

Auto Dealer Loan Intermediation: Consumer Behavior and Competitive Effects[†]

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Abstract

This paper studies the intermediation of auto loans through auto dealers using new and comprehensive data. Lenders give auto dealers discretion to price loans. Our project leverages details of the contracts between lenders and dealers to demonstrate that many consumers are substantially less responsive to finance charges than to vehicle charges. Dealers take this consumer-specific wedge into account when jointly pricing the car and the loan, leading to a form of price discrimination. Whether or not this price discrimination is beneficial or harmful for consumers depends on the nature of the wedge. If it is mostly driven by intertemporal considerations, such as credit constraints, dealer discretion can be welfare-improving. If instead the wedge is not an accurate representation of underlying preferences or constraints, this price discrimination may decrease consumer welfare. The data favors the latter view. In counterfactual exercises we explore what happens to consumer welfare if dealers have no discretion to price loans. We find that the total price for consumers would drop by about \$350.25 on average, leading to an increase in annual consumer surplus of \$1.78 billion.

JEL classification: L13, L62, D90.

Keywords: Auto Loans, Add-On Pricing, Obfuscation, Oligopoly Competition.

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1 Introduction

Goods and services are often bundled with financial products, such as installment loans, deferred-interest financing, extended warranties, and most importantly auto loans. American consumers have more than \$1 trillion in auto debt, making it the third-largest debt market in the United States.¹ Consumers can unbundle vehicles from loans by obtaining financing “directly” from lenders, but more than 80% of auto loans are obtained “indirectly” through dealers as part of the vehicle sales process.² Dealers have considerable discretion to price loans, and so dealers and consumers bargain over both the car price (Ayres and Siegelman, 1995, Goldberg, 1996) and the interest rate on the loan.³ In this project we study how consumer demand responds to these two different prices and quantify the equilibrium implications. We pay particular attention to the institutional arrangements between lenders and dealers that enable this price discrimination.

First we show that consumers are substantially more sensitive to changes in the car price than the loan price. To identify the size of the wedge between buyers’ disutility from an increase in the car price and an equal increase in finance charges of the same amount, we use the contractual incentives facing dealers. To arrange a loan, dealers first request *buy rates* from lenders. The buy rate is in general the lowest interest rate the lender will allow for the loan. After receiving buy rates, dealers choose a lender to provide the loan as well as a markup on the buy rate of the loan. Dealers’ compensation, called *dealer reserve*, typically consists of a flat payment plus a fixed share of the revenue generated by the markup. Our analysis uses new transaction-level administrative data that includes buy rates, markups, and dealer reserve. This data allows us to directly back out the contractual incentives facing dealers, as well as the resulting loan outcomes.

Based on these vertical arrangements between dealers and lenders, the intuition for our approach to estimate the wedge for the disutility of these two different types of expenses is straightforward. Dealers share profits from loan markups with lenders, but keep all profit from vehicle price markups. If consumers treat vehicle and finance charges equally, profit maximization would require that dealers charge the highest possible markup on the car and set the loan markup to zero. Conversely, if consumer utility is sufficiently less responsive to finance charges, then dealers should mark up loans. A dealer’s markup choice therefore reveals information on a consumer’s disutility from the car price relative to the loan price. Since we observe the markup for each contract in our data, we can derive individual-specific estimates of the wedge between buyers’ disutilities.

We find that, on the margin and in equilibrium, consumers behave as if they would pay a dollar more in finance charges to reduce the vehicle price by \$.86. Hence, consumer utility

¹See <https://www.newyorkfed.org/medialibrary/interactives/householdcredit/data/pdf/HHDC.2018Q1.pdf>.

²We estimate this number in Appendix B.1. See also Davis (2012).

³Consumers and dealers also typically negotiate over other terms of the deal, including vehicle add-ons and the price of a trade-in vehicle.

is substantially more responsive to the vehicle price than the loan price. We also derive a lower bound of \$380 for the difference between actual finance charges and finance charges consumers appear to perceive. Since these measures are obtained for each consumer separately (i.e. non-parametrically), we can study the population heterogeneity in responsiveness to finance charges. We find that consumers with lower incomes, as well as consumers who live in areas with lower education levels and slower internet access, have the most attenuated response to an increase in the loan price.

We consider a number of explanations for these results, including intertemporal discounting and credit constraints, vehicle taxes, loan prepayment, and repeated dealer-lender interactions. These explanations can either qualitatively or quantitatively not account for our results. However, our findings are consistent with consumers systematically failing to minimize total expenses for the bundle, which is then used by dealers to increase revenue.⁴

To further explore how the joint pricing of cars and loans plays out in a competitive environment we estimate an equilibrium model in which dealers compete for customers, taking contracts with lenders as given. This exercise allows us to estimate the extent to which the wedge in consumers' disutilities affects various market outcomes, e.g., dealer competition, lender pricing decisions, and consumer surplus. In addition to the administrative data, this part of the project uses a comprehensive dataset of dealer sales and loan terms that tracks most of the US car market.

In the model, dealers play a differentiated product-pricing game. To model consumer demand and competition we build on Berry *et al.* (1995), allowing dealers to set loan interest rates in addition to vehicle prices. We also model lender competition in the buy-rate auction. In this auction lenders win the contract if they quote the lowest buy rate. However, relative to a standard first price auction, they also take into account the downstream pricing decision of the dealer and the resulting likelihood of sale, which affects profits through their share of the finance charges. In this modified auction game similar insights as in Guerre *et al.* (2000) prevail and allow us to recover lender cost as a function of observables and the primitives that govern dealer price competition.

Counterfactual simulations from the model show that overall prices in the market would be 1.12 percent lower and consumer surplus 10.63 percent higher if consumers did not treat finance charges differently from vehicle charges. In equilibrium, dealers therefore substantially benefit from consumers' attenuated response to an increase in finance charges. If dealers instead had to pass through the interest rates that lenders quote to them, without additional discretion, prices would decrease by 1.25 percent and consumer surplus increase by 5.14 percent. These changes are partly due to dealers' informational advantage. Dealers interact directly with customers and their markup choice likely depends on customer attributes that

⁴In particular, the car price might be more salient to consumers, (Chetty *et al.*, 2009, Bordalo *et al.*, 2013, Kőszegi and Szeidl, 2012), consumers might lack financial literacy in general (Lusardi and Mitchell, 2014), dealers might exploit the complexity of financial contracts to shroud or obfuscate crucial information (Gabaix and Laibson, 2006, Ellison and Ellison, 2009), or consumers might neglect some dimensions of the price because their capacity to process information is limited (Sims, 2006, Mackowiak *et al.*, 2018)

they observe but lenders do not. Without delegation, lenders cannot price discriminate as effectively as dealers.

We contribute to the literature studying consumer and dealer decisions in vehicle financing. Charles *et al.* (2008) study auto loan rate outcomes by borrower race and lender type. Several previous studies focus on the subprime market, and how it is affected by down payment requirements (Einav *et al.*, 2012), cash sensitivity (Adams *et al.*, 2009), credit scoring (Einav *et al.*, 2013), and the presence of binding credit constraints (Attanasio *et al.*, 2008). More recently, Argyle *et al.* (2018) show that loan maturities affect prices for used vehicles, and Argyle *et al.* (2019) show that consumer demand for used vehicles responds more to the maturity of a loan than to its interest rate. We complement these papers by analyzing the vertical arrangements between auto dealers and lenders, for prime consumers purchasing new vehicles. This analysis identifies the extent to which consumers in our data are less sensitive to the price of a loan than the price of a vehicle. While we analyze prime consumers, our insights may not be limited to them. In particular, the relatively low consumer sensitivity to loan interest rates that we document may extend to the subprime and used car markets.

There is a growing literature estimating empirical models incorporating some form of suboptimal consumer decision making.⁵ When relying only on observational data, this type of work faces a major challenge identifying parameters that determine the importance of deviations from standard models of decisionmaking. In particular, it is often not clear how such parameters would be separately identified from those that capture preferences. Several studies in the literature have overcome this challenge in the context of health insurance plans (Handel, 2013), signing cell phone plans (Grubb and Osborne, 2015), and uptake of extended warranties (Abito and Salant, 2017). We complement this research by showing that, in the prime new car market, many consumers do not minimize the cost of financed vehicles. Moreover, previous studies either leverage some form of exogenous variation or auxiliary data in addition to prices and quantities. In our case, we leverage instead the incentive structure that the *supply side* faces to derive insights about the *demand side*. An important advantage of our approach is that our estimates do not rely on the exact functional form of consumer preferences, nor do they require assumptions on market structure.

To study the competitive effects of the joint pricing of cars and loans, we exploit our data on the vertical arrangements between dealers and lenders. While dealer revenues generated by the intermediation of loans are substantial (Davis, 2012), the literature on competitive effects in the car market has largely abstracted from the joint pricing of cars and loans (Berry *et al.*, 1995, Morton *et al.*, 2001, 2003, Gavazza *et al.*, 2014, Nurski and Verboven, 2016, Murry, 2017).⁶ We complement these studies by accounting for the strategic considerations that arise from joint pricing when estimating demand and conducting counterfactual simula-

⁵Overviews on structural work in behavioral economics in general and within the field of industrial organization can be found in DellaVigna (2018) and Grubb (2015), respectively.

⁶For franchise dealers that sell vehicles to private costumers Davis (2012) estimates that more than half of their profits are generated through their F& I department.

tions. The own-price demand elasticities that we estimate are similar to other estimates in the literature, though slightly lower. Accounting for joint pricing allows us to evaluate policies that change the bargaining process prior to a car purchase, e.g., eliminating the discretion of the car dealer to price the loan.

While the auto market is important in its own right, this work also contributes to our understanding of other markets for durable goods that are commonly bundled with financial contracts. For example, household durables are often sold along with extended warranties, airline tickets with travel insurance, and car rentals with liability insurance. A common theme in these markets is that sales agents and intermediaries market products to consumers that are either unsophisticated or face substantial search costs (Woodward and Hall, 2010, Allen *et al.*, 2014, Egan, 2018, Egan *et al.*, 2019, Guiso *et al.*, 2018, Robles-Garcia). Our counterfactual exercises show that the discretion that sales agents have when bargaining with consumers may lead to price discrimination that lowers consumer welfare. This insight may transfer to these other markets if the intermediary can price the financial product as well as the durable.

Finally, there are several papers at the intersection of financial decision making and behavioral economics whose results are in line with our findings.⁷ For example, present bias has been used to explain why consumers are willing to hold high-interest debt (Ausubel, 1991) and why some consumers with substantial illiquid assets borrow at high interest rates (Laibson *et al.*, 2015). Stango *et al.* (2017) use RAND’s American Life Panel to relate various behavioral anomalies to each other and to financial decisionmaking. Stango and Zinman (2009) argue that consumer misperception of interest rates can be explained by a tendency of households to linearize exponential functions. These papers inform our analysis. At the same time, we also contribute to this literature by showing that consumers are less sensitive to loan prices than to car prices. To the extent that this wedge in sensitivities is driven by suboptimal financial decision making, we also document how market outcomes depend on such anomalies. Our results suggest that some of the expansion in auto loan credit might be driven by a combination of car buyers’ failure to minimize the total expenses of financed vehicles and dealers’ corresponding incentive to charge markups. Since auto loans are a major contributing factor to the overall increase in household debt (Mian and Sufi, 2016, Schlagenhauf and Ricketts, 2012) these results may be of broader interest to the household finance literature.

2 Institutional Details

Car prices and loan terms are negotiated between dealers and customers, so actual prices and interest rates often differ substantially from advertised ones. Typically, a sales agent and the consumer first negotiate vehicle specifics, e.g. trim level, options, and price.⁸ Afterwards, the

⁷For a recent survey on this literature see Madrian *et al.* (Forthcoming).

⁸Sales agents are often paid based on commission and sales targets. The commission is often a function of the sale (e.g. a “flat” commission) and / or the simple profit to the dealer (i.e. price paid less direct vehicle cost). The sales targets are often discontinuous, and

dealer's "Finance and Insurance" (F&I) agent and the consumer negotiate loan terms.⁹ To get rate quotes, the F&I agent typically submits the customer's financial information into at least one of three major systems: DealerTrack, RouteOne, and/or Credit Union Direct Lending. Dealers may select specific lenders from which to solicit bids, or send the application to all lenders (DealerTrack advertises 1,500+ lenders). On average, dealers appear to maintain active relationships with more than 9 lenders, and are likely to request quotes from several of them for any given deal.

Each solicited lender submits a *buy rate*, which in general is the minimal interest rate at which it is willing to make the loan.¹⁰ The dealer may then add a markup to the buy rate.¹¹ Most lenders allow markups of at most 200-250 basis points, but markups are otherwise discretionary.¹² The revenue from this markup is split between dealer and lender according to pre-specified agreements. Details on these revenue sharing agreements are provided below.

Since dealers only act as intermediaries for financing, loans generally go directly on the balance sheet of the lender.¹³ Loans presents both default risk and prepayment risk. Default risk is minimal for prime consumers. For subprime consumers, contracts often discipline markups and split default risk between dealers and lenders. In both the subprime and prime markets, prepayment risk is substantial.¹⁴ Dealers typically assume all prepayment risk for the first 3 to 6 months. If the loan is prepaid during this time period, the dealer often returns the entire dealer reserve to the lender. Lenders assume all prepayment risk after this time period.

We estimate that at least 80% of auto loans are "indirect", i.e. obtained through auto dealers as described above.¹⁵ However, consumers can also get loan quotes directly from lenders. They can obtain these quotes either before negotiating with the dealer or afterward. If

can result in direct bonuses and / or increases in the commission percent earned (either for additional sales, or occasionally for all sales in a month).

⁹F&I agents are compensated by the dealer via a commission (or commission-like) mechanism based on the additional value of the deal above the sales price (often called the buy rate) (more on the profit netted, less on the number of deals done). F&I agents' incentives are typically to sell add-ons and get the best "reserve" (net payment) from the lender.

¹⁰This process can happen very quickly (seconds to minutes), or can take longer (hours to days). Super prime quotes (e.g. credit score 740+) are often fully automated, and take virtually no time. "High prime" deals (e.g. credit score 700+) are sometimes automated (depending on the lender) but are usually handled quickly. One bank that "manually" underwrites prime loans targets 2 minutes to a decision/rate. Non-automated rates typically vary by more than automated rates, so the likelihood of getting a lower rate is higher, though it can take more time. "Near/low prime" deals (credit score 620+) that require some manual pricing/underwriting are where lenders differ most. Some lenders try to move as quickly as possible, other lenders contact the dealer to discuss terms (figuring "hands on" approach is more likely to secure deal) or engage in a thorough assessment of risk (takes longer), but offer more favorable compensation to dealer. Subprime (credit score < 620) quotes are often available from only a few lenders, and often require phone calls and / or additional information and time. These customers are usually on the extensive margin of borrowing, and are unlikely to be particularly sensitive to rates (e.g. one subprime lender sets all rates to 23.99%, unless the customer has a competing offer).

¹¹These markups can be negative. "Markdown" is allowed by most lenders, where the dealer pays a fixed fee to decrease the contract rate below the lender's buy rate. This is rare and usually happens when the buyer has a lower competing offer, and/or when the F&I agent has made enough on add-ons to be willing to subsidize the buyer's rate.

¹²Lender-imposed caps on markups arose after a series of class-action lawsuits against auto lenders that settled between 2003 and 2006. Before, many markups were even higher. See Cohen (2012).

¹³Banks do sometimes sell loans on the secondary market, but this is rare. Captive finance companies and Buy-Here-Pay-Here dealerships do so much more frequently, but neither kind of lender is in our data.

¹⁴Consumers may prepay an auto loan in cash, through refinancing, or through trading in their vehicle for a different one.

¹⁵See Section B.1.

the consumer finances the vehicle directly, the dealer receives no revenue from the financing.

3 Data and Descriptive Evidence

This section first describes the datasets and then provides descriptive evidence. We pay special attention to the relationships between lenders and dealers and the compensation that dealers receive for intermediating loans.

3.1 Data

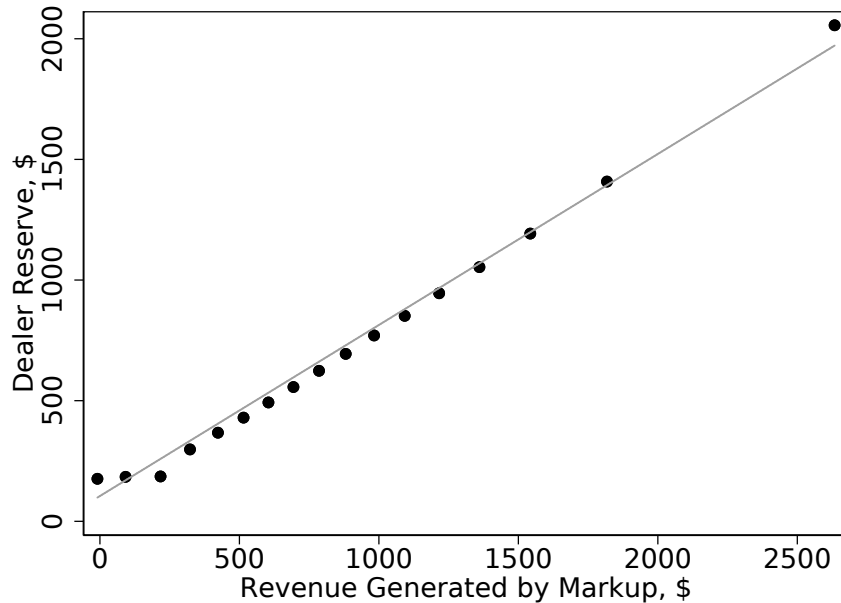
The project combines three different datasets. First, and most importantly, we use a new administrative dataset of auto loans from various financial institutions. The data records car, loan, and buyer characteristics and includes several million transactions from 2010 to 2014. We observe the make and models of cars, whether they were new or used, their mileage and model year, and in some cases the price of add-ons. We observe a buyer's zip code, income, and credit score. For each transaction, we also observe the encrypted numeric identifier of the lender. There are several lenders in our data, and an average of over 7,000 dealers per lender. The loan characteristics we observe include the interest rate, the term length, the down payment, and the trade-in value for the old car. Additionally, we observe whether loans are “subvented”, i.e. subsidized by car manufacturers to increase vehicle demand.¹⁶ Crucially, we observe the buy rate, the markup, and the dealer reserve. Recall that the buy rate is the rate at which the lender is willing to finance the transaction. The markup is the discretionary interest that the dealer adds to the buy rate, and the dealer reserve is the payment that the dealer obtains from the lender for originating and marking up the loan.

The administrative data provides detailed information on observed transactions, but it does not cover the entire market. We therefore use complementary data from AutoCount, from which we can observe market shares of lenders and dealers for the majority of states in the U.S. AutoCount also records whether dealers are franchised (i.e. associated with a car manufacturers) or independent. In the 2011 AutoCount Data we can look at the market shares of different types of lenders. Banks, captives, credit unions, finance companies, and Buy Here Pay Here companies had respectively 46.1%, 26%, 14.1%, 9%, and 4.8% of the market. However, the data from AutoCount does not include information on buy rates and mark ups.

Finally, we also use the CFPB's Consumer Credit Panel (CCP), which is built from data from one of the three nationwide consumer reporting agencies. The CCP also does not contain data on buy rates or markups, nor does it include data on the vehicle securing the loan. However, we can use it to address questions on loan performance over time.

¹⁶Subvented loans are typically from captives, but non-captive lenders do sometimes have agreements with car manufacturers to extend subvented loans.

Figure 1: Markup Revenues and Dealer Reserve



NOTE: The figure shows a bin-scatter plot where the x-axis is the distribution of revenues generated by dealers markups over the lifetime of the loan and the y-axis the distribution of dealer reserves. The graph shows that the relationship is well approximated by a linear contract.

3.2 Contracts Between Lenders and Dealers

Markup revenue is shared between the dealer and the lender according to a contractually-specified formula. Figure 1 plots dealer reserve against loan markup revenue in a binscatter plot. On average, dealers receive a fixed payment of \$137 per loan plus about 66% of markup revenue. The dealer share of markup revenue varies slightly from lender to lender with a coefficient of variation of 0.079.¹⁷ Adjustments of those terms across dealers and geographic regions appear to be rare. Two points are worth noting about the observed contracts. First, contracts are very nearly linear.¹⁸ Hence, dealers receive a pre-specified amount of every dollar of extra revenue they generate through loan markups. Second, the slope of the linear contract is substantially below unity. A dealer therefore receives only a fraction of markup revenue. We build on these observations in our theoretical considerations in Section 4.

¹⁷For one lender we directly observe the dealers' share. It varies somewhat across observations, so we take the median dealer share for this lender for the calculation of the coefficient of variation.

¹⁸If we do not pool lenders but instead plot the same graph for lenders separately, contracts are still very nearly linear. To protect the confidentiality of lenders in our data, we cannot show these graphs.

Table 1: Summary Statistics of Mark Up and Dealer Reserve

	CREDIT SCORE QUARTILE		INCOME QUARTILE		VEHICLE PRICE	
	MEAN	STD DEV	MEAN	STD DEV	MEAN	STD DEV
MARKUP (%-POINTS)						
1st Quartile	1.20	0.83	1.20	0.82	1.24	0.87
2nd Quartile	1.14	0.82	1.13	0.81	1.13	0.82
3rd Quartile	1.09	0.82	1.09	0.81	1.08	0.80
4th Quartile	1.08	0.81	1.08	0.80	1.09	0.77
MARGIN OVER BUY RATE						
1st Quartile	0.39	0.32	0.42	0.32	0.39	0.33
2nd Quartile	0.42	0.33	0.40	0.32	0.43	0.34
3rd Quartile	0.43	0.36	0.40	0.32	0.43	0.35
4th Quartile	0.45	0.37	0.43	0.35	0.46	0.36
DEALER RESERVE						
1st Quartile	693.98	555.98	581.24	453.41	385.72	292.84
2nd Quartile	651.98	528.79	611.44	475.29	554.31	370.02
3rd Quartile	601.09	489.33	636.54	508.02	661.45	445.30
4th Quartile	584.73	470.48	753.58	661.39	950.35	708.13

NOTE: Summary statistics of markups (upper panel), margin refers to mark ups as a fraction of the buy rate (middle panel) and reserve refers to the dealer reserve (lower panel) by credit score, income, and vehicle price.

3.2.1 Markups and Dealer Compensation

In our data 77.8 percent of loans are marked up.¹⁹ The average mark up in the dataset is 1.08, which at $\approx 43\%$ over the buy rate is substantial. While markups are common for all types of buyers, their size varies systematically with buyer observables. Table 1 shows how markup and dealer reserve vary with the buyer’s credit score, income, and the price of the vehicle. Markups are higher for buyers with low credit scores. As a consequence, dealer reserve is also higher on average for buyers with low credit scores. Markups are also higher for low income buyers. However, dealer reserve is *lower* for low income buyers, because they typically buy cheaper cars with smaller loans that generate less revenue for a given markup.

The results from Table 1 also inform the theoretical considerations below. In particular, the descriptive evidence suggests that dealers often mark up loans even though they must share the resulting profit with lenders. This is true regardless of buyer income, risk characteristics, and vehicle segment.

¹⁹In very rare occasions dealers might also be allowed to mark down a loan. This is the case for 0.7 percent of loans we observe. Anecdotal evidence suggests that mark downs are typically not possible. However, lenders might allow large dealers a very limited number of mark downs per month if they are less than 0.25 percentage points.

3.2.2 Subvented Loans

The core idea of Section 4 is to use dealers’ markup decisions to estimate buyers’ sensitivity to loan charges relative to vehicle charges. We will use dealers’ incentive structure and a model of optimal pricing to derive the conditions for identification of the *consumer* utility function. This analysis requires that dealers perceive the pricing of the car and the loan as a joint maximization problem.

Brown and Jansen (2019), Argyle *et al.* (2018) and Argyle *et al.* (2019) provide strong evidence that loan and vehicle prices are jointly determined. Additional evidence for strategic markup allocation comes from our own data on subvented loans. Recall that vehicle manufacturers subsidize interest rates on subvented loans, so markups on these loans are typically restricted and often prohibited. As a consequence, the mean markup for subvented loans is only 0.06 compared to 1.12 for non-subvented loans. Hence, dealers’ profit for these types of sales comes almost entirely from the markup on the vehicle price.

Table 2: Predicted Effects on Price and Loan Outcomes

	CAR PRICE	FINANCE CHARGES	OVERALL CHARGES
Subvented	846.4** (2.13)	-148.1* (-1.91)	780.1* (1.74)
Credit Score	123.7*** (3.21)	-577.1*** (-57.59)	-443.1*** (-9.93)
Log Monthly Income	0.0759*** (15.97)	0.0108*** (14.76)	0.0924*** (16.90)
Loan Term	181.3*** (8.54)	970.2*** (203.27)	1166.5*** (48.05)

NOTE: Bank, month, model, and zip code fixed effects also included, but not shown. Standard errors clustered at zip code level.

Table 2 shows the estimates from a linear regression model that predicts the effects of subvention on the price of the car and the loan. We include fixed effects for the lender that issued the loan, the time the loan was issued, the purchased car model and make, and the buyer’s zip code. If car and loan prices are chosen independently in competitive markets, we would expect car prices not to be affected by loan subvention. Columns (1) and (2) show that this is not true. Subvention implies two changes in the prices. On the one hand, the price of the loan decreases by approximately \$150. On the other hand, the price of the car increases by approximately \$850. Hence, dealers seem to increase vehicle markups if their discretion to price the loan is reduced. In fact, overall transaction prices are estimated to be higher if loans are subvented.

4 Consumer Demand

Building on the institutional details described above, we now outline our empirical strategy to quantify consumer sensitivity to changes in finance charges relative to vehicle price. Our basic identification argument is the following. Dealers share a substantial fraction of loan markup revenue with lenders, but keep all vehicle markup revenue. If customers are indifferent between loan charges and vehicle charges, dealers should maximize the car markup and keep all profit from the transaction. If instead dealers set positive markups, it must be because markups allow them to increase the total price of the loan and vehicle by at least the markup revenue remitted to the lender. This in turn can only be true if customers are less sensitive to loan charges than to vehicle charges.

This basic insight allows us to estimate consumers' price sensitivity under very mild assumptions on the dealers' pricing problem. We do not have to specify either the exact market structure under which dealers compete or the consumer model that generates the wedge between the disutilities arising from vehicle and loan price. Our approach is therefore reminiscent of recent structural work that does not require a full specification of the model (Pakes *et al.*, 2015). It also shares certain advantages with the sufficient statistics approach (Chetty, 2009) in that it is less prone to errors due to model misspecification.

We start by developing the identification in a one-period model. Later, Section 5 considers a number of alternative explanations for our findings. In particular, we investigate to what extent time preferences (Section 5.1)²⁰, prepayment risk (Sections 5.2 and 5.3) and relational contracts between dealers and lenders (Section 5.4) can account for our results.

4.1 One-period model

Denote the buy rate for consumer i by b_i and the states sales tax by τ_i . The car dealer has a linear markup revenue sharing agreement with the lender (see Section 3.2). This agreement is characterized by slope α and intercept β , both of which are lender-specific. The dealer makes an offer to the consumer consisting of the vehicle price p_i and the loan interest rate $r_i \geq b_i$, taking the downpayment $d_i \geq 0$ as given. The consumer can react in three different ways. First, she can take the loan and buy the car. Second, she can decline the entire offer and revert to some outside option with expected value \bar{u}_i , e.g., she does not buy a car or does so at a different dealer. We assume that $\bar{u}_i < 0$ and $|\bar{u}_i| > d_i$. Third, she can buy the car but get a loan *directly* from a lender. We denote the consumer's interest rate in this scenario by $r^L > 0$, which she believes to be distributed according to the continuously differentiable density function $g_i(r^L)$, which has compact support. Moreover, her expected cost from shopping is $s_i \geq 0$. We assume that consumer i 's disutility from finance charges x is given by $M_i(x)$ where

²⁰Since auto loans are typically fully amortizing loans, the allocation of payments between finance charges and car charges does not affect the inter-temporal allocation of payments. Therefore, our argument in this section is also valid in a multi-period model.

$M_i(x) \in C^2$. Importantly, we do not impose any further structure on this function, i.e., we allow the consumer utility to follow any twice continuously differentiable pattern.

Assumption 1. *Consumer utility is additive in the disutility of vehicle charges p and the disutility of finance charges $M_i(x)$, where $M_i(x) \in C^2$.²¹*

If $M_i(x) = x$ the consumer treats financial and vehicle costs identically. If $M_i(x) \neq x$ for some x , the consumer treats the two dimensions differently. As we do not specify the exact form of $M(\cdot)$, our model nests a variety of explanations for the wedge in consumer disutilities, e.g., limited financial sophistication, obfuscated loan terms, or limited bargaining skills. An advantage of this approach is that it makes our identification procedure independent of the exact underlying model. On the flip side, this implies that our findings will be agnostic about different models that could give rise to such behavior. Note also that the general formulation of our model nests different bargaining institutions. We model the haggling procedure as if a dealer makes a take it or leave it offer to the buyer that needs to be above \bar{u} for the buyer to accept. However, here we don't take a stance on the level of \bar{u} and there can be different determinants, e.g., it could reflect the expected utility from further search at alternative dealers, a Nash-Bargaining solution, or the value of buying no car at all. As a consequence, our identification procedure is valid irrespectively of the underlying determinants of the reservation utility of the buyer. In the full model that we present later on for the equilibrium calculations the outside utility is going to be specified in terms of the inclusive value of other options in the market. The dealer's maximization problem is given by:

$$\begin{aligned}
\max_{r_i, p_i} \quad & p_i + (\tau_i \cdot p_i - d_i) \cdot (r_i - b_i) \cdot \alpha - c_i + \beta & (1) \\
\text{s.t.} \quad & -\tau_i \cdot p_i - M_i((\tau_i \cdot p_i - d_i) \cdot r_i) \geq \bar{u}_i \\
& -M_i((\tau_i \cdot p_i - d_i) \cdot r_i) \geq - \int M_i((\tau_i \cdot p_i - d_i) \cdot r^L) \cdot g_i(r^L) dr^L - s_i, \\
& r_i \geq b_i, p_i \geq 0
\end{aligned}$$

To understand the basic intuition of our argument, first consider the case of $M_i(x) = x$. For this case, the optimal policy for the dealer is a corner solution. If the incentives provided by the lender are not too high (formally, $\alpha < \frac{1}{(1+b_i)\tau_i}$), the dealer sets the interest rate as low as possible ($r_i = b_i$). The reason is that the consumer dislikes loan and vehicle price markups equally, but the dealer prefers vehicle price markups because he does not share them with the lender.

Proposition 1. *Suppose $M_i(x) = x$ and $\alpha < \frac{1}{(1+b_i)\tau_i}$. Then any solution to the maximization problem in (1) features $r_i^* = b_i$.*

²¹For our argument we implicitly assume that the dealer is aware of the consumer's utility function $M_i(\cdot)$. However, our estimation procedure does not rely on this assumption. If the dealer does not know $M_i(\cdot)$ but has a point belief about it, our estimates reveal this point belief.

We delegate proofs to Appendix A. Proposition 1 has an important observable implication: if $M_i(x) = x$, the dealer does not mark up loans with $\alpha < \frac{1}{(1+b_i)\tau_i}$. This inequality holds for 97.5 percent of observations in our data, and so the substantial markups documented in Table 1 are incompatible with $M_i(x) = x$, i.e. equal consumer sensitivity to loan price and car price.

Using the size of markups in the data, we can go further and quantify the extent to which finance and vehicle charges are treated differently. Suppose next that the perceptions of finance charges x by consumer i are given by $M_i(x)$.

Proposition 2. *For any optimal offer (r_i^*, p_i^*) with $r_i^* > b_i$, $p_i^* > 0$ one of the following two statements holds:*

(i) *At the optimum only the first constraint is binding and the optimal solution satisfies*

$$M'_i(r_i^*(\tau_i p_i^* - d_i)) = \frac{\alpha \cdot \tau_i}{1 - \alpha \cdot \tau_i \cdot b_i}. \quad (2)$$

(ii) *Both constraints bind at the optimum and*

$$M'_i(r_i^*(\tau_i p_i^* - d_i)) < \frac{\alpha \cdot \tau_i}{1 - \alpha \cdot \tau_i \cdot b_i}.$$

Proposition 2 allows us to use the prices set by the dealer to infer consumers' sensitivity to additional charges at the equilibrium contract. We observe all variables on the right hand side in (2), as well as the argument $r_i^* \cdot (\tau_i p_i^* - d_i)$ of function $M_i(\cdot)$. Therefore, the data provides individual-specific estimates of the marginal disutility $M'_i(\cdot)$ at the observed contract. Furthermore, $M'_i(r_i^* \cdot (\tau_i p_i^* - d_i))$ has a transparent economic interpretation: it is the marginal disutility, in dollars, that a consumer associates with an increase in the loan price. If $M'_i(\cdot)$ is smaller than unity, for example, the consumer is less sensitive to an increase in the loan price than to an equal increase in the car price. Whether (i) or (ii) holds for any given consumer depends on unobservables. Hence, our sufficient statistic establishes an upper bound for $M'_i(\cdot)$ at the observed contract. This is due to the second constraint in the dealer's problem. When this constraint binds, it is because the dealer cannot charge a higher interest rate without causing the consumer to obtain the loan directly from a lender, even though the consumer would otherwise agree to pay a higher interest rate in exchange for a lower vehicle price. Hence search costs determine our estimates for $M'_i(\cdot)$ in these cases, which are greater than actual $M'_i(\cdot)$. This logic holds because our model does not allow dealers to condition the price of the vehicle on the source of financing. If instead we allowed dealers to charge higher prices for vehicles financed directly, the second constraint in the dealer's problem would never bind, and our estimates for $M'_i(\cdot)$ would be tight.²²

Our $M'(\cdot)$ estimates measure consumers' marginal valuation of finance charges. However, each marginal valuation is estimated at the specific contract terms in the data. As a result, two individuals with the same finance charges and the same estimated $M'(\cdot)$ may still differ

²²Anecdotally, dealers often do condition the price of the vehicle on the source of financing.

in their valuation of their finance charges. Next we calculate bounds on the perceived value of total finance charges.

Proposition 3. *Suppose (r_i^*, p_i^*) with $r_i^* > b_i$ and $p_i^* > 0$ is an optimal offer.*

(i) *If $M'(x) \leq 1 \quad \forall x$, it holds that*

$$\begin{aligned} & (\tau_i p_i^* - d_i) \cdot (r_i^* - b_i) - [M_i(r_i^* \cdot (\tau_i \cdot p_i^* - d_i)) - M_i(b_i \cdot (\tau_i \cdot p_i^* - d_i))] \\ & \geq (\tau_i \cdot p_i^* - d_i) \cdot (r_i^* - b_i) \cdot [1 - \tau_i \cdot \alpha \cdot (1 + b_i)] = B_i^M \end{aligned} \quad (3)$$

(ii) *If $M''(x) > 0 \quad \forall x$, it holds that*

$$(\tau_i \cdot p_i^* - d_i) \cdot r_i^* - M_i(r_i^* \cdot (\tau_i \cdot p_i^* - d_i)) \geq (\tau_i \cdot p_i^* - d_i) \cdot r_i^* \cdot \left[1 - \frac{\alpha \cdot \tau_i}{1 - \alpha \cdot \tau_i b_i} \right] = B_i^O. \quad (4)$$

Proposition 3 establishes two different lower bounds on the difference between actual and perceived finance charges. Both can be estimated in our data. Part (i) of Proposition 3 derives an individual-specific lower bound B_i^M for the difference between actual and perceived finance charges due to markup. Intuitively, this result leverages the fact that dealers choose the markups seen in the data rather than setting them to zero. This behavior can only be optimal if consumers' disutility from the markups is not too high.

Part (ii) of Proposition 3 derives a lower bound B_i^O for the difference between actual and perceived total finance charges. For this result, we have to make the additional assumption that $M_i(\cdot)$ is convex. If $M_i(\cdot)$ is convex, our estimates of $M'_i(\cdot)$ provide a natural lower bound on $M_i(\cdot)$.

While the two estimated bounds are highly correlated and the underlying ideas are similar, we still consider them to be important complements. B_i^M is derived under milder assumptions, but only considers finance charges due to markups. Convexity of $M_i(\cdot)$ is a stronger assumption but allows us to consider all finance charges. B_i^O is also important from the dealer's perspective as it characterizes the extent to which he can profit from differences in price sensitivities.

4.2 Estimation

We now turn to estimation of the measures of consumer price sensitivities given by Propositions 2 and 3. Note that we can only estimate $M'(\cdot)$ and B^O for the approximately 77.8% of our sample with positive markup; there are several potential explanations for zero markups (e.g. the consumer has a good outside option or low loan search costs, or the consumer is indifferent between vehicle and finance charges) that we cannot disentangle. However, we can estimate B^M for the whole sample as it is zero for observations with zero markup.

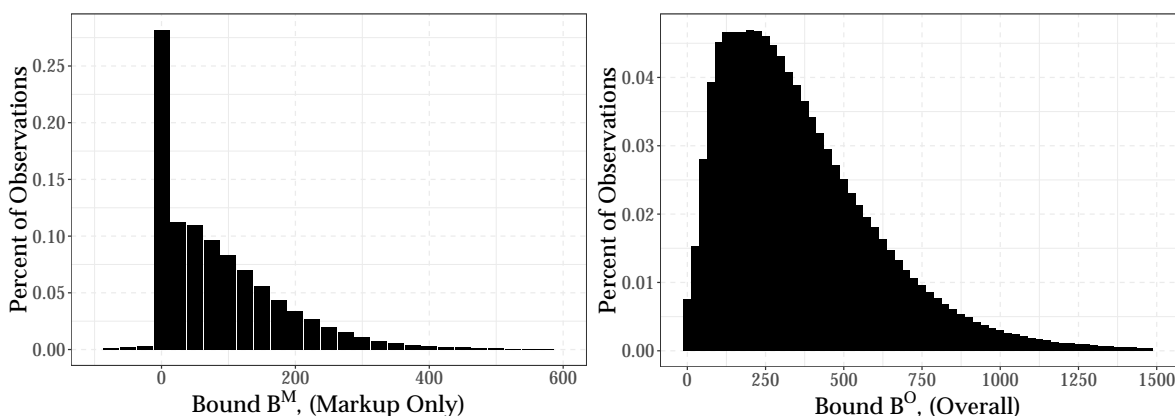
Our procedure is non-parametric and yields individual-specific estimates. For each contract in our data, we obtain a specific $M'_i(\cdot)$, B_i^M , and B_i^O estimate by applying equation (2), (3),

Table 3: Summary Statistics of Estimates

MEASURE	MEAN	PIO	P25	P50	P75	P90
$M'_i(\cdot)$	0.86	0.77	0.80	0.86	0.91	0.95
B^O (\$)	380.12	105.71	186.81	324.33	510.73	721.56
B^M (\$)	96.16	0.00	16.56	72.09	145.21	228.07

NOTE: Selected summary statistics of consumers' sensitivity to finance charges and the dollar amounts that are not taken account of when making a purchase. For $M'_i(\cdot)$ and B^O_i the estimation is conditional on the mark-up being positive, while the estimates B^M_i are derived for the full sample.

Figure 2: Histogram of Estimated Bounds



NOTE: The left panel shows B^M_i the bound on the difference between the consumer valuation of finance charges and finance charges under equal disutilities. The right panel shows this difference only for the finance charges implied by the dealers decision B^O_i .

and (4), respectively. We restrict our sample to prime consumers with a credit score above 720 to ensure that our results are driven by default risk.^{23,24} Table 3 provides a summary of our estimates, which reveal a substantial wedge between car and loan price sensitivities. In particular, the mean $M'_i(\cdot)$ is only 0.86. This implies that, at the contract terms seen in our data, an extra dollar of finance charges is treated as worth approximately 86 cents. For consumers at the 10th percentile, this value drops to 77 cents.

Figure 2 shows the estimated distribution of our estimates with respect to the two lower bounds B^M and B^O . Two points are worth noting. First, the estimated bounds are substantial. On average, consumers act as if perceived finance charges are \$380 less than actual finance charges. Similarly, on average consumers act as if perceived finance charges due to

²³In a sample of prime auto loans in the CCP originated in 2014 and 2015, 0.4% had resulted in either repossession, chargeoff, or bankruptcy by three years after origination. $M'_i(\cdot)$ is positively correlated with credit scores in our restricted sample but negatively correlated with credit scores in our full sample. This suggests that, for consumers with low credit scores, dealers may be incentivized or forced to restrict markups, which is consistent with anecdotal evidence.

²⁴For one lender, payments were not well described by a linear contract in the loan amount. In an earlier version of the estimation this led to very low $M'_i(\cdot)$ estimates and, hence, very low sensitivity to finance charges. To ensure that our results are not driven by these specific observations, we drop this lender entirely.

markup are \$96 less than actual finance charges due to markup. This estimate corresponds to approximately 20.3 percent of total finance charges, and about 19.2 percent of the markup. Second, there is significant heterogeneity in our estimates. The difference between actual and perceived finance charges at the 90th percentile is seven times larger than at the 10th percentile. An obvious question of interest is therefore how these estimates correlate with other observables in our data. We answer this question in Section 6.

On a more speculative note, our estimates also allow us to explore the average curvature of the function $M_i(\cdot)$. Specifically, we can investigate the effect of higher finance charges on our estimates on $M'(\cdot)$. Finance charges are obviously endogenous to $M_i(\cdot)$. However, the buy rate offered by the lender is strongly correlated with finance charges, and – because our data includes virtually all the information the lender has – exogenous to any unobservable consumer characteristics such as the consumer’s utility function $M'(\cdot)$. It is therefore a valid instrument. The results of the corresponding 2SLS regression are summarized in Table 9. The estimated shape suggests that $M_i(\cdot)$ is on average a convex function. Hence, consumers treat finance charges more accurately if more is at stake. This finding is reminiscent of recent work studying attention allocation (Bordalo *et al.*, 2012, 2013, Kőszegi and Szeidl, 2012). A common theme of this work is that consumers pay more attention to dimensions with more pronounced differences across products. In our setting with increasing finance charges the difference of the outside option (not taking out a loan) and signing the proposed loan is scaled up. The proposed attention based theories would therefore predict more focus on loan terms if the implied finance charges rise, which is indeed what we find. Below, we assume a functional form for $M(\cdot)$ that is in line with this finding.

5 Explanations for Differential Price Responsiveness

5.1 Time Structure

The previous section illustrated our main identification argument in a one-period model. It may appear intuitive that in a multi-period model consumers who are impatient or liquidity-constrained may be willing to pay higher interest rates, and that this could partly explain our results. However, this intuition is largely incorrect, because auto loans have fixed monthly payments that fully amortize. For a given down payment, there is a one-to-one mapping between total transaction costs and monthly payments. This mapping does not depend on the allocation of transaction costs between loan and vehicle costs, and so if down payments are independent of this allocation, then intertemporal preferences play no role in our results.²⁵ Section A.1 shows this formally.

However, if a larger car price causes a larger down payment, then intertemporal prefer-

²⁵Down payments will be independent of the allocation of charges if, for example, the down payment is determined before the price is determined, is at the discretion of the consumer, or is zero.

ences could affect our results. Suppose, for example, the down payment is a fixed percentage of the car price. In this case, impatient or credit-constrained consumers may prefer to pay more for the loan to reduce the car price and hence the down payment. Figure 7 shows the distribution of down payments as a fraction of the car price. This figure, together with our discussions with industry experts, reveal that down payments for prime consumers are generally not determined in this way. Variation of the relative size of the down payment is large and a marginal increase in the car price does not appear to increase the down payment.

Still, we break down our estimates of $M'_i(\cdot)$ and B_i^O by the size of the down payment in the appendix in Tables 10 and 11, respectively. We find a considerable wedge between car and loan price disutilities across the entire distribution of down payments. In particular, the wedge is substantial for zero and negative down payments, for which time preferences cannot explain any of our estimates. The median B_i^O for consumers in the 10th to 25th percentile of the down-payment distribution is \$630 while it is \$563 for consumers between the 75th and 90th percentile. Overall, these results show that intertemporal preferences and credit constraints cannot explain the substantial dealer markups in our data.

To further address this point, in Section A.2 we recompute $M'_i(\cdot)$ under the (evidently counterfactual) assumption that dealers require a down payment that is a fixed percentage of the car price, conditional on various discount factors for the consumer.²⁶ The results are summarized in Table 16. Recall that we are restricting our sample to individuals with credit scores above 720. Hence, the sample consists of individuals that are unlikely to be either impatient or credit constrained and should therefore have reasonably high discount factors. Our results show quantitatively that even if the down payment is a fixed fraction of the price, our estimates barely change for discount factors above 0.90.

5.2 Early Prepayment Risk

Consumers often prepay auto loans, either by trading in their vehicle for a new one, by prepaying in cash, or (less commonly) through refinancing. The potential effects of prepayment on our results depends on when it occurs. Contracts between dealers and lenders include a “clawback” period, typically the first three to six months of the loan, during which the dealer bears prepayment risk. If the consumer prepays during the clawback period, the dealer refunds the entire dealer reserve to the lender. We define “early” prepayment as prepayment that occurs during the clawback period, and “late” prepayment as prepayment that occurs after it.

First, we explore the role of early prepayment. Early prepayment is not uncommon; in a sample of prime auto loans in the CCP, 5.9% are prepaid within the first 120 days. To account for this, we add to our baseline model an early prepayment probability $(1 - \gamma)$. Hence, the

²⁶In doing so we first compute the fraction of the price that is equal to the observed down payment. We then assume that the dealer would require this fraction for any car price.

dealer's maximization problem becomes:

$$\begin{aligned}
\max_{r_i, p_i} \quad & p_i + (\tau_i p_i - d_i) \cdot (r_i - b_i) \cdot \gamma \cdot \alpha - c & (5) \\
\text{s.t.} \quad & -\tau_i \cdot p_i - \gamma \cdot M_i((\tau_i p_i - d_i) \cdot r_i) \geq -\bar{u}_i \\
& -\gamma \cdot M_i((\tau_i p_i - d_i) \cdot r_i) \geq -\gamma \cdot M_i((\tau_i p_i - d_i) \cdot r_i^E) - s_i, \\
& r_i, p_i \geq 0
\end{aligned}$$

This problem can be solved along the same lines as the one in Proposition 2. On the one hand, consumers are now less sensitive to interest rates so dealers have an additional incentive to mark up the loan. On the other hand, the dealer values markups less because he may not keep the dealer reserve. The following corollary shows that the latter effect dominates. As a consequence, our estimates for $M'(\cdot)$ are upper bounds because they do not account for early prepayment risk.

Corollary 1. *Suppose that consumer i repays the loan early with probability $1 - \gamma$. Then, the statements from Proposition 2 hold true with the only change that:*

$$M'_i(r_i^* \cdot (\tau_i \cdot p_i^* - d_i)) \leq \frac{\alpha \cdot \tau_i}{1 - \gamma \cdot \tau_i \cdot \alpha \cdot b_i}.$$

5.3 Late Prepayment Risk

Lenders bear all prepayment risk after the end of the clawback period. If borrowers consider late prepayment when buying a car, and if dealers can screen “late” prepayers from “early” prepayers, then the logic outlined in 5.2 does not hold, and borrowers may appear less sensitive to finance charges because they expect not to pay them. Late prepayment risk is substantial and so this is an important concern; 27% of prime auto loans (with term greater than two years) in the CCP are prepaid after 120 days but before two years.

There are two plausible kinds of late prepayment risk we need to examine. The first is risk that is observable to both the borrower and the dealer. To create a proxy for this risk, we run a logit regression predicting late prepayment in the CCP, using credit score, log loan amount, loan length, and state fixed effects. Coefficients are reported in Table 12. This is clearly a limited subset of the information available to both the borrower and the dealer, and yet it is remarkably predictive. 18.2% of those those in the bottom decile of predicted risk prepay late, while 42.9% in the top decile do.

While these variables are highly predictive of late prepayment and readily observable to lenders, recall lenders do not condition α on them. This is the first indication that borrowers with predictably higher prepayment risk do not pay higher markups.

Still, because lenders do not condition α on this information set, borrowers with predictably higher prepayment risk may agree to higher markups because the effective cost is lower. Tables 12, 13, and 14 provide percentiles of markup, $M'_i(\cdot)$ and B_i^M , respectively, conditional on percentiles of predicted late prepayment risk. Table 18 provides estimates from a

regression that controls for a number of consumer characteristics. The conditional correlation between observable late prepayment risk and our wedge estimates is *negative*. Hence, we estimate higher $M'_i(\cdot)$'s and lower B_i^M 's for consumers with *higher* prepayment risk. This is strong evidence against the possibility that observable late prepayment risk drives our results.

One potential explanation for this result is that dealers cannot distinguish late prepayment risk from early prepayment risk. Indeed, the correlation between our measures of early and late prepayment risk in the CCP is .66. In this case, our finding that higher prepayment risk predicts higher $M'_i(\cdot)$ estimates suggests that the early prepayment result in Section 5.2 quantitatively dominates the opposing effect from predictable late prepayment. In this case, ignoring prepayment biases against our results in Section 4.2.

Another possibility with substantial empirical support is that, instead of considering the cost of a financed vehicle through the life of a loan, consumers instead care about monthly payments (Argyle *et al.* (2019)). Because there is a one-to-one mapping between monthly payment and the total cost of a loan if it is paid on schedule, this model is equivalent to ours if we ignore prepayment risk.

We still need to consider prepayment risk that is observable to the borrower but not to the dealer. Because we observe prepayment but not markup in the CCP, and markup but not prepayment in the supervisory data, we cannot test for this explicitly. However, recall that markup revenue sharing agreements between dealers and lenders are linear. This means that the dealer receives a fixed payment for every marginal dollar in finance charges he generates, assuming the loan is paid on schedule and not prepaid. If there were adverse selection on late prepayment risk in markups, then lender revenue would be concave in markups and this contract would not be optimal.

5.4 Relational Contracts between Lenders and Dealers

Lenders and dealers interact repeatedly, so dealers may mark up loans to increase lenders' profits in exchange for favorable treatment on later deals, such as financing for a subprime consumer who might otherwise not qualify for a loan. This argument is particularly plausible in light of our finding in Section 5.3 that markups are *higher* for consumers with lower prepayment risk. Fortunately, our AutoCount data includes important characteristics of dealer-lender relationships. This enables us to directly check the extent to which markups are higher in dealer-lender relationships that are more intense or that have lasted longer.

We proxy the intensity of the relationship between dealer i and lender j by the fraction f of loans intermediated by dealer i that are from lender j . Table 15 shows the results from an OLS regression where markups are the dependent variable and f is the independent variable of interest. Importantly, the regression includes dealer fixed effects, so that the estimates reveal if dealers choose higher markups when working with preferred lenders. We find that the intensity of a dealer-lender relationship has virtually no predictive effect for the markup.

Markups for lenders that finance more than 20 % of a dealer’s sales are only 3 basis points higher than markups for lenders that finance less than one percent of a dealer’s sales. Recall that the average markup in our data is 108 basis points. Even for lenders that finance less than five loans a year for a given dealer, we find that markups are on average 106 basis points. It is therefore implausible that dealers’ markup decisions arise from their relationships with lenders.

6 Heterogeneity Analysis

In this section, we explore how our estimates covary with other observables.²⁷ This exercise is enabled by the fact that all estimates and much of our data are measured at the individual level. Importantly, $M'(\cdot)$ is not suitable for a heterogeneity analysis, because it only describes marginal disutilities. Hence, two individuals with identical $M'(\cdot)$ may still have very different utility functions, because $M'(\cdot)$ might have been measured at different contract terms. We therefore focus on the heterogeneity in B_i^M and B_i^O . Using these bounds, however, has one potential caveat. The correlation between a bound and the objects it bounds may vary across segments of the population in a way that is unobservable but affects our results. In particular, the tightness of B_i^O and B_i^M may depend on the curvature of $M_i(\cdot)$ and i ’s unobservable search cost s_i . A regression of the bounds on observables may therefore suffer from omitted variable bias. Before exploring the heterogeneity in the bounds, we therefore make the following assumption on the sales process and the shape of $M(\cdot)$, which circumvents this potential caveat.

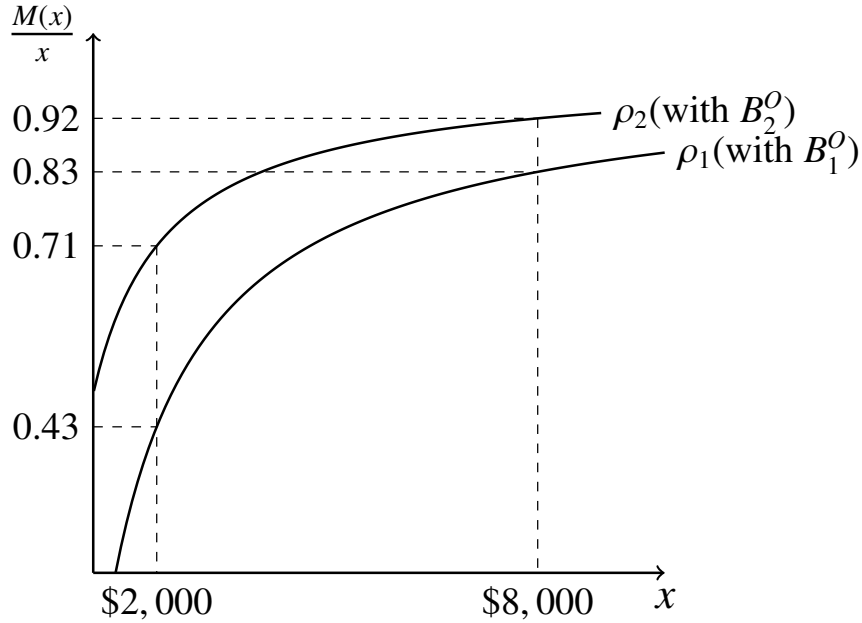
Assumption 2. *Suppose that the dealer can choose the car price contingent on whether the consumer finances the car at his place or not. Furthermore, suppose for every consumer i that $M_i(\cdot)$ can be written as $M_i(x) = x - h(\rho_i) \cdot \ln(x)$ for some positive, increasing, and continuously differentiable function $h(\cdot)$.*

As discussed in Section 4 the estimates on $M'(\cdot)$ are tight if dealers can choose the car price contingent on whether the consumer finances the car at their place or not.²⁸ Combined with the additional structure on the functional form of $M(\cdot)$, we can ensure that the estimates on B_i^O correspond to the ordering of the individual wedges between disutilities. If $M(\cdot)$ can be represented by the family of functions described in Assumption 2, the parameter ρ_i specifies the magnitude of the wedge between disutilities for consumer i , where larger ρ_i ’s correspond to a larger wedge. Figure 3 depicts an example of the functional form. While the additional structure imposed on $M(\cdot)$ is a caveat, the corresponding functional form seems plausible. Essentially it requires that the marginal wedge in disutilities is large for small amounts of

²⁷While B_i^M is estimated on the full sample, recall that B_i^O is estimated only on the set of loans with positive markups.

²⁸We think that it is reasonable to assume that quoted car prices are contingent on the consumer taking the loan. In fact, in many conversations about this project people have pointed out to us that the dealer expected them to finance the car at the dealership with the quoted price.

Figure 3: Example of Assumed Functional Form For $M(\cdot)$



NOTE: This graph shows two examples for the functional form of $M(\cdot)$ that we assume from hereon. Note that as the amount on the x-axis increases the ratio of how consumers treat charges and actual charges converge to one.

financing but converges to zero for large amounts of financing. This notion is reminiscent of the idea that consumers have scarce cognitive resources and allocate more of these to matters that are more important.²⁹

Proposition 4. *Suppose that Assumption 2 holds. Then $B_i^O \geq B_j^O \Leftrightarrow \rho_i \geq \rho_j \quad \forall i, j$*

According to Proposition 4 the functional form introduced in Assumption 2 indeed implies that the ordering of the bounds B_i^O induces an ordering on the space of all ρ_i 's. Hence, whenever $B_i^O \geq B_j^O$ for two consumers i and j it also holds that $\rho_i \geq \rho_j$. As a direct consequence, we can use the terms B_i^O to conduct a heterogeneity analysis on the magnitude of the wedge in disutilities.

6.1 Individual Characteristics and Regional Variation

In Column (1) and (3) of Table 4, we correlate our estimates for the bounds B_i^O and B_i^M with credit scores and income. We find that consumers with lower incomes and credit scores exhibit larger wedges between disutilities.

Next we turn to the regional variation of our estimates. As a starting point Figures 8 and 9 in Appendix B show how our estimates for B_i^O and B_i^M differ across counties. To eliminate

²⁹For papers that explore the behavioral implications of limited attention and the determinants of attention allocation see ?, Bordalo *et al.* (2012), Bordalo *et al.* (2013), and Mackowiak *et al.* (2018)

Table 4: Estimated Effect of Transaction and County Characteristics on Estimated Bounds

	OVERALL BOUND B_i^O	DEALER ONLY BOUND B_i^M		
	(1)	(2)	(3)	(4)
Log Monthly Income	-9.277*** (0.262)	-8.688*** (0.261)	-1.847*** (0.135)	-1.528*** (0.135)
Credit Score, 100 points	-29.99*** (0.386)	-30.02*** (0.386)	-3.576*** (0.197)	-3.588*** (0.198)
Mileage, Tens of Thousands	5.054*** (0.081)	5.014*** (0.081)	-0.602*** (0.039)	-0.625*** (0.039)
New Car	-4.931*** (0.411)	-4.915*** (0.411)	-8.058*** (0.232)	-8.058*** (0.232)
Log Loan Amount	393.8*** (0.951)	393.4*** (0.950)	87.72*** (0.324)	87.51*** (0.324)
Average Years of Education		-3.734*** (0.336)		-1.028*** (0.208)
Fraction with Internet Access		-8.425*** (1.469)		-8.531*** (0.895)

NOTE: Table shows estimates from an OLS regression. Columns (1) and (3) control for transaction-specific observables. Columns (2) and (4) include county-level data from the ACS. Lender, model, and state fixed effects also included, but not shown. Standard errors clustered at zip code level.

lender-specific variation, we plot residual variation in the bounds after removing lender fixed effects. A county is lightly colored on the map if car buyers in that county exhibit larger wedges in disutilities compared to buyers in other counties with loans from the same lender.

To examine county-level variation more formally, columns (3) and (6) in Table 4 add county-level data from the American Community Survey (ACS) to the regression. To proxy for education, we use the percentage of inhabitants in a county with a college degree.³⁰ To proxy for digital infrastructure, we use the speed and availability of internet access as measured on a scale from 1 to 5, where a score of 5 represents counties in which internet access is fast and readily available, while a score of 1 means that internet access is either not available or slow. Education and digital infrastructure are both negatively correlated with our estimates. Hence, consumers that live in areas with less education and with lower internet connectivity display larger wedges between disutilities.

Finally, we can also break down our estimates by car model. Table 19 depicts our average estimates for B_i^M and $M_i^M(\cdot)$ for the 20 most common models in our data, showing that there is some variation across different models.

7 Full Model Setup

The following section develops a full model to explore how the wedge between consumers' disutility from finance charges and vehicle price affects outcomes in a competitive environment. First, we quantify the effect of the wedge on consumer behavior and on the pricing strategies of dealers. We then use these estimates to conduct two counterfactual experiments: one in which consumers treat all charges equally, and one in which dealers are required to pass through the buy rate. The model captures the essential institutional details faced by auto lenders, dealers, and consumers.

7.1 Consumer Utility and Dealer Market Shares

Consumers decide on a dealer-model combination. There is a set of markets \mathcal{M} and for every market $m \in \mathcal{M}$ a set of active dealers \mathcal{D}_m . Every dealer $d \in \mathcal{D}_m$ offers a specific set of makes \mathcal{J}_d , which we take to be exogenously given. Furthermore, each dealer works with a set of lenders \mathcal{B}_d that extend loans to her customers. Dealers engage in differentiated product Bertrand competition, setting both interest rates and car prices optimally, given consumer tastes, competing dealers' behavior, their marginal cost of lending, and the revenue sharing agreement with lenders.

To specify consumer i 's indirect utility function, we denote her travel costs to dealer d by $g(d, i)$. Furthermore, consumer i has marginal utility of money γ_i , which we allow to

³⁰The ACS also provides the percentage of inhabitants that obtained a high school degree. Our results also hold if we use this proxy for education or both proxies simultaneously.

depend on her demographics such as her income. Importantly, consumers may treat different components of the overall price differently. To translate actual charges into perceived charges we parameterize the utility function of the consumers $M_i(\cdot)$. In particular, we assume that

$$M_i(x) = x - \rho_i \cdot \log(x).$$

Hence, ρ_i is an individual-specific parameter describing how responsive consumer i 's utility is to changes in finance charges. If ρ_i becomes large, consumer utility becomes less responsive to changes in finance charges. If ρ_i becomes small, so does the wedge between the price and finance charges disutilities. Our estimates of $M'_i(\cdot)$ from Section 4 allow us to back out ρ_i immediately. Summary statistics on the corresponding estimates can be found in Table 20. Given the observed car price $p_{j,d}$ and interest rate $r_{j,d}$ for a car j at dealer d , the perceived overall transaction price $\tilde{p}_{j,d}$ is:

$$\tilde{p}_{j,d} = p_{j,d} + p_{j,d} \cdot r_{d,d_j} - \rho_i \cdot \log(p_{j,d} \cdot r_{d,d_j})$$

Besides the travel distance and car price, consumers' indirect utility depends on other observable loan and car attributes which we collect in the vector \mathbf{x}_j , whose relative attractiveness is captured by vector β . Furthermore, there are two types of unobservable taste shocks in the model. First, the relative attractiveness of purchasing make j at dealer d is captured by a dealer-model specific scalar variable $\xi_{j,d}$. Second, every consumer's choice is affected by her individual-specific taste shock $\epsilon_{i,j,d}$ for a dealer-model combination, which are i.i.d Type-1 extreme value distributed.

$$u_{i,j,d} = g(d, i) - \gamma_i \cdot \tilde{p}_{j,d} + \beta \cdot \mathbf{x}_j + \xi_{j,d} + \epsilon_{i,j,d} \quad (6)$$

where

$$\gamma_i = \beta_0 + \beta_y \cdot y_i + v_i \quad \text{where } v_i \sim \mathcal{N}(0, \sigma_v) \quad (7)$$

In practice, we collapse $g(d, i)$ at the market level as a population-weighted average over the travel distances to dealer d from different zip-code centroids so that we have $g(d)$. As is customary in the literature we refer to mean utility as $\delta_{j,d} = g(d) - \alpha_c \cdot \tilde{p}_{j,d} + \beta \cdot \mathbf{x}_j + \xi_{j,d}$. We refer to the vector of those mean utilities for an entire market as δ_m .

We now describe the customers' choices, which determine the overall market share of a dealer-model combination. For this purpose, we integrate over the unobserved customer type v . Exploiting the logit structure of our model, the share of make j at dealer d is given by:

$$s_{j,d}^m(\mathbf{p}_d, \mathbf{r}_d; \mathbf{p}_{-d}, \mathbf{r}_{-d}) = \int \frac{\exp(g(i, k) - \gamma_i \cdot \tilde{p}_{j,d} + \beta \cdot \mathbf{x}_j + \xi_{j,d})}{\sum_{d \in \mathcal{D}_m} \sum_{k \in J_d} \exp(g(i, k) - \gamma_i \cdot \tilde{p}_{k,d} + \beta \cdot \mathbf{x}_k + \xi_{k,d})} f(v) \cdot dv$$

7.2 Dealer Maximization Problem

Dealers decide on prices and interest rates for all models that they sell. The buy rates that dealers face are determined in equilibrium by the set of bidders \mathcal{B}_d for loans at dealer d . The expected buy rate is a function of all the prices and interest rates that are charged in the market since lenders internalize that the buy rate (and the implied markup) will affect a dealer's chance of selling the car. The optimal considerations of the lender are described in more detail in subsection 7.3. Given a buy rate and a downpayment $down_{j,d}$, dealer d 's maximization problem is

$$\max_{\mathbf{p}_d, \mathbf{r}_d} \sum_{j \in \mathcal{J}_d} s_{j,d}^m(\mathbf{p}_d, \mathbf{r}_d; \mathbf{p}_{-d}, \mathbf{r}_{-d}) \cdot \left(p_{j,d} + \alpha_{j,d} \cdot (p_{j,d} - down_{j,d}) \cdot (r_{j,d} - b_{j,d}) - c_{j,d} \right) \quad (8)$$

Denote the dealer's profit except the random component under lender l 's terms and the optimal price/interest rate combination as $\pi_d^l(\mathbf{p}_d(b_l), \mathbf{r}_d(b_l); \mathbf{p}_{-d}, \mathbf{r}_{-d})$.

7.3 Lender Maximization Problem

In modeling the lenders's maximization problem, we make a number of simplifying assumptions. First, we assume that there is one auction for each make-dealer combination. Hence, each of the lenders in \mathcal{B}_d associated with dealer d bids once for all the sales of make j . Second, lenders play a symmetric game, i.e, all α 's are identical for a dealer. Empirically there is relatively little variation in α and allowing for heterogeneity would complicate the analysis considerably. Third, lenders take all buy rates arising in auctions for other models as given when making their bids for a particular contract.³¹

Assumption 3. (i) All lenders $k \in \mathcal{B}_d$ are drawing from the same cost distribution $r_k^b \sim \mathcal{F}()$ and have the same contractual arrangement α, β with a given dealer d . (ii) In each auction (j,d) bidders take the buy-rates arising in auctions for other makes as given.

The objective function is composed of the market share of the model for which the lenders are bidding, the loan amount $p_{j,d} - down_{j,d}$, the probability of winning the auction, and the profit margin, which is composed of a share of the markup and a direct payment. To estimate the model, we extend the result of Guerre *et al.* (2000) and show that unobserved cost can be expressed in terms of already known (after estimating the demand model) or observed objects.

³¹This simplification is reminiscent of the Nash-in-Nash approach that is frequently used in the analysis of bilateral oligopoly (see Horn and Wolinsky, 1988, Gaynor and Town, 2011, Collard-Wexler *et al.*, 2014). In this literature, the bargains between a particular upstream supplier and a downstream firm take the outcome of all other bargains as given. Similarly, we assume that, when bidding for a particular contract, a lender takes all buy rates in other auctions as given.

A lender wins the bid and issues the loan for a particular transaction if their buy rate is the lowest one submitted. Let N be the number of lenders bidding for a contract and $r_k^b \sim \mathcal{F}(\cdot)$ the distribution of wholesale interest rates r , which characterize the lenders' cost of financing a loan. Lenders anticipate that the likelihood of a sale depends on b through the dealer's downstream decision on all prices and interest rates. Bank k 's objective function when bidding for a particular contract is therefore given by:

$$\max_{b_{j,d}^k} s_{j,d}^m(\mathbf{p}_d(b_{j,d}^k), \mathbf{r}_d(b_{j,d}^k); \mathbf{p}_{-d}, \mathbf{r}_{-d}) \cdot (p_{j,d}(b_{j,d}^k) - \text{down}_{j,d}) \cdot \left(1 - \mathcal{F}(\beta_{j,d}^{-1}(b_{j,d}^k))\right)^{N_d-1} \cdot \left[(1 - \alpha_{j,d}) \cdot m_{j,d}(b_{j,d}^k) + b_{j,d}^k - r_{j,d}^k\right]. \quad (9)$$

For notational convenience we omit some of the function's arguments and denote it by $s_{j,d}(b)$. For the derivation, define $\psi_{j,d}(b) = s_{j,d}^m(\mathbf{p}_d(b_{j,d}), \mathbf{r}_d(b_{j,d}); \mathbf{p}_{-d}, \mathbf{r}_{-d}) \cdot (p_{j,d}(b) - \text{down}_{j,d})$.

Lenders anticipate that dealers mark up a specific model by $m_{j,d}(b)$. The markup function depends on observable attributes and unobservable attributes of customers that purchase model j as well as the other prices and interest rates in the market. Given our demand model, we can simulate $\hat{m}_{j,d}$. We apply the key insight from Guerre *et al.* (2000) that there is a relationship between the observed distribution of buy rates and the unobserved distribution of costs. In particular, $G(b) = F(\beta^{-1}(b)) \quad \forall b \Rightarrow g(b) = \frac{1}{\beta'(r)} \cdot f(r) \quad \forall b$. This insight allows us to substitute all unknown terms in the lender's first order condition with either observed or already estimated objects (based on the demand model and dealer pricing incentives given demand) (see section A.2 for details).

Proposition 5. *Lenders' costs can be recovered as:*

$$r_{j,d}^k = (1 - \alpha_{j,d}) \cdot m_{j,d}(b_{j,d}^k) + b_{j,d}^k + \frac{1 + (1 - \alpha) \cdot m'_{j,d}(b_{j,d}^k)}{\tilde{\psi}'(b_{j,d}^k) - (N_d - 1) \cdot g(b_{j,d}^k) \cdot (1 - \mathcal{G}(b_{j,d}^k))^{-1}} \quad (10)$$

All expressions on the right hand side are observed or can be constructed from the demand side estimates. We can therefore back out the cost distribution of lenders in this market.

7.4 Discussion of Model Specification

Some of our modeling assumptions deserve discussion. First, the model treats car prices as posted, and so it neglects the price dispersion that arises from negotiation over loan terms and vehicle prices. Retail markets for financial products are often analyzed through the lens of search models, since they often feature large price dispersion despite being relatively homogeneous (Allen *et al.*, 2013). We study a bundle of a retail financial product and an extremely differentiated durable. This latter component requires us to account for unobservable product-specific components such as make cache. This is why we use a posted-price demand model,

which provides a well-established framework to deal with unobserved heterogeneity, at the cost of being unable to speak to the within-product price dispersion that exists in this market.

Second, we assume that buyers who obtain loans indirectly are distinct from buyers who obtain loans directly, and the latter are outside our model.³² In practice, the set of buyers who obtain loans directly includes both consumers who never obtained a rate quote from a dealer, and those who obtained but rejected a rate quote from a dealer. We expect this latter group to be quite small; dealers can obtain buy rate quotes from a very large number of lenders very quickly, so it is unlikely that they will be unable to beat an outside rate quote obtained by a consumer if they are given the chance.

Lastly, the structure in this market is somewhat unusual in that multiple upstream suppliers, the lenders, are competing to supply a homogenous product in form of the loan. To our knowledge, there are no canonical empirical models for such a situation. For example, a double-marginalization model in which a monopolistic upstream firm supplies the loan would deviate from the relative competitive nature of the upstream market. On the other hand, different lenders will have slightly different cost for different types of customers, which we would like to take into account here. We therefore stay relative close to the actual market implementation in our model with the important deviation that we model the auction not at the contract level but instead at the dealer-model level.

8 Estimation

To estimate the model, we use data from 30 states, which amounts to 1134 counties.³³ We consider each county to be one market and estimate demand for the 70 most popular models, which account for the large majority of total sales. The remaining models are assigned to the outside good. We restrict our estimation to counties that have less than 45 dealers and in which at least one of the 70 most popular models is sold. After these data restrictions we are left with 917.0 markets which each include on average 6.916 dealers and a median of 5.0 dealers.

As described in Section 3, the AutoCount data covers the entire auto market in these 30 states while the supervisory data only covers a fraction of the market. We therefore, define the total market as all car purchases observed in the AutoCount data. Since the data are constructed from records from the states' Departments of Motor Vehicles, they should be close to comprehensive. However, the AutoCount data lacks information on dealer reserves and buy rates. To estimate the model we therefore impute buy rates in the AutoCount data from

³²Empirical models of inter-modal competition, are, for example provided in Allen *et al.* (2014), where consumers obtain loan quotes from their home bank or run an auction among non-home lenders. Another example is Salz (2017), where buyers can search bilaterally or through brokers.

³³We have data on Alabama, Arkansas, California, Colorado, Connecticut, Florida, Georgia, Idaho, Illinois, Indiana, Kentucky, Maine, Maryland, Michigan, Mississippi, Missouri, Montana, Nebraska, New Jersey, New Mexico, North Carolina, North Dakota, Ohio, South Carolina, Texas, Utah, Vermont, Virginia, Washington, and Wisconsin.

a saturated model that is informed by the supervisory data ($R^2 \geq 0.86$). While this procedure introduces some measurement error, we do not see this approach as a large shortcoming. Dealers sometimes offer loan terms before observing buy rates, and so use predicted buy rates to construct the offer. Later, we use the additional first order condition from dealers' interest rate choices to recover the dealer profit shares α . These α estimates provide a robustness check of the imputation, as we can compare them to the observed values in the supervisory data.

Estimating the model also requires a proxy for the travel distance to each dealer. To generate this proxy, we subdivide each county into zip-code tabulation areas and then query the travel distance from the centroid of each of those areas to the dealer using the Google distance matrix API. The overall travel distance to a dealer within a county is the population-weighted sum of the travel-distances from each of those centroids.

The price of the vehicle is potentially endogenous to the unobserved dealer-model specific demand shock $\xi_{j,d}$. Failure to account for this potential endogeneity will result in biased price coefficients. We therefore interact $\xi_{j,d}$ with the following set of instruments: the average miles per hour of other models at the same dealer, the vehicle length of other models at the same dealer, the mileage of other models at the same dealer, the average travel distance to other dealers in the same market, the buy rate, and the average price of the same model in other markets.³⁴

$$\delta_m^{h+1} = \delta_m^h + \log(s_m) - \log(\hat{s}(\delta^h, \sigma)) \quad (11)$$

Following Berry *et al.* (1995) we use the observed aggregate market shares for a specific model-dealer combination, $s_m \forall m$ to compute a contraction mapping that recovers mean utilities.³⁵ We then regress those mean utilities on product attributes to uncover the linear parameters of the mapping (Nevo, 2000). Using $\delta_{j,d}$ we can compute $\xi_{j,d} = \delta_{j,d} - \beta_x \cdot \mathbf{x}$. Equation 12 provides the moment condition for estimation.

$$G(\theta) = \sum_{d \in \mathcal{M}_d} \sum_{j \in \mathcal{J}_d} \xi_{j,d}(\theta) \cdot z_{j,d} \quad (12)$$

9 Estimation Results

9.1 Demand Results

Table 5 shows the coefficients from the demand model along with standard errors.³⁶ The price interaction terms show that buyers with lower income are more price-elastic. The coefficient on the price-income interaction is estimated somewhat imprecisely. Most other coefficients

³⁴Except for the buy-rate and the distance, these instruments are standard in the demand estimation literature (Nevo, 2000).

³⁵Unlike the nested logit model in Berry (1994), the random coefficient model does not allow for an analytic inversion.

³⁶Table 21 shows demand coefficients associated with different models and their estimated standard deviation.

are precisely estimated and their sign lines up with intuition and the previous literature. The coefficients on horsepower and vehicle length are both positive but decreasing in income. However, the coefficient on miles per gallon is negative but increasing in income, suggesting that higher income households place greater value on fuel efficiency. Consumers dislike travel distance to the dealer. We now discuss the size of the elasticities that are implied by those coefficients.

Table 5: Demand Model Coefficients

VARIABLE	COEFFICIENT	STANDARD ERROR
PRICE	-0.0772	0.00018
HORSEPOWER	0.1765	0.00161
VEHICLE LENGTH	0.7627	0.00898
MPG	-1.5557	0.04973
DISTANCE TO DEALER	-0.162	0.00156
INCOME \times PRICE	0.8213	0.02629
INCOME \times HORSEPOWER	-2.25044	0.24702
INCOME \times MPG	15.6446	6.62776
INCOME \times CAR LENGTH	-7.6912	1.34387

NOTE: The table shows the main coefficient estimates from the model. Travel time is in log-minutes and prices are in dollars. Income is measured in units of standard deviations.

Our model estimates consumers' price elasticities for the overall transaction price including the car price and all finance charges. Over all market-dealer-model combinations we obtain about 35,000 different elasticities, with an average of -3.73.

The own-price elasticities of the fifteen different makes that are included in the demand model vary from -6.2 for GMC to -2.9 for Hyundai (see Table 21 in Appendix B). Our total price elasticities are close to previous estimates in the literature. Nurski and Verboven (2016), for example, find an average price elasticity of -3.14 for the Belgian market and Murry (2017) estimates an average own-price elasticity of -4.9 for the US market. Note that it is intuitive that we estimate demand to be slightly less elastic. Our estimates are relative to the overall price, including finance charges, while previous papers consider the car price alone. As increases in the car price are often accompanied by increases in the size of the loan and hence finance charges, ignoring finance charges should lead to lower estimates for demand elasticities. At an average of -0.16 consumers appear not to be too sensitive to changes in distance to different dealer locations.³⁷

³⁷Murry (2017) also documents distance elasticities using the distance in miles instead of average travel times as a measure for the disutility associated with traveling to a dealership. He finds that buyers are more elastic to distance with estimated elasticities ranging from -1.1 to -1.8. This might be a result of a different subset of markets that Murry (2017) focuses on.

9.2 Dealer Cost

In order to conduct the counterfactual experiments, we use the first order conditions from a dealer's pricing problem to recover dealer costs. In this process, we also estimate $\alpha_{j,d}$ that determines the contractually specified transfer (as a function of the markup) that dealer d receives from a bank when selling a car of make j . A dealer maximizes her profits with regard to both interest rate and car price. We therefore obtain a set of $2 \times \mathcal{J}_d$ first order conditions, which are shown in the following two sets of equations.

$$s_{j,d}^m(\mathbf{p}_d, \mathbf{r}_d; \mathbf{p}_{-d}, \mathbf{r}_{-d}) \cdot (1 + \alpha_{j,d} \cdot (r_{j,d} - b_{j,d})) + \sum_{k \in \mathcal{J}_d} \frac{\partial s_{k,d}^m(\mathbf{p}_d, \mathbf{r}_d; \mathbf{p}_{-d}, \mathbf{r}_{-d})}{\partial p_{j,d}} \cdot (p_{k,d} + \alpha_{k,d} \cdot (p_{k,d} - \text{down}_{k,d}) \cdot (r_{k,d} - b_{k,d}) - c_{k,d}) = 0 \quad \forall j \in \mathcal{J}_d \quad (13)$$

$$s_{j,d}^m(\mathbf{p}_d, \mathbf{r}_d; \mathbf{p}_{-d}, \mathbf{r}_{-d}) \cdot \alpha_{j,d} \cdot (p_{j,d} - \text{down}_{j,d}) + \sum_{k \in \mathcal{J}_d} \frac{\partial s_{k,d}^m(\mathbf{p}_d, \mathbf{r}_d; \mathbf{p}_{-d}, \mathbf{r}_{-d})}{\partial p_{j,d}} \cdot (p_{k,d} + \alpha_{k,d} \cdot (p_{k,d} - \text{down}_{k,d}) \cdot (r_{k,d} - b_{k,d}) - c_{k,d}) = 0 \quad \forall j \in \mathcal{J}_d \quad (14)$$

Typically, it is possible to obtain a closed form matrix expression for the inversion to recover the costs. However, in our case, such a closed form does not exist for the joint set of costs and unobserved $c_{j,d}$ -terms. We therefore conduct a non-linear search over this joint set to determine the solution of the first order conditions. The cost estimates that we obtain from this procedure are shown in Table 6. We estimate average cost of 17.6, ranging from 7.6 in the 10th percentile to 27.6 in the 90th percentile. The implied average Lerner index is 0.294.

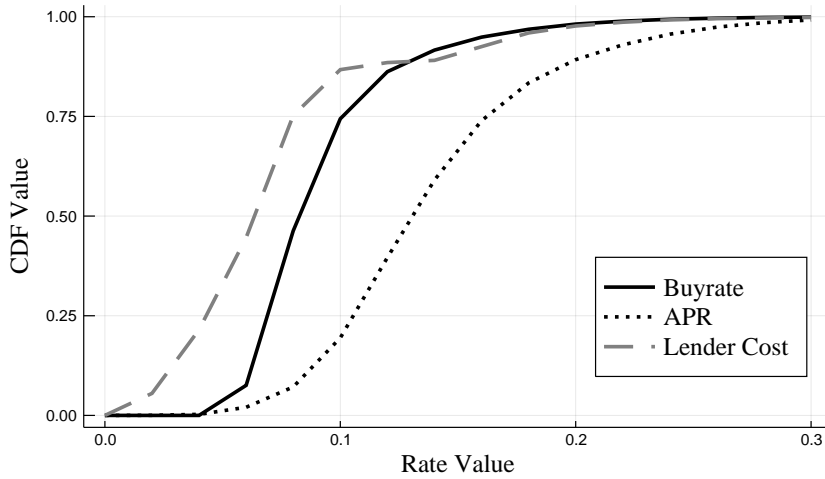
Table 6: Lerner Index, and Cost, Summary Statistics

VARIABLE	MEAN	P10	P25	P50	P75	P90
LERNER INDEX	0.294	0.102	0.147	0.228	0.383	0.606
COST (\$ 1000)	17.6	7.6	11.9	17.5	23.6	27.6

NOTE: The table shows summary statistics for the Lerner index across all estimated markets. In each market we weight the index according to the market shares of the respective model.

We use the second first order condition to back out the revenue sharing agreement $\alpha_{j,d}$. Since we also directly observe those agreements in the supervisory data, the inferred values will serve as a validation of the model. From the inversion of the dealer FOC we recover an average revenue split of 0.68, very close to the 0.66 observed in the supervisory data.

Figure 4: CDF's of Interest rates, buy rates, and lender costs.



NOTE: This graph shows the CDF's of the distribution of APR, buy rate, and lender cost.

9.3 Lender Cost Estimates

We use Equation 20 (in the appendix) to recover lenders' costs. On average, we estimate them to be 0.072. Lenders are competing with other lenders that have an established relationship with the dealer.³⁸ A dealer conducts business with on average 4.35 lenders and 4.0 lenders at the median. If we condition only on lenders that have a significant market share with the dealer those numbers drop to 3.35 and 3.0, respectively.

The average buy rate is above cost at 0.091, but at higher quantiles buy rates are *below* cost because lenders expect dealers to mark these loans up substantially. Table 7 shows means and quantiles of the lender cost distribution and compares them to the same summary statistics for buy rates and interest rates. The lender cost distribution stochastically dominates the interest rate distribution over the entire domain, but it does not dominate the buy rate distribution.

Table 7: Lerner Index, and Cost, Summary Statistics

VARIABLE	MEAN	P10	P25	P50	P75	P90
LENDER COST	0.072	0.026	0.044	0.063	0.08	0.148
BUYRATE	0.091	0.062	0.07	0.082	0.101	0.132
APR	0.139	0.086	0.106	0.13	0.162	0.204

NOTE: The table shows summary statistics for the Lerner index across all estimated markets. In each market we weight the index according to the market shares of the respective model.

³⁸Remember that the dealer and lender need a revenue sharing agreement to split the additional surplus that the dealer markup generates.

10 Counterfactual Experiments

We present results from two different counterfactual experiments—one in which consumers treat all charges identically and one in which dealers are obliged to pass through the interest rate that the lender sets. We start by investigating the market equilibrium under the assumption that buyer utility is equally responsive to finance charges and vehicle charges. We refer to this as the NO WEDGE counterfactual. While this counterfactual has no direct policy relevance, it provides a useful benchmark for the overall effect of the differential price sensitivities in the market as well as a comparison point against which the changes in the second counterfactual are to be interpreted. Our main outcome measures will be the effects on prices, consumer surplus, and producer surplus.

10.1 Equal Sensitivities Counterfactual

To simplify the presentation of our results and to make interest rates comparable across contracts with different term length, we compute the total finance charges and show the implied two-period interest rate. For this counterfactual we hold buy-rates fixed.

Table 8: Overview Counterfactual Results

Outcome Measure	BASELINE	NO WEDGE	$\Delta\%$	NO DEALER DISCRETION	$\Delta\%$
AVERAGE TOTAL PRICE ($p \cdot (1 + r)$) (\$)	27181.0	26874.1	-1.13	26906.4	-1.29
AVERAGE CAR PRICE (\$)	24139.0	26683.9	10.54	23897.0	-1.26
AVERAGE APR (TWO PERIOD)	0.134	0.017	-87.14	0.12	-13.58
TOTAL CONS. SURPLUS ($\hat{\rho}$) (\$BILLION)	36.5	35.95	-1.38	38.0	4.12
TOTAL CONS. SURPLUS ($\rho = 0$) (\$BILLION)	32.3	35.75	10.63	34.0	5.14
TOTAL DEALER PROFITS (\$BILLION)	2.755	2.206	-26.6	2.19	-26.11
TOTAL LENDER PROFITS (\$BILLION)	3.5	-	-	3.36	-4.11

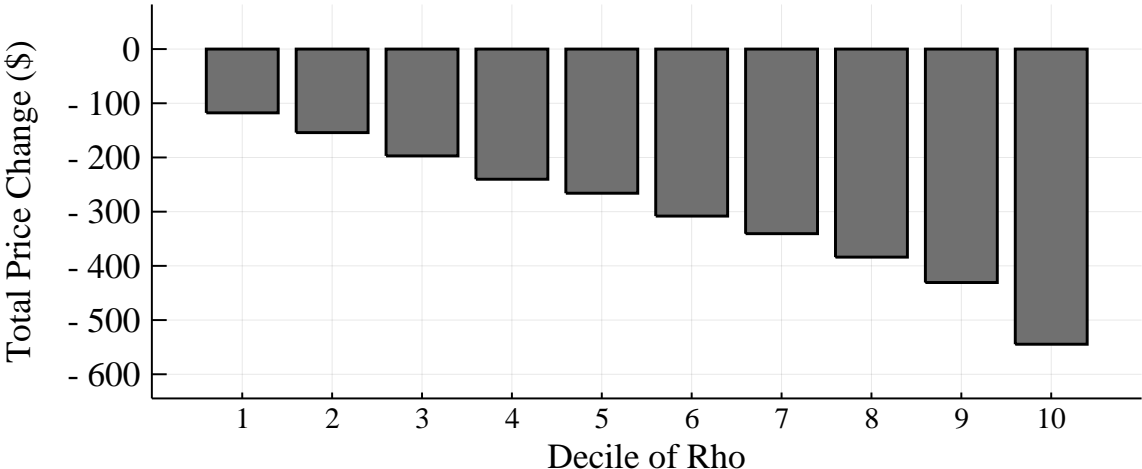
NOTE: This table shows counterfactual outcomes for two different scenarios. In scenario $\rho = \bar{\rho}$ all markets are assigned the same ρ , which is the mean across all markets. In scenario NO DEALER DISCRETION lenders set interest rates directly and dealers compete downstream in prices taking them as given. The first three rows (Total Price, Car Price, APR) are averages across all markets. The last four rows are totals over all markets.

In NO WEDGE total transaction prices are on average \$306.9 lower than in BASELINE, which corresponds to a reduction of 1.12 percent. This overall price change is due to opposing effects on the two dimensions of the pricing problem. On the one hand, dealers increase the prices of their cars on average from \$24139.0 to \$26683.9. On the other hand, dealers have a strong incentive to reduce interest rates because consumers now take the full amount of finance charges into account when deciding where to buy. The estimated decline in interest rates is from 0.134 to 0.017. The latter effect more than outweighs the former, which leads to the overall reduction in transaction prices. Intuitively, dealers are now competing for consumers that are overall much more price sensitive. Total prices fall as a result.

To analyze the change in consumer surplus, we compute average utility both under the initially estimated $\hat{\rho}$ as well as under the paternalistic welfare criterion where we assume

that $\rho = 0$. If utilities are computed with $\hat{\rho}$, consumer surplus decreases by -1.38 percent while it increases by 10.63 percent under the paternalistic welfare criterion. Total producer-surplus, aggregated across all markets, changes from \$2.755 billion to \$2.206 billion, which amounts to a 26.6 percentage decrease. Hence, dealer profits would be drastically reduced if consumers were to treat finance charges and vehicle charges the same. Interestingly, there is a strong asymmetry in the change of the two different consumer surplus measures. Under the recovered consumer utility function, this counterfactual leads to a decrease in consumer surplus. The change, however, is relatively small compared to the increase in consumer surplus under the no-wedge utility function.

Figure 5: Price Effects of the No WEDGE Scenario ρ -decile.



NOTE: The figure shows the estimated price effect of the No WEDGE counterfactual by estimated ρ -decile. For individuals with a larger wedge prices would fall by more in the counterfactual.

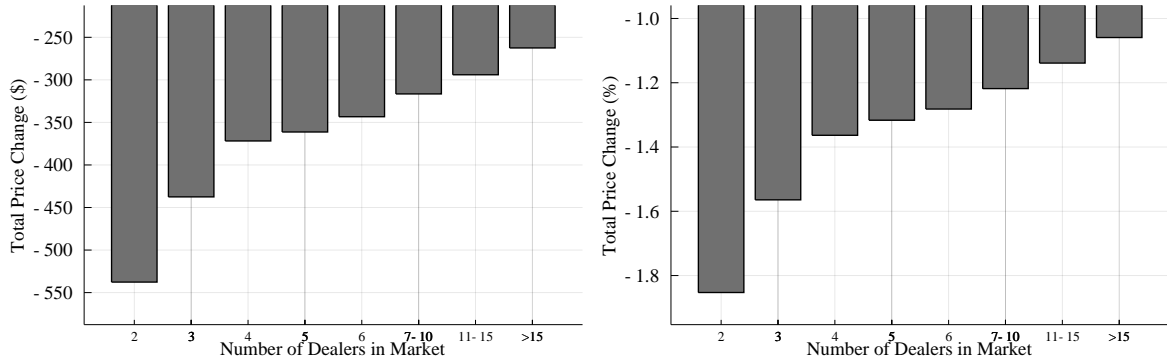
The overall counterfactual price change is largest for consumers who previously exhibited the largest wedge. To illustrate the heterogeneity of the equilibrium outcome Figure 5 shows the change in total price by quantiles of our ρ_i -estimates. In the lowest quantile, the counterfactual leads to a price decrease of about \$100 whereas in the highest quantile the decrease is more than \$500.

10.1.1 The Effect of Competition

One natural question is to what extent competition can undo consumer harm when consumers are not fully aware of all price components (see Gabaix and Laibson, 2006). To analyze how competition interacts with our results, we partition the response in the No WEDGE counterfactual by number of dealers in the market. Figure 6 shows the results from this exercise. In markets with only two competitors the total price decreases by -537.7, whereas in markets with more than 15 competing dealers it decreases by -262.5. Additional competition, there-

fore, strongly mitigates the detrimental effects of consumers’ reduced sensitivity to finance charges.

Figure 6: Price Effects of the No WEDGE Scenario by Number of Dealers



NOTE: The figure shows the estimated price effect of the No WEDGE scenario by the number of dealers in the market. The left panel depicts the corresponding scatter plot, the middle panel the histogram of estimated absolute price effects, and the right panel the histogram of estimated relative price effects.

Similar to the market studied in this paper, many markets for products with add-ons are characterized by oligopolistic competition. Therefore, our results also provide an interesting benchmark for the interaction between competition and sub-optimal consumer behavior in other markets.

10.2 No Dealer Discretion Counterfactual

In our key counterfactual we explore what happens if dealers have no discretion to set interest rates, which are instead set directly by lenders and passed through to consumers. As lenders previously set buy rates in anticipation of a certain profit from the dealer markup, one would expect that the interest rates that lenders quote lie significantly above the previous level of the buy-rates. We assume that lenders in this counterfactual bid according to the dominant strategy in a second price auction. This means that interest rates are set by the second lowest bid of N_d bids, where N_d is the number of lenders that contract with dealer d .³⁹

There are two important forces that determine the outcome in the No DISCRETION counterfactual. On the one hand, dealers’ *contractual incentives* change as they no longer participate in finance charges. Holding interest rates fixed, this leads them to increase prices and reduce output. This effect is somewhat reminiscent of double marginalization: lenders maximize their own profits when setting interest rates, and dealers simply take this behavior as given. The difference is that the interest rate is not an input price to the dealers profit maximization problem. Instead it is one of two prices faced by the consumer.

³⁹Note that while Proposition 5 provides a relatively straightforward way to compute lender cost, the reverse is not true. With the estimates in hand, it is computationally very hard to recompute an equilibrium, since the differential equation that results from the dealer bidding problem does not permit a closed form solution.

On the other hand, there is an *informational component*. Lenders do not have as much information about consumers and therefore cannot optimally price discriminate across consumer-specific wedges. Arguably, this may be an important reason for the existence of dealer markups.

To test whether dealers in fact have access to pricing-relevant information that lenders cannot observe, we estimate a fully saturated regression model of markups on virtually all information that lenders have for a given loan application. As shown in Table 22 in the Appendix, even this fully saturated model has an adjusted R^2 of less than 0.12. Hence, lenders have almost no ability to condition their buy rate decisions on the wedge in disutilities in consumer preferences. A direct implication is that the effects of the counterfactual experiments should be heterogeneous across the population—consumer with higher ρ should profit to a larger extent than their counterparts with lower ρ . The assumption that lenders bid according to the dominant strategy in a second-price auction, which means to simply bid the cost, automatically implies that they do not set interest rates with regard to the consumer-specific wedge.

An overview of the results from the first step can be found in Table 8, which shows that such a policy would lead to a decrease in overall transaction prices of about \$-351.5 which corresponds to -1.29 percent. In terms of consumer welfare the effect is more subtle. On the one hand, consumer welfare measured according to $\hat{\rho}$ is estimated to decrease by 4.12 percent as a response to such a policy. In particular, dealers cannot allocate charges to the interest rate dimension anymore which implies that they will increase the car price which in turn has a stronger impact on consumer utility. On the other hand, consumer welfare is estimated to increase on average by 5.14 according to the paternalistic welfare criterion with $\rho = 0$ for all consumers. While the effect is positive, eliminating dealer discretion only generates a portion of the maximal attainable consumer surplus of the NO WEDGE counterfactual.⁴⁰

11 Conclusion

This paper explores the intermediation of auto loans through auto dealers. Based on the specific incentives that dealers face, we construct a measure that captures consumers' differential responsiveness to loan and vehicle charges. We therefore leverage optimal supply-side behavior to study demand side-primitives, which is an approach that may be useful in other settings. These results do not rely on specific functional form assumptions for consumer utility, or on a fully-specified model of competition. We find that consumers are significantly less responsive to finance charges than to the price of a car. The size of the wedge in responsiveness is negatively related to credit scores and education.

To quantify the strategic implications of consumers' attenuated responsiveness to finance

⁴⁰Figure 6 shows how the price effect of this counterfactual varies across markets populated by different numbers of dealers.

charges, we use these results in a two-step estimator, which assumes differentiated-product Bertrand competition among dealers. Simulations from the model show that total vehicle prices would be lower and consumer surplus higher if consumers did not exhibit such a wedge in responsiveness to the two different prices in the market. Counterfactual simulations also show that, without dealer discretion to price loans, total prices in the market would fall and consumer surplus would increase.

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A Proofs

Proof of Proposition 1

To solve the maximization problem in (1), ignore the second constraint and the constraint that $p_i \geq 0$ such that it becomes:

$$\begin{aligned} \max_{r_i, p_i} \quad & p_i + (\tau_i p_i - d_i)(r_i - b_i)\alpha + \beta - c_i \\ \text{s.t.} \quad & -\tau_i p_i - (\tau_i p_i - d_i)r_i \geq \bar{u}_i. \quad r_i \geq b_i \end{aligned}$$

Any solution to this problem clearly fulfills its constraint with equality. Therefore, we can rewrite this problem to be:

$$\max_{r_i} -\frac{r_i d_i - \bar{u}_i}{(1+r_i)\tau_i} + \left[\frac{r_i d_i - \bar{u}_i}{1+r_i} - d_i \right] (r_i - b_i)\alpha + \beta - c_i \quad r_i \geq b_i$$

The derivative with respect to r_i is:

$$\begin{aligned} & \frac{d_i + \bar{u}_i}{(1+r_i)^2 \tau_i} + \frac{d_i + \bar{u}_i}{(1+r_i)^2} (r_i - b_i)\alpha - \frac{d_i + \bar{u}_i}{1+r_i} \alpha \leq 0 \\ & \Leftrightarrow \left[\frac{1}{\tau_i} + (r_i - b_i)\alpha - (1+r_i)\alpha \right] \leq 0 \\ & \Leftrightarrow 1 \geq \alpha(1+b_i)\tau_i \end{aligned}$$

Whenever the last equation is fulfilled, the derivative is negative such that the optimal solution features $r_i = b_i$, which corresponds to a zero markup. Also note that the derived price is positive because $|\bar{u}_i| \geq d_i$ is assumed for all i . Hence, the constraint $p_i \geq 0$ is fulfilled. Finally, consider the second constraint. It will be fulfilled if:

$$-b_i(\tau_i p_i - d_i) \geq -(\tau_i p_i - d_i)\mathbb{E}[r^L] - s_i,$$

which is trivially fulfilled for $b_i \leq \mathbb{E}[r^L]$. If in contrast, $b_i > \mathbb{E}[r^L]$, we get that the second constraint is fulfilled if:

$$\begin{aligned} p & \leq \left(\frac{s_i}{r_i - \mathbb{E}[r^L]} + d_i \right) \frac{1}{\tau_i} \\ & \Leftrightarrow \frac{r_i d_i - \bar{u}_i}{(1+r_i)\tau_i} \leq \left(\frac{s_i}{r_i - \mathbb{E}[r^L]} + d_i \right) \frac{1}{\tau_i} \\ & \Leftrightarrow s_i \geq (\mathbb{E}[r^L] - b_i) \left(\frac{\bar{u}_i + d_i}{1+b_i} \right). \end{aligned} \quad (15)$$

As long as (15) holds, we will thus get that $r_i^* = b_i$ for any optimal offer by the dealer. Finally, suppose that there is an optimal offer featuring $r_i > b_i$ if (15) is not satisfied such that we have:

$s < (\mathbb{E}[r^L] - b_i) \left(\frac{\bar{u}_i + d_i}{1 + b_i} \right)$. From the proof of Proposition 2, we know that for any solution with $r_i^* > b_i$ the first constraint will be binding. Then from the arguments above it can not be the case that only the first constraint is binding, because $r_i = b_i$ would be optimal. Hence, both constraints have to be binding. Then, we get

$$p = \frac{r_i d_i - \bar{u}_i}{(1 + r_i) \tau_i} = \left(\frac{s_i}{r_i - \mathbb{E}[r^L]} + d_i \right) \frac{1}{\tau_i}$$

$$\Leftrightarrow s_i = -\frac{r_i - \mathbb{E}[r^L]}{1 + r_i} (d_i + \bar{u}_i)$$

This however, is a contradiction to $s_i < (\mathbb{E}[r^L] - b_i) \left(\frac{\bar{u}_i + d_i}{1 + b_i} \right)$, as $|\bar{u}_i| > d_i$ and $\frac{r_i - \mathbb{E}[r^L]}{1 + r_i}$ is increasing in r_i . As a consequence, even if (15) does not hold, there cannot be an optimal offer featuring $r_i^* > b_i$, which concludes the proof.

Proof of Proposition 2

First note that the optimal solution to the maximization problem in (1) will, in this case, satisfy at least one of its constraints with equality. Otherwise the dealer could increase p_i and thereby increase profits. In the first step of the proof we argue that if the second constraint is binding at the optimum also the first one is binding. For this purpose, suppose in contradiction that there exists an optimal solution $(r_i^* > b_i, p_i^* > 0)$ such that only the second constraint binds. Then (r_i^*, p_i^*) is a maximizer of:

$$\max_{p_i, r_i} L = p_i + (\tau_i p_i - d_i)(r_i - b_i)\alpha + \beta - c_i +$$

$$\mu \left(M_i(r_i(\tau_i p_i - d_i)) - \int M_i((\tau_i p_i - d_i)\tau_i r^L) g_i(r^L) dr^L - s_i \right)$$

Leading to the following first order conditions:

$$\frac{dL}{dp_i} = 1 + \tau_i \alpha (r_i - b_i) + \mu \left(M'_i(r_i(\tau_i p_i - d_i)) \tau_i r_i - \int M'_i((\tau_i p_i - d_i) r^L) \tau_i r^L g_i(r^L) dr^L \right) = 0$$

$$\frac{dL}{dr_i} = \alpha (\tau_i p_i - d_i) + \mu M'_i(r_i(\tau_i p_i - d_i)) (\tau_i p_i - d_i) = 0$$

Since both of these hold in equilibrium we get

$$\frac{1 + \alpha \tau_i (r_i - b_i)}{M'_i(r_i(\tau_i p_i - d_i)) \tau_i r_i - \int M'_i((\tau_i p_i - d_i) r^L) \tau_i r^L g_i(r^L) dr^L} = \frac{\alpha}{M'_i(r_i(\tau_i p_i - d_i))}$$

$$M'_i(r_i(\tau_i p_i - d_i)) (1 + \tau_i \alpha (r_i - b_i)) = \alpha (M'_i(r_i(\tau_i p_i - d_i)) \tau_i r_i - \int M'_i((\tau_i p_i - d_i) r^L) \tau_i r^L g_i(r^L) dr^L)$$

$$M'_i(r_i(\tau_i p_i - d_i)) (1 - \tau_i \alpha b_i) = -\alpha \int M'_i((\tau_i p_i - d_i) r^L) r^L \tau_i g_i(r^L) dr^L$$

The last equality cannot be fulfilled since the left hand side is positive but the right hand side is negative, which establishes the contradiction.

Using the insights from the first step, there are only two possibilities left, either both constraints are binding or only the first one is. Suppose only the first one is binding such that the optimal solution to the maximization problem in (1) maximizes:

$$\begin{aligned} \max_{p_i, r_i} \quad & p_i + (\tau_i p_i - d_i)(r_i - b_i)\alpha + \beta - c_i \\ \text{s.t.} \quad & -\tau_i p_i - M_i((\tau_i p_i - d_i)r_i) = \bar{u}_i \\ & r_i > b_i, p_i \geq 0 \end{aligned}$$

The corresponding Lagrange function is given by:

$$\max_{p_i, r_i} L = p_i + (\tau_i p_i - d_i)(r_i - b_i)\alpha + \beta - c + \mu(\bar{u}_i + \tau_i p_i + M_i(r_i(\tau_i p_i - d_i))),$$

leading to the following first order conditions:

$$\begin{aligned} \frac{dL}{dp_i} &= 1 + \tau_i \alpha (r_i - b_i) + \mu \left(\tau_i + M'_i(r_i(\tau_i p_i - d_i)) \tau_i r_i \right) = 0 \\ \frac{dL}{dr_i} &= \alpha (\tau_i p_i - d_i) + \mu M'_i(r_i(\tau_i p_i - d_i)) (\tau_i p_i - d_i) = 0 \end{aligned}$$

Since both of these hold in equilibrium we get:

$$\begin{aligned} \frac{1 + \tau_i \alpha (r_i - b_i)}{1 + M'_i(r_i(\tau_i p_i - d_i)) \tau_i r_i} &= \frac{\alpha}{M'_i(r_i(\tau_i p_i - d_i))} \\ \Leftrightarrow M'_i(r_i(\tau_i p_i - d_i)) &= \frac{\alpha \tau_i}{1 - \tau_i \alpha b_i} \end{aligned}$$

In particular, any solution to the problem in which only the first constraint is binding will satisfy this equation. Next suppose that both constraints are binding. In this case, the corresponding Lagrange function is:

$$\begin{aligned} L &= p_i + (\tau_i p_i - d_i)(r_i - b_i)\alpha + \beta - c \\ &+ \mu \left(\int M_i((\tau_i p_i - d_i)r^L) g_i(r^L) dr^L + s_i - M_i(r_i(\tau_i p_i - d_i)) \right) \\ &+ \lambda (-\bar{u}_i - \tau_i p_i - M_i(r_i(\tau_i p_i - d_i))) \end{aligned}$$

Then from the Kuhn-Tucker Theorem, we know that there exists $\lambda > 0$ and $\mu > 0$ such that the following two equations are fulfilled:

$$\begin{aligned} \frac{dL}{dp_i} &= 1 + \tau_i \alpha (r_i - b_i) + \mu \left(\int M'_i((\tau_i p_i - d_i)r^L) \tau_i r^L g_i(r^L) dr^L - M'_i(r_i(\tau_i p_i - d_i)) r_i \tau_i \right) \\ &+ \lambda \left(-\tau_i - M'_i((\tau_i p_i - d_i)r_i) \tau_i r_i \right) = 0 \\ \frac{dL}{dr_i} &= \alpha (\tau_i p_i - d_i) - \mu M'_i(r_i(\tau_i p_i - d_i)) (\tau_i p_i - d_i) - \lambda M'_i(r_i(\tau_i p_i - d_i)) (\tau_i p_i - d_i) = 0 \end{aligned}$$

From the second equation, we get:

$$\frac{\alpha - \mu M'(r_i(\tau_i p_i - d_i))}{M'(r_i(\tau_i p_i - d_i))} = \lambda$$

Substituting this into the first equation yields:

$$\begin{aligned} & 1 + \tau_i \alpha (r_i - b_i) + \mu \left(\int M'_i((\tau_i p_i - d_i) r^L) \tau_i r^L g_i(r^L) dr^L - M'_i(r_i(\tau_i p_i - d_i)) \tau_i r_i \right) \\ & + \frac{\alpha - \mu M'_i(r_i(\tau_i p_i - d_i))}{M'_i(r_i(\tau_i p_i - d_i))} \left(-\tau_i - M'_i((\tau_i p_i - d_i) r_i) r_i \tau_i \right) = 0 \\ \Leftrightarrow & 1 - \tau_i \alpha b_i + \mu \int M'_i((\tau_i p_i - d_i) r^L) \tau_i r^L g_i(r^L) dr^L - \tau_i \frac{\alpha - \mu M'_i(r_i(\tau_i p_i - d_i))}{M'_i(r_i(\tau_i p_i - d_i))} = 0 \\ \mu = & \frac{\tau_i \alpha b_i + \frac{\tau_i \alpha}{M'_i(r_i(\tau_i p_i - d_i))} - 1}{\tau_i + \int M'_i((\tau_i p_i - d_i) r^L) r^L \tau_i g_i(r^L) dr^L} \end{aligned}$$

since μ is positive $\tau_i \alpha b_i + \frac{\tau_i \alpha}{M'_i(r_i(\tau_i p_i - d_i))} - 1 > 0$ holds, which is equivalent to the statement that $M'_i(r_i^*(\tau_i p_i^* - d_i)) < \frac{\tau_i \alpha}{1 - \tau_i \alpha b_i}$.

Proof of Proposition 3

For the first part assume that $M'_i(x) \leq 1 \quad \forall x$. Let $r_i^* > b_i, p_i^* > 0$ be the optimal offer. Denote by \tilde{p}_i the price that is optimal for the dealer given that he offers $r_i = b_i$. Note first that $\tilde{p}_i > p_i^*$ holds. In particular, both constraints in (1) have to be slack if $r_i = b_i$ and $p_i = p_i^*$. Thus, the dealer can profit from increasing the price and we get $\tilde{p}_i > p_i^*$. As a consequence, the first constraint in 1 will also be binding at b_i, \tilde{p}_i . To see this, recall that the first constraint is binding at r_i^*, p_i^* due to Proposition 2. We therefore get:

$$\bar{u}_i + \tau_i p_i^* = -M_i((\tau_i p_i^* - d_i) r_i) \geq - \int M_i((\tau_i p_i^* - d_i) r^L) g_i(r^L) dr^L - s_i$$

As $\tilde{p}_i > p_i^*$,

$$\bar{u}_i + \tau_i \tilde{p}_i > \bar{u}_i + \tau_i p_i^* \geq - \int M_i((\tau_i p_i^* - d_i) r^L) g_i(r^L) dr^L - s_i \geq - \int M_i((\tau_i \tilde{p}_i - d_i) r^L) g_i(r^L) dr^L - s_i$$

Thus the second constraint is slack and the first one has to be binding. Hence, \tilde{p}_i and p_i^* are given by:

$$\begin{aligned} -\tau_i \tilde{p}_i - M((\tau_i \tilde{p}_i - d_i) b_i) &= \bar{u} \\ -\tau_i p_i^* - M_i((\tau_i p_i^* - d_i) r_i) &= \bar{u}_i. \end{aligned}$$

The optimal offer has to imply a weakly higher profit than offering $r_i = b_i$. Hence,

$$\begin{aligned}
p_i^* + (\tau_i p_i^* - d_i)\alpha(r_i^* - b_i) + \beta - c_i &\geq \tilde{p}_i + \beta - c_i \\
\Leftrightarrow \frac{-\bar{u}_i - M_i((\tau_i p_i^* - d_i)r_i)}{\tau_i} + (\tau_i p_i^* - d_i)\alpha(r_i^* - b_i) &\geq \frac{-\bar{u}_i - M_i((\tau_i \tilde{p}_i - d_i)b_i)}{\tau_i} \\
\Leftrightarrow M_i((p_i^* - d_i)r_i) - M_i((\tilde{p}_i - d_i)b_i) &\leq \tau_i(\tau_i p_i^* - d_i)\alpha(r_i^* - b_i)
\end{aligned} \tag{16}$$

Using that $\tilde{p}_i \geq p_i^*$, we therefore get that:

$$\begin{aligned}
&(\tau_i p_i^* - d_i)(r_i^* - b_i) - \left[M_i((\tau_i p_i^* - d_i)r_i) - M_i((\tau_i p_i^* - d_i)b_i) \right] \\
&= (\tau_i p_i^* - d_i)(r_i - b_i) - \left[M_i((\tau_i p_i^* - d_i)r_i) - M_i((\tau_i \tilde{p}_i - d_i)b_i) \right. \\
&\quad \left. + M_i((\tau_i \tilde{p}_i - d_i)b_i) - M_i((\tau_i p_i^* - d_i)b_i) \right] \\
&\geq (\tau_i p_i^* - d_i)(r_i^* - b_i) - \tau_i(\tau_i p_i^* - d_i)\alpha(r_i^* - b_i) - \left[M_i((\tau_i \tilde{p}_i - d_i)b_i) - M_i((\tau_i p_i^* - d_i)b_i) \right] \\
&\geq (\tau_i p_i^* - d_i)(r_i - b_i) - \tau_i(\tau_i p_i^* - d_i)\alpha(r_i^* - b_i) - ((\tau_i \tilde{p}_i - d_i)b_i - (\tau_i p_i^* - d_i)b_i) \\
&= (\tau_i p_i^* - d_i)r_i - (\tau_i \tilde{p}_i - d_i)b_i - \tau_i(\tau_i p_i^* - d_i)\alpha(r_i^* - b_i),
\end{aligned} \tag{17}$$

where the last inequality follows from the fact that $M'(x) \leq 1 \forall x$. Moreover, (16) implies that

$$\begin{aligned}
p_i^* + (\tau_i p_i^* - d_i)\alpha(r_i^* - b_i) + \beta - c_i &\geq \tilde{p}_i + \beta - c_i \\
\Leftrightarrow b_i[\tau_i p_i^* - d_i + \tau_i(\tau_i p_i^* - d_i)\alpha(r_i^* - b_i)] &\geq [\tau_i \tilde{p}_i - d_i]b_i
\end{aligned}$$

Substituting this into ??, yields

$$\begin{aligned}
&(\tau_i p_i^* - d_i)r_i - (\tau_i p_i^* - d_i)b_i - (M_i((\tau_i p_i^* - d_i)r_i) - M_i((\tau_i p_i^* - d_i)b_i)) \\
&\geq (\tau_i p_i^* - d_i)r_i - b_i[\tau_i p_i^* - d_i + \tau_i(\tau_i p_i^* - d_i)\alpha(r_i^* - b_i)] - \tau_i(\tau_i p_i^* - d_i)\alpha(r_i^* - b_i) \\
&= (\tau_i p_i^* - d_i)(r_i - b_i) [1 - \tau_i b_i \alpha - \tau_i \alpha],
\end{aligned}$$

which concludes the proof of the first part of the proposition. Part (ii) of the proposition follows from Proposition 2 and the assumed convexity of M . In particular, convexity implies that

$$\begin{aligned}
M((\tau_i p_i^* - d_i)r_i) - M_i(0) &\leq M_i'((\tau_i p_i^* - d_i)r_i)(\tau_i p_i^* - d_i)r_i \\
&\leq \frac{\tau_i \alpha}{1 - \tau_i \alpha b_i}(\tau_i p_i^* - d_i)r_i
\end{aligned}$$

Which implies that a lower Bound for the finance charges that are not perceived is given by:

$$\begin{aligned}
(\tau_i p_i^* - d_i)r_i - M((\tau_i p_i^* - d_i)r_i) &\geq (\tau_i p_i^* - d_i)r_i - \frac{\tau_i \alpha}{1 - \tau_i \alpha b_i}(\tau_i p_i^* - d_i)r_i = \\
&(\tau_i p_i^* - d_i)r_i \left[1 - \frac{\tau_i \alpha}{1 - \tau_i \alpha b_i} \right]
\end{aligned}$$

Proof of Corollary 1

With the same arguments developed in the proof of Proposition 2, we know that either only the first one or both constraints are binding at the optimum. If only the first constraint is binding, we get the following Lagrange function:

$$\max_{p_i, r_i} L = p_i + (\tau_i p_i - d_i)(r_i - b_i)\alpha\gamma + \beta - c + \mu(\bar{u}_i + \tau_i p_i + \gamma M_i(r_i(\tau_i p_i - d_i)))$$

Leading to the following first order conditions:

$$\begin{aligned} \frac{dL}{dp_i} &= 1 + \tau_i\gamma\alpha(r_i - b_i) + \mu(\tau_i + \gamma M'_i(r_i(\tau_i p_i - d_i))\tau_i r_i) = 0 \\ \frac{dL}{dr_i} &= \gamma\alpha(\tau_i p_i - d_i) + \mu\gamma M'_i(r_i(\tau_i p_i - d_i))(\tau_i p_i - d_i) = 0 \end{aligned}$$

Since both of these hold in equilibrium we get:

$$\begin{aligned} \frac{1 + \tau_i\gamma\alpha(r_i^* - b_i)}{\tau_i + \gamma M'_i(r_i^*(\tau_i p_i^* - d_i))\tau_i r_i} &= \frac{\alpha}{M'_i(r_i^*(\tau_i p_i^* - d_i))} \\ \Leftrightarrow M'_i(r_i^*(\tau_i p_i^* - d_i)) &= \frac{\tau_i\alpha}{1 - \tau_i\gamma\alpha b_i} \end{aligned}$$

If both constraints are binding, we can again use the same arguments as in the proof of Proposition 2 to show that:

$$M'_i(r_i^*(\tau_i p_i^* - d_i)) < \frac{\tau_i\alpha}{1 - \tau_i\gamma\alpha b_i}$$

A.1 Model with Exogenous Downpayment

In this subsection we derive the results in Proposition 2 and 1 taking the time structure of the decision problem into account. For this purpose, suppose the consumer discounts each month with δ . If he signs a fully amortizing loan with a term of x months, his overall payments on the loan are going to be

$$x \cdot P = x \cdot \frac{r(1+r)^x}{(1+r)^x - 1} (\tau_i p_t - d_t) \equiv (1 + \hat{r}_t)(\tau_i p_t - d_t)$$

Recall that we assume financial payments to generate different disutilities than payments on the car. $\hat{r}_t(\tau_i p_t - d_t)$ is the part of the payments that are finance charges. Assume that the consumer has a stream of utility over money where he splits up payments every period into finance charges and non finance charges:

$$\begin{aligned} u &= -d_t - \sum_{i=1}^x \frac{\delta^i}{x} [(\tau_i p_t - d_t) + M((\tau_i p_t - d_t)\hat{r}_t)] = \\ &= -d_t - \frac{\delta - \delta^{x+1}}{(1-\delta)x} [(\tau_i p_t - d_t) + M((\tau_i p_t - d_t)\hat{r}_t)] \end{aligned}$$

Hence, the utility is the same as before except for the multiplication by a constant and subtracting and adding exogenous variables. Therefore, we can redefine the utility of the outside option such that the maximization problem is identical to the one studied before. None of the calculations from above would change.

A.2 Downpayment as a Fixed Fraction of the Price

In this subsection, we assume that the downpayment d_t is given by $d\tau_i p_i$, where $d < 1$ is an exogenous fraction. Moreover, we assume that the downpayment is due immediately while all other payments are financed by a fully amortizing loan. Denote by x the term of the loan in months, by δ the monthly discount rate, and by $\hat{r}_i = \frac{r_i(1+\frac{r_i}{12})^x}{(1+\frac{r_i}{12})^x - 1}x - 1$ the fraction of the payment that is due to finance charges if the yearly interest rate is r_i . Taking the arguments from before the utility of a consumer from buying the car is then given by:

$$u = -d\tau_i p_i - \sum_{j=1}^x \frac{\delta^j}{x} [(1-d)\tau_i p_i + M((1-d)\tau_i p_i \hat{r}_i)] =$$

$$-d\tau_i p_i - \frac{\delta - \delta^{x+1}}{(1-\delta)x} [(1-d)\tau_i p_i + M((1-d)\tau_i p_i \hat{r}_i)]$$

The car dealers optimization problem then becomes:

$$\begin{aligned} \max_{\hat{r}_i, p_i} \quad & p_i + (1-d)\tau_i p_i (\hat{r}_i - \hat{b}_i) \alpha + \beta - c_i \\ \text{s.t.} \quad & -d\tau_i p_i - \frac{\delta - \delta^{x+1}}{(1-\delta)x} [(1-d)\tau_i p_i + M((1-d)\tau_i p_i \hat{r}_i)] \geq \bar{u} \\ & -M_i((1-d)\tau_i p_i \hat{r}_i) \geq - \int M_i((1-d)\tau_i p_i \hat{r}^L) g(r^L) - s_i, \\ & r_i, p_i \geq 0 \end{aligned}$$

With the same arguments as above, we can concentrate on the case where the first constraint is binding, but the second not. The Lagrangian is then given by:

$$L = p_i + (1-d)\tau_i p_i (\hat{r}_i - \hat{b}_i) \alpha + \beta - c_i + \mu \left[\bar{u} + d\tau_i p_i + \frac{\delta - \delta^{x+1}}{(1-\delta)x} [(1-d)\tau_i p_i + M((1-d)\tau_i p_i \hat{r}_i)] \right]$$

The derivatives are given by:

$$\frac{dL}{d\hat{r}_i} = (1-d)\tau_i p_i \alpha + \mu \frac{\delta - \delta^{x+1}}{(1-\delta)x} M'((1-d)\tau_i p_i \hat{r}_i) \tau_i p_i (1-d)$$

$$\frac{dL}{dp_i} = 1 + (1-d)(\hat{r}_i - \hat{b}_i) \tau_i \alpha + \mu \left[d\tau_i + \frac{\delta - \delta^{x+1}}{(1-\delta)x} [\tau_i (1-d) + M'((1-d)\tau_i p_i \hat{r}_i) \tau_i \hat{r}_i (1-d)] \right]$$

Since both have to equal to zero simultaneously, we get:

$$\begin{aligned}
\frac{\alpha}{\frac{\delta - \delta^{x+1}}{(1-\delta)x} M'((1-d)p_i \tau_i \hat{r}_i)} &= \frac{1 + (1-d)(\hat{r}_i - b_i) \tau_i \alpha}{d \tau_i + \frac{\delta - \delta^{x+1}}{(1-\delta)x} [\tau_i(1-d) + M'((1-d)\tau_i p_i \hat{r}_i) \hat{r}_i (1-d) \tau_i]} \\
\Leftrightarrow \frac{\delta - \delta^{x+1}}{(1-\delta)x} M'((1-d)\tau_i p_i \hat{r}_i) [1 + (1-d)\tau_i \alpha (\hat{r}_i - b_i) - (1-d)\tau_i \hat{r}_i \alpha] &= \alpha \left[\tau_i d + (1-d)\tau_i \frac{\delta - \delta^{x+1}}{(1-\delta)x} \right] \\
\Leftrightarrow \frac{\delta - \delta^{x+1}}{(1-\delta)x} M'((1-d)\tau_i p_i \hat{r}_i) [1 - (1-d)\tau_i \alpha \hat{b}_i] &= \tau_i \alpha \left[d + (1-d) \frac{\delta - \delta^{x+1}}{(1-\delta)x} \right] \\
\Leftrightarrow M'((1-d)\tau_i p_i \hat{r}_i) &= \frac{\tau_i \alpha \left[d + (1-d) \frac{\delta - \delta^{x+1}}{(1-\delta)x} \right]}{\frac{\delta - \delta^{x+1}}{(1-\delta)x} [1 - \tau_i(1-d)\alpha \hat{b}_i]}
\end{aligned}$$

Proof of Proposition 4

We construct $M(x, \rho_i)$ such that the ordering of $B_i^O = [1 - M'(x, \rho_i)]x$ induces an ordering on ρ_i . Hence, $\rho_i > \rho_j \Leftrightarrow B_i^O > B_j^O$ for all i, j . As a direct consequence of continuity it them must hold that $\rho_i = \rho_j$ if and only if $B_i^O = B_j^O$. Consider the set of observations such that this is true. Hence,

$$[1 - M'(x, \rho)]x = C$$

Then with changing x, ρ needs to stay constant:

$$\begin{aligned}
\frac{d\rho}{dx} &= \frac{1 - M'(x, \rho) - M''(x, \rho)x}{xM'_\rho(x, \rho)} = 0 \\
\Leftrightarrow 1 - M'(x, \rho) - M''(x, \rho)x &= 0
\end{aligned}$$

This is a separable ODE such that we can solve it the following way:

$$\begin{aligned}
\frac{M''(x, \rho)}{1 - M'(x, \rho)} &= \frac{1}{x} \\
\Leftrightarrow \int \frac{1 - M'}{d} M' &= \int \frac{1}{x} dx \\
\Rightarrow -\ln(1 - M') &= \ln(x) + g(\rho) \\
\Leftrightarrow \frac{1}{1 - M'} &= xg(\rho) \\
\Leftrightarrow M' &= 1 - \frac{1}{xg(\rho)} \\
\Rightarrow M &= x - h(\rho)\ln(x),
\end{aligned}$$

where $h(\rho)$ is some arbitrary function of ρ . Hence, every M function that satisfies the above induces the ordering on the bounds to be also an ordering on the rhos. Note that these functions are convex as long as $h(\rho) > 0$ and that higher ρ corresponds to a larger wedges in disutilities if $h'(\rho) > 0$.

Cost Recovery $\{\alpha_{j,d}\}$ and $\{c_{j,d}\}$ from First Order Conditions of Dealers

Recall that:

$$\tilde{p}_{j,d} = p_{j,d} + p_{j,d} \cdot r_{j,d} - \rho_i \cdot \log(p_{j,d} \cdot r_{j,d}).$$

Dealer d 's problem:

$$\max_{\{p_{k,d}, r_{k,d}\}_{j \in \mathcal{J}_d}} \sum_{k \in \mathcal{J}_d} (p_{k,d} + \alpha_{k,d} \cdot (p_{k,d} - \text{down}_{k,d}) \cdot (r_{k,d} - b_{k,d}) - c_{k,d}) \cdot s_{k,d}^m(\mathbf{p}_d, \mathbf{r}_d; \mathbf{p}_{-d}, \mathbf{r}_{-d}).$$

FOCs for each $j \in \mathcal{J}_d$

$$\begin{aligned} & s_{j,d}^m(\mathbf{p}_d, \mathbf{r}_d; \mathbf{p}_{-d}, \mathbf{r}_{-d}) (1 + \alpha_{j,d} (r_{j,d} - b_{j,d})) \\ & + \sum_{k \in \mathcal{J}_d} \frac{\partial s_{k,d}^m(\mathbf{p}_d, \mathbf{r}_d; \mathbf{p}_{-d}, \mathbf{r}_{-d})}{\partial p_{j,d}} \cdot (p_{k,d} + \alpha_{k,d} \cdot (p_{k,d} - \text{down}_{k,d}) \cdot (r_{k,d} - b_{k,d}) - c_{k,d}) = 0 \end{aligned}$$

$$\begin{aligned} & s_{j,d}^m(\mathbf{p}_d, \mathbf{r}_d; \mathbf{p}_{-d}, \mathbf{r}_{-d}) \cdot \alpha_{j,d} \cdot (p_{j,d} - \text{down}_{j,d}) \\ & + \sum_{k \in \mathcal{J}_d} \frac{\partial s_{k,d}^m(\mathbf{p}_d, \mathbf{r}_d; \mathbf{p}_{-d}, \mathbf{r}_{-d})}{\partial r_{j,d}} \cdot (p_{k,d} + \alpha_{k,d} \cdot (p_{k,d} - \text{down}_{k,d}) \cdot (r_{k,d} - b_{k,d}) - c_{k,d}) = 0. \end{aligned}$$

Note that car prices affect shares only through perceived prices. Similarly, interest rates affect shares only through perceived prices. That is,

$$\frac{\partial s_{k,d}^m(\mathbf{p}_d, \mathbf{r}_d; \mathbf{p}_{-d}, \mathbf{r}_{-d})}{\partial p_{j,d}} = \frac{\partial s_{k,d}^m(\mathbf{p}_d, \mathbf{r}_d; \mathbf{p}_{-d}, \mathbf{r}_{-d})}{\partial \tilde{p}_{j,d}} \cdot \left(1 + r_{j,d} - \frac{\rho_i}{p_{j,d}} \right)$$

and

$$\frac{\partial s_{k,d}^m(\mathbf{p}_d, \mathbf{r}_d; \mathbf{p}_{-d}, \mathbf{r}_{-d})}{\partial r_{j,d}} = \frac{\partial s_{k,d}^m(\mathbf{p}_d, \mathbf{r}_d; \mathbf{p}_{-d}, \mathbf{r}_{-d})}{\partial \tilde{p}_{j,d}} \cdot \left(p_{j,d} - \frac{\rho_i}{r_{j,d}} \right)$$

Substituting these into the FOCs for j and rearranging give

$$\frac{1 + \alpha_{j,d} (r_{j,d} - b_{j,d})}{1 + r_{j,d} - \frac{\rho_i}{p_{j,d}}} = \frac{\alpha_{j,d} \cdot (p_{j,d} - \text{down}_{j,d})}{p_{j,d} - \frac{\rho_i}{r_{j,d}}}.$$

This in turn gives

$$\alpha_{j,d} = \frac{p_{j,d} - \frac{\rho_i}{r_{j,d}}}{(p_{j,d} - \text{down}_{j,d}) \left(1 + r_{j,d} - \frac{\rho_i}{p_{j,d}} \right) - (r_{j,d} - b_{j,d}) \left(p_{j,d} - \frac{\rho_i}{r_{j,d}} \right)}.$$

After obtaining $\{\alpha_{j,d}\}_{j \in \mathcal{J}_d}$, we can use the FOCs in interest rates to obtain costs (from a linear system)

$$\begin{aligned}
& \sum_{k \in \mathcal{J}_d} \frac{\partial s_{k,d}^m(\mathbf{p}_d, \mathbf{r}_d; \mathbf{p}_{-d}, \mathbf{r}_{-d})}{\partial \tilde{p}_{j,d}} \cdot c_{k,d} \\
= & \sum_{k \in \mathcal{J}_d} \frac{\partial s_{k,d}^m(\mathbf{p}_d, \mathbf{r}_d; \mathbf{p}_{-d}, \mathbf{r}_{-d})}{\partial \tilde{p}_{j,d}} \cdot (p_{k,d} + \alpha_{k,d} \cdot (p_{k,d} - \text{down}_{k,d}) \cdot (r_{k,d} - b_{k,d})) \\
& + \frac{s_{j,d}^m(\mathbf{p}_d, \mathbf{r}_d; \mathbf{p}_{-d}, \mathbf{r}_{-d}) \cdot \alpha_{j,d} \cdot (p_{j,d} - \text{down}_{j,d})}{p_{j,d} - \frac{p_i}{r_{j,d}}}.
\end{aligned}$$

Let Δ denote the matrix of the derivatives of shares in perceived prices and let \mathbf{c} denote the vector of costs of dealder d for different models. Let π denote the ‘‘adjusted revenue’’ vector. Finally, collect the last additive term, or ‘‘adjusted share’’, from each j ’s equation into \mathbf{a} , we have

$$\mathbf{c} = \pi + \Delta^{-1} \cdot \mathbf{a}.$$

Proof of Proposition 5

The lenders maximization problem is given by:

$$\max_{b_k} s_{j,d}(b) \cdot (p_{j,d}(b_k) - d) \cdot (1 - \mathcal{F}(\beta_{j,d}^{-1}(b_k)))^{N-1} \cdot [(1 - \alpha) \cdot m_{j,d}(b) + b_k - r_k^l]. \quad (18)$$

Taking the first order condition, we obtain:

$$\begin{aligned}
& [(1 - \alpha) \cdot m'_{j,d}(b_k) + 1] \cdot \psi(b_k) \cdot (1 - \mathcal{F}(\beta_{j,d}^{-1}(b_k)))^{N-1} + [(1 - \alpha) \cdot m_{j,d}(b_k) + b_k - r] \\
& \cdot [\psi'(b_k) \cdot (1 - \mathcal{F}(\beta_{j,d}^{-1}(b_k)))^{N-1} - \psi(b_k) \cdot (N - 1) \cdot f(r) \frac{1}{\beta'(b_k)} \cdot (1 - \mathcal{F}(\beta_{j,d}^{-1}(b_k)))^{N-2}] = 0 \quad (19)
\end{aligned}$$

Which can be simplified to the following equation, using the insight that $G(b) = \mathcal{F}(\beta_{j,d}^{-1}(b_k)) \quad \forall b$ and therefore $g(b) = \frac{1}{\beta'(r)} \cdot f(r)$.

$$\begin{aligned}
& [(1 - \alpha) \cdot m'_{j,d}(b_k) + 1] \cdot \psi(b_k) \cdot (1 - \mathcal{F}(\beta_{j,d}^{-1}(b_k))) + [(1 - \alpha) \cdot m_{j,d}(b_k) + b_k - r_k^l] \cdot \\
& [\psi'(b_k) \cdot (1 - \mathcal{F}(\beta_{j,d}^{-1}(b_k))) - \psi(b_k) \cdot (N - 1) \cdot g(b_k)] = 0
\end{aligned}$$

Solving this equation for r and defining $\tilde{\psi}(b_k) = \frac{\psi'(b_k)}{\psi(b_k)}$ to simplify the exposition we get the following expression for the lender’s refinancing costs.

$$r_k = (1 - \alpha) \cdot m_{j,d}(b_k) + b_k + \frac{1 + (1 - \alpha) \cdot m'_{j,d}(b_k)}{\tilde{\psi}'(b_k) - (N - 1) \cdot g(b_k) \cdot (1 - \mathcal{G}(b_k))^{-1}} \quad (20)$$

B Additional Facts, Graphs and Figures

B.1 Dealer Issued Loans

This section explains our procedure to estimate the fraction of auto loans originated “indirectly”, i.e. through auto dealers. The CCP includes data on hard credit inquiries, and so is one of very few datasets that covers search behavior outside of online markets. When an auto dealer intermediates a loan, the process should always begin with a hard credit inquiry so that the dealer can determine the kind of loan a borrower can qualify for. We take the percent of loans originated within a short window of at least one hard credit inquiry from a dealer as our proxy for the fraction of indirect loans. If the CCP included data on *all* hard credit inquiries, this would be straightforward to estimate. The main difficulty is that we only observe hard credit inquiries reported to the credit bureau our data is from; we do not see hard credit inquiries reported to the other two major credit bureaus.

We can deal with this difficulty if we assume a constant probability P_o that a hard credit inquiry is observed in the CCP.⁴¹ Let $P_d(i)$ denote the probability that a loan is originated within a short time window of i hard credit inquiries from dealers, and let $P_{do}(i)$ denote the probability that a loan is originated within a short time window of i hard credit inquiries from dealers *that we observe*. Finally, assume that no more than N dealers perform a hard credit pull on a consumer within the time window. Then we need to estimate $P_d(0)$, and have the following equation:

$$P_{do}(i) = \sum_{n=i}^N P_d(n) \cdot \binom{n}{i} \cdot P_o^i \cdot (1 - P_o)^{n-i} \quad (21)$$

First, we set $N = 3$. The next step is to estimate $P_{do}(i)$ and P_o . We do that by matching new auto loans to auto loan inquiries from the company the loan is from (for P_o) and to inquiries from auto dealers (for P_{do}). We match auto loans to auto loan inquiries if they are for the same consumer and if the inquiry date is no more than 14 days before or 7 days after the origination date of the auto loan. We restrict the sample during this step to consumers with credit scores above 680, to minimize the possibility of one dealer pulling credit records from multiple credit bureaus.⁴²

⁴¹In particular, we assume that the probability of observing a given hard credit inquiry from a lender (which we can estimate) is the same as observing a given hard credit inquiry from a dealer (which we need). This is equivalent to assuming that the credit bureau’s market share for dealer inquiries is the same as its market share for lender inquiries. Unfortunately we cannot test this assumption, but our conversations with market experts lead us to believe it is reasonable. Dealers have an incentive to pull credit from the same credit bureau as the lenders they work with, so that they are operating with the same information.

⁴²Lenders pay credit bureaus for every inquiry they make, so when deciding on the number of bureaus to pull from, they face a tradeoff between the cost of an additional pull and the benefit of obtaining more information. Because of the very large sums of money involved, mortgage lenders nearly always pull from all three major credit bureaus. Auto lenders typically only pull information from one credit bureau for borrowers who do not appear to be a credit risk, which is why we focus on consumers with good credit scores. Auto dealers have even less incentive to pull from multiple bureaus than auto lenders do, because auto dealers do not bear default risk.

For a given guess of the vector $P_d(n)$, Equation 21 yields implied values of the vector $P_{do}(i)$. We take as our estimate of $P_d(n)$ the vector that minimizes the sum of squared deviations between implied and estimated values of $P_{do}(i)$. Using data for the U.S. as a whole, this yields an estimate of $P_d(0) = .17$. This implies that an estimated 83% of auto loans are opened a short time before or after a hard credit inquiry from an auto dealer, which we interpret to mean that roughly 83% of auto loans are indirect. A number of assumptions were required to obtain this estimate, and we do not view it as precise. However, we do interpret it as strong evidence that the vast majority of auto loans in the United States are indirect.

B.2 Other Tables Regressions and Graphs

Table 9: Regressions of M' on Finance Charges, instrumented by Buy Rate

Finance Charges, in thousands, instrumented by Buy Rate	0.00512*** (0.000)
Credit score score, in 100s	-0.00801*** (0.000)
Log Monthly Income	-0.00261*** (0.000)

NOTE: A regression of markup on log applicant income, log price, credit score bins (of width 20), mileage, log loan amount, and state, lender, model, and new car fixed effects yields an R^2 of .07. This goes up to .11 when using zip fixed effects instead of state fixed effects, or .10 if restricting the regression to non-negative markups no higher than 2.5 (the 99th percentile in the data). We interpret this as evidence that banks cannot predict markups.



Figure 7: Distribution of Down Payment as a Fraction of Price

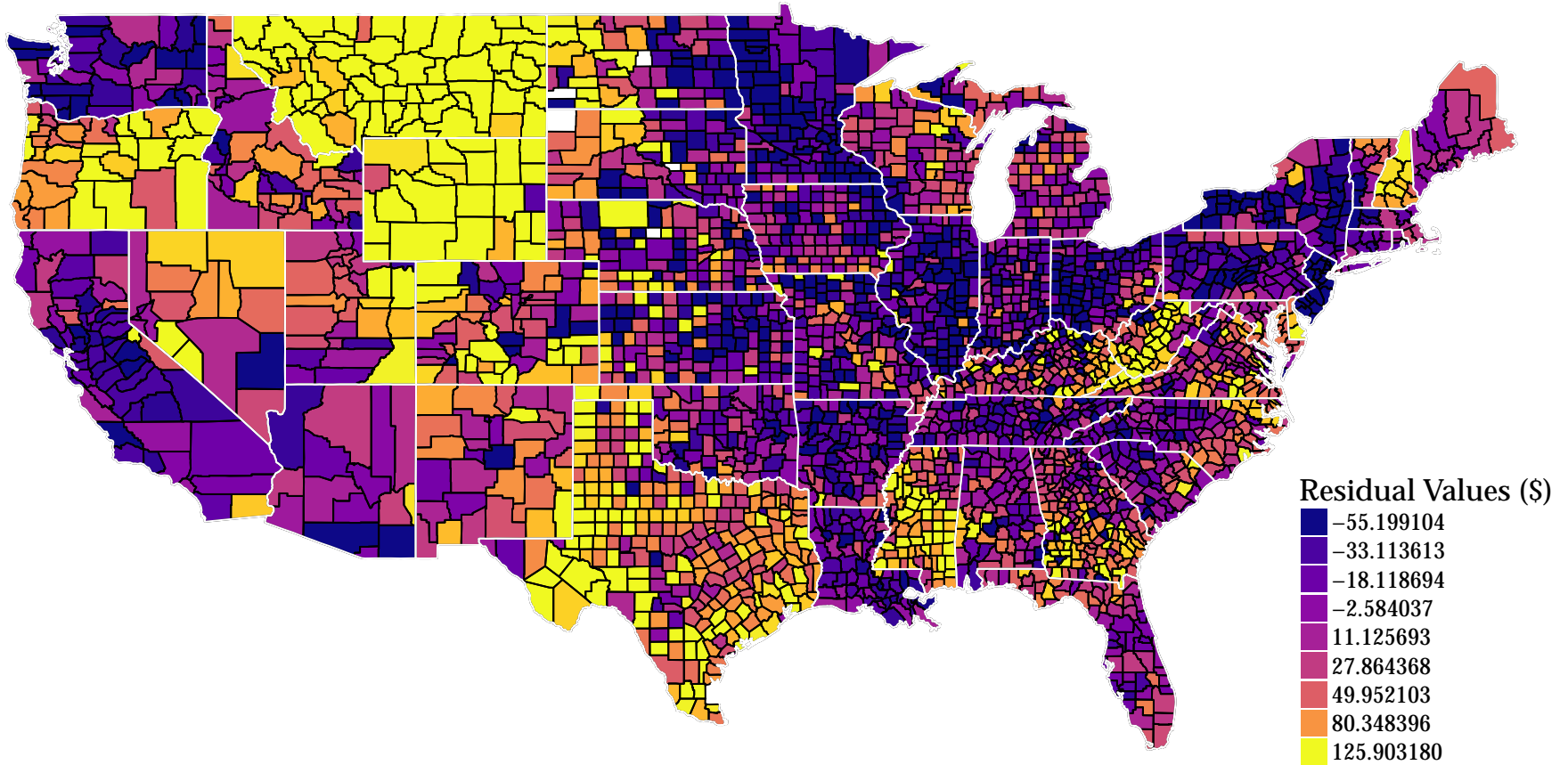


Figure 8: This map shows the residual of bound B^O (the overall bound) after taking out lender fixed effects.

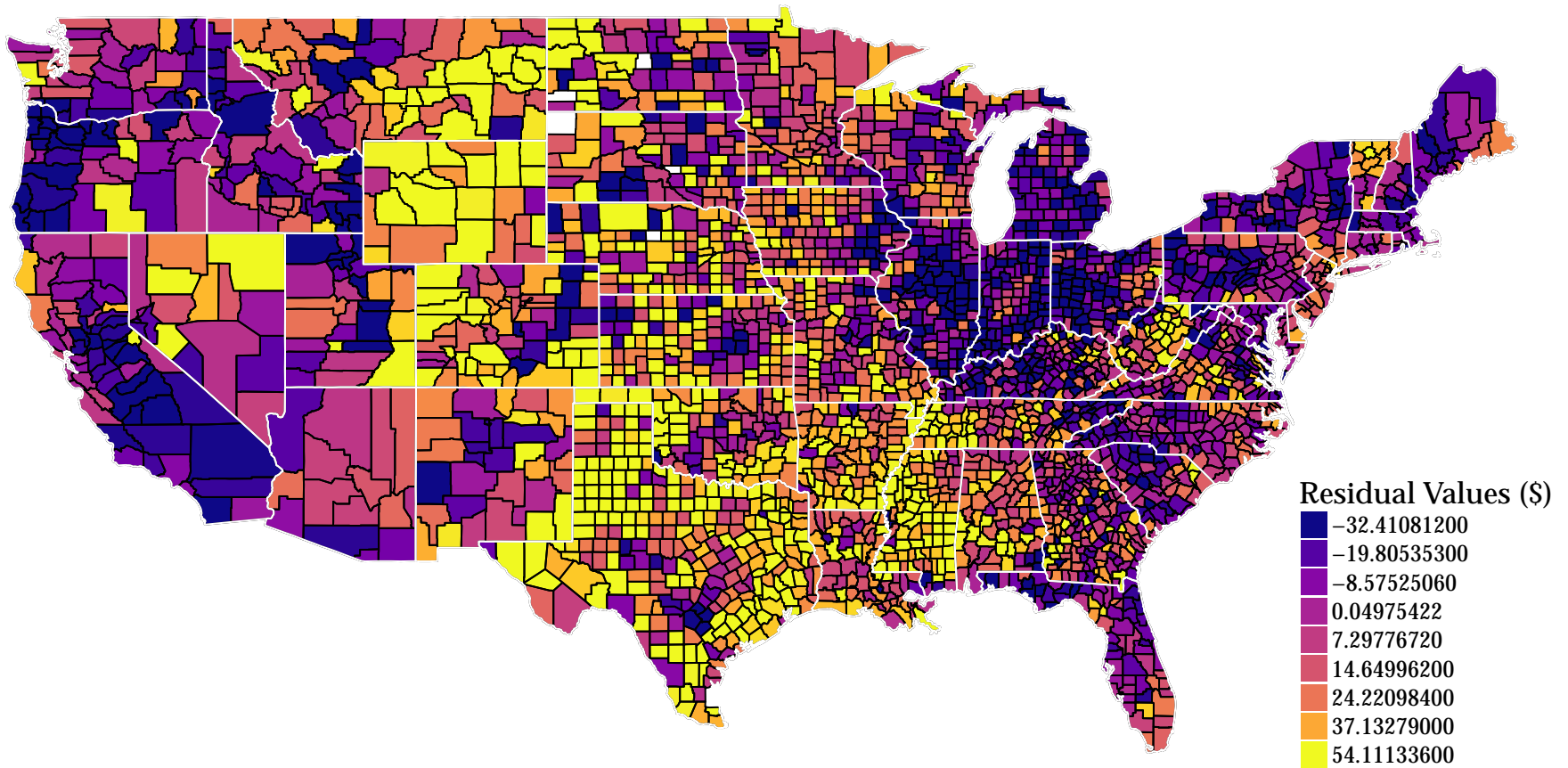


Figure 9: This map shows the residual of bound B^M (the bound due to markups) after taking out lender fixed effects.

Table 10: *Estimates for $M'_i(\cdot)$ for different down-payments*

DOWN PAYMENT	$M'(\cdot)$ Percentile				
	p10	p25	p50	p75	p90
Downpayment=0	0.65	0.73	0.87	0.90	0.93
Below 10th	0.67	0.71	0.82	0.86	0.92
10th-25th	0.66	0.68	0.74	0.85	0.92
25th-50th	0.65	0.68	0.75	0.84	0.91
50th-75th	0.43	0.67	0.80	0.84	0.89
75th-90th	0.41	0.67	0.81	0.83	0.88
Above 90th	0.41	0.69	0.81	0.83	0.87

NOTE: The table shows the estimated values for $M'(\cdot)$ for different percentiles of the population by the size of their down payment.

Table 11: *Estimates for B_i^O for different downpayments*

DOWN PAYMENT PERCENTILE	B_i^O Percentile				
	p10	p25	p50	p75	p90
Downpayment=0	161.01	244.49	395.39	700.38	1067.71
Below 10th	217.41	340.80	571.11	919.34	1322.05
10th-25th	220.59	357.79	601.75	938.75	1312.74
25th-50th	223.79	346.60	563.09	891.19	1282.16
50th-75th	219.43	333.86	517.28	813.26	1223.58
75th-90th	196.04	303.80	480.08	753.24	1133.76
Above 90th	172.61	272.81	441.50	706.84	1080.66

NOTE: The table shows the estimated values for B_i^O for different percentiles of the population by the size their down payment.

Table 12: *Mark ups for different prepayment probabilities*

PREPAYMENT PERCENTILE	Mark up Percentile				
	p10	p25	p50	p75	p90
Below 10th	0	0.22	1.01	2	2
10th-25th	0	0.21	1.25	2	2
25th-50th	0	0.25	1.23	2	2
50th-75th	0	0.36	1.2	2	2
75th-90th	0	0.48	1.19	1.98	2
Above 90th	0	0.5	1.16	1.91	2.1

NOTE: The table shows mark ups for different percentiles of the population by the probability that they prepay early. Prepayment rates are estimated using the CCP.

Table 13: *Estimates for $M'(\cdot)_i$ for different prepayment probabilities*

PREPAYMENT PERCENTILE	$M'(\cdot)_i$ Percentile				
	p10	p25	p50	p75	p90
Below 10th	0.78	0.81	0.87	0.91	0.96
10th-25th	0.78	0.80	0.85	0.91	0.96
25th-50th	0.77	0.80	0.85	0.90	0.96
50th-75th	0.77	0.80	0.86	0.91	0.95
75th-90th	0.77	0.79	0.86	0.91	0.94
Above 90th	0.77	0.79	0.87	0.90	0.94

NOTE: The table shows the estimated values for $M'(\cdot)_i$ for different percentiles of the population by the probability that they prepay early. Prepayment rates are estimated using the CCP.

Table 14: *Estimates for B_i^M for different prepayment probabilities*

PREPAYMENT PERCENTILE	B_i^M Percentile				
	P10	P25	P50	P75	P90
Below 10th	0	14.6	73.68	159.61	247.61
10th-25th	0	9.29	71.45	147.04	225.02
25th-50th	0	12.38	72.21	143.88	220.72
50th-75th	0	18.80	72.27	142.47	223.99
75th-90th	0	21.86	70.97	137.76	220.82
Above 90th	0	24.51	71.93	141.61	233.89

NOTE: The table shows the estimated values for B_i^M for different percentiles of the population by the probability that they prepay early. Prepayment rates are estimated using the CCP.

Table 15: Dealer-Lender Relationships and Markups

	MARKUPS		$M'(\cdot)$	
Lender finances 5 – 20% of sales	0.0435*** (0.00331)	0.0405*** (0.00332)	-0.00123*** (0.000131)	-0.00126*** (0.000131)
Lender finances > 20% of sales	0.0126*** (0.00411)	0.00773* (0.00411)	0.000122 (0.000162)	0.0000675 (0.000163)
Credit Score	-0.000843*** (0.0000298)	-0.000840*** (0.0000297)	-0.0000805*** (0.000000883)	-0.0000803*** (0.000000883)
Log Monthly Income	-0.0260*** (0.00205)	-0.0261*** (0.00205)	-0.00186*** (0.0000694)	-0.00187*** (0.0000694)
Loan Term	0.00174*** (0.000133)	0.00177*** (0.000133)	0.000761*** (0.00000410)	0.000762*** (0.00000410)
New Car	-0.217*** (0.00278)	-0.218*** (0.00278)	-0.00727*** (0.0000790)	-0.00727*** (0.0000789)
Dealer market share 2.5 – 10%		-0.0155*** (0.00382)		-0.000895*** (0.000111)
Dealer market share > 10%		-0.0453*** (0.00499)		-0.000520*** (0.000161)
HH index 500 – 1500		-0.00813 (0.00495)		-0.000300* (0.000157)
HH index > 1500		0.00644 (0.00610)		-0.000897*** (0.000197)
Constant	1.608*** (0.0663)	1.625*** (0.0664)	0.777*** (0.00269)	0.778*** (0.00270)

NOTE: Lender, month, model, and zip code fixed effects also included, but not shown. Standard errors clustered at zip code level.

Table 16: *Estimates if down payments are a fixed fraction of the car price*

	Mean	p10	p25	p50	p75	p90
M' with $\delta = 1$	0.80	0.64	0.69	0.84	0.89	0.93
M' with $\delta = 0.98$	0.80	0.64	0.69	0.84	0.89	0.92
M' with $\delta = 0.95$	0.81	0.66	0.70	0.85	0.91	0.94
M' with $\delta = 0.90$	0.84	0.67	0.73	0.86	0.94	0.98
M' with $\delta = 0.6$	1.08	0.73	0.87	1.03	1.27	1.51

NOTE: Table shows percentiles of the distribution of estimated M' , assuming loan term length varies as in the data but all consumers have an annual discount factor equal to the given value of δ .

Table 17: Logit Regression of Prepayment Risk

	Prepayment	Early Prepayment	Late Prepayment
730 ≤ Credit score ≤ 749	-0.0338*** (0.013)	0.0427 (0.028)	-0.0461*** (0.013)
750 ≤ Credit score ≤ 769	-0.0367*** (0.013)	0.0963*** (0.029)	-0.0621*** (0.014)
770 ≤ Credit score ≤ 789	-0.0117 (0.013)	0.252*** (0.028)	-0.0745*** (0.014)
790 ≤ Credit score ≤ 809	-0.0307** (0.012)	0.378*** (0.026)	-0.133*** (0.013)
810 ≤ Credit score ≤ 829	-0.0140 (0.012)	0.537*** (0.026)	-0.168*** (0.013)
830 ≤ Credit score ≤ 849	0.0350 (0.024)	0.545*** (0.044)	-0.114*** (0.025)
Log loan size	-0.381*** (0.007)	-0.316*** (0.013)	-0.328*** (0.007)
30 ≤ Loan term ≤ 41	-0.962*** (0.067)	0.00358 (0.104)	-0.889*** (0.062)
42 ≤ Loan term ≤ 53	-1.306*** (0.067)	-0.429*** (0.105)	-1.133*** (0.062)
54 ≤ Loan term ≤ 65	-1.472*** (0.067)	-0.149 (0.104)	-1.393*** (0.062)
66 ≤ Loan term ≤ 77	-1.403*** (0.067)	-0.134 (0.104)	-1.319*** (0.062)
78 ≤ Loan term ≤ 89	-1.306*** (0.069)	-0.257** (0.112)	-1.187*** (0.065)
90 ≤ Loan term ≤ 101	-1.603*** (0.196)	-0.229 (0.401)	-1.526*** (0.206)
102 ≤ Loan term ≤ 113	-1.935*** (0.664)	0 (.)	-1.575** (0.663)
114 ≤ Loan term ≤ 125	-1.491*** (0.160)	-0.966** (0.427)	-1.250*** (0.162)

Note: The table shows the results from a logit regression. The dependent variable for column (1) is one if the consumer prepaid the loan in the first two years. The dependent variable for column (2) is one if the consumer prepaid the loan in the first 120 days, which is our proxy for prepayment during the clawback period. The dependent variable for column (3) is one if the consumer prepaid the loan after the first 120 days but within the first two years. All regressions condition on loans of length greater than two years.

Table 18: Regressions of Prepayment Risk on Estimated Bias

	OVERALL BOUND B_i^O		DEALER MARKUP BOUND B_i^M	
Log Monthly Income	-9.340***	-9.353***	-1.813***	-1.799***
	(0.244)	(0.244)	(0.130)	(0.130)
Credit score, 100 points	-30.58***	-32.82***	-3.562***	-5.322***
	(0.377)	(0.481)	(0.196)	(0.233)
Mileage, Tens of Thousands	4.524***	4.543***	-0.827***	-0.802***
	(0.077)	(0.078)	(0.038)	(0.038)
New Car	-6.891***	-6.943***	-8.509***	-8.456***
	(0.390)	(0.390)	(0.228)	(0.228)
Log Loan Amount	381.4***	384.5***	76.28***	77.90***
	(1.253)	(1.272)	(0.401)	(0.410)
Average years of education	-3.807***	-3.791***	-0.981***	-0.973***
	(0.335)	(0.335)	(0.210)	(0.210)
Fraction with internet access	-9.523***	-9.472***	-8.801***	-8.770***
	(1.482)	(1.482)	(0.918)	(0.918)
Estimated prepayment probability	-24.16***		-69.71***	
	(6.432)		(1.722)	
Estimated early prepayment probability		96.93***		19.18***
		(14.727)		(6.114)
Estimated late prepayment probability		-12.77**		-69.75***
		(6.453)		(1.790)

NOTE: Note: Lender, model, and state fixed effects also included, but not shown. Standard errors clustered at zip code level. Regressions drop observations in the top percentile of loan size. Early prepayment is defined as prepayment in the first 120 days. Late prepayment is defined as prepayment after 120 days but within the first 2 years. Estimated prepayment probabilities in the supervisory data are imputed using coefficient estimates from the CCP.

Table 19: $M'(\cdot)$, B^O , and B^M by Car Model

MODEL	$M'(\cdot)$	B^O	B^M	MODEL	$M'(\cdot)$	B^O	B^M
Ram	0.76	795.89	239.31	Chevrolet Equinox	0.81	499.41	169.74
Chevrolet Silverado	0.77	693.59	219.19	Ford Escape	0.79	493.89	170.68
Ford F-150	0.79	660.66	220.28	Ford Fusion	0.79	480.00	161.90
Kia Sorento	0.78	614.92	189.59	Toyota Camry	0.77	475.85	143.56
Ford Explorer	0.80	602.00	212.74	Hyundai Elantra	0.77	474.41	156.04
Jeep Gr. Cherokee	0.80	585.28	200.07	Chevrolet Malibu	0.80	450.21	154.90
Jeep Wrangler	0.81	576.16	201.04	Honda Civic	0.78	442.62	139.26
Hyundai Sonata	0.77	529.34	157.96	Chevrolet Cruze	0.81	437.70	144.71
Honda Odyssey	0.80	519.13	169.13	Honda Accord	0.78	437.70	150.26
Nissan Altima	0.79	507.10	159.52	Ford Focus	0.80	424.82	147.52

NOTE: The table shows for the 20 most common car models in the data the average estimates for the lower bound B_i^O , B_i^M and $M(\cdot)$.

Table 20: *Selected summary statistics of consumers' misperception of financial charges.*

	MEAN	P10	P25	P50	P75	P90
$\hat{\rho}$	0.77	0.67	0.74	0.78	0.82	0.83

Note: Table gives summary statistics on the distribution of estimated values of ρ .

Table 21: Demand Model Coefficients

MAKE	MEAN UTILITY SHIFT	STANDARD ERROR	MAKE SPECIFIC OWN PRICE ELASTICITY
Chevrolet	-4.1	0.047	-4.2
Chrysler	-4.4	0.047	-4.2
Dodge	-4.8	0.044	-3.7
Ford	-4.0	0.047	-4.1
GMC	-2.7	0.073	-5.4
Honda	-3.5	0.047	-3.2
Hyundai	-4.0	0.047	-2.5
Jeep	-3.7	0.04	-4.1
Kia	-3.9	0.045	-2.7
Mazda	-4.1	0.048	-2.7
Nissan	-4.3	0.045	-2.9
RAM	-3.7	0.051	-4.9
Subaru	-3.8	0.044	-2.7
Toyota	-3.8	0.047	-3.4
Volkswagen	-4.2	0.052	-2.8

NOTE: The table shows how mean utility is shifted for different types of brands, the standard errors of those mean shifts, as well as own-price elasticities for different makes.

Table 22: Regressions of observables on markup (new cars only)

	LOAN MARKUP	LOAN MARKUP	LOAN MARKUP
Log Monthly Income	-0.0158*** (0.002)	-0.0242*** (0.002)	-0.0176*** (0.002)
Log Car Price	0.166*** (0.006)	0.397*** (0.007)	0.357*** (0.007)
Credit score, 100 points	-0.0989*** (0.003)	-0.0840*** (0.003)	-0.0860*** (0.003)
Mileage, Tens of Thousands	0.0228*** (0.006)	0.0286*** (0.005)	0.0217*** (0.006)
Log Loan Amount	-0.133*** (0.004)	-0.241*** (0.004)	-0.223*** (0.004)
Buy Rate	-0.0980*** (0.002)	0.000952 (0.002)	-0.000826 (0.002)
Model Fixed Effects	Yes	Yes	Yes
Term Fixed Effects	Yes	Yes	Yes
Month-Year Fixed Effects	Yes	Yes	Yes
Lender Fixed Effects	No	Yes	Yes
Zip Fixed Effects	No	No	Yes
Adjusted R^2	.049	.08	.11

NOTE: The table shows three different regressions of dealer markup on customer observables that are available to the lender at the time of the buy-rate auction. Even though these regressions are very saturated, only a small percent of the variation in markups can be explained by the independent variables.