Pass-through in selection markets: evidence from car loans in Brazil

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Introduction

Credit markets are one leading example of selection markets: a bank cares not only about lending but to whom they are lending, given that borrowers differ in their probability of repayment. If banks are unable to distinguish borrowers' risk through observed characteristics, it can lead to adverse selection. In such markets conventional economic wisdom may not apply: for example, more market power can lead to more efficient outcomes, as firms internalize the effect of prices into selection (Mahoney and Weyl 2017; Crawford, Pavanini, and Schivardi 2018; Lester et al. 2019).

Selection can also affect the analysis of cost pass-through and tax incidence. For conventional markets under imperfect competition, Weyl and Fabinger (2013) show that the pass-through depends on demand and supply elasticities, demand curvature and the level of market power. However, it can also be affected by selection. For example, in the case of a positive cost shock in perfect competition with constant marginal costs, in conventional markets we would expect a unitary pass-through. In contrast, in credit markets with adverse selection this would also increase default, which would cause a further price increase. In this circumstance, the pass-through could be higher than one, depending on the demand elasticity and the level of selection.

The setting I study in this paper is a tax on loans in Brazil. The tax level has changed significantly in the last decade, ranging from zero to 4.1% a year of the loan's principal, providing a clear setting for estimating the tax incidence. From aggregate data for car loans, I show descriptive evidence that the tax has been borne mostly by the banks, displaying a very low pass-through to interest rates.

From this fact, I build a simplified model of demand and supply of loans based on Crawford, Pavanini, and Schivardi (2018). In the model, potential borrowers choose to get a loan or not and also decide whether to default. A positive correlation between the willingness to borrow, which is privately observed by consumers, and the probability of default characterizes adverse selection. The banks compete à la Bertrand-Nash and set a common interest rate for all borrowers, considering the expected default rates.

I show from simulations that this simplified model predicts that under perfect competition the pass-through is greater than one. However, if the level of selection is high and the banks have significant market power, then we can get a lower pass-through, consistent with the descriptive evidence on the Brazilian market.

In the final section, I show how this simple model can be taken to data. However, the lack of variation makes the model non-identified. This is expected, given the availability of only national-level data and the absence of cross-market variation. Still, this strategy could be pursued in later stages of the research if market-level data becomes available.

This paper is related to two main strands of the literature. The first analyzes markets with asymmetric information in credit markets based on the theoretical contributions of Jaffee and Russell (1976) and Stiglitz and Weiss (1981). Empirically, Chiappori and Salanie (2000) showed that selection can be estimated from ex-post outcomes, such as default in credit markets. Their reduced-form approach was incorporated into structural estimation by Adams, Einav, and Levin (2009) and Einav, Jenkins, and Levin (2012), which analyzed subprime car loans under a monopolistic setting. Recent studies, such as Crawford, Pavanini, and Schivardi (2018), Allen, Clark, and Houde (2019) and Cuesta and Sepulveda (2021) contributed by allowing for imperfect competition, search costs and product differentiation.

The second main literature is on the structural estimation of pass-throughs. Eugenio J. Miravete, Seim, and Thurk (2018) estimates the impact of the Pennsylvania Liquor Control Board monopoly on prices, and use this to estimate a counterfactual on the optimal revenue-raising prices. Dubois, Griffith, and O'Connell (2020) contribute to a large literature estimating the impact of excise taxes, showing that soda taxes cause a significant decrease in the consumption of sugary soft drinks. On the theoretical side, Eugenio J. Miravete, Seim, and Thurk (2023) show how to flexibly estimate the demand curvature, which impacts the pass-through, using the workhorse methods in Industrial Organization.

I note that, while taxes on loans are possibly unique to the Brazilian case, the same economic forces would be at play when estimating the pass-through of cost shocks in any market with asymmetric information. Also, taxation is common in insurance markets, in which premiums are taxed in the United States and the United Kingdom, for example.

The paper is organized as follows: in Section 1 I describe the loans' tax and show how it varied since 2008. Then, I describe the market for car loans and give descriptive evidence of the impact of the tax on the interest rates. In Section 2 I describe how I model demand, default and supply decisions, and how I parameterize the adverse selection. In Section 3 I simulate the model for different parameter combinations and show that the model can generate pass-through estimates that are consistent with data. I present in Section 4 how I can estimate the model from aggregate data, although the lack of variation makes the model non-identified. Then, I present my final remarks and the next steps of my research.

1 Data and Institutional Background

1.1 Tax on loans (IOF)

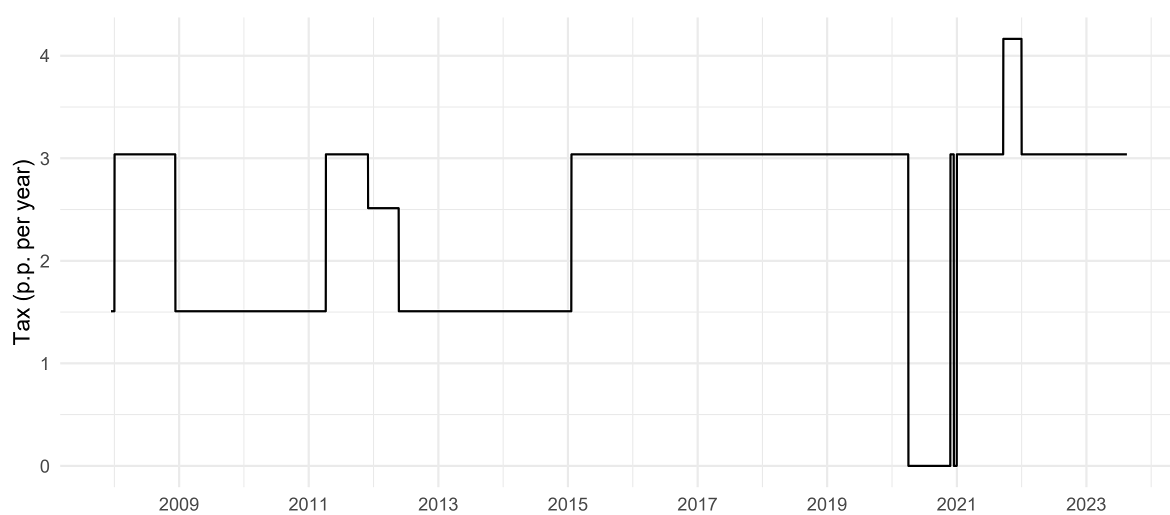
Brazil has a tax on financial operations, including loans (IOF). The IOF is currently set at 3% per year for loans to households, and 1.5% a year for loans to businesses, added by a 0.38% flat rate that is independent of the duration. For example, if a bank would charge a 30% interest rate a year, after the taxes the effective rate to a borrower would be 33% per year plus 0.38% of the loan amount. In 2021, the total revenue raised from the tax was R$ 36.8 billion (US$ 7.4 billion) (Federal Revenue of Brazil 2021). The tax applies to almost all loans, including revolving credit lines and discount operations. For credit card bills, it applies only when the bill is not paid in full. Mortgages and some types of loans for small businesses are exempt.

The tax on loans was created as a regulatory tax to be used as an extra instrument of the monetary authority and was not meant to generate significant revenue for the Treasury. By this principle, Brazilian law does not require the government to seek legislative approval nor to respect the usual 90-day "grace period" before any tax increase takes effect. This authorizes the government to raise the IOF by executive order, and the raise can take effect almost immediately. This feature led fiscal authorities to subvert the original principle of the tax, publicly claiming that raises were meant to fund public policies. In Figure 1 we can see how the tax for loans to households evolved since 2008. The flat fee of the IOF on loans (not pictured) was instituted in 2008 and remained in the same value until 2020 when it was reduced to zero as part of a policy during the Covid pandemic. It was reinstated permanently to 0.38% in January 2021.

One feature of the recent tax changes is that they were unexpected. In 2020, the tax was set to zero due to the Covid-19 pandemic. This rate was announced to last until December 31. Nevertheless, on November 25 the government announced that after November 27 the tax would be reinstated to 3% a year. The justification was that it was necessary to fund a benefit to the population of a remote state, Amapá, which suffered a massive power outage that month. After a backlash and given that enough funds had been raised, in December 11 the administration backtracked and reduced the rate back to zero on loans taken between December 15 and December 31.

Similarly, at the end of 2021 the government did not have enough space in the budget to fund a raise in the conditional cash-transfer scheme. The administration chose to raise the rate on the loans tax for both households and businesses, which increased from 3% to 4.08% and from 1.5% to 2.04%, respectively. Both raises were temporary, lasting until December 31.[1]

Figure 1: Tax rate for consumer loans



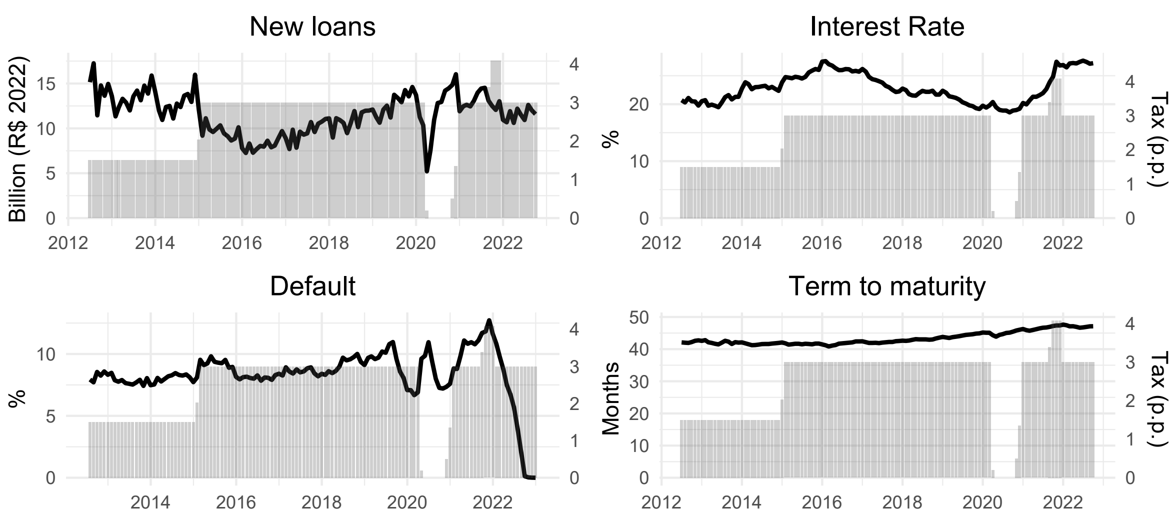
[1]An online search for rumors of the tax hikes on the media before the official announcement did not yield any results, evidencing that these increases were likely not anticipated by the population.

1.2 Car loans

I use aggregate data on car loans provided by the Central Bank of Brazil. Aggregating across all banks, I observe monthly new loans, outstanding loans, interest rates, default rates, and term to maturity. All these variables are observed for both new and outstanding loans. The default rate is defined as the percentage of originated loans that are more than 90 days past due. Apart from default, prepayment and refinancing are likely to be a significant risk to the loan issuer. However, there is no public dataset with information on these variables. For this reason, I ignore both factors in this article.

The evolution of these variables is in Figure 2, which includes the loans' tax in the right-hand axis. On average, there were R$ 11.6 billion[2] in new loans each month, adjusting for inflation. The average default rate per cohort until 2021 was 8.8%.[3] The average interest rate was 22.9% a year, among the lowest in Brazil's credit markets. The average term to maturity of new loans has grown from 42 months in 2012 to 47 in 2022.

Figure 2: Indicators of car loans in Brazil



At the bank level, data on interest rates, default rates and market shares are available but are released in different aggregation levels. A 5-day moving average of the interest rate per bank is available at a daily frequency, but it does not contain information on the volume of new

[2]Around US$ 2.3 billion using the current exchange rate
[3]Default rates have right censoring, as the most recent cohorts did not have enough time to default.

loans originated by each bank. Quarterly market shares and default rates are available only for outstanding loans.

For this reason, some assumptions were needed to build the dataset used in this paper. Whenever interest rates had to be used alongside shares and default rates, I averaged it across the quarter, which ignores any in-quarter seasonality in loan origination. For market shares, I extrapolated the aggregate outflow of outstanding loans to each bank. With that, I can infer the market shares in the origination of new loans. For default rates, I observe their evolution across time for each cohort since loan origination. I extrapolate the average time to default to each bank, allowing me to infer from the default rate in outstanding loans what was the default rate per cohort.[4]

Summary statistics on the 5 banks with the largest market shares are in Table 1. While 4 of the 5 have similar interest and default rates, Votorantim offers a higher interest and experiences a much higher default. This behavior is compatible with selection, as a bank that charges a higher price induces higher default by selecting a worse pool of borrowers. One feature of car loans in Brazil is that all of the banks with larger market shares are private, which allows us to ignore the discussion of whether public banks are maximizing profits or not.

1.3 Interest rates and tax changes

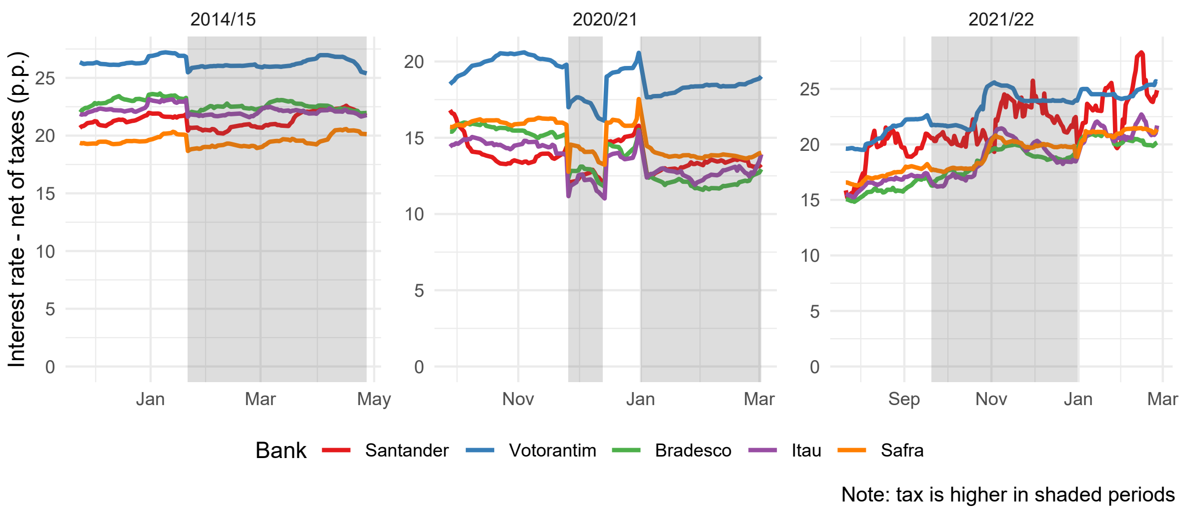
We can use the daily data on interest rates to analyze how the banks reacted to the tax changes. I focus on the tax increases because they were not anticipated, as discussed in Section 1.1. On Figure 3 we observe how the banks' interest rates on car loans evolved, net of taxes, for each of the three most recent periods in which the tax changed. Despite the Covid-19 pandemic, the changes at the end of 2020 offer a cleaner setting to study the pass-through, as there were no major cost shocks around that time. In 2015, on the same day of the tax increase there was a 50bps increase in the federal funds rate, which is a major component of the cost of originating a loan. In September 2021 there was a 100bps increase in the federal funds rate only two days after the tax hike.

We see that in all three periods the pass-through was much lower than 1, as the interest rate net of taxes drops after the tax hike. If the pass-through was unitary, we would see the net

[4]As observed in my research proposal, I have applied for access to the loan-level data possessed by the Central Bank of Brazil, which records all loans above R$200 (~US$40). In this case, I would be able to calculate these statistics directly from data. This dataset has already been used by other researchers, such as in Fonseca and Van Doornik (2022) and in Joaquim, Doornik, and Ornelas (2020) (job market paper).

interest not changing before and after the shift. Note that in 2015 the effect is noticeable despite the 50bps increase in the federal funds rate, which pressed interest rates upwards. In September 2021 there seems to be no change in the net interest rates, but this is due to the 100bps increase in the federal funds rate that happened in the same period. In other words, it implies that, net of taxes, the interest rates remained constant even under such a cost shock, which also evidences a pass-through lower than 1.

Figure 3: Interest rates of car loans during tax changes



In the last column of Table 1, I present the average pass-through by bank in the first two periods. I exclude the third period given that there was also a high cost shock simultaneously. While these are simple unconditional averages comparing interest rates before and after the tax shifts, they suggest that banks have some heterogeneity. Results from Crawford, Pavanini, and Schivardi (2018) and Mahoney and Weyl (2017) indicate that market power can lower the effect of adverse selection, as banks take into account the selection effect in their pricing decisions. In my setting, that would translate to banks with higher market shares bearing a higher share of the tax, while smaller banks should present a higher pass-through to consumers. The data shows a different picture, with Santander and Votorantim presenting higher pass-throughs than the smaller competitors. Possible explanations include some degree of market segmentation, in which banks could face consumers with different average elasticities to the interest rates or focus on markets with less competition. However, this would need more detailed data for an in-depth analysis.

Alternatively, I also try to estimate the pass-through from a regression including the federal

Table 1: Summary statistics of car loans by bank (2018-2021)

Bank	Market share (%)	Interest rate (APR)	Default (%)	Pass-through (%)
Santander	25.0	19.3	7.7	60.1
Votorantim	17.9	22.5	11.0	51.2
Bradesco	13.8	17.8	6.0	21.7
Itau	11.6	18.8	7.0	48.6
Safra	7.0	19.6	5.1	46.4

Note:
Interest rates are aggregated from daily data. Market shares and default rates are extrapolated from outstanding loans (IFData/BCB) and aggregate data. Pass-through is the average of interest rates before and after the tax hikes in 2015 and 2020/21.

funds rate as a control, as in Table 2. Given the lack of a control group, I am unable to include time fixed effects, and the results should be interpreted with caution. In regressions 1 to 4 I use the full sample, from 2012 to 2022, with different controls. In regressions 5 and 6, I use only a window around the tax changes. No specification is very convincing, but generally they confirm that the tax pass-through is less than 1, just as in the graphical analysis.

2 Model

2.1 Overview

The evidence from Section 1 indicates that the pass-through of the loan tax is below one. However, it is not possible to identify directly what are the mechanisms that yield this result. In regular markets, Weyl and Fabinger (2013) show that the pass-through will depend on the elasticity of demand and supply, the level of competition, and the curvature of demand. In credit markets, the level of selection will also play a role: if a tax weakly increases interest rates, this can worsen the pool of borrowers and increase default, generating further rate increases. Such an environment can theoretically generate pass-through above 1, even under standard log-concave demand functions. In this section, I will describe a simple model that does not require micro-level data and accounts for different elasticities of demand, selection, and imperfect competition. In **?@sec-sec-simulations**, I will show that it can generate a range of pass-throughs, both below and above 1. The model can also be extended to account for more general demand curvatures, as in Eugenio J. Miravete, Seim, and Thurk (2023).

Table 2: Estimates of pass-through of loan tax to interest rates

	(1)	(2)	(3)	(4)	(5)	(6)
Tax	1.637	0.673	0.676	0.115	0.975	0.279
	(0.037)	(0.023)	(0.238)	(0.110)	(0.226)	(0.026)
Fed Rate		0.764	0.765	0.897	0.756	1.215
		(0.005)	(0.063)	(0.061)	(0.077)	(0.103)
Num.Obs.	11 608	11 608	11 608	11 608	1819	1819
Std.Errors	IID	IID	by: bank	by: bank	by: bank	by: bank
FE: bank			X	X	X	X
FE: year				X		X
FE: month				X		

Note:
Regressions (1) to (4) use the entire sample, from 2012 to 2022. In (5) and (6) only a window 60-day windows around the tax changes was included.

As a clarification, I follow Adams, Einav, and Levin (2009) in defining adverse selection as any situation in which high-risk consumers are more likely to take a car loan. This could be either a rational strategy, when the borrower knows that she has a low likelihood of repayment, or due to some behavioral aspect, in which less financially-savvy customers might be in a higher need for a loan and later also be more likely to default. The definition of moral hazard follows the same logic, as a situation in which consumers who have taken a loan with a higher interest rate are more likely to default, regardless of their private shock.

2.2 Demand

The model is a simplified version of Crawford, Pavanini, and Schivardi (2018). At time $t = 1, ..., T$, potential borrowers $i = 1, ..., I_t$ can choose to get a car loan from bank $j = 1, ..., J$ or not to borrow. The borrower's utility is given by[5]

$$U_{ij}^D = \epsilon_i^D + \alpha^D P_j + \xi_j + \nu_{ij},$$

where ϵ_i^D represents the borrower's idiosyncratic preference for taking a car loan, which is her private information. P_j is the interest rate charged by bank j, ξ_j denotes unobserved attributes of bank j and ν_{ij} represents unobserved shocks to borrower's i demand for bank j,

[5]I drop the subscript t for clarity.

which follow a Type-I Extreme Value distribution. The utility of the outside option is denoted by U_{i0}^D, which is normalized to zero.

Conditional on taking a loan, each borrower decides to default or not. Consider that F_{ij}^* is a latent variable characterized by the following equation:

$$F_{ij}^* = \delta + \alpha^F P_j + \epsilon_i^F$$

Borrower i defaults on bank j, or $F_{ij}(P_j) = 1$, if $F_{ij}^*(P_j) > 0$. For tractability, I follow Einav, Jenkins, and Levin (2012) and Crawford, Pavanini, and Schivardi (2018) and make the assumption that the errors ϵ_i^D and ϵ_i^F are jointly normal, such that

$$\begin{pmatrix} \epsilon_i^D \\ \epsilon_i^F \end{pmatrix} \sim N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma^2 & \rho\sigma \\ \rho\sigma & 1 \end{pmatrix}\right)$$

In this setting, a positive correlation between ϵ_i^D and ϵ_i^F, measured by ρ, accounts for adverse selection, as the borrower's private information makes her more likely to take a loan and increases her chance of defaulting. Mechanically, a bank that increases its interest rate selects more consumers with a high ϵ_i^D, and therefore faces a higher chance of default. The model also accounts for moral hazard through the price coefficient in the default equation: if α^F is positive, a higher interest rate makes all borrowers more likely to default.

This model is very simple, as I do not add any borrower or bank covariates that are likely to matter for demand and default decisions. These variables could be readily incorporated once more detailed data becomes available. One way of interpreting this model is to think of the decision of observationally similar borrowers that differ only in their willingness to take a loan. In this case, banks have to charge them the same interest rate, even though they have different underlying default probabilities.

Another assumption is that I abstract away from loan size. Crawford, Pavanini, and Schivardi (2018) study credit lines and assume that loan size is a borrower's choice. In the case of credit cards, Matcham (2023) shows that this assumption is not true, as banks use credit limits as a screening tool instead of interest rates. As for car loans, Grunewald et al. (2023) describe that consumers usually first choose the car and then they go to a lender to negotiate the loan, and for this rate they take loan size as exogenous. In my setting, as I do not have micro-level data I am unable to take a stand on this issue, and from the model perspective I implicitly assume that all loans have the same size.

2.3 Supply

Banks engage in Bertrand-Nash competition in interest rates. Bank j's profit is given by

$$\Pi_j = (P_j - \tau)S_j(\mathbf{P})(1 - F_j(\mathbf{P})) - MC_j S_j(\mathbf{P}),$$

where P_j is the interest rate charged by bank j, τ is the tax on loans, $S_j(\mathbf{P})$ denotes its expected market-share, $\mathbf{P}$ is the vector of prices of all banks, $F_j(\mathbf{P})$ is the expected default, and MC_j is a constant marginal cost.

The first order condition for profit maximization is given by

$$P_j = \frac{MC_j + (1 - F_j(\mathbf{P}))\mathcal{M}(\mathbf{P})}{1 - F_j(\mathbf{P}) + F'(\mathbf{P})\mathcal{M}(\mathbf{P})} + \tau, \tag{1}$$

where $\mathcal{M} = -\frac{S_j(\mathbf{P})}{S_j'(\mathbf{P})}$ is the markup term. Note that this expression simplifies to the usual first order condition of Berry, Levinsohn, and Pakes (1995) if there is no default decision.

The expression for the market shares is usual:

$$S_j(\mathbf{P}) = \int \frac{exp(\varepsilon_i^D + \alpha^D P_j + \xi_j)}{1 + \sum_k exp(\varepsilon_i^D + \alpha^D P_k + \xi_k)} f(\varepsilon_i^D) d\varepsilon_i^D$$

Denote the expected default conditional on taking a loan from bank j as

$$F_j(\mathbf{P}) = P(\epsilon_i^F + \delta + \alpha^F P_j > 0)|D_j = 1)$$

To calculate this expression, we use the properties of the multivariate normal to write it as a conditional expectation:

$$
\begin{aligned}
F_j(\mathbf{P}|\varepsilon_i^D) &= P(\epsilon_i^F + \delta + \alpha^F P_j > 0|\varepsilon_i^D) \\
&= P(\varepsilon_i^F > -(\delta + \alpha^F P_j)|\varepsilon_i^D) \\
&= 1 - F_{\varepsilon^F|\varepsilon^D}(-(\delta + \alpha^F P_j)) \\
&= 1 - \Phi_{\varepsilon^F|\varepsilon^D}(-(\delta + \alpha^F P_j)) \\
&= 1 - \Phi\left(-\frac{\delta + \alpha^F P_j + \frac{\varepsilon_i^D \rho}{\sigma}}{\sqrt{1-\rho^2}}\right) \\
&= \Phi\left(\frac{\delta + \alpha^F P_j + \frac{\varepsilon_i^D \rho}{\sigma}}{\sqrt{1-\rho^2}}\right),
\end{aligned}
$$

We then integrate over ε^D, conditional on taking the loan from bank j:

$$
F_j(\mathbf{P}) = \int \Phi\left(\frac{\delta + \alpha^F P_j + \frac{\varepsilon_i^D \rho}{\sigma}}{\sqrt{1-\rho^2}}\right) f(\varepsilon_i^D|D_j = 1) d\varepsilon_i^D
$$

Using Bayes' Rule, the conditional density can be expressed as

$$
\begin{aligned}
f(\varepsilon_i^D|D_j = 1) &= \frac{P(D_j = 1|\varepsilon_i^D) f(\varepsilon_i^D)}{P(D_j = 1)} \\
&= \frac{\frac{exp(\varepsilon_i^D + \alpha^D P_j + \xi_j)}{1 + \sum_k exp(\varepsilon_i^D + \alpha^D P_k + \xi_k)}}{\int \frac{exp(\varepsilon_i^D + \alpha^D P_j + \xi_j)}{1 + \sum_k exp(\varepsilon_i^D + \alpha^D P_k + \xi_k)} dF_{\varepsilon_i^D}} f(\varepsilon_i^D)
\end{aligned}
$$

Then, the derivative of the conditional default is given by[6]

$$
\begin{aligned}
F'_{ij}(\mathbf{P}) =& \frac{\alpha^F}{\sqrt{1-\rho^2}} \int \phi\left(\frac{\delta + \alpha^F P_j + \varepsilon_i^D \rho \sigma^{-1}}{\sqrt{1-\rho^2}}\right) f(\varepsilon_i^D|D_j = 1) d\varepsilon_i^D + \\
&+ \int \Phi\left(\frac{\delta + \alpha^F P_j + \varepsilon_i^D \rho \sigma^{-1}}{\sqrt{1-\rho^2}}\right) f'(\varepsilon_i^D|D_j = 1) d\varepsilon_i^D,
\end{aligned}
$$

One important assumption in the context of car loans is that I am not accounting for repossession. It has been documented by Assunção, Benmelech, and Silva (2014) that a 2004 law

[6]The second term seems to have been omitted by Crawford, Pavanini, and Schivardi (2018). Intuitively, if bank j increases the interest rate the density of $\varepsilon_i^D|D_j = 1$ will shift slightly to the right. That is because marginal borrowers, with a relatively low ε_i^D, choose not to borrow from that lender.

facilitated the selling of repossessed cars and increased access to credit. However, I do not have any data that allows me to estimate the proportion of defaulted loans for which the car is repossessed, nor the proportion of the loan that is recovered, considering that cars can quickly depreciate.

3 Simulations

From the model discussed on Section 2, we can generate predictions on the impact of a tax for different combinations of the parameters $\alpha^D, \alpha^F, \sigma$, and ρ. In this section, I will show that when consumers are very elastic to the interest rates (high α^D) and competition is close to perfect competition, the model predicts that the pass-through is higher than 1 under the presence of adverse selection and/or moral hazard (positive ρ and/or α_F). In extreme cases, the market can completely unravel, as predicted in Stiglitz and Weiss (1981). However, if consumers are less elastic, and therefore banks have more market power, under asymmetric information the pass-through is lower, as lenders take into account the effect of raising the prices on default, consistent with the theoretical literature (Mahoney and Weyl 2017).

The algorithm for the simulation is the following[7]: 1) fix a tuple of parameters $t = (\alpha^D, \alpha^F, \sigma, \rho)$; 2) use a contraction as in Berry, Levinsohn, and Pakes (1995) to pin down ξ, such that the model matches the market shares in the data[8]; 3) use an optimization algorithm to find the δ that minimizes the quadratic distance between the default predicted by the model and the data. After these steps, we can fully characterize the demand system. Then, I can invert the banks' first order condition, as in Equation Equation 1 to back out the marginal costs implied by t. I discard the tuples which imply negative marginal costs or negative profits.

With that, I simulate a counterfactual in which the tax is increased from zero to 3%. The new interest rates are found by solving the first order condition as a "dampened" fixed point:[9]

$$\mathbf{P} \longleftarrow \rho\mathbf{P} + (1-\rho)\left(\frac{\mathbf{MC} + (1-\mathbf{F}(\mathbf{P}))\mathcal{M}(\mathbf{P})}{1-\mathbf{F}(\mathbf{P}) + \mathbf{F}'(\mathbf{P})\mathcal{M}(\mathbf{P})} + \tau\right),$$

[7]As data, I use a single period of observations, just before the tax increase in November 2020.

[8]The integrals are solved numerically using 100 Halton draws.

[9]Conlon and Gortmaker (2020) note that this approach may not converge or may converge to a vector that may not be an equilibrium. However, his suggested approach, based on Morrow and Skerlos (2011), cannot be applied directly due to the differences between the usual first-order condition in demand estimation and the "default-augmented" one.

As this is not necessarily a contraction, it does not always converge. While this might be due to the algorithm, in most cases I interpret this as the market unraveling: if consumers are sufficiently elastic to the interest rate and there is a high level of selection, it may not be feasible to have a market for car loans.

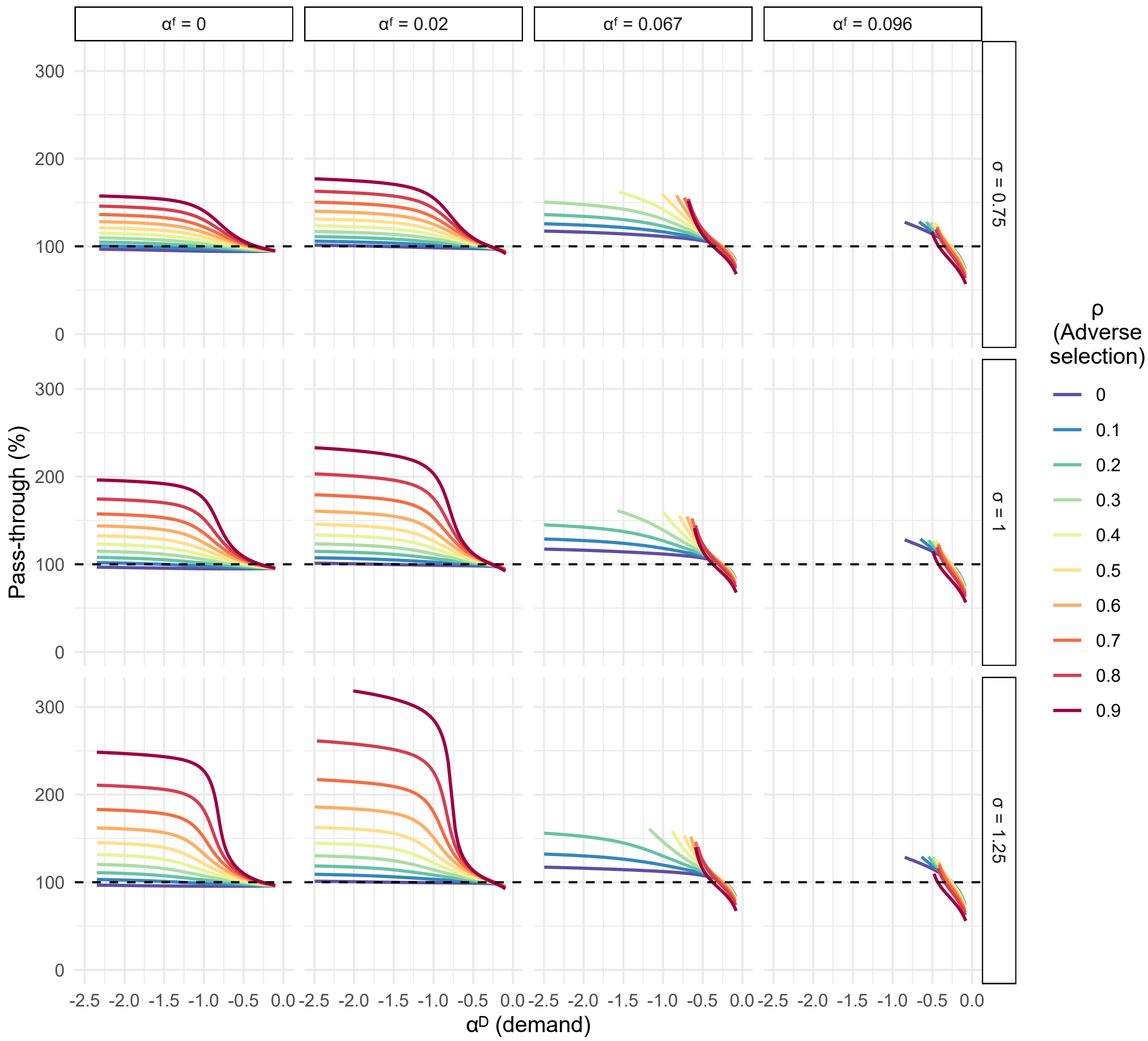
In Figure 4, I plot the pass-through implied by a combination of parameters α^D, α^F, ρ and σ. When the model has no selection ($\rho = \alpha^F = 0$), it simplifies to a simple logit, in which pass-through is close to 1 for any level of price elasticity. While in general we expect that the pass-through is lower for higher elasticities, this does not happen here because competition intensity is also changing: when consumers are very elastic, competition is closer to perfect competition, reducing markups.

When we add adverse selection ($\rho > 0$) but no moral hazard ($\alpha^F = 0$), the pass-through can be much higher than one when borrowers are very elastic. The intuition is the same as before: in this setting, competition approaches perfect competition, such that banks have to fully pass the tax onto prices. Under adverse selection, this worsens the pool of borrowers, causing default to rise and eroding marginal revenue, which causes banks to increase rates even further. In practice, this means that if average interest rates were close to 16% a year in November 2020, if consumers were highly elastic and $\sigma = 1$, then after tax the interest rates would shoot up to around 22%, on average. On the other hand, if consumers are price inelastic, the predicted pass-through is close to the predicted by the simple logit model. Note that even with a pass-through close to unit this generates lower profits than before the tax increase, given that the new default rate is higher than before, as seen in Figure 5.

Including both adverse selection ($\rho > 0$) and moral hazard ($\alpha^F > 0$), we obtain an even higher pass-through when consumers are relatively elastic. On the other hand, when consumers are relatively inelastic, we start to observe lower pass-throughs. The intuition is that under moral hazard a price increase affects all borrowers, not only the marginal. When banks have market power, they take this effect into account and refrain from passing the entire tax to consumers. In other words, the limit to market power here is not given by the price elasticity of demand, but by the price elasticity of default. In particular, the pass-through is even lower when both adverse selection and moral hazard are present, as higher prices induce default for both marginal and inframarginal borrowers. This description is not significantly changed by the variance of the willingness to get a loan, σ. As we can see in Figure 4, a higher variance only amplifies the effects described previously.

The effect of the tax on default rates is in Figure 5. Naturally, when $\rho = \alpha^F = 0$, there is no

Figure 4: Simulated average pass-through after 3% tax



change compared to baseline default rates. In all other cases, a positive pass-through means that default rates increase. This increment is generally higher the greater ρ and α^F, except for when demand is very inelastic, in which case banks decrease the pass-through, as previously described.

The simulated impacts of the tax on access to credit can be seen in Figure 6. For higher levels of demand elasticity, the market collapses almost completely, as under the new equilibrium prices only consumers with a very high logit shock take a loan. On the other hand, when the consumers are relatively inelastic and the pass-through is lower, default rates do not grow as much and the decrease in demand is also lower.

One drawback of the simulations is that, to generate lower pass-throughs, the model requires a high sensitivity of default to interest rates. For example, the combination ($\alpha^D = -0.079, \alpha^F = 0.096, \rho = 0.8, \sigma = 1$) implies a default elasticity above 2. This is much higher than what is predicted by the estimates in Crawford, Pavanini, and Schivardi (2018), in which a 32% increase in the interest rates (4.6 p.p) implies only a 2% increase in default (0.12 p.p.).

Another limitation is that the model fails to predict the pass-through of each bank, as seen in Figure 7. For the parameter combination that yields an average pass-through closer to the data, the model predicts that each bank changes prices similarly. More than that, the ones who bear most of the tax are the ones with higher market shares, in contrast to what we observed in Section 1. A possible explanation is the lack of bank-level covariates in the model. Also, there can be some market segmentation, with banks targeting different regions and types of consumers, all of which are absent from the model due to the lack of more granular data.

One characteristic of the previous analysis of this section is that it does not disentangle the effect of demand elasticity and competition. This generates the unintuitive result that the pass-through is higher the more elastic consumers are, when in fact this is driven by fiercer competition. The intuition is that, regardless of the number of firms in the market, when consumers are very elastic the main competitor is the outside good.

One approach to disentangle is to simulate a counterfactual in which the consumers have to choose one of the banks, "shutting down" the outside option, which keeps the competition level constant when demand elasticity varies. However, this procedure rules out any adverse selection, in which the pool of borrowers is worse than the pool of non-borrowers. For this reason, in this counterfactual I focus only on the impact of moral hazard on the pass-through simulations. The results are in Figure 8. Now we get the expected result that when demand is elastic, the pass-through is lower. We also get that for most levels of demand elasticity, the

Figure 5: Simulated average change in default

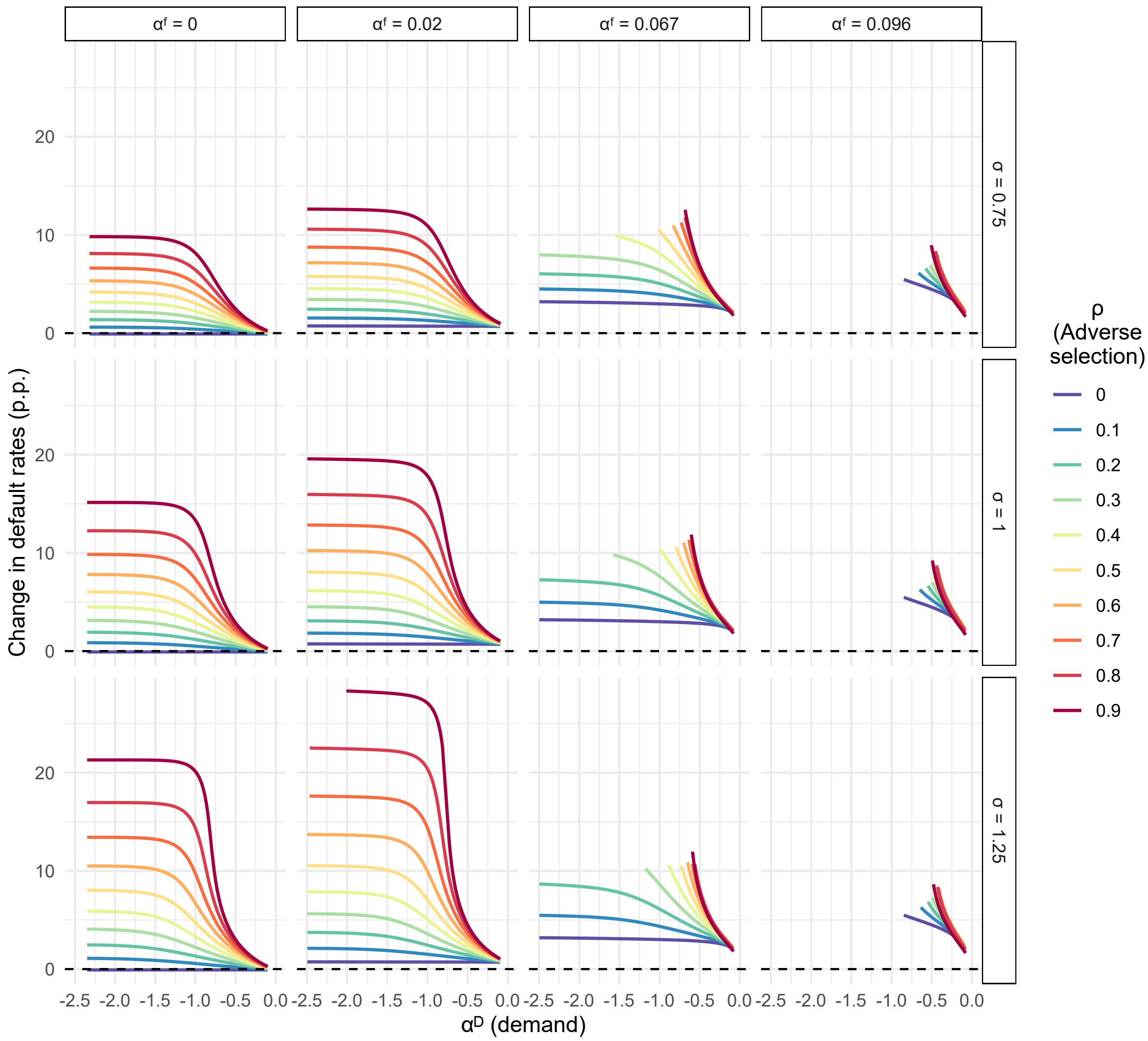


Figure 6: Simulated change in access to car loans

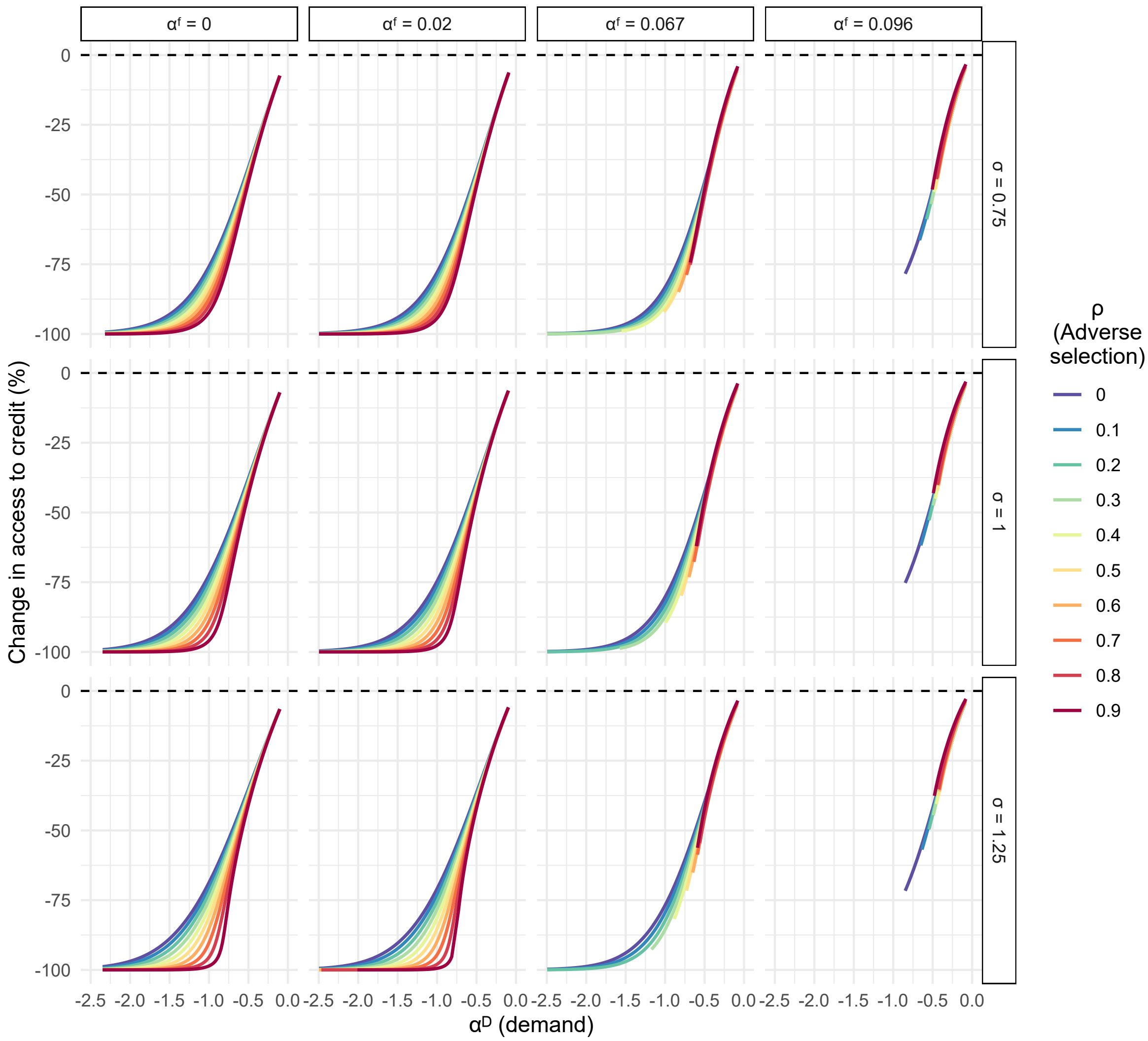
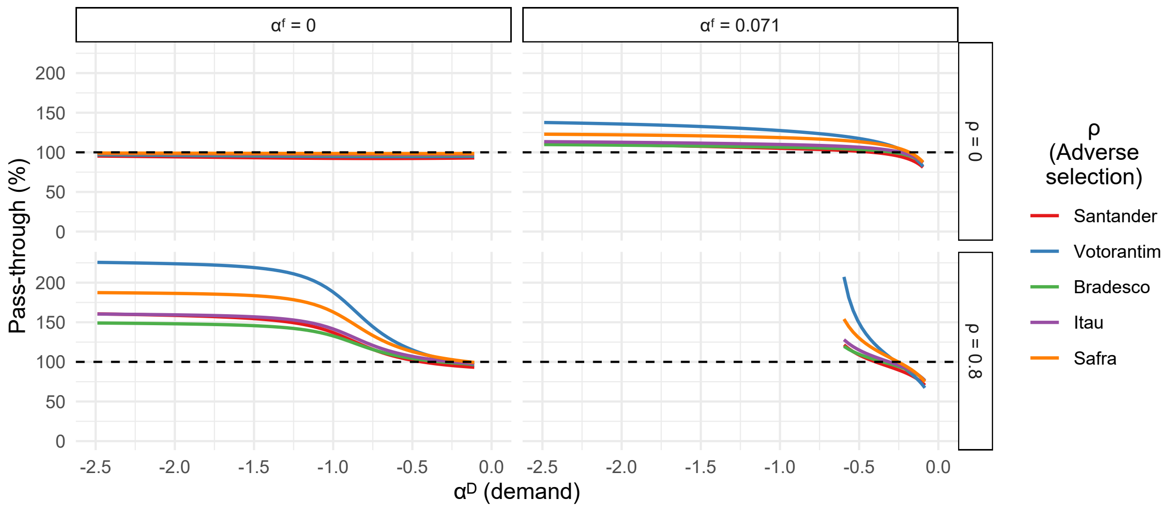


Figure 7: Simulated pass-through per bank after 3% tax



pass-through is increasing on the level of moral hazard. However, when default becomes very elastic, then firms start to bear a greater share of the tax burden.

To account for the impact of both adverse selection and moral hazard, I also simulate what would be the pass-through if the banks in the data were either jointly owned or were fully colluding in both the baseline scenario and the counterfactual. The results are in Figure 9. We can see that, as implied by theory, for all parameter combinations the pass-through is lower under joint ownership than under standard Bertrand-Nash competition.

4 Estimation

The simplified model can be estimated from aggregate data, as it does not include any covariates observed at the borrower level. Conditional on having enough variation in data, it can be estimated using a GMM approach, combining the estimation procedure from Berry, Levinsohn, and Pakes (1995) with additional moments to identify the parameters in the default equation. However, it is to be expected that there is not enough variation in data, as I have only national-level variables, and competition is likely to be on a more local level. For Brazil, previous studies such as Coelho, De Mello, and Rezende (2013) and Sanches, Junior, and Srisuma (2018) have used municipalities, while Crawford, Pavanini, and Schivardi (2018) has defined a market as an administrative region comparable to counties.

Figure 8: Simulated pass-through with fixed competition level

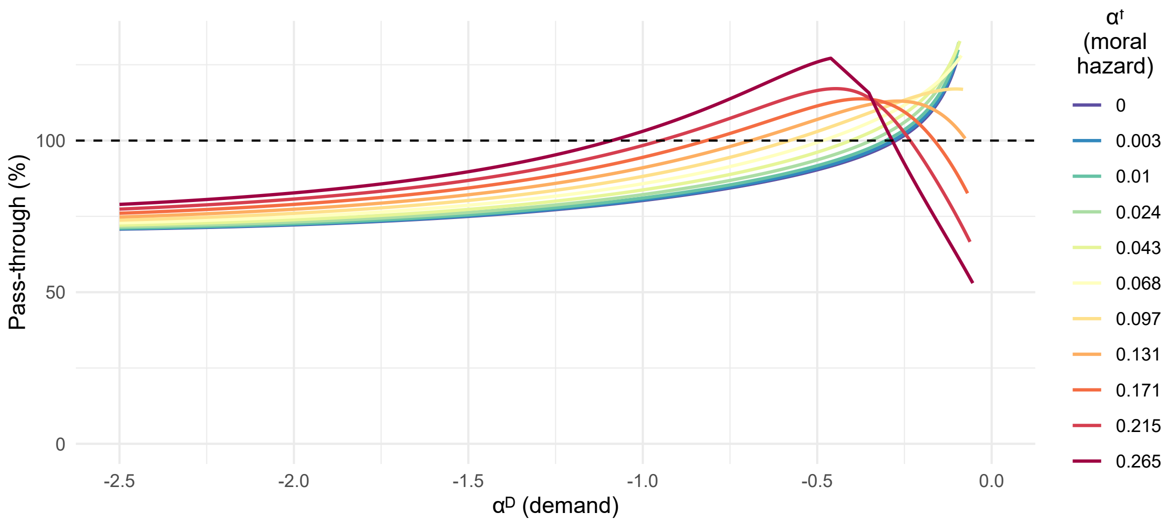


Figure 9: Pass-through estimates with different ownership structures

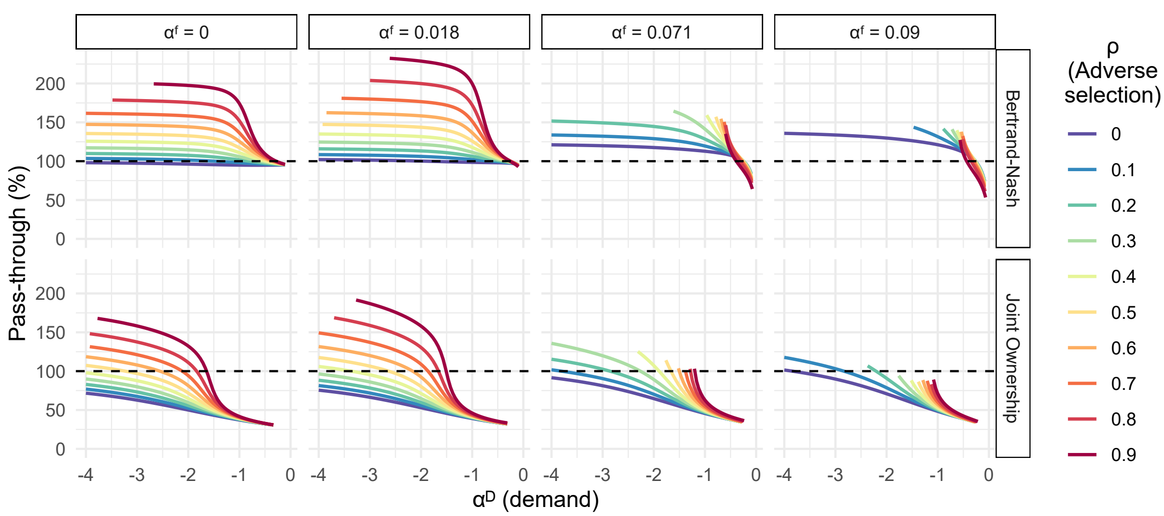


Table 3: Estimation results

Parameter	Estimate
α^D	-0.132
α^F	0.000
ρ	0.875
σ	0.001
δ	-1.443

Putting this concern aside, the main concern in estimation is the endogeneity of interest rates, which are likely to be correlated with the unobserved attributes of each bank, ξ_j. I use as instruments the average interest rates in other types of loans, the federal funds rate and the tax on loans. The first resembles Hausman-instruments, but instead of prices in different regions I use the fact that banks provide other types of loans than car loans[10] While we expect that the federal funds rate affects demand, the implicit assumption I make is that it has an immediate impact on supply and a delayed impact on demand. Finally, the changes in the tax rate on loans affect only the supply and thus it is a standard cost-shifter. The market size is defined as 50% greater than the maximum observed volume of new loans, as in Miller and Weinberg (2017).

The moment conditions are the following:

$$\begin{pmatrix} E[\xi\mathbf{Z}] \\ E[\hat{\mathbf{F}} - \mathbf{F}] \end{pmatrix},$$

where $\hat{\mathbf{F}}$ denotes the probability of default generated by the model.

The results from a 1-step GMM estimation are in Table 3. A 2-step estimation was attempted, but the weight matrix is singular, which is a symptom of a non-identified model. In particular, it seems that the second moment does not contribute to the estimation, such that the parameters α^F, ρ, σ and δ are fundamentally not identified. Because it seems that this is a matter of lack of data, I did not persist in trying to improve the estimation.[11]

[10]The exception in my sample was the General Motors Bank, which did not offer any other type of loan during most of the sample. However, its market share was only 1.5%, so I opted to exclude it from the sample.

[11]When I have access to loan-level data from the Central Bank of Brazil the estimation approach will also change, as then I would be able to use Simulated Maximum Likelihood, as in Crawford, Pavanini, and Schivardi (2018).

5 Final remarks

In this paper I analyze how asymmetric information can impact pass-throughs. I show that a tax on loans in Brazil is associated with only a mild increase in interest rates, implying that banks are taking a significant part of the tax burden.

I develop a model allowing for adverse selection, moral hazard and imperfect competition, and show that, despite its simplicity, it can account for a wide range of pass-throughs. I show that when demand elasticity is high and competition resembles perfect competition, asymmetric information leads to pass-throughs greater than one. Contrarily, when demand is inelastic and banks have high market power, under adverse selection and moral hazard the tax burden is shared with the banks. I also attempt to estimate the model using aggregate data, but there is not enough variation to identify the parameters.

As topics for further research, one could think of using random coefficients in the price sensitivity coefficient, instead of on the intercept. This might generate extra flexibility for predicting lower pass-throughs, which in the current specification are reached only under high levels of default elasticity. Another topic that could be explored further is understanding what generates different pass-throughs across banks, and how could the model better take this into account. Endogenizing loan size and accounting for car repossession are also avenues to be examined. Most of all, more granular data is required to have a better grasp of the market and to allow for proper estimation of the model.

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