3The Effect of Interest Rate on Borrower Performance: Disentangling Moral Hazard from Adverse Selection

3.1.Introduction

Since the seminal work of Stiglitz and Weiss (1981), the field of information economics has made remarkable progress in clarifying the role of asymmetric information in the functioning of credit markets. It is by now better understood how moral hazard and adverse selection can, even in a perfectly competitive market, result in credit rationing.

However, empirical studies have lagged behind the burgeoning theoretical literature on the subject. This is so simply because it is often too difficult to separately quantify the effects of adverse selection and moral hazard, since both lead to an observed positive correlation between loan size and default. For instance, adverse selection arises when there is unobserved heterogeneity in the pool of potential borrowers and endogenous matching of borrowers to contracts. More specifically, high risk individuals are more willing to take on higher loans since they are less likely to incur in repayment costs. In turn, moral hazard occurs because individuals who have a higher debt burden are more likely either to renege on their loans or to become unable to honor it after the realization of a negative shock.

In this paper, we use micro-level data from one of the largest banks in Brazil to study the functioning of a particular market for consumer credit, that for auto loans. We estimate that an increase in 0.1% in the interest rate charged leads to an average increase in 2.3%% in the probability of default. We find evidence that adverse selection is not statistically significant. This effect is mostly due to moral hazard.

Our identification strategy has two stages. First, we explore a quasi-experimental source of variation in the interest rate offered by the bank for loans generated in different dealerships. More specifically, the bank grants a subset of its registered dealers priority status, and we argue that assignment is random once we control for all the observable characteristics. According to the bank's policy, a priority dealer may offer loans with lower interest rates to its clients. We find that, on average, a client of a priority dealer receives a discount of 0.17% in the monthly contracted interest rate when compared to a client of a non priority dealer. Using this quasi-experiment, we estimate the effect of an increase in the interest rate on borrower delinquency rate.

Yet this is not the end of the story, since it is impossible to control for adverse selec- tion effects by simply randomizing contract offers. After all, in the presence of endogenous selection of contracts, one might expect that, even after controlling for all observable client characteristics, the pool of clients who accept the contract charging higher interest rates is of inferior unobservable characteristics when compared to the pool of customers who buy a car under more favorable terms.

To circumvent this problem and determine the extent of adverse selection, we estimate the probability of default of both pools of borrowers - those contracting at priority and non priority dealers - in other loan modality with the same bank that are contracted upon equal terms. As both pools receive the same menu of contract in personal credit, if adverse selection is still an issue, borrowers from "dealer priority pool" would perform better. Through this second stage of our identification strategy, we find no statistically significant difference in the likelihood of default among both pool of borrowers in personal credit. This result points to the absence of unobserved heterogeneity in the pool of borrowers, and allows us to conclude that an increase in the interest rate leads to a higher delinquency rates. This effect is mostly due to moral hazard.

Our paper relates to the recent empirical literature in information economics that sepa- rates moral hazard from adverse selection. Ausubel (1999), Karlan and Zinman (2009), and Adams, Einav, and Levin (2009) analyze consumer credit markets. Ausubel (1999) finds that credit rationing results from adverse selection. In turn, Finkelstein and Poterba (2002) analyze annuities and Finkelstein and McGarry (2006) insurance markets.

The rest of the paper is organized as follow. In section 2, we briefly describe the insti- tutional background and the data. In section 3, we discuss the methodology. Then, results are shown is section 4. In section 5, we have the conclusion.

3.2.Institutional Background and data

Institutional Background

We briefly describe the auto industry pointing out its relevant for the Brazilian economy. Nowadays, this industry is responsible – direct and indirect – for 22% of the total industry GDP. The total car production has been growing since 2003 (before our sample starts), when the yearly production was 1.9 million. In 2005, the last year of our sample, the yearly production was 2.5 million – an increase of almost 40%. The total credit supplied is also representative and grew during the sample period. It was R$ 30.6 billion (US$ 10.9 billion) and R$ 50.6 billion (US$ 17.9 billion) at the beginning and ending of our sample period respectively, showing an increase of 66%.

We, now, describe the interaction between potential customers, auto dealers, and The Bank in this market. When buying a car, a customer can request through the auto dealer that a bank finance the acquisition. More specifically, the customer fills out a loan application that is subsequently submitted for the bank's appraisal. If The Bank approves the customer's request, the bank is entirely liable for the loan, which is always collateralize by the car. An auto dealer can intermediate credit to its customers only if it has previously registered with the bank. In 2003, the bank had over one thousand registered auto dealers.

The bank resets lending policy whenever it finds it appropriate, which in practice is quite often. Our contact at the bank informed us that lending policy often vary on a weekly basis, in response to changes in the bank's economic environment. When re-setting policy, The Bank responds to microeconomic (funding conditions, competition within the auto loan market), and macroeconomic conditions (aggregate default levels, unemployment, interest rate and so forth) as well.

A borrower is considered in default if he does not pay three consecutive monthly install- ments. A bank informs both the Central Bank of Brazil and the country's largest credit agency, Serasa, of all customers in default. The bank may then either attempt to renegotiate the loan or trigger the repossession process.

Finally, we describe how the bank classifies its registered dealers. The classification process involves two steps. First, The Bank evaluates the performance of borrowers who had taken a loan with each dealer in the previous periods. Indeed, The Bank gives each dealer a grade from the set G = {A+, A, A−, B+, B, C, C −, D+, D, D−, E} based on the proportion of borrowers who had taken a loan from this dealer in the past and had default. Higher proportion of "defaulter" borrowers, worsen the grade of the dealer. Then, dealers that receive a grade of B+ or higher are classified as priority dealers. Remaining dealers are non priority. Priority dealers are able to offer loans with lower interest rates to its clients.

Data

We use proprietary data from one of the three largest Brazilian private banks in terms of total assets.[1] The bank is also a major player in the auto loans market, with more than 15% of national market share in 2003. Our data set consists of a random and balanced sample of 15, 610 loan contracts signed between 2004 and 2005, that contains contract level detailed information on contract terms (interest rate, maturity and total due) and borrower characteristics (income, marital status, risk classification, type of job, type of residence, gender, presence of a guarantor and whether or not the customer is a bank client) and car characteristics (car value and whether or not the car is new).

Table 1 panel A displays summary statistics for contract terms. The average interest rate charged is 2.43% per month, which is high. Loan maturity is on average slightly above three years (37.9 months), with a significant fraction of the contracts having maturity of between 1.5 and 5 years. The average car value at the time of the signing of the contract is R$ 17,229.9 (US$ 6.109,9), and the average down payment is R$ 6,706.6 (US$ 2,378.2). Average monthly installments are R$ 452.6 (US$ 160,5) and the average default rate is 9%.[2]

Panel B shows summary statistics for borrowers' personal characteristics. The largestfraction of the borrowers are considered low risk (72%), with a significant part classified as medium risk (25%). Only a small fraction of borrowers are considered high risk (3%). Average monthly income is R$ 2,408 (US$ 854). Home owners represent 82% of the sample of borrowers, while 13% still live with their parents. Furthermore, 66% are male; 43% are married and 41% are single. Regarding their occupation, 58% work for a third party (firm) whereas 29% declared to be self-employed/entrepreneurs. Of the total pool of borrowers, 24% consist of bank clients; and 26% bought a new car. Contracts that were guaranteed by a third party represent only 7% of the sample.

We take advantage of our unique data set by augmenting the data on car loans with information on personal loans. The Bank provided us with a sample of 1,754 contracts of personal loans signed with borrowers that are in our original auto loan sample and have also taken a personal loan before December 2005. Panel C presents summary statistics. Most notably different, the average monthly interest rate is 3.5% and the maturity is 13.3 months. Also, the average of total due and installment value are R$ 3,383 and R$ 389 respectively.

3.3.Methodology

This section is divided into three parts. In the first part, we present a simple credit market model that, despite being quite standard, will help clarify the arguments behind our iden- tification strategy. In the second part, we relate the theoretical model to patterns observed in the data, specifying how selection bias naturally emerges in the current environment. Fi- nally, in the third part of this section, we explain how our identification strategy corrects for selection bias, and allows us to estimate the parameters of interest.

A Simple Model of Loan Origination and Repayment

We assume that there is a unique dealership, with a continuum of mass one of potential customers. Each customer is fully characterized by a vector of consumer characteristics given by θ.[3] Let F be the distribution function of θ in the population. Contratual terms are determined by the bank and fully characterized by the parameter vector γ, whose entries represent the relevant dimensions of the contract.

A customer of type θ derives expected utility of $U(\theta, \gamma)$, when accepting a contract of type γ. The term $U(\theta, \gamma)$ depends on all future contingencies, such as potential default, contract renegotiation, or full loan repayment. A customer of type θ derives an outside utility of $\bar{U}(\theta)$ if he does not accept the contractual terms offered and leaves the dealership without buying a car.

By setting contract terms γ, the bank implicitly defines its pool of borrowers. This pool is composed of the potential customers who self select into the contract by closing a deal at the terms offered. Mathematically, the borrower pool is given by

$$Q(\gamma) \equiv \int 1_{\{U(\theta,\gamma) \geq \bar{U}(\theta)\}} dF(\theta) = \Pr\{U(\theta,\gamma) \geq \bar{U}(\theta)\}$$

where $1_{\Delta}(\cdot)$ is the indicator function of the set Δ. Equation (1) specifies aggregate consumer demand for loans as a function of contractual terms offered. We assume that underlying primitives guarantee that $Q(\gamma)$ is continuous and differentiable.

In anticipation of our identification strategy, it is useful to determine the average default of the pool of borrowers. Let $p = p(\theta, \gamma)$ be the probability that a customer of type θ defaults on his loan after signing a contract γ. The dependence of p on γ captures the presence of moral hazard in the bank-customer relationship.

Average non-performing loans are:

$$L(\gamma) = \frac{1}{Q(\gamma)} \int p(\theta, \gamma)\, 1_{\{U(\theta,\gamma) \geq \bar{U}(\theta)\}} dF(\theta) = E[p(\theta, \gamma) \mid U(\theta,\gamma) \geq \bar{U}(\theta)] \quad (2)$$

The above expression averages default rates over customers who close a deal at a dealership. The marginal default is

$E[p(\theta, \gamma) | U(\theta, \gamma) \geq \overline{U}(\theta)]$ (3)

Differentiation of $L(\gamma)$ with respect to γ, yields:[4]

$\frac{\partial L}{\partial \gamma} = E[\frac{\partial p(\theta,\gamma)}{\partial \gamma} | U(\theta, \gamma) \geq \overline{U}(\theta)] - \frac{\partial Q'(\gamma)}{\partial Q(\gamma)} (E[p(\theta, \gamma) | U(\theta, \gamma) \geq \overline{U}] - E[p(\theta, \gamma) | U(\theta, \gamma) = \overline{U}(\theta)])$ (4)

The first term on the right-hand side of Equation (4) represents the change in default behavior of the infra-marginal customers at the new contractual terms offered. It represents the effect of moral hazard.

The second term on the right-hand side of Equation (4) represents variation in average default due to changes in the pool of customers self-selecting into the contract offered by the bank. The key feature of adverse selection is that the individuals who have the highest willingness to close a deal are precisely those who, in expectation, have the highest probability of defaulting on their loans. Therefore, we expect that, the term inside the parenthesis is positive. For example, assume that γ represents the interest charged by the bank. As γ increases the pool of customers closing a deal shrinks, and the more creditworthy customer are precisely the ones being screened out.

It is instructive to interpret $L(\gamma)$ as a proxy for the bank's costs when offering contractual terms γ to its potential customers. As is standard in models with selection, costs are not only determined by total quantities and technological features of the production technology, but also by the composition of the pool of clients that choose to contract with the bank. As a result, costs and prices are endogenous.

Finally, the bank anticipates repayment behavior on the part of its customers, and sets contract terms accordingly. Therefore, we have the following loan offer curve

$$\gamma = \gamma(L, \xi), \quad (5)$$

where ξ is a vector of macro and micro-economic shocks that affect the bank's s profitability in the auto-loan market. Equations (1) and (5) are simultaneously determined, therefore, so are equations (2) and (5).

Moral Hazard and Adverse Selection

With the theoretical model as a guide, it is useful to be clear about how adverse selection and moral hazard manifest itself in the data.[5] We claim that there is adverse selection if the pool of consumers who sign an auto loan contract at a non priority dealer exhibits inferior characteristics when compared to the pool of consumers that sign a contract at a priority dealer. Under adverse selection, asymmetry of information is already present at the time the contract is signed.

We use the term Moral Hazard in a broad sense to describe a situation where an increase in the amount due by an individual increases the likelihood that he default on his loan. Our definition of Moral Hazard not only covers the case where there is potential ex-post asymmetry of information, so that actions on the part of individuals have a direct impact on the likelihood of repayment, but also situations where individuals have little influence over the environment. Disentangling these two channels - strategic versus non-strategic defaults - through which Moral Hazard operates would be very interesting, but it is beyond the scope of the article. We restrict our self with establishing the average causal effect of loan size on default.

Using the standard notation of potential outcomes, the following decomposition is straight- forward:

$$E[d_i \mid i \in c_n] - E[d_i \mid i \in c_p] = \{E[d_i \mid i \in c_p , \gamma_n] - E[d_i \mid i \in c_p , \gamma_p]\} + \{E[d_i \mid i \in c_n , \gamma_n] - E[d_i \mid i \in c_p , \gamma_n]\} \quad (6)$$

where γ_p and γ_n are contractual terms offered at priority and non-priority dealers respectively. It is easy to see that the first term of the right side of the equation is the moral hazard effect and the second term is adverse selection effect.

If we refer to the pool of customers signing an auto loan contract at a non priority dealer as the population being treated, then it can be readily seen from the above decomposition that adverse selection is simply the selection bias that arises when treatment and potential outcomes are correlated. In what follows, we will often refer to the customers of non priority dealers as the treatment group and to customers of priority dealers as the control group.

It must be noted that random assignment of contract offers does not solve selection problems, since acceptance of an offered contract is a customer's choice variable. Therefore, one might expect that, even after controlling for all observable borrower characteristics, the pool of consumers who accept the contract charging higher interest rates is of inferior unobservable characteristics when compared to the pool of customers who buy a car under more favorable terms.

Nevertheless, there is still some hope in uncovering the causal relationship of an increase in interest rates on the likelihood of default. After all, we can measure adverse selection, given by the second term on the right-hand side of the equation (6), if we are able to offer the same contractual terms to both the treatment and control groups, and then compute the difference in their repayment behavior.

Identification Strategy

We adopt a two stage identification strategy. First in section 4.1, we estimate the combined effect: moral hazard as well as adverse selection. At this initial stage, we ignore the potential selection bias that still persists with the randomization of contract offers, and estimate the observed difference in default, the left-hand side of equation (6) using exogenous variation of the auto loan offer curve. To do so, we have to deal with the problem of simultaneous determination of observed prices and quantities. We estimate $L(\gamma)$, an object intimately related to the demand for consumer loans, by exploring quasi-experimental variation in the supply of contractual terms offered. This is similar to the traditional approach in using exogenous price variation to trace out the demand curve.

We do the second stage of our identification strategy in the section 4.2, where we try to disentangle both effects. Indeed, we try to measure the second term in the right-hand side of equation (6), given by $E[d_i|i \in c_n, \gamma] - E[d_i|i \in c_p, \gamma]$. The idea is to measure the extent of selection bias that persists even after randomization of contract offers. If there is in fact adverse selection into contracts, then borrowers from a non priority dealer should have a higher likelihood of default than borrowers from a priority dealer. The second term in the right-hand side of Equation (6) suggests that we can obtain a reliable measure of selection bias if we were able to offer the same contractual terms to both pools of borrowers, and then compare their observed repayment behavior.

We take advantage of our unique data set and compare the delinquency rate in both pool of borrower in a different credit modality, that for personal loan. The second stage of our identification strategy hinges on the assumption that selection bias is constant over contractual terms. More specifically, we assume

$$E[d_i|i \in c_n, \gamma] - E[d_i|i \in c_p, \gamma] = E[d_i|i \in c_n, \gamma'] - E[d_i|i \in c_p, \gamma'], \quad (7)$$

for any pair (γ, γ') of contractual terms offered. We are particularly interested in the case where γ is an auto loan and γ' is a personal loan.

Before we continue, we do a battery of exercise in order to validate dealer priority as our exogenous source of variation. Two conditions must be satisfied and we discuss each of them in turn. First, the variable dealer priority must affect the contracted interest rate, even after controlling for contract terms as well as personal and car characteristics. In Table 2, we report the relationship between contracted interest rates and auto dealers' priority status. In panel A column 1, we first regress interest rate on the dummy variable priority dealer. We find that the average monthly interest rate of a contract originated in a priority dealer is 0.45% lower than in a non priority dealer, and the result is significant at 1% level. In panels B and C, we run the same regression after adding respectively personal and car characteristics and contract terms as explanatory variables. Despite the attenuation of the effect of priority dealer on interest rate, the coefficient of interest remains negative and significant under both specifications. Thus, we are confident that the inclusion condition holds.

We now discuss the validity of the exclusion restriction, the second condition that must be met for our identification strategy to be valid. The exclusion restriction implied by our instrumental variable regression is that, conditional on the controls included in the regression, the classification of a dealer as priority or non priority has no effect on default, other than through the interest rate. The validity of our instrument is questionable if unobservable factors correlated with dealer classification affect repayment behavior.

But we believe that this is unlikely. First, we observe all the information that The Bank uses when defining the priority status of a particular auto dealer. Therefore, after controlling for all observable characteristics, priority status assignment can be considered to be random. To further substantiate this claim, we perform a battery of tests, running regressions of maturity, total due, down payment and car value as dependent variables on all observable variables - contract terms as well as personal and car characteristics. As panel A shows, contracts originated in priority dealers present better terms. Nevertheless, the difference narrows (or even desappears) once we control for personal and car characteristics (Panel B), and finally disappears when we properly control for contract terms as well (Panel C).

There is a second concern with the exclusion restriction. Dealers may screen potential borrowers based on soft information that are available for them (dealers and The Bank), but are unobservable to the econometrician. If this were the case, we would expect that on average consumers from priority dealers receive better contract terms when borrowing through a personal loan as well. To address this potential concern, we run the following regression:

$$\text{loan characteristic}_i = \alpha \times \text{dealer priority}_i + T_i\lambda + b_i\psi + \eta \quad (8)$$

Where T is a vector of contract terms that includes interest rate, maturity, total due, and installment value; b is a vector of controls containing information about borrower char- acteristics that includes income, marital status, type of risk, type of job, type of residence, gender, presence or not of a guarantor and a dummy variable that equals 1 if the customer is a bank client, and 0 otherwise. Standard errors are clustered at the dealer priority level. Our parameter of interest is α, which measures whether consumers who bought a car through dealer priority experiment better contract terms in personal credit or not. If α is insignificant, the fact that the consumers have financed his car through a dealer priority is not relevant in determining contract terms in personal credit. On the other hand, if α is nega- tive it means that dealer priority carries unobservable characteristics for the econometrician about the borrower type of risk.

We report results in Table 3, in odd columns we regress without controls and in even columns we regress with all controls. In column one, α is negative and significant, suggesting that, unconditional, dealer priority variable carries information about borrower type of risk. However, in column 2, α is much smaller and no longer significant. Thus, after properly controlling for contract terms as well as personal characteristics, the dummy dealer priority does not carry information about borrower type of risk. In addition, we do the same exercise for maturity and total due in columns 3 to 6. As we can see, we have similar results.

There is one important caveat. A personal credit contract is quite different from an auto loan contract. First, personal credit is uncollateralized. Second, while the money received through an auto loan is automatically used to finance the acquisition of a vehicle, the proceeds from a personal loan are used at the discretion of the debtor. Finally, personal credit is not intermediated by a third party, but is contracted directly between the bank and its customer.

3.4.Results

3.4.1.The Aggregate Effect of Interest Rate on Default

We estimate a Probit model of the following equation:

$$\text{default}_i = \beta \times \text{interest rate}_i + T_i\lambda + b_i\psi + c_i\theta + \varepsilon_i, \quad (9)$$

We control for contract terms, borrowers characteristics as well as car characteristics. The variables default and interest rate and the vectors T and b are defined as previously. The vector c contains information about car value and whether the car is new or not. Standard errors are clustered at the dealer priority level. Our parameter of interest is β, which measures the total effect of interest rate on the probability of default. Table 4 presets the results.

The coefficient is always positive and significant at 1 percent level indicating that a higher interest rate is associate with a higher probability of default. In the first column we run a probit and the average marginal effect of the interest rate on default is 0.124. In second column, we have our preferable estimation, we instrumentalized interest rate using dealer priority. As we can use, the average marginal effect is about 10% higher and still significant. After properly controlling for contract term, personal and car characteristics, interest rate 0.1% higher per month (1% higher per year) have a delinquency probability that is 2.3% higher (1.9% higher). The magnitude of the effect is similar to Ausubel

(1999), who estimates that an interest rate 1% higher per year leads to a delinquency rate 1.2% higher.

A concern about the results regards the way The Bank define dealer priority. As we mentioned in section 3, The Bank gives a grade to each dealer based on the performance from borrowers who had taken a loan from this dealer in the past. Even after controlling for contract terms, personal characteristics as well as car characteristics, its possible that the dummy dealer priority carries information that are correlated with borrower performance. Ideally to tackle this problem, we should add a variable controlling for the performance of all borrowers from each dealer in the past years.

Unfortunately, we do not have information linking each borrower to each dealer. Never- theless, we have information linking each borrower to the category of the dealer which he has taken the loan. For instance, we do not know from which dealer "Bruno" has taken his loan.

But we know that the dealer from where he has taken the loan is classified as B+. Then, we create the variable def_{t-1}, which measures the aggregate borrowers performance in the past from each dealer category. This variable is defined as the proportion of borrowers who had had taken a loan between June of 2003 and December of 2003 from each dealer category andhad default[6]. Thus, all dealers from category "X " have the same number for def_{t-1}.

Back to table 4, in column 3 we run the same regression as column 2, but adding def_{t-1} as an independent variable. The average marginal effect of interest rate on default is 0.241, which is very similar to column 2. Thus, we can be confident that the way The Bank is classifying dealers is not biasing our preferable estimation.

3.4.2. Disentangling Moral Hazard from Adverse Selection

The aim of this section is to disentangle moral hazard from adverse selection. In section 4.1, we calculate the right hand side of the equation (6) and conclude that an increase of 0.1% in the monthly interest rate is associate, on average, with a probability of default 2.3% higher. Now, we estimate the adverse selection component, given by $E[d_i | i \in c_n, \gamma] - E[d_i | i \in c_p, \gamma]$.

Ideally, we would evaluate in a comparative way the delinquency rate in the car loan market from a pool of borrower in a dealer priority and in a dealer not priority offering for all borrowers the same menu of contracts. Unfortunately, we can not do this experiment. Nevertheless, we take advantage of our unique data set and evaluate the above expression in personal credit.

As we documented in table 3, after controlling for contract terms and personal charac- teristics, the same menu of contracts is offered to all borrowers in personal credit regardless if the borrower has bought his car in a dealer priority. In terms of above expression, γ is constant, which is a necessary condition. Thus, assuming that equation (7) is valid, we are able to assess the size of the adverse selection by estimating the following equation using data from personal loan:

$$\text{default}_i = \alpha \times \text{dealer priority}_i + T_i\lambda + b_i\psi + \varepsilon_i \quad (10)$$

Where the variables default and dealer priority and the vectors T and b are defined as previously. We are interested in the coefficient α. If α is insignificant, it means that borrowers from dealer priority and not priority have the same delinquency rate when faced equal contract terms and, thus, the adverse selection in equation (6) is statistically insignificant. If α is negative, after controlling for contract term and personal characteristics, the dummy dealer priority still carries information about borrower type of risk.

The adverse selection effect in equation (6) would be positive. Table 5 shows the result.

In first column, we have our estimation without controls points to an estimate of α that is negative and significant, which suggests some level of heterogeneity in default behavior among borrowers according to dealer status. Nevertheless once we properly control, it can be seen in second column that α_2 becomes statistically indistinguishable from zero. Therefore, we attribute the difference in riskiness among treatment and control group entirely to observable characteristics. [7]

In sum, in terms of equation (6), in section 4.1 we estimate the left hand side, which is the sum of the effects of moral hazard and adverse selection. An increase in 0.1% in the monthly interest rate leads to probability of default 2.3% higher. In this section, we assess the size of adverse selection effect. As table 5 shows, this effect is statistically insignificant. Therefore, we claim that the result we find in section 4.1 is mostly due to moral hazard.

3.4.3.Robustness test

As a robustness check, we re-run every regression using the proportion of installments paid by the borrower as the dependent variable, as opposed to a default dummy. We do this in order to address potential criticisms that previous result may be driven by the fact that a binary default variable does not make any distinction between borrowers with different amounts of “skin in the game” at the time of their default. For example, by using a default dummy, we treat borrowers who paid every installment except the last one in exactly the same manner as those who did not pay any installments at all. All results are qualitative the same once we use proportion of installments paid.[8]

3.5.Conclusion

Using contract level information from a unique data set provided by one of the most im- portant players in the auto loans market in Brazil, we estimate that an increase of 0.1% in the monthly interest rate is associated with an increase in the probability of default of 2.3%. This effect is mostly due to Moral Hazard. On the other hand, we find evidence that adverse selection on unobservable is statistically insignificant. Our findings provide support for credit rationing based on informational considerations, since an increase in the interest rate charged on a loan contract leads to a higher default rate.

Table 19

Table 1:
Summary Statistics
This table provides descriptive statistics for the variables used in the empirical analysis.

	Mean	5th Percentile	Median	95th Percentile	Standard Deviation
Interest rate	2.43	1.58	2.39	3.64	0.70
Maturity	37.9	18.0	36.0	60.0	11.7
Down payment	6,707	1,374	4,222	17,204	27,398
Total due (R$)	16,905	5,439	14,790	34,799	9,892
Installment Value	453	205	387	901	262
Car value (R$)	17,230	6,651	15,169	32,490	28,137
Default	0.09	0.0	0.0	1.0	0.29

Panel B: Borrower characteristics

	Mean	5th Percentile	Median	95th Percentile	Standard Deviation
Income (R$)	[illegible]	701	1	5,533	9,746
Client of the bank		0.0		1.0	0.42
Guarantor		0.0		1.0	0.26
High risk		0.0		0.0	0.19
Medium risk		0.0		1.0	0.43
Low risk		0.0		1.0	0.45
Male		0.0		1.0	0.47
Single		0.0		1.0	0.49
Married		0.0		1.0	0.50
Homeowner		0.0		1.0	0.39
Lives with parents		0.0		1.0	0.34
Employee		0.0		1.0	0.49
Retired/pensioner		0.0		1.0	0.30
Self-		0.0		1.0	0.45

Panel C: Car characteristics

	Mean	5th Percentile	Median	95th Percentile	Standard Deviation
New	0.43	0.0	0.0	1.0	0.43
Dealer priority	0.81	0.0	1.0	1.0	0.39

Table 20

Table 2:

The Effect of Dealer Priority on Contract Terms

This table reports results from regressing loan characteristics on dealer priority. We use five measures of loan characteristics: interest rate, loan maturity, total due, car value, and default. All regressions include an intercept. In Panel A, we do not use controls. In Panel B, we control for borrower characteristics (income, borrower type of risk, gender, presence of a guarantor, type of job, type of residence, marital status, and whether the borrower is a client of The Bank), and car characteristics (a dummy for new car, and car value). Standard errors are calculated by clustering at dealer priority level. Variables definitions are provided in the Appendix. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A:
No Controls

Dependent Variable=	interest rate	maturity	log(total due)	log(car value)	default
Dealer Priority	-0.454***	1.451***	0.222***	0.297***	0.064***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Contract terms	No	No	No	No	No
Personal characteristics	No	No	No	No	No
Car characteristics	No	No	No	No	No
Observations	16,610	16,610	16,610	16,610	16,610
Adjusted R^2	0.065	0.002	0.023	0.057	0.007

Panel B: All Controls, Except for Contract Terms

Dependent Variable=	interest rate	maturity	log(total due)	log(car value)	default
Law	-0.127***	0.806	0.015	0.978**	-0.029
	(0.007)	(0.219)	(0.006)	(0.007)	(0.001)
Contract terms	No	No	No	No	No
Personal characteristics	Yes	Yes	Yes	Yes	Yes
Car characteristics	Yes	Yes	Yes	Yes	Yes
Observations	16,610	16,610	16,610	16,610	16,610
Adjusted R^2	0.361	0.035	0.287	0.483	0.044

Table 2- cont'd

The Effect of Dealer Priority on Contract Terms

This table reports results from regressing loan characteristics on dealer priority. We use five measures of loan characteristics: interest rate, loan maturity, total due, car value, and default. All regressions include an intercept. In Panel C, we control for contract terms (interest rate, maturity, total due, and installment value), borrower characteristics (income, borrower type of risk, gender, presence of a guarantor, type of job, type of residence, marital status, and whether the borrower is a client of The Bank), and car characteristics (a dummy for new car, and car value). Standard errors are calculated by clustering at dealer priority level. Variables definitions are provided in the Appendix. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel C: All Controls

Dependent Variable=	interest rate	maturity	log(total due)	log(car value)	default
Dealer Priority	-0.119***	0.104	0.002	0.021	0.029**
	(0.007)	(0.025)	(0.002)	(0.010)	(0.001)
Contract terms	Yes	Yes	Yes	Yes	Yes
Personal characteristics	Yes	Yes	Yes	Yes	Yes
Car characteristics	Yes	Yes	Yes	Yes	Yes
Observations	16,610	16,610	16,610	16,610	16,610
Adjusted R^2	0.065	0.002	0.023	0.057	0.007

Table 21

Table 3:
The effect of dealer priority on contract terms - personal credit

This table reports results from regressing loan characteristics on dealer priority. We use three measures of loan characteristics: spread, loan maturity and total due. All regressions include an intercept. In odd columns, we do not control. In even columns, we control for contrac terms (interest rate, maturity, installment value and total due), and borrower characteristics (income, borrower type of risk, gender, presence of a guarantor, type of job, type of residence, marital status, and whether the borrower is a client of The Bank). Standard errors are calculated by clustering at dealer priority level. Variables definitions are provided in the Appendix. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable=	interest rate	interest rate	maturity	maturity	Log (total due)	Log (total due)
Dealer Priority	-0.118***	-0.001	0.321***	0.104	0.049***	0.009
	(0.001)	(0.006)	(0.001)	(0.023)	(0.001)	(0.006)
Contract terms	No	Yes	No	Yes	No	Yes
Personal characteristics	No	Yes	No	Yes	No	Yes
Car characteristics	No	Yes	No	Yes	No	Yes
Observations	16,610	16,610	16,610	16,610	16,610	16,610
Adjusted R^2	0.065	0.002	0.023	0.057	0.031	0.007

Table 22

Table 4:

The Effect of Interest Rate on Default - Car Loan

This table reports results from regressing default on interest rate. Our instrument is dealer priority. All regressions include an intercept. The regressions control for contract terms (spread, maturity, installment value and total due), borrower characteristics (income, borrower type of risk, gender, presence of a guarantor, type of job, type of residence, marital status, and whether the borrower is a client of The Bank), and car characteristics (a dummy for new car, car age, and dealer priority). Standard errors are calculated by clustering at dealer priority. We estimated using a probit. Variables definitions are provided in the Appendix. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable=	default probit	default ivprobit	default ivprobit
Interest rate	0.890***	1.472***	1.506***
	(0.024)	(0.050)	(0.026)
Average marginal effect (dy/dx)	0.124***	0.233***	0.241***
	(0.002)	(0.017)	(0.012)
Contract terms	Yes	Yes	Yes
Personal characteristics	Yes	Yes	Yes
Car characteristics	Yes	Yes	Yes
Dealer previous performance	No	No	Yes
Observations	17,349	17,349	17,349
Adjusted R^2	0.357	0.058	0.071

Table 23

Table 5:

The Effect of Dealer Priority on Default - Personal Credit

This table reports results from regressing default on dealer priority. All regressions include an intercept. The regressions control for contract terms (spread, maturity, installment value and total due), and borrower characteristics (income, borrower type of risk, gender, presence of a guarantor, type of job, type of residence, marital status, and whether the borrower is a client of The Bank). Standard errors are calculated by clustering at dealer priority. We estimated using a probit. Variables definitions are provided in the Appendix.

***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable=	default probit	default probit
Dealer Priority	0.076***	0.007
	(0.001)	(0.015)
Average marginal effect (dy/dx)	0.013***	0.001
	(0.001)	(0.003)
Contract terms	Yes	Yes
Personal characteristics	Yes	Yes
Car characteristics	Yes	Yes
Dealer previous performance	Yes	Yes
Observations	17,349	17,349
Adjusted R^2	0.357	0.058