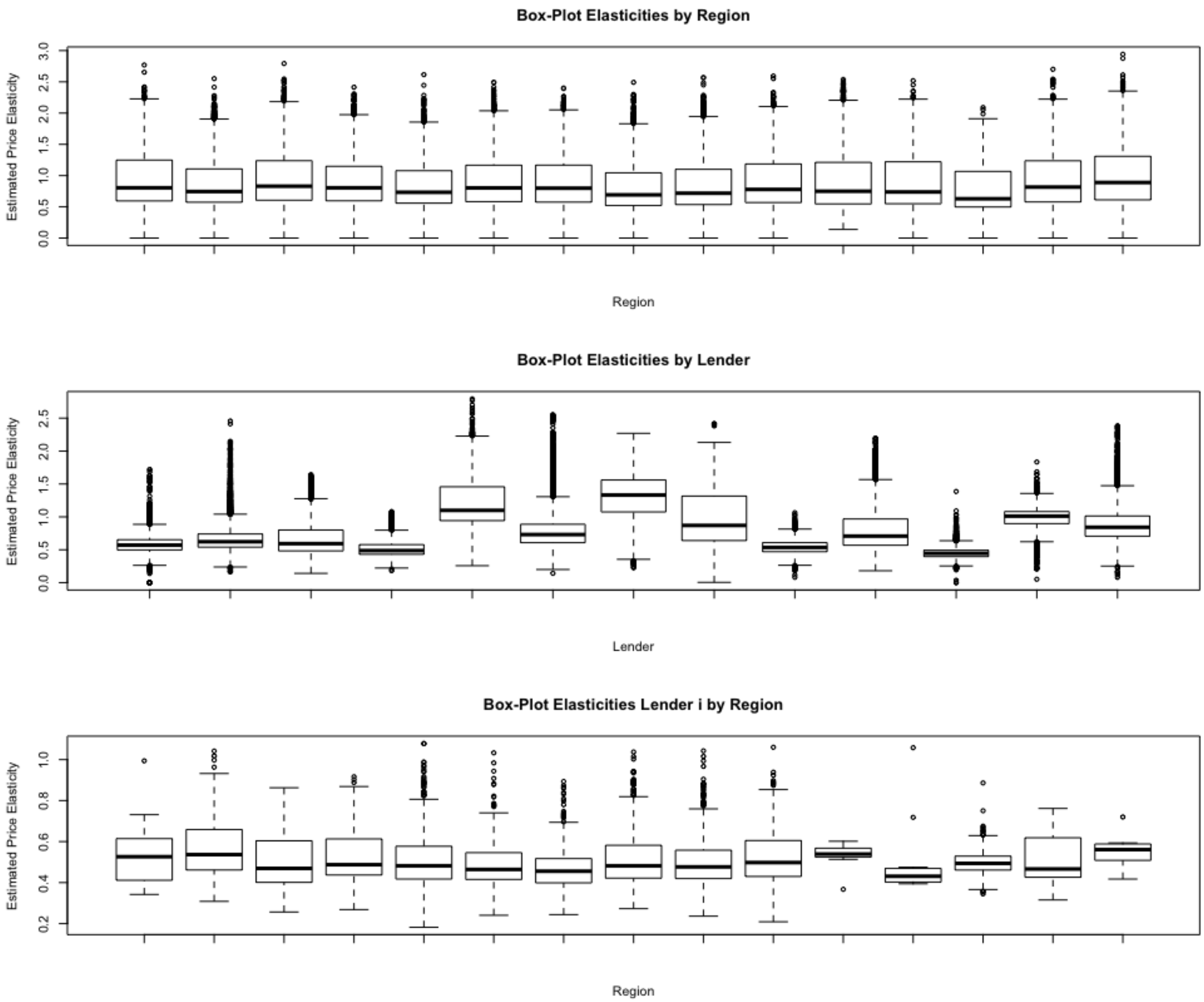
Box-plot captures predicted elasticities by Lender

Figure 5: Gross vs Net Flows



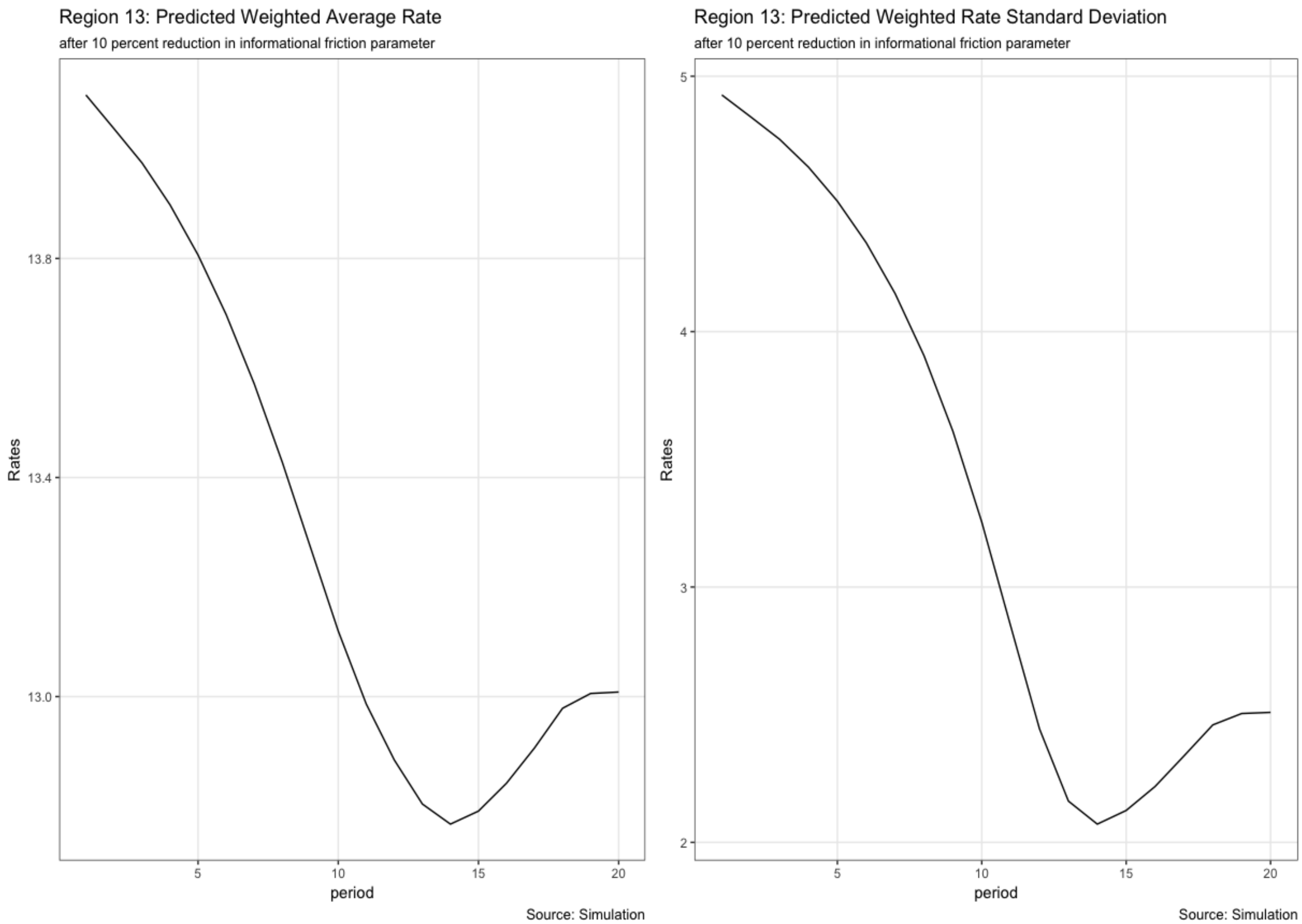
This figure plots the ratio between daily total switches to daily net switches for all banks in a given region.

Figure 6: Predicted Elasticities by Region, Lender and LR



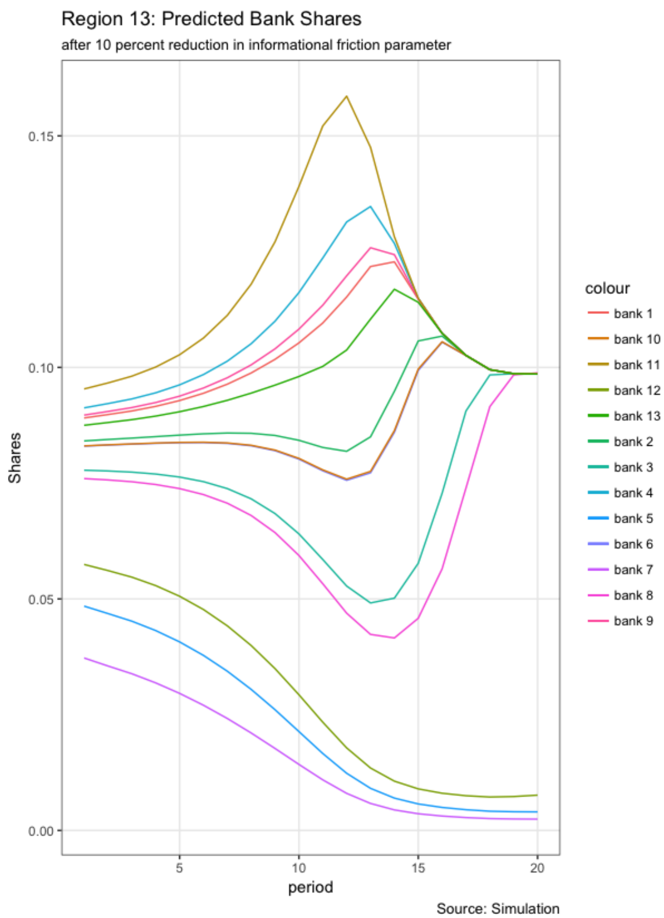
Box-plot captures predicted elasticities by Lender

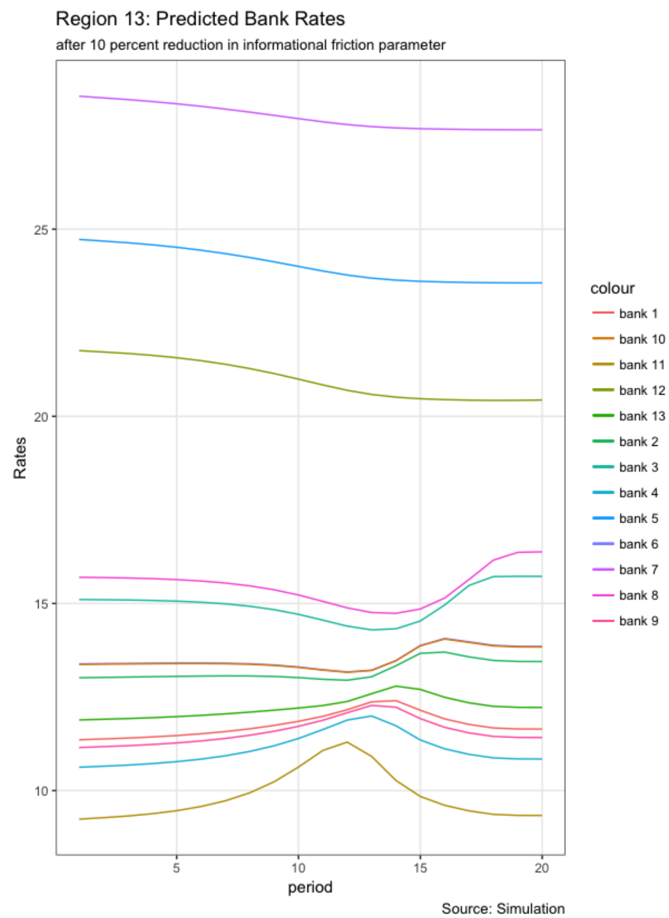
Figure 7: Simulations: Weighted Average Interest Rate and Standard Deviation



Simulated evolution for region 13 after 10 percent decrease in informational friction parameter.

Figure 8: Simulations: Predicted Shares and Rates by Bank





Simulated evolution for region 13 after 10 percent decrease in informational friction parameter.

Figure 9: Simulations: Summary of Results

	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

After 10 percent drop in informational friction parameter