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. Auto lenders incentivize dealers to use their "showroom-information" about consumers to engage in price discrimination by charging discretionary interest rate markups. Using new and uniquely rich administrative data, we show that markups have large effects on interest rates, vary widely across consumers, and are very poorly predicted by variables lenders have access to. We estimate a model that allows us to quantify the effects of banning discretionary dealer markups. Banning dealer markups decreases average transaction prices, and is especially beneficial for consumers with lower income and less financial sophistication.

JEL classification: L00, L5, L13, L62, G41, G51.

Keywords: Auto Loans, Obfuscation, Oligopoly Competition.

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1 Introduction

We study a controversial practice in the U.S. car market whereby auto dealers, rather than auto lenders, determine consumers' interest rates on loans. Specifically, lenders set minimum interest rates ("buy rates") but allow dealers to add considerable markups to these buy rates; dealers often do so and, through incentive contracts, are compensated with much of the resulting revenue. Some regulations (e.g. the Equal Credit Opportunity Act) are meant to mitigate the distributional consequences of this kind of price discrimination, but in practice dealer markup may lead consumers with similar loans and risk profiles to pay very different interest rates. As a result, dealer markup has received considerable attention from consumer advocacy groups and regulators. Several, including the Federal Trade Commission (FTC) and the Consumer Financial Protection Bureau (CFPB), have stated that the incentive contracts enabling dealer markup likely harm consumers.[1] The U.K.'s Financial Conduct Authority (FCA) banned these incentive contracts entirely in 2021. In this project, we study the consequences of dealer markup for consumer welfare.

There are two main reasons dealer markup may harm consumers and one main reason it could help them. First, it allows dealers to earn more profits from consumers with worse outside options in the credit market. As a result, dealers may compete less aggressively on car prices, because car prices determine loan amounts and dealer markup is more profitable for larger loans. The complementarity between these two pricing dimensions implies that price discrimination with respect to interest rates in the loan market can attenuate price competition in the car market, hurting all consumers through higher prices. Second, the price dispersion induced by dealer markup may be regressive and particularly harm lower-income consumers even after controlling for risk. This price dispersion is especially problematic if it derives, even in part, from consumers' misperceptions about their outside options in the auto loan market. But dealer markup could also benefit consumers. Incentive contracts align dealers' and lenders' interests, which reduces the scope for double marginalization; eliminating these contracts eliminates dealers' incentives to keep car prices low to earn profit from loans.

Understanding these conflicting forces, and how they interact, is critical given the size and importance of the auto loan market.[2] There are over one hundred million auto loans in

[1]See CFPB (2016), FCA (2019), Reynolds and Cox (2020) and Sullivan *et al.* (2020).

[2]The affordability of auto loans is a major concern, and has been for years. For examples, see an article from the Wall Street Journal, another article from National Public Radio, or a blog post by the CFPB.

the United States with a total face value of almost \$1.5 trillion, and about ninety percent of auto loans are obtained "indirectly" through dealers.[3] Nevertheless, the implications of dealer loan price discretion for the auto loan market, and for consumer welfare, are poorly understood.

To explore the equilibrium implications of dealer discretion, we build and estimate a model that captures three key aspects of the auto loan market. First, dealers determine both car and final loan prices. In our model, dealers determine car prices via a differentiated-product pricing game by posting car prices for the entire market; then they determine consumer-specific loan prices through Nash bargaining with the consumers that visit. The second key aspect of the auto loan market that we capture is that we allow dealers to condition interest rate offers on their soft "showroom information", which they gather during a sales process that is typically several hours long.[4] Specifically, we assume that consumers have heterogeneous outside options for financing, and that dealers can observe these outside options. Third, lenders submit buy rate quotes in an auction. Consistent with the actual process, lenders observe the underwriting variables that dealers submit to them when requesting those quotes but no information beyond that.

To estimate the model, we use new and detailed administrative data. Crucially, we observe – at the individual contract level – both the buy rates set by lenders and the markups chosen by dealers. Intuitively, buy rates give us a measure of the lender's information about a given consumer, while markups give us a measure of the additional information dealers gather in the showroom above and beyond what lenders have. We estimate the consumer outside options that rationalize the dealer markups we observe. Because of our identification strategy, we do not need to impose any other restrictions on the outside options of consumers. While we refer to these objects as outside options for brevity, they might also capture other phenomena that make consumers accept high interest rates. In particular, they do not necessarily have to correspond to the actual interest rates consumers would obtain from outside lenders. With this in mind, we estimate that the average prime consumer expects to pay 20.6% of the loan principal in interest over the life of the loan if she finances at an outside lender. We find that there is substantial variation in the estimated outside options that rationalize dealers' markups. A prime consumer at the 10th percentile expects to pay 10.8% of the loan principal

[3]For an estimate of total auto loan debt outstanding from the Federal Reserve Bank of New York, see here. We estimate the percent of auto loans obtained indirectly in Appendix B.1; see also Davis (2012).

[4]See survey evidence from askwonder.com.

in interest over the life of the loan if she finances at an outside lender; at the 90th percentile the number is nearly three times higher at 30.5%.

In addition to estimating consumers' outside options, our model also allows us to identify dealer and lender costs. We find that lenders are willing to set buy rates close to their own costs of financing the loan, as long as dealers can mark up loans. Hence, they rely on dealers' showroom information about consumers to increase their profits. Furthermore the average own-price elasticities implied by our demand estimation are in the ballpark of, but somewhat lower than, previous estimates in the literature (see for example Nurski and Verboven, 2016, Murry, 2017). This is intuitive since our model recovers elasticities taking into account the pricing of the loan as well as the car.

Our main counterfactual explores the consequences of eliminating dealer markup. This counterfactual closely approximates policies that regulators have considered or enacted.[5] In this counterfactual, lenders fully determine loan prices, but because they do not interact directly with consumers they cannot price discriminate as effectively as dealers can. Eliminating dealer discretion thus has substantial redistributional effects; it increases the surplus of consumers with worse-than-average outside options by 3.18%, and it decreases the surplus of consumers with better-than-average outside options by 1.1%.

These findings beg the question: what drives the variation in consumers' outside options? Our evidence suggests the variation in recovered outside options is not fully driven by the actual cost of credit from outside lenders. To study this question we first use our supply-side estimates to construct an alternative proxy for consumers' outside options: the interest rate that would result from a minimally-competitive auction. This approach provides a conservative estimate of what consumers could achieve if they searched on the credit market. Nevertheless, we find that consumers act as if their outside options are 25% worse than these conservatively-estimated outside options. Second, we find that worse outside options are strongly correlated with lower income and lower levels of education, even after we control for consumers' default risk via credit scores and many other car, loan, and consumer characteristics. Third, and most importantly, we directly surveyed consumers about their beliefs

[5]For example, the FCA banned dealer markups in 2021. See this BBC article for more background on the FCA ban. In the U.S. in 2013, the Consumer Financial Protection Bureau issued guidance urging auto lenders to consider alternatives to the current system, including eliminating dealer markup, in order to avoid violations of the Equal Credit Opportunity Act. In 2018, this guidance was rescinded. See this link for more background from the CFPB. In one survey in the U.S., 93% of respondents favored requiring dealers to disclose the lowest interest rate borrowers qualified for (Center for Responsible Lending *et al.* (2012)).

about the auto loan market. This survey data has the unique advantage that it is linked to credit bureau data on individual loan outcomes, including auto loan interest rates. We find that dealer markups are significantly higher for consumers that incorrectly believe (i) that all lenders offer the same rates or (ii) that dealers always offer them the best rate they qualify for. Taken together, this evidence strongly suggests that dealer loan price discretion is regressive.

Beyond these distributional effects, eliminating dealer markup has two opposing effects on total consumer surplus. It eliminates the complementarity between high car prices and loan price discrimination, leading dealers to decrease car prices. But it also increases the scope for double marginalization, thereby increasing total prices. We find that the former force dominates the latter, so that eliminating dealer markup increases consumer surplus by 1% ($670 million higher on an annual basis).

Because our evidence suggests that consumers may judge their outside options to be worse than they really are, we also consider a counterfactual in which consumers' actual outside options are given by outside options we derive from the supply side of our model. If consumers have these better outside options, but are not informed of them, there is almost no change in car and loan prices. The reason is that for bargaining only (potentially misspecified) expectations matter and as a result there is very little bargaining breakdown. We also consider a second version of the counterfactual in which consumers become aware of these better outside options, which captures the effect of an informational intervention. This counterfactual has quantitatively smaller but qualitatively similar effects as eliminating dealer markup. Again, the effects vary widely across consumers and consumers with poor outside options benefit the most. Total consumer surplus increases by 0.28% or $190 million annually.

Our work contributes to the literature on retail financial markets. A common theme of closely-related papers is that financial intermediaries often market loans to consumers that are either financially unsophisticated, face substantial search costs, or are unaware of sellers' conflict of interest (Woodward and Hall, 2010). This stream of papers has mostly focused on mortgage intermediation. In this setting it has been documented that less sophisticated consumers and small businesses are steered towards inferior products that earn brokers and lenders higher profits (Allen *et al.*, 2014a, Guiso *et al.*, 2018, Egan, 2018, Robles-Garcia, 2019, Benetton *et al.*, 2022). One intervention that has been discussed to counteract the potentially adverse welfare effects of steering is to extend fiduciary duty to all financial advisers (Bhattacharya *et al.*, 2019, Egan *et al.*, 2022). Our study complements these papers by looking at the role of car dealers as financial intermediaries. While dealers also receive commission payments from lenders, their incentive structure is very different from those of financial advisors or those of mortgage brokers. Examples include (i) car dealers sell the product to be financed and therefore profit from both dimensions of the deal, (ii) unlike mortgage brokers auto dealers determine the final interest rates on loans themselves and (iii) dealer commissions depend on dealer markup, while mortgage brokers typically receive as commission a fixed percentage of the loan amount.

While dealer revenues from auto-loan intermediation are substantial (Davis, 2012), the literature on competition in auto markets has largely abstracted from dealer loan intermediation and the implied 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, Biglaiser *et al.*, 2019, Benetton *et al.*, 2021, Grieco *et al.*, 2021).[6] We complement these studies by quantitatively studying dealer loan intermediation. For this purpose, our model combines posted-price competition in car markets with individually-negotiated loan prices. The latter is essential for understanding how dealer markups differentially affect market outcomes, while the former allows us to account for unobserved car and dealer attributes and connect to the existing literature. More broadly, we believe that our modeling strategy can also be useful in other settings where sellers post prices but still negotiate with consumers at the sales location about additional discounts on the posted price, add-ons, or product configurations.

There are a number of other papers that connect the literatures on cars and loans. In the subprime market, many consumers are liquidity-constrained (Adams *et al.*, 2009) and sensitive to monthly payments (Attanasio *et al.*, 2008, Argyle *et al.*, 2018). As a consequence, consumers postpone car purchases if the credit market becomes less liquid, leading to adverse effects on the market for used and new cars (Gavazza and Lanteri, 2021). In part because of binding credit and liquidity constraints for subprime consumers, loan performance can be improved by down payment requirements (Einav *et al.*, 2012), credit scoring (Einav *et al.*, 2013), and post-default wage garnishment (Brown and Jansen, 2019). Our study focuses on prime borrowers with negligible default risk. The discretion of dealers to price loans opens the door to contract-specific pricing even for consumers that actually pose no default risk. Our work suggests that this feature leads to loan price heterogeneity even in subpopulations with minimal default risk, harming consumers who expect poor outside options in the credit

[6] Davis (2012) estimates that franchise dealerships selling to private consumers generate more than half of their profit through their Finance and Insurance departments.

market.[7]

We also contribute to the empirical literature on price discrimination. Previous work has investigated second-degree (Miravete, 1996, Hendel and Nevo, 2013, Luo *et al.*, 2018) and third-degree (Hendel and Nevo, 2013, List, 2004, Bauner, 2015, Levitt *et al.*, 2016) price discrimination, as well as personalized and non-linear pricing, e.g. (Rossi *et al.*, 1996, Shiller, 2013, Nevo *et al.*, 2016, Dubé and Misra, 2019, Buchholz *et al.*, 2020). Price discrimination that disadvantages minorities has long been a concern in the car market, (Ayres and Siegelman, 1995, Goldberg, 1996, Morton *et al.*, 2003). Here we use novel data to quantitatively study an institution that is believed to facilitate loan price discrimination in this setting. For this purpose, we propose a model that combines a posted-price aspect with individually negotiated prices. As in Grennan (2013) price discrimination happens through Nash-bargaining.

Lastly, we contribute to the literature that quantitatively studies unsophisticated consumers (Stango and Zinman, 2011, Abaluck and Gruber, 2011, Handel, 2013, Grubb and Osborne, 2015, Hortaçsu *et al.*, 2017, Abito and Salant, 2017). In our setting, we find that the dispersion in interest rates that dealers offer and consumers accept can only be rationalized if consumers with uniformly very low default risk nonetheless have vastly different views of their outside options in the credit market. To estimate such consumers' beliefs about their outside options, we use data on pricing decisions by lenders (who have little information on consumers' beliefs) and dealers (who have more). In particular, lenders do not interact with consumers directly while dealers can gain knowledge of consumer outside options during a sales process that often lasts several hours. Moreover, our survey evidence suggests that the heterogeneity in consumer beliefs arises at least in part from consumer misperceptions. This indicates that discretionary dealer markups hurt financially-unsophisticated consumers. This finding is in line with the idea that firms can charge higher prices to less sophisticated consumers on less transparent product dimensions (Lal and Matutes, 1994, Verboven, 1999, Ellison, 2005).

[7] In Appendix B.6 we argue that the variation in discretionary markups is not driven by prepayment risk and that variation in prepayment risk is not confounding our counterfactual computations.

2 Institutional Details

Consumers typically begin the car buying process by picking a make, model, trim, and agreeing on car price.[8] Then, the consumer arranges financing with the dealer's "Finance and Insurance" (F&I) department at which stage they negotiate loan terms.[9] To get rate quotes, the F&I agent typically submits the customer and vehicle information into at least one of three major systems: DealerTrack, RouteOne, and Credit Union Direct Lending. Dealers may select specific lenders from which to solicit bids, or send the application to all lenders; DealerTrack advertises access to more than 1,500 lenders. Dealers appear to work with significantly fewer lenders than they potentially have access to. On average, dealers maintain active relationships with about 4.69 lenders.

Each solicited lender submits a *buy rate*, which is the minimal interest rate at which it is willing to make the loan.[10] For prime borrowers, this process happens very quickly.[11] The dealer then adds a markup to the buy rate. "Markdowns", in which the dealer pays a fixed fee to decrease the contract rate below the lender's buy rate, are allowed by most lenders but are rare. Most lenders allow markups of at most 200-250 basis points, but markups are otherwise discretionary. Lender-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). The additional revenue generated by markups is split between dealers and lenders according to pre-specified contracts. The dealer's share of the markup revenue is included in a one-time, upfront payment from the lender to the dealer for intermediating the loan called the "dealer reserve".

Since dealers only act as intermediaries for financing, loans are generally transferred directly

[8] Sales agents are often paid based on commission and sales targets. The commission is often a function of the sale (e.g. a "flat" commission) or the simple profit to the dealer. The sales targets are often discontinuous, and can result in direct bonuses or increases in the commission percent earned.

[9] F&I agents are compensated by the dealer via a commission or commission-like mechanism based on the profit generated by F&I products, including loan markups.

[10] Technically, the dealer originates the loan and then sells it to the lender. The buy rate is then the lowest interest rate at which the lender will buy the loan from the dealer. Dealers know the buy rate in advance and sell the loan almost instantly, so for all practical purposes the lender originates the loan.

[11] Super prime quotes (e.g. credit scores above 740) are often fully automated and virtually instantaneous. "High prime" deals (e.g. credit scores above 700) are sometimes automated and are usually handled quickly. One bank that manually underwrites prime loans targets a decision time of two minutes. "Near/low prime" deals (e.g. credit scores above 620) often require manual pricing and underwriting and therefore take longer. Subprime (e.g. credit scores below 620) quotes are often available from only a few lenders and often require phone calls, and so take even longer.

to the balance sheet of the lender.[12] Loans present both default risk and prepayment risk. For prime consumers, default risk is minimal; in our data it is much less than one percent. Default risk is higher for subprime consumers, and so in the subprime market contracts often discipline markups and split default risk between dealers and lenders. In both the subprime and prime markets, prepayment risk is substantial. Dealers typically assume all prepayment risk for the first three 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 discuss prepayment risk in detail in Appendix B.6.

We estimate that approximately 89% of purchase auto loans are "indirect", i.e. obtained through auto dealers as described above (see Section B.1 for details). However, consumers can also get loan quotes directly from lenders. They can obtain these quotes either before negotiating with the dealer or afterwards. If 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 we use and then provides descriptive evidence on markups. We establish three facts. First, the contracts between lenders and dealers to split markup revenue are nearly linear, a fact which we use in our model. Second, dealer markups contribute substantially to customers' final price of credit. Third, the variation in markups is not systematically predicted by variables lenders observe.

3.1 Data

This project uses four different datasets. First, and most importantly, we use a new administrative dataset of auto loans from various financial institutions. The data includes car, loan, and buyer characteristics covering 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. In terms of buyer characteristics, 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

[12] Banks do sometimes sell loans on the secondary market, but this is rare. Finance companies owned by car manufacturers ("captives") and dealers that finance sales themselves ("buy-here-pay-here" dealerships) do so much more frequently, but neither kind of lender is in our data.

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.[13] Crucially, we also 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 subprime auto loan market is more complex than the prime market in a number of ways, the most important of which is default risk. To abstract from these concerns, we restrict our attention to "prime" consumers, i.e,. those with credit scores above 720. Because we frequently use model fixed effects, we also drop observations from models that appear less than 50 times in the data. Price, loan amount, income, and down payment are winsorized by model at the 99.9 percent level.

The administrative data provides detailed information on observed transactions, but it does not cover the entire market. We therefore use complementary commercial data with the market shares of lenders and dealers for the majority of states in the U.S.[14] These data do not include information on buy rates or markups.

Because our administrative dataset does not come from the universe of auto lenders, it is not nationally representative. To examine how similar our dataset is to the national market, Table A3 presents summary statistics of several variables from our data and from the 2011 commercial data. Our administrative data appear broadly comparable to nearly nationally-representative data.

The third dataset we use is the CFPB's Consumer Credit Panel (CCP). The CCP is a longitudinal sample of approximately five million de-identified records from one of the three nationwide consumer reporting agencies ("NCRA"). The CCP also does not contain data on buy rates or markups, nor does it include data on the vehicle securing the loan. We mainly use it to study loan performance, including default and prepayment, and to estimate the fraction of loans that are intermediated by dealers.

The fourth dataset is the Making Ends Meet (MEM) survey, which is sampled from and linked to the CCP. The MEM dataset is smaller than the other datasets we study – the wave

[13]Additionally, we observe whether loans are "subvented", i.e., subsidized by car manufacturers to increase vehicle demand. Subvented loans are typically from captives, but non-captive lenders do sometimes have agreements with car manufacturers to extend subvented loans.

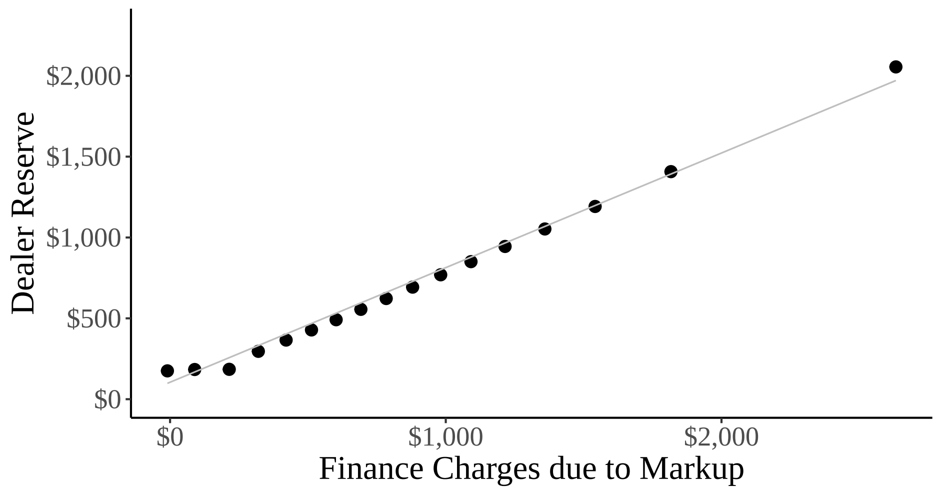
[14]See here for more details on these data. In the 2011 data, banks, captives, credit unions, finance companies, and buy-here-pay-here companies respectively had 46.1 percent, 26 percent, 14.1 percent, 9 percent, and 4.8 percent of the market.

we use had around 2,000 respondents – but it provides valuable supplementary information on borrowers' demographics and their views on the auto loan market. More information on MEM is in subsection B.3.

3.2 Contracts Between Lenders and Dealers

We start by using the administrative data to study the relationships between dealers and lenders. Markup revenue is shared between dealers and lenders according to contractually-specified formulas. Figure 1 plots dealer reserve against loan markup revenue in a bin-scatter plot.

Figure 1: Markup Revenues and Dealer Reserve



NOTE: The figure is a binscatter plot. The x-axis is the revenue generated by dealer markup over the lifetime of the loan, and the y-axis is dealer reserve. The graph shows that the relationship is nearly linear.

Revenue-sharing agreements are almost linear and almost homogeneous across lenders. A simple linear regression of dealer reserve on markup revenue for the entire sample yields an intercept of roughly $100, a slope of roughly .71, and an R^2 of .92.[15] Running lender-specific versions of this regression instead yields slopes with an interquartile range of only about .08;

[15]In analogy to the arguments by Holmström (1979), one may conjecture that the optimal contract between lenders and dealers make dealers the full residual claimant of all mark up profits, which would imply that the slope is equal to 1. Several market experts were not sure why this is not the case, but one potential explanation is that the lower slope compensates lenders on average for the prepayment risk (see here).

the R^2 from these lender-specific regressions are typically about .95.[16]

To understand in more detail where the variation in dealer reserve in our data comes from, we conduct a simple experiment. We create a counterfactual version of our data in which an identical copy of every loan in our data is made by each lender in our data. Using the estimated contract terms for each lender, we then estimate the dealer reserve each lender would pay dealers for these loans. In this counterfactual data, regressing dealer reserve on consumer fixed effects yields an R-squared of .97. Regressing dealer reserve on lender fixed effects yields an R-squared of .02. Hence, understanding variation in dealer reserve requires understanding variation in consumer-specific markups, but variation in contract terms across lenders is less important.

Motivated by these findings, in this paper we study and model the variation in markups across consumers. To focus on this variation, our model assumes that contracts between dealers and lenders are linear and homogeneous across lenders. Besides providing a good approximation of the data, this assumption also has the advantage that we do not need to model asymmetric buy rate auctions, which would introduce significant additional modeling complexity.

3.2.1 Markups

In our data 78.5 percent of loans are marked up and 0.8 percent of loans are marked down. The average markup is 113 basis points. Markups are on average 43% of buy rates. While markups are large on average, they are also very heterogeneous. Even though over a fifth of loans in our data have zero (or negative) markups, for consumers that pay their loans as scheduled loan markups cost \$647 at the median and \$1,655 at the 90th percentile. More formally, as interest rates are simply buy rates plus markup, the variance in interest rates across consumers can be studied with a standard variance decomposition. This exercise yields that, of the variation in consumers' interest rates, 71% is explained by variance in buy rates while 28% is explained by variance in markups. Only 1% is explained by covariance between markups and buy rates. Hence, understanding why markups vary across consumers is critical for understanding loan price heterogeneity.

Table 1 shows how markup and dealer reserve vary with the buyer's credit score, income, and the price of the vehicle. Markups are slightly higher for buyers with lower credit scores.

[16] To protect the confidentiality of lenders in our data, we cannot provide detailed results from these lender-specific regressions.

Table 1: Summary Statistics of Markup and Dealer Reserve

	Credit Score		Income		Car Price	
	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
Markup (%-points)						
1st Quartile	1.20	0.83	1.20	0.82	1.23	0.87
2nd Quartile	1.14	0.82	1.12	0.81	1.13	0.82
3rd Quartile	1.09	0.82	1.08	0.81	1.08	0.80
4th Quartile	1.08	0.81	1.08	0.80	1.08	0.77
Margin over Buy Rate						
1st Quartile	0.39	0.32	0.41	0.32	0.38	0.33
2nd Quartile	0.42	0.34	0.40	0.32	0.43	0.34
3rd Quartile	0.43	0.36	0.40	0.32	0.43	0.36
4th Quartile	0.45	0.37	0.43	0.35	0.46	0.36
Dealer Reserve						
1st Quartile	694	561	582	456	388	294
2nd Quartile	652	535	612	477	556	371
3rd Quartile	601	494	637	510	663	447
4th Quartile	585	475	760	682	952	724

Note: Table displays summary statistics of markups (upper panel), margins (middle panel), and dealer reserve (lower panel), by credit score, income, and vehicle price quartile. Margin refers to markup as a fraction of the buy rate.

As a consequence, dealer reserve is also higher on average for buyers with low credit scores. Markups are also higher for lower-income buyers. However, dealer reserve is *lower* for lower-income buyers, because they typically buy cheaper cars with smaller loans that generate less revenue for a given markup.

Table 2: R^2 for Markups and Buy Rates

	(1)	(2)	(3)	(4)
R^2 for Buy Rate	.089	.187	.285	.379
R^2 for Markup	.009	.016	.042	.074
Borrower Controls	✓	✓	✓	✓
Loan Controls		✓	✓	✓
Vehicle Controls			✓	✓
Month & Lender Fixed Effects				✓

NOTE: Table shows the R^2 from OLS regressions of buy rate and markup on observables. Borrower controls include borrower credit score dummies (in buckets of ten), borrower log income, and a dummy for whether the loan has a coapplicant. Borrower log income is winsorized at the 95th percentile. Loan controls include LTV dummies (in buckets of five), loan length dummies (rounded to nearest 12 months), and down payment. LTV is winsorized below by 20 and above by 150; loan length is winsorized below by 24 months and above by 84 months. Vehicle controls include model dummies and a dummy for whether the vehicle is new.

Table 1 suggests that some of the most important variables lenders use to price loans, including credit score and borrower income, are hardly predictive of markup. Table 2 investigates this in more detail. In particular, we use underwriting variables in our data to predict markups; for comparison, we use the same variables to predict buy rates. We divide the controls into borrower-specific controls, loan-specific controls, vehicle-specific controls, and month as well as lender fixed effects. Borrower controls include credit score dummies (in buckets of ten), borrower log income, and a dummy for whether the loan has a co-applicant. The loan-specific controls include the loan-to-value ratio (in buckets of five), loan length, and down payment. Vehicle controls include model dummies and a dummy for whether the vehicle is new. This rich information set available to lenders predicts buy rates well but markups poorly, suggesting that dealers determine markups using showroom information that lenders do not have. This finding will inform our model in Section 4.

4 The Model

Building on the institutional details described above, we now outline our model. 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 $d \in \mathcal{D}_m$ intermediates loans for a given set of lenders $\mathcal{L}_d$ and offers a specific set of models $\mathcal{J}_d$, which we take to be exogenous. Finally, there are consumers $i \in \mathcal{I} = \{1, ..., I\}$.

The timing is as follows. First, dealers and lenders agree on the linear contracts that determine dealer reserve as a function of markup revenue. In reality these contracts are very homogeneous across lenders as discussed in section 3 and lenders can freely adjust their expected margins through buy rates, so we do not model this contract formation explicitly.

Second, dealers engage in Nash-Bertrand competition by posting car prices.[17] They do so under an expected distribution of loan outcomes. Third, consumers observe car prices and decide which dealer to visit and which model to purchase. Fourth, dealers elicit buy rates for each consumer separately from their set of lenders in a buy-rate auction; given the winning buy rates, they then bargain with consumers over final loan interest rates. Fifth, consumers decide whether to finance the car at the dealer or at an outside lender.

Next, we describe the objectives and actions of the different players in detail. Figure 2 provides a schematic overview of the entire model.

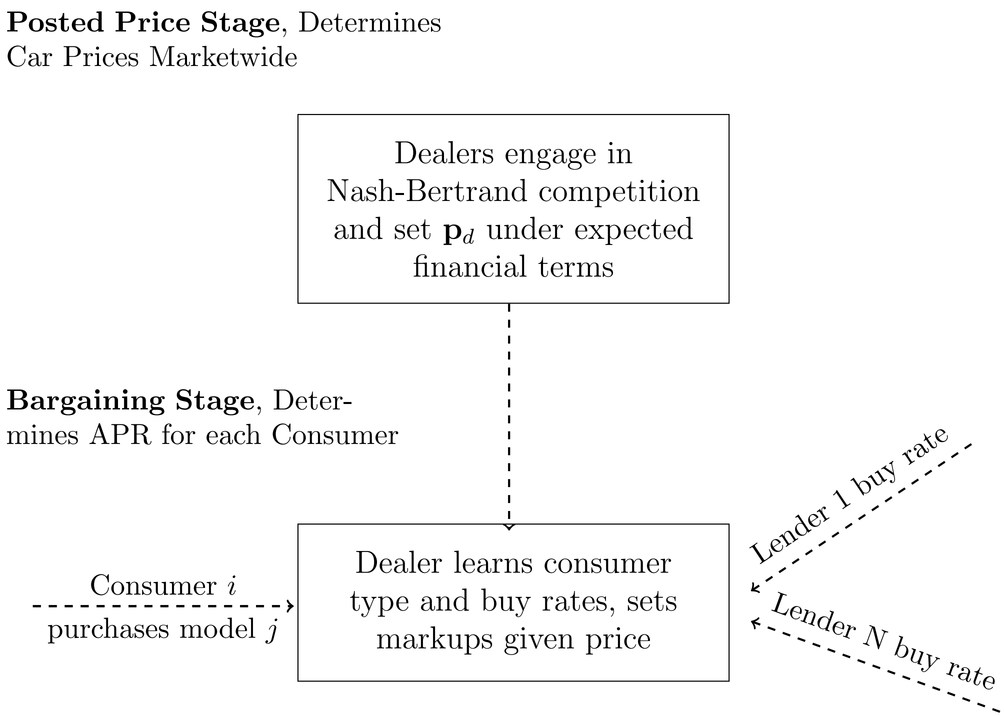
4.1 Consumers' Discrete Choice over Products

Every consumer $i \in \mathcal{I}$ observes the dealers in her market, the models offered by those dealers, and the car prices p_{jd} posted by dealer d for model j. She then forms expectations about the interest rate r_{ijd} that she will have to pay to finance the amount $p_{jd} - \kappa_i$ if she buys car j at dealer d, where we take the down payment κ_i to be exogenous.

We model four sources of heterogeneity across consumers. First, we denote the travel costs of consumer i to dealer d by $g(d, i)$. Second, consumer i has marginal utility of money γ_i, which may depend on her income y_{im}, drawn from the county-level income distribution. Third, different consumers have different down payments κ_i. Fourth, and most importantly, different consumers have different expected outside options in the credit market. We denote a consumer's expected outside option — i.e., the interest rate consumer i believes she would

[17] By assuming Nash-bargaining, we follow several papers in the IO-literature (see for example Binmore *et al.*, 1986, Crawford and Yurukoglu, 2012, Ho and Lee, 2017, Collard-Wexler *et al.*, 2019). Note that the model where dealers have all the bargaining power and make take-it-or-leave-it offers is nested within our model.

Figure 2: Model Schematic



NOTE: The figure gives an overview of the model. First, dealers set car prices for all consumers. They do so under an anticipated distribution of interest rates that result from the bargaining problem. Then, for each consumer separately, buy rates are determined by the buy rate auction and interest rates through Nash-Bargaining of consumers and dealers.

obtain from an outside lender — by $\theta_i \in \mathbb{R}^+$. Moreover, we collect all consumer types in the vector $\theta \in \mathbb{R}^{|\mathcal{I}|}$. We do not need to impose that consumers' expected outside options equal their actual outside options. The expected outside options help us rationalize the large discretionary markups in our data, and they may be driven at least in part by search costs or incorrect consumer beliefs about the auto loan market. Besides these individual-level differences, consumers' indirect utility depends on other observable car attributes which we collect in the vector $\mathbf{z}_j$.

Finally, there are three product attributes that are unobservable to the econometrician. First, we assume that consumers have preferences ψ_j over makes. Second, for every dealer-model combination there is an unobserved aggregate taste shock ξ_{jd}. Third, every consumer's choice is affected by her i.i.d. taste shock ϵ_{ijd} for a dealer-model combination, which has an extreme value distribution. Consumer utility is thus given by:

$$u_{ijd} = g(d,i) - \gamma_i \cdot \Big[p_{jd} + \mathbb{E}[r_{ijd}|\theta_i, \kappa_i, p_{jd}] \cdot (p_{jd} - \kappa_i)\Big] + \zeta \cdot \mathbf{z}_j + \psi_j + \xi_{jd} + \epsilon_{ijd}, \tag{1}$$

where

$$\gamma_i = \phi_0 + \phi_y \cdot y_{im} + \nu_i \ \text{ with } \nu_i \sim \mathcal{N}(0, \sigma_\nu). \tag{2}$$

When a consumer makes a purchase decision she expects an interest rate $\mathbb{E}[r_{ijd}|\theta_i, \kappa_i, p_{jd}]$ based on her outside option θ_i. This interest rate is the outcome of a Nash-bargaining problem between the dealer and the consumer, which we describe below. From the dealer's perspective, these interest rates are random at the time of posting car prices, because they depend on both unknown consumer types θ_i and the buy-rate auctions. The interest-rate expectation thus acts like a random coefficient on the price. However, unlike a normal random coefficient, this one is endogenously determined through the bargaining problem between the dealer and the consumer and also depends directly on the car prices that dealers set.

Let $\mathbf{p}_m$ denote the vector of prices in market m. With this notation we now describe consumers' choices, which determine the overall market share of a dealer-model combination. For this purpose, we integrate over the unobserved consumer type ν_i. Exploiting the logit structure of the idiosyncratic taste shocks, and denoting the anticipated total price by $\tilde{p}_{ijd} = \Big[p_{jd} + \mathbb{E}[r_{ijd}|\theta_i, \kappa_i, p_{jd}] \cdot (p_{jd} - \kappa_i)\Big]$, the market share of model j at dealer d among consumers with outside option θ and down payment κ is given by:

$$s^m_{jd}(\mathbf{p}_m, \theta, \kappa) = \int \frac{exp(g(d,i) - \gamma_i \cdot \tilde{p}_{ijd} + \xi_{jd} + \zeta \cdot \mathbf{z}_j + \psi_j)}{\sum_{l \in \mathcal{D}_m} \sum_{k \in J_l} exp(g(l,i) - \gamma_i \cdot \tilde{p}_{ikl} + \xi_{kl} + \zeta \cdot \mathbf{z}_k + \psi_k)}. \tag{3}$$

4.2 Dealer Pricing

Dealers post car prices for the entire market but negotiate loan prices separately with each consumer. We model the former as Nash-Bertrand pricing and the latter as Nash bargaining.[18]

[18] By assuming Nash-bargaining, we implicitly assume that dealers and consumers have complete information about all parameters that affect the bargaining outcome. In particular, consumers' outside options are not private information. Private information would lead to inefficiencies in trade (Larsen, 2021, Larsen and Zhang, 2021) and some observed variance in markups could be driven by variation in dealers' signals. We believe that the assumption of no private information is plausible. In the CCP, we estimate that less than three percent of prime borrowers get pre-qualified by a lender before going to a dealer. Without getting pre-qualified, auto loan borrowers

It is easier to go backwards and first describe the bargaining problem, which takes posted car prices and the buy rate b_{ijd} as given.

Dealer d faces costs c^D_{jd} for model j. Furthermore, the dealer's incentives depend on the share α of the markup revenue that the dealer keeps and the fixed payment from the lender β (see Section 3.2). For simplicity, we assume that α and β are constant across lenders within a given dealer.[19] During the loan-price negotiation, the dealer learns the consumer's outside option θ_i. The threat point for the consumer is to finance the car at θ_i, in which case her utility is given by $g(d,i) - \gamma_i \cdot [p_{jd} + \theta_i(p_{jd} - \kappa_i)] + \zeta \cdot \mathbf{z}_j + \psi_j + \xi_{jd} + \epsilon_{ijd}$. If the consumer finances the car at her outside option, the dealer still sells the car to the consumer but does not receive the dealer reserve for intermediating the loan. Hence the threat point of dealer d is given by $p_{jd} - c^D_{jd}$, which implies that the negotiated interest rate $\tilde{r}_{ijd}$ satisfies:

$$\begin{aligned}
&\tilde{r}_{ijd} \in argmax_r \Big[p_{jd} - c^D_{jd} + (p_{jd} - \kappa_i) \cdot \alpha \cdot (r - b_{ijd}) + \beta - p_{jd} + c^D_{jd}\Big]^{\rho} \\
&\cdot \Big[g(d,i) - \gamma_i \cdot [p_{jd} + r(p_{jd} - \kappa_i)] + \zeta \cdot \mathbf{z}_j + \psi_j + \xi_{jd} + \epsilon_{ijd} \\
&\qquad\qquad - g(d,i) + \gamma_i \cdot [p_{jd} + \theta_i(p_{jd} - \kappa_i)] - \zeta \cdot \mathbf{z}_j - \psi_j - \xi_{jd} - \epsilon_{ijd}\Big]^{1-\rho},
\end{aligned}$$

which simplifies to:

$$\tilde{r}_{ijd} \in argmax_r \Big[(p_{jd} - \kappa_i) \cdot \alpha \cdot (r - b_{ijd}) + \beta\Big]^{\rho} \cdot \Big[\gamma_i(p_{jd} - \kappa_i) \cdot (\theta_i - r)\Big]^{1-\rho},$$

where $\rho \in [0,1]$ is the relative bargaining weight of dealers. Dealers and consumers only come to an agreement as long as there is positive surplus that can be split. This is the case if the outside option of the consumer is worse than a critical value $\underline{\theta}_i$, which depends on the buy rate, the consumer's down payment, and the price of the car and is defined by

$$\underline{\theta}_i \equiv b_{ijd} - \frac{\beta}{\alpha \cdot (p_{jd} - \kappa_i)}. \tag{4}$$

Anticipating the distribution of bargaining outcomes $\tilde{r}_{ijd}$, dealer d posts prices for all models $\mathcal{J}_d$. In particular, for a given buy rate and consumer type dealers know the interest rate $\tilde{r}$ they will agree on with the consumer and whether or not the consumer will finance

would not be able to obtain reliable rate quotes.

[19]This allows us to avoid modeling an asymmetric auction which would complicate the analysis considerably. More importantly, this assumption is a good approximation to the data. Revenue-sharing agreements are quite homogeneous across lenders (see Section 3 for details).

the car at the dealership. Let $\mathbb{I}\{\theta_i \geq \underline{\theta}_i\}$ denote the indicator function that is one if $\theta_i \geq \underline{\theta}_i$ and zero otherwise and $F_\theta(\theta, \kappa, b)$ the joint distribution of outside options, downpayments and buyrates b.[20] Then, dealer $d's$ objective function $\pi_d(\mathbf{p}_m)$ is

$$\pi_d(\mathbf{p}_m) = \sum_{j \in \mathcal{J}_d} \int s^m_{jd}(\mathbf{p}_m, \theta, \kappa) \cdot \Big(p_{jd} + \mathbb{I}\{\theta_i \geq \underline{\theta}_i\} \cdot \\ (\alpha_d \cdot (p_{jd} - \kappa) \cdot (\tilde{r}_{ijd} - b) + \beta) - c^D_{jd}\Big) dF(\theta, \kappa, b). \quad (5)$$

A notable feature of this objective function is that consumer heterogeneity not only determines market shares, as in a standard random coefficient model, but also directly determines the dealer margin through the bargaining outcome. Moreover, there is an interesting link between the posted prices and the bargaining outcome $\tilde{r}_{ijd}$. Higher car prices increase $\underline{\theta}_i$ for all consumers, thereby changing the composition of consumers who finance at the dealership. Intuitively, higher car prices make it more likely that consumers obtain financing from outside lenders, because the fixed payment β covers a smaller range of markdowns if the price of the car is higher.

4.3 Lenders

We assume that dealers always select the lowest buy rate from lenders' bids. Therefore, the lender-bidding problem is a first-price auction. Each lender in $\mathcal{L}_d$ bids a buy rate for each consumer i that visits dealer d. All lenders $\ell \in \mathcal{L}_d$ draw from the same distribution of wholesale interest rates $c^L_{\ell i} \sim \mathcal{F}_L(\cdot|p, \kappa)$ with support $[\underline{c}^L(p, \kappa), \bar{c}^L(p, \kappa)]$ for a given tuple (p, κ). The winner of the auction issues the loan if the consumer finances the car at the dealer. If the consumer finances the car at an outside lender, none of the lenders that bid in the auction issues the loan.

Let n_d be the number of lenders bidding for a contract. Lenders anticipate that the dealer markup $m_{ijd} = \tilde{r}_{ijd} - b_{ijd}$ will depend on the buy rate, the consumer type, and the car price through the dealer's downstream decisions in the Nash bargaining game.[21] A lender issues a loan if she offers a lower buy rate than competing lenders and the consumer does not take outside financing. Lender ℓ conditions her bid b^ℓ_{ijd} on her information set $\mathcal{I}_{il}$ about consumer i, which consists of the price of the car p_{jd}, and the downpayment κ_i. Assuming a symmetric

[20] To ease notation, we omit the arguments of the indicator function (see Equation (4) for details).

[21] Since we study only prime consumers, we implicitly assume that the bids of competing banks also do not contain any additional information on expected default rates.

Bayesian Nash Equilibrium with monotone bidding functions δ which map lender costs $c^L_{\ell i}$ and information set $\mathcal{I}_{il}$ to buy rate offers b^{ℓ}_{ijd}, we can write (as shown in Appendix A) the lender objective function as:

$$\max_{b^{\ell}_{ijd}} \left(1 - F_\theta\left(\underline{\theta}_i | \mathcal{I}_{il}\right)\right) \cdot \left[1 - \mathcal{F}_L\left(\delta^{-1}\left(b^{\ell}_{ijd}, p_{jd}, \kappa_i\right) | \mathcal{I}_{il}\right)\right]^{n_d - 1} \cdot \left[\left((1-\alpha) \cdot \mathbb{E}_\theta[m_{ijd} | b^{\ell}_{ijd}, p_{jd}, \kappa_i] + b^{\ell}_{ijd} - c^L_{\ell}\right) \cdot (p_{jd} - \kappa_i) - \beta\right], \quad (6)$$

where δ^{-1} is the inverse bidding function which maps the buyrate into the corresponding lender costs given the car price and the downpayment. The first term in expression 6 is the probability that the consumer does not get outside financing, the second term is the probability that lender ℓ offers the lowest buy rate, and the third term is the expected interest rate margin conditional on the buyrate. Since θ_i is unknown to the lender, this setup resembles a first-price auction with a random reserve price. The lender only issues the loan if (i) it offers the lowest buy rate and (ii) the buy rate it offers is low enough for the dealer and the consumer to agree on an interest rate for the loan.

4.4 Discussion of Modeling Choices

Before we discuss the identification and estimation of our model, we briefly comment on two important modeling choices. First, we model the pricing game as a two-stage process in which dealers first post car prices for the entire market and then negotiate individual loan terms with consumers at the dealership. We see this structure as a feature of our model. In particular, the price-posting assumption allows us to control for unobserved car characteristics and to use instrumental variables to address endogeneity concerns as is standard in the literature on the car market (Berry *et al.*, 1995, Murry, 2017, Nurski and Verboven, 2016, Grieco *et al.*, 2021). While car prices are typically observable and negotiated ex-ante, loan prices can only be negotiated at the dealership after consumers' credit risk has been determined. At the second stage of our model loan prices are therefore negotiated individually and car prices taken as given.[22] This stage allows us to capture the large heterogeneity in loan prices that

[22]In a previous version of this paper, we estimated a model in which car and loan prices are set simultaneously by the dealer. In such a model one would have to explain why dealers ever set positive loan markups. In Appendix A.6, we show that the two parties would also agree on zero markups on the loan if dealers and consumers conducted Nash bargaining over both car and loan prices. As discussed in Grunewald *et al.* (2020), one approach to rationalize positive markups in a model in which dealers set both prices simultaneously is to allow consumers' utility to be more

we observe empirically (see Section 3) as is common in the modern quantitative literature on credit markets (for example Allen *et al.* (2014b), Cuesta and Sepúlveda (2021), Galenianos and Gavazza (2022)).

A caveat of our model is that it does not capture the fact that consumers may also negotiate individual discounts for the car price itself. This would be particularly problematic if there was a systematic correlation between car and loan markups. In Appendix B.2, however, we find that the correlation between loan markups and a proxy for car price markups is only .03.

The second feature of the model that is worth discussing is that it does not endogenize prepayments. We do not explicitly model prepayments because of two important observations. First, dealers only bear prepayment risk for early prepayments (e.g. the first three months). As very few loans are prepaid early, dealers are almost unaffected by prepayments.[23] Second, while lenders may be concerned about prepayment risk, Appendix B.6 shows that auto loan prepayments unlike e.g. mortgage prepayments are not often driven by strategic interest rate considerations but are typically driven by other factors, such as vehicle trade-ins. In particular the time series correlation between interest rates and prepayment rates is much weaker for auto loans than it is for mortgages. Conversely, there is a strong seasonality to auto loan prepayments that is absent for mortgage prepayments; auto loan prepayments peak in March, coinciding with a well-known peak in auto sales when tax refunds arrive.[24] The finding that auto loan prepayments are mainly driven by factors exogenous to interest rate considerations has several implications for the interpretation and identification of our model. First, we show in Appendix B.6 that Nash Bargaining outcomes (and therefore the identification of θ) are invariant to consumer-specific exogenous prepayment risk; such prepayment risk would therefore not contribute to variation in θ. Intuitively, this is because prepayment risk only scales the Nash-bargaining problem. Second, to the extent that lenders account for prepayment risk when pricing loans, the implied variation in buy rates would be rationalized by variation in lenders' cost.

sensitive to changes in the car price than in the loan price.

[23] For early prepayments dealers have to refund the dealer reserve. We estimate that such early prepayment only occurs in approximately five percent of contracts (for further details see Section B.6).

[24] As a consequence, interest rate variation explains only 11% of the time series variation in auto loan prepayment rates while month fixed effects – capturing in part seasonal variation in auto sales – explain almost 24%. For mortgages, interest rate variation explains over 40% of the time series variation in prepayment rates, while month fixed effects explain less than 3%.

5 Identification

This section derives the identification of the model primitives, which are (i) consumers' bargaining power and the distribution of consumer beliefs, (ii) the dealer cost distribution and (iii) the lender cost distribution.

5.1 Consumer Bargaining Power and Outside Options

A key object in our model is consumers' outside options, θ_i. Here we show that we can recover θ_i for each individual contract, so the joint distribution of θ_i, buy rates, and down payments $F_\theta(\theta, \kappa, b)$ is also identified.

The identification relies on two features of our data. First, the parameters of the linear contracts between lenders and dealers (α and β) are identified, because we observe the dealer reserve for each individual loan. Second, we observe markups and buy rates separately. We therefore observe the outcome as well as all the determinants of the Nash-bargaining problem except for θ_i and ρ. Without any additional restrictions $F_\theta(\theta, \kappa, b)$ is thus identified up to the scalar ρ. We then use the fraction of consumers that obtain loans through dealers as an additional restriction to jointly identify ρ and the distribution of consumer types F_θ.

Denote the observed joint distribution of interest rates, buy rates, and down payments by $F_{r,b,\kappa}(\cdot,\cdot,\cdot)$.[25] Proposition 1 formally states our identification result.

Proposition 1. *There exists at most one tuple $(\rho, F_\theta(\theta, \kappa, b))$ such that $F_{r,b,\kappa}(\cdot,\cdot,\cdot)$ is the equilibrium distribution of interest rates, buy rates, and down payments and W is the fraction of consumers that finance at outside lenders. Consumer types θ_i are given by:*

$$\theta_i = \frac{r_{ijd}}{\rho} + \frac{1-\rho}{\rho} \cdot \left[\frac{\beta}{\alpha \cdot (p_{jd} - \kappa_i)} - b_{ijd}\right], \tag{7}$$

and

$$W = \sum_{m \in \mathcal{M}} \sum_{d \in \mathcal{D}_m} \sum_{j \in \mathcal{J}_d} \int_{b,\kappa,\theta} s^m_{jd}(\mathbf{p}_m, b, \kappa)(1 - \mathbb{I}\{\theta_i \geq \underline{\theta}_i\}) dF_\theta(\theta, \kappa, b).$$

[25]Note that we assume for the identification argument that we observe the buy rates, down payments, and interest rates for the entire market, while our dataset only covers loans that are originated through dealers. We estimate that about 90% of loans are originated through dealers. In Section 6, we explain how we estimate buy rates and interest rates for loans that are not obtained through dealers.

Proof: The proof is relegated to Appendix A.

Proposition 1 identifies the consumer types jointly with the Nash-bargaining weights. To understand how the variation in the data identifies both objects simultaneously, recall that we assume ρ to be constant across the population. Hence, we attribute variation in markups $r_{ijd} - b_{ijd}$ to variation in θ_i. Given this variation we estimate ρ to match the share of loans intermediated by dealers. Consumer outside options are also a key ingredient for the identification of dealers' and lenders' costs, described below. Section 6 discusses how we use Proposition 1 to estimate the bargaining weight and the distribution of consumer types in our data.

5.2 Dealer Costs

We use the first-order conditions from the dealers' pricing problem to recover dealer costs. While the dealer objective function resembles the one in Berry *et al.* (1995), there are two differences that are worth noting. First, in our setup, the interest rates on the loan are uncertain to dealers at the moment when they post their prices. In the model and the estimation, the expected interest rate therefore works like an additional random coefficient that only multiplies the loan amount instead of the overall price of the car. Second, dealers have to form expectations about the fraction of consumers that will finance cars through their dealership, which depends in part on the car prices they post. As can be seen from (4) higher car prices decrease the likelihood that dealers intermediate loans. This is because higher car prices imply that the lump sum payment β_d covers only a smaller mark down of the interest rate.

In Appendix A.2 we show that, despite these additional features in the model, we can perform an inversion like in Berry *et al.* (1995) to recover dealers' costs. In particular, the set of first order conditions for dealer d with respect to price p_{jd} can be written as:

$$Q(\mathbf{p}_m) + \nabla_p \cdot s(\mathbf{p}_m) \cdot \begin{pmatrix} p_{1d} - c^D_{1d} \\ \vdots \\ p_{N_d d} - c^D_{N_d,d} \end{pmatrix} = 0,$$

where $\nabla_p s(\mathbf{p}_m)$ is the $N_d \times N_d$ Jacobian of the market share and $Q(\mathbf{p}_m)$ is a vector-valued function of posted car prices in the market that we define in (13) in the appendix. $Q(\mathbf{p}_m)$ distinguishes our setup with uncertain interest rates from the typical BLP setting. In particular, $Q(\mathbf{p}_m)$ describes how a change in the posted car price changes the expected revenues for the dealer from loan markups. It therefore comprises (i) the direct effect of increases in the car price on the revenue generated by the loan and (ii) how changes in the price affect the likelihood that consumers finance at the dealership. We estimate this change by exploiting our estimates for the marginal consumer types from (4) and the observable contracts between dealers and lenders. In analogy to Berry *et al.* (1995), retrieving estimates for dealer costs thus requires inverting $\nabla_p s(\mathbf{p}_m)$.

5.3 Lender Costs

Lenders bid for each loan in a first-price auction. When doing so, they know that their buy rate influences the chance of winning the auction as well as the loans' profitability conditional on winning. As shown by (4) a higher buy rate makes it less likely that the consumer finances the car at the dealership. Since the lender does not know θ_i, the auction is strategically equivalent to an auction with a random reserve price. In this auction, we seek to identify the distribution of lender costs $\mathcal{F}_l$ from the distribution of buy rates $G(b, p, \kappa)$ with support $[\underline{b}, \bar{b}]$ for each tuple (p, κ). Following in part the arguments by Li and Perrigne (2003), Appendix A derives the first order conditions of the lenders in the auction assuming that they play a symmetric Bayesian Nash Equilibrium in monotonically increasing strategies. Denote the hazard rate of consumer types conditional on information set $\mathcal{I}$ as $\tilde{f}_\theta(\cdot|\mathcal{I}) = f_\theta(\cdot|\mathcal{I})/(1 - F_\theta(\cdot|\mathcal{I}))$ and of the bid distribution as $\tilde{g}(\cdot|\mathcal{I}) = g(\cdot|\mathcal{I})/(1 - G(\cdot|\mathcal{I}))$. The first order conditions imply that lender costs are given by:

$$c_{li}^L = \lambda(b_{ijd}^l, G, F_\theta, p_{jd}, \kappa_i) \equiv (1-\alpha) \cdot \mathbb{E}[\tilde{r}_{ijd} - b_{ijd}^l | p_{jd}, \kappa_i] + b_{ijd}^l - \frac{\beta}{p_{jd} - \kappa_i} - \frac{\alpha}{(n_d - 1) \cdot \tilde{g}(b_{ijd}^l | \mathcal{I}_{il}) + \tilde{f}_\theta(\underline{\theta}_i | \mathcal{I}_{il})} \tag{8}$$

Lenders' costs can therefore be expressed in terms of their buy rates and the distribution of consumers' beliefs about their outside options F_θ. However, in our setup the valuation of the loan is unknown to the bidders. Therefore, our estimates also depend on the expected revenue that is generated by the downstream decisions of dealers in the bargaining process. To derive identification of $\mathcal{F}_L$, we have to ensure that (8) is well-behaved. We therefore make the following assumption on the support of the distribution of consumer beliefs F_θ.

Assumption 1. *For all observed $\mathcal{I}_{il}$, the support of $F_\theta(\cdot|\mathcal{I}_{il})$ includes the marginal type $\underline{\theta}_i$.*

Assumption 1 ensures that for each buy rate the probability that the consumer finances at the dealer is strictly positive but less than one. Given the first order condition in (8), we can then identify the distribution of lender costs $\mathcal{F}_l$ that lead G to be the equilibrium distribution of buy rates. Proposition 2 states this formally.

Proposition 2. *Suppose G is absolutely continuous and let $G_{n_d}(b^1_{ijd}, \dots, b^{n_d}_{ijd})$ be the joint distribution of buy rates in the auction by dealer d for consumer i who purchases model j and let the support of G_{n_d} be $[\underline{b}, \bar{b}]^{n_d}$. For information set $\mathcal{I}$, there exists an absolutely continuous conditional distribution of lender costs $\mathcal{F}_L(c|\mathcal{I})$ with support over $[\underline{c}^L(p,\kappa), \bar{c}^L(p,\kappa)] \equiv [\lambda(\underline{b}, G, F_\theta, p, \kappa), \lambda(\bar{b}, G, F_\theta, p, \kappa)]$ such that G_{n_d} is the distribution of equilibrium bids if and only if:*

(i) $G_{n_d}(b^1_{ijd}, \dots, b^{n_d}_{ijd}) = \prod_{i=1}^{n_d} G(b_i|p,\kappa)$

(ii) The function λ defined in (8) is strictly increasing in b_{ijd} and its inverse is differentiable on $[\underline{c}^L(p,\kappa), \bar{c}^L(p,\kappa)]$.

Then, $\mathcal{F}_L(c^L|\mathcal{I})$ is unique and $\mathcal{F}_L(c^L|\mathcal{I}) = G(\lambda^{-1}(c^L, G, F_\theta, p, \kappa))$ and $c^L_{li} = \lambda(b_{ijd}, G, F_\theta, p, \kappa)$ for all $b_{ijd} \in [\underline{b}, \bar{b}]$.

6 Estimation Details

For estimation we assume that F_θ is a normal distribution that is left-truncated at zero, since we do not observe loan prices for the approximately 10% of consumers who do not obtain loans through dealers. To estimate the consumer bargaining weight ρ, we perform an iterative procedure where we first guess ρ and then compute a candidate distribution $F_\theta(\cdot)$. We then calculate the resulting number of indirect loans via Equation 4, and compare this number to the actual number of indirect loans. We repeat this process until the predicted and the actual number of indirect loans agree. Then when we have an estimate of $F_\theta(\cdot)$ we can directly apply Equation 8 and recover the lenders' cost distribution. The distribution of consumer types $F_\theta(\cdot)$ also serves as an input to the demand estimation. With this distribution, we can compute expected interest rates for consumers. These conditional interest rate expectations can be thought of as an endogenous random price coefficient, which is already known to the econometrician.

When applying our identification results, we consider only new cars financed with a loan, i.e. we exclude used cars, leased cars, and cars purchased with cash. The commercial data that we use in addition to the supervisory data provides very good but not perfect coverage; in total our car sales data cover 30 states and 1134 counties.[26] The commercial data is binned, so we do not observe borrowers' credit scores at the individual level; to align with our focus on prime consumers, we drop dealers whose consumers have an average credit score below 680.

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 use the Google distance API to build 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. For computational reasons, 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. Even with these restrictions, we have to solve a very high-dimensional fixed-point problem for our counterfactuals that involves all dealers and all cars that they offer. This leaves 917 markets of which we use a random subset of 50% for estimation.

The price of the vehicle is potentially endogenous to the unobserved dealer-model specific demand shock ξ_{jd}. Failure to account for this will result in biased price coefficients. We therefore interact ξ_{jd} with the following set of instruments: the average miles per gallon of other models at the same dealer, the vehicle length 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. Except for the buy rate and the distance, these instruments are standard in the demand estimation literature (Nevo, 2000).

Following Berry *et al.* (1995) we use the observed aggregate market shares for a specific dealer-model combination to compute a contraction mapping that recovers mean utilities. We then regress those mean utilities on product attributes to uncover the linear parameters of the mapping (Nevo, 2000). Using the mean utilities we can compute ξ_{jd} and construct (9), the moment condition for estimation.

[26]The data includes the following states: 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.

$$G(\theta) = \sum_{d \in \mathcal{M}_d} \sum_{j \in \mathcal{J}_d} \xi_{jd}(\theta) \cdot z_{jd} \tag{9}$$

We then solve the following minimization problem:

$$\arg\min_{\theta} \; G(\theta)' \cdot \Omega \cdot G(\theta). \tag{10}$$

For Ω we use the optimal GMM weights from a first stage estimation of a standard logit model without random coefficients.

7 Estimation Results

We first present our estimation results for consumers and then discuss the demand estimates. Afterwards, we move to the supply side and present results on lenders' and dealers' costs.

7.1 Beliefs About Outside Options

For every contract in our data, we observe θ_i by applying Proposition 1. θ varies considerably: its tenth percentile is 10.84% while its 90th percentile, at 30.54%, is almost three times larger. Within the model, θ_i can be interpreted as the interest rate (calculated over the lifetime of the loan) that a consumer would expect to pay if she obtained a loan directly from an outside lender. The question is what θ_i represents in reality.

Table 3: Summary Statistics of Estimates

	Mean	p10	p25	p50	p75	p90
Outside option θ	20.58%	10.84%	15.14%	20.48%	25.52%	30.54%
Outside option θ relative to:						
(i) Buy rate b	2.5	2.35	2.63	2.68	2.64	2.47
(ii) Derived Outside Option θ^D	1.24	0.75	1.01	1.27	1.42	1.56

Note: The first row shows the mean and different percentiles of the distribution of θ. The second row shows the ratio of those summary statistics divided by the same summary statistics for the buy rate. The last row shows the ratio of the summary statistics for theta divided by the same summary statistics for the distribution of interest rates from a hypothetical auction with two lenders.

To investigate this question we first compare summary statistics for θ to those of two other objects of interest. The second row in Table 3 compares θ to buy rates. Because a buy rate is the interest rate at which a lender has committed to providing a loan for a consumer, it can be viewed as a proxy for a consumer's actual outside option in the credit market. Our θ estimates are typically more than double buy rates. However, the relationship between buy rates and outside options is unclear; buy rates might be higher than outside options (if some lender in the market would have provided a lower rate than the lender the dealer chose) or lower (since lenders expect dealers to mark them up). To create another proxy for consumers' outside options, we therefore also calculate the interest rates consumers would obtain if they ran a minimally-competitive first-price auction with only two lenders; we denote these rates by θ^D. These estimates provide conservative upper bounds for consumers' actual outside options since motivated consumers could obtain more than two price quotes. Nevertheless, θ is on average about 25% higher than θ^D. The divergence between θ and θ^D is especially large in the upper tail of the distribution. The fact that θ is substantially larger than buy rates and θ^D, suggests that it captures much more than consumers' actual outside options in the credit market. Next, we investigate what else it might represent.

First, we study how θ correlates with demographic variables in the supervisory data. Lenders observe only very limited demographic information about borrowers, so our supervisory data has only very limited demographic information. Therefore, we bring in county-level data on household education from the American Community Survey (ACS) and tract-level data on internet access from the FCC. Table 4 shows that θ varies with demographics: borrowers with lower income, less education, and less internet access bargain as if they had worse outside options. Variation in default risk is an unlikely explanation for this finding – recall that in our supervisory data we focus only on prime consumers with minimal default risk – but the result holds controlling for consumers' default risk with credit scores and many other car, loan, and consumer characteristics. Figure A2 provides estimates of θ by county to give a sense for their geographic distribution.

Table 4: Regressions of θ on Demographics

	θ			Markup as % of Loan Amount		
	(1)	(2)	(3)	(4)	(5)	(6)
Log Monthly Income	-1.159***	-1.208***	-1.032***	-0.257***	-0.202***	-0.178***
	(0.013)	(0.012)	(0.012)	(0.003)	(0.003)	(0.003)
Average Years of Education	-0.0891***	-0.298***	-0.255***	-0.00213	-0.0469***	-0.0419***
	(0.028)	(0.025)	(0.024)	(0.008)	(0.007)	(0.007)
Fraction with Internet Access	-3.423***	-2.120***	-1.727***	-0.552***	-0.446***	-0.404***
	(0.119)	(0.103)	(0.098)	(0.034)	(0.028)	(0.028)
R^2	0.066	0.113	0.156	0.017	0.061	0.073
Borrower Controls	✓	✓	✓	✓	✓	✓
State and Lender Fixed Effects		✓	✓		✓	✓
Vehicle Controls			✓			✓

NOTE: Table shows estimates from an OLS regression. Columns (1) and (4) control for the log of borrower income, average years of education of households in the borrower's county, the fraction of households in the borrower's census tract with internet access, borrower credit score (in bins) and log loan amount. Columns (2) and (5) adds state and lender fixed effects. Columns (3) and (6) add vehicle mileage and a dummy variable for whether the car is new. Standard errors are clustered at the zip code level. *** denotes statistical significance at the 1 percent level.

These results hint at the possibility that dealer loan-price discretion may be regressive. However, there are drawbacks to correlating θ with demographics that are observable to lenders. As shown in Table 2 the information lenders have explains very little variation in markups, implying that it also explains very little variation in θ. This is why the R^2 are low in Table 4. Instead, as we have argued, markup decisions are largely based on information that dealers acquire about consumers during the sales process.

But what information about consumers do dealers price? To learn more, we included several questions related to the sales process of auto loans and borrower financial literacy in the Making Ends Meet ("MEM") survey. The MEM is a rich and novel dataset that includes information on borrower financial literacy measured directly at the individual level; it is also linked to the CCP, so it also has administrative data on auto loans including their interest rates. The MEM data are also a very valuable supplement in predicting interest rates in the CCP, because they provide information on borrower finances (income, savings, etc.) that is otherwise missing from credit bureau data. This is especially valuable here because a correlation between financial literacy and markups could in reality be explained by borrower finances (e.g. ability to pay or default risk), so an important advantage of the MEM-CCP data is it allows us to control for borrower finances.

Because the CCP does not have data on markups or buy rates, we cannot estimate θ for the survey participants directly. Instead, we construct a markup proxy and then correlate this proxy with survey responses. To construct the proxy, we take the residual from segment- (prime or non-prime) and year-specific regressions of interest rates on month, credit score, loan term, co-borrower presence, and lender type dummies. In a second step, we regress these markup proxies on the responses of three MEM questions of interest.[27] In particular, we added questions to the MEM survey to try to understand (i) borrowers' self-assessed financial knowledge, (ii) whether borrowers know that it is valuable to shop for loans, and (iii) whether borrowers are aware that dealers charge discretionary markups. More specifically, we asked whether they mostly agree (true/false) with the following statements:

(i) *"I'm comfortable interacting with banks and other lenders"*

(ii) *"All lenders give about the same rates for the same type of loan"*

(iii) *"Auto dealers give the best loan interest rates people qualify for"*

In our sample, 69% of borrowers answer yes to the first question. Remarkably, 43% answer yes to the second and 21% to the third question.

Table 5 provides coefficient estimates for our markup proxy regressions. Because the sample size is small and our markup proxy is measured with error, many variables we might expect to predict markup proxies are statistically insignificant. This includes borrower race, education, income, and income variability; the only partial exception is borrower savings. We also do not find a significant statistical effect for whether respondents feel comfortable interacting with lenders. Remarkably, the only variables that do consistently predict our markup proxies are our other two measures of borrower financial literacy. Their estimated statistical effects are large; agreeing that all lenders give about the same rates predicts a markup that is 47

[27] To reduce the role of measurement error, we drop loans with markup proxies in the bottom two percentiles and the top two percentiles. We restrict our attention to auto loans on credit records in 2022 (whether still open or closed) that were originated in 2015 or later. To drop loans subsidized by manufacturers (which are only available through dealers) we drop loans from captives and loans with interest rates below one percent. We also drop loans from non-captive finance companies, because they focus on subprime consumers who are not the focus here. We report results including loans from captives and other finance companies in Appendix B.4.

basis points higher (which is almost 50% of the average discretionary markup), while agreeing that dealers give the best rates predicts a markup that is 35 basis points higher (which is more than 30% of the average discretionary markup). The two variables become somewhat less predictive when included in the regressions together. This is because they are correlated, providing some support for our treatment of θ as a one-dimensional object.

Together our results show that many consumers act as if their outside options in the auto loan market are much worse than they actually are, and consumers with less financial literacy are particularly likely to act this way. These findings are consistent with other survey evidence that most consumers are not aware that dealer markups occur, that most consumers think that dealer markups are illegal, and that consumers who were told or believed that their dealer found them the best rate in fact obtained particularly high interest rates (Center for Responsible Lending *et al.*, 2012). They are also consistent with evidence from the FTC that few consumers are aware that interest rates are negotiable (Reynolds and Cox, 2020, Sullivan *et al.*, 2020).[28] Our results are also in line with the view of many industry professionals that dealer markups help raise revenue from consumers who do not understand that dealers are not acting in their interest.[29] These kinds of concerns prompted the U.K.'s FCA to ban these markups in 2021.[30]

We conclude that price discrimination based on θ is regressive, leading to higher loan prices for people with lower levels of education, lower income, and less access to information. This suggests that policies that reduce price discrimination across θ should have positive redistributional effects.

[28]There is also strong evidence from the mortgage market that intermediaries exploit borrowers' confusion to increase prices (Woodward and Hall, 2012), that many borrowers do not believe there is price dispersion even though it is substantial (Alexandrov and Koulayev, 2018), and that mortgage knowledge varies substantially across prospective borrowers, is correlated with other socioeconomic characteristics, and has a strong relationship with ultimate interest rates obtained (Bhutta *et al.*, 2019).

[29]For example, one expert witness testified that *"the standard industry practice is to prepare financing documents so that the customer is not alerted in any manner that the person with whom he is dealing has the ability to control the customer's price of credit. [...] This type of pricing system is particularly successful when used in conjunction with the sale of an automobile, because the credit applicant's attention is naturally focused on the price of the automobile [...]."* For this quote and more details see the Expert Report of Edward Ford Jr. in the matter of Addie T. Coleman et al. vs GMAC, U.S. District Court for the Middle District of Tennessee, August 21, 2003. McDonald, Kevin M., and Kenneth J. Rojc. "Automotive Finance: Shifting Into Regulatory Overdrive." The Business Lawyer 69.2 (2014): 599-607.

[30]See the FCA's website.

Table 5: Conditional Correlations of Markup Proxy with MEM Survey Responses

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Shopping Proxies							
All Lenders Give Same Rates	0.469***	0.462***					0.396**
	(0.177)	(0.175)					(0.170)
Dealers Give Best Rates			0.354*	0.425**			0.314
			(0.208)	(0.210)			(0.203)
Comfortable Making Decisions					-0.226	-0.126	-0.144
					(0.195)	(0.198)	(0.191)
Borrower Finances							
80k< Income < 125k		-0.070		-0.027		-0.038	-0.013
		(0.310)		(0.317)		(0.316)	(0.293)
Income > 125k		0.067		0.055		0.074	0.106
		(0.275)		(0.280)		(0.274)	(0.260)
Variable Monthly Income		0.224		0.178		0.163	0.211
		(0.210)		(0.213)		(0.221)	(0.205)
Small Financial Buffer		0.386*		0.330		0.357	0.372*
		(0.222)		(0.231)		(0.232)	(0.215)
Borrower Race							
(white omitted)							
Black		-0.234		-0.298		-0.279	-0.235
		(0.294)		(0.298)		(0.314)	(0.298)
Hispanic		0.288		0.298		0.310	0.280
		(0.257)		(0.261)		(0.259)	(0.255)
Other		-0.188		-0.158		-0.147	-0.217
		(0.361)		(0.350)		(0.337)	(0.351)
Borrower Education							
(≤ high school omitted)							
> High School		0.249		0.269		0.264	0.234
		(0.288)		(0.297)		(0.299)	(0.277)
≥ College		0.188		0.148		0.142	0.168
		(0.281)		(0.289)		(0.289)	(0.271)
N	825	747	825	747	825	747	747

NOTE: The table shows estimates from OLS regressions. The markup proxy is defined as the residual from segment- (prime or nonprime) and year-specific regressions of interest rates on month, credit score, loan term, coborrower, and lender type dummies. Monthly income is defined to be "variable" if respondents report that it varies "somewhat" or "a lot" from month to month. Respondents' financial buffer is defined to be "small" if they report they could cover expenses for one month or less after losing their main source of income. Columns (1), (2), and (5) regress markup proxies on survey responses related to loan shopping behavior. Columns (2), (4), and (6) add survey controls for borrower finances, race, and education. To avoid subvented loans and outliers, loans with interest rates below one percent are dropped, as are loans with markup proxies below the 2nd or above the 98th percentile. Loans originated before 2015 are also dropped. Regression is weighted by sampling weights. Some consumers have multiple loans, so robust standard errors are clustered at the consumer level. *, **, and *** denotes statistical significance at the 10, 5, and 1 percent level respectively.

7.2 Demand Results

Table 6 shows the coefficients from the demand model along with standard errors. The price interaction terms show that buyers with lower income are slightly more price-elastic. However, the estimate of the income interaction is quite noisy. The signs of most coefficients line up with intuition and the previous literature. The coefficients on horsepower and miles per gallon are negative on average but increasing in income. The coefficient on vehicle length is positive but decreasing in income.

Table 6: Demand Model Coefficients and Elasticities

Variable	Coefficient	Standard Error
Price	-0.01	(0.0001)
Horsepower	-0.88	(0.0026)
Vehicle Length	2.17	(0.0026)
MPG	-5.34	(0.0033)
Distance to Dealer	-2.59	(0.001)
Income × Price	0.02	(0.0154)
Income × Horsepower	9.96	(0.3436)
Income × MPG	58.14	(0.4376)
Income × Car Length	-22.68	(0.3228)

Income Type	Outside Option Type	Average Elasticity
$y_{im} \leq y_m^{p50}$	$\theta_i \leq \theta^{p50}$	-3.03
$y_{im} \leq y_m^{p50}$	$\theta_i > \theta^{p50}$	-3.28
$y_{im} > y_m^{p50}$	$\theta_i \leq \theta^{p50}$	-2.88
$y_{im} > y_m^{p50}$	$\theta_i < \theta^{p50}$	-3.12

Note: The table shows the main coefficient estimates and the standard errors from the model. Standard errors are rounded to second digit after the comma. Travel time is in log-minutes and prices are in dollars. Income is measured in units of standard deviations.

To provide some intuition for the magnitudes of our estimates, we now discuss the average elasticities they imply. At an average of -0.16 consumers appear not to be too sensitive to changes in distance to different dealer locations.[31] Over all market-dealer-model combinations

[31] Murry (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

we obtain an average price elasticity of -3.05. The lower part of Table 6 also shows how elasticities vary by consumers' income and outside option. We find that consumers with lower income and worse outside options are more price sensitive. For example, consumers with income below the median and outside options above the median have an average price elasticity of -3.2. In contrast, consumers with income above the median and outside options below the median have an average price elasticity of only -2.88. Moving from the bottom fifty percent to the top fifty percent of outside options has about the same effect for price elasticities as moving from the top fifty percent of the income distribution to the bottom fifty percent. Consumers' outside options in the loan market therefore have important implications for how dealers set car prices.

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. However more recent work (Grieco *et al.*, 2021) uses rich micro moments for identification and finds larger elasticities. These estimates use aggregate U.S. model market shares and so are not directly comparable to ours, but they raise the question of how our results depend on demand elasiticities. To answer this question we provide a robustness check in Appendix B.7 where we run our counterfactuals with double the demand elasticity and find similar results. Hence our counterfactual results are qualitatively robust to different demand elasticities.

7.3 Dealer Cost

Our dealer cost estimates are in Table 7. We estimate an average cost of \$15,405, ranging from \$6,116 in the 10th percentile to \$24,255 in the 90th percentile. The implied average Lerner index is 38.64.[32]

might be a result of a different subset of markets that Murry (2017) focuses on.

[32] The Lerner index is equal to the price of a good minus its marginal cost, normalized by the price of the good. It is often used as a measure of market power, with values near 0 indicating a competitive market and values near 1 indicating a concentrated market.

Table 7: Lerner Index, and Cost, Summary Statistics

Variable	Mean	P10	P25	P50	P75	P90
Lerner Index	38.64	22.51	26.94	35.07	46.6	58.62
Cost	$15,405	$6,116	$10,078	$14,823	$21,168	$24,255

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

7.4 Lender Cost Estimates

Lenders compete with other lenders that have an established relationship with the dealer. The mean and median number of lenders through which a dealer extends loans is 4.35 and 4, respectively. If we do not count lenders that originate less than five percent of a dealer's loans, those numbers drop to 3.35 and 3, respectively.

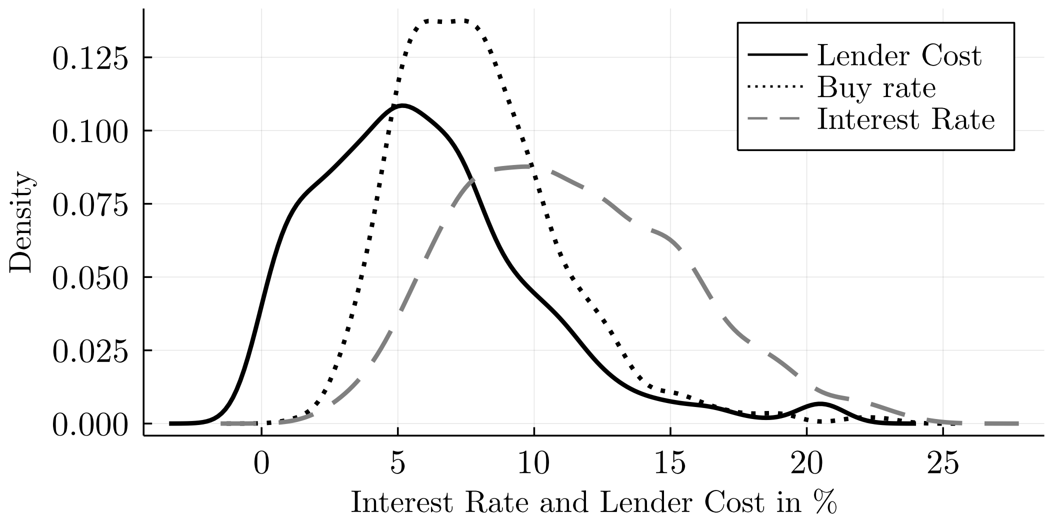
Table 8: Lender Cost, Buy Rate, Interest Rate

Variable (all in %)	Mean	P10	P25	P50	P75	P90
Interest rate	11.59	6.16	8.08	11.05	14.38	17.15
Buy rate	8.24	4.62	5.77	7.63	9.67	12.35
Lender revenue, $(1-\alpha)\cdot m+b$	9.24	5.36	6.69	8.62	10.88	13.6
Lender marginal cost (winner)	4.79	-1.42	1.51	4.97	7.78	10.92

Note: The table shows summary statistics for interest rates, buy rates, lender revenue, and lender marginal cost. All quantities are expressed as a percent of the original loan amount.

On average, we estimate lenders' cost of funds to be 6.72%. An overview of our lender cost estimates, buy rates and interest rates is given in Table 8. This table also shows the lender revenue, i.e., the overall percentage of the loan amount that lenders receive for financing the respective loans. Figure 3 depicts the estimated lender cost distribution together with the observed distributions of interest rates and buy rates. While the distributions of lender costs and buy rates look similar, the distribution of final interest rates is clearly shifted to the right. Hence, lenders anticipate dealer markups and are therefore willing to bid buy rates close to their own costs. Lenders therefore rely on dealers to mark up loans in order to generate profits. Like in other settings that apply an IPV auction framework to lender bidding, we find that the lender cost estimates that rationalize their bids are very dispersed. This is partly because we treat all loans in our data, which have different loan lengths, as two-period loans. Additionally, some of the variation maybe driven by idiosyncratic constraints on lenders (Fuster *et al.*, 2017).

Figure 3: CDFs of interest rates, buy rates, and lender costs.



NOTE: This graph shows the CDFs of the interest rate, buy rate, and lender cost distributions.

8 Counterfactual Experiments

We now present results from two different counterfactual experiments. We compare outcomes under these counterfactual experiments to the outcomes from our estimated model, which we refer to as BASELINE.

In our main counterfactual, NO DISCRETION, we remove dealers' ability to mark up loans. This may be the most obvious intervention to address the consequences of dealer loan intermediation; indeed the U.K.'s FCA banned dealer markups in 2021. Without dealer loan markups, the lowest bids from lenders' auctions are the final interest rates that consumers pay. Dealers only control car prices.

This policy change would likely also lead to adjustments in the fixed payment. Therefore we begin by assuming that lenders compensate dealers for their lost markup revenues by increasing the fixed payment β such that average dealer reserve, conditional on selling a vehicle, does not change. Coincidentally, this also leaves dealers' share of financial revenues unchanged. Then in subsection 8.2 we re-run the No Discretion counterfactual for different values of β. We find that our qualitative conclusions depend little on specific assumptions about β.

In a second counterfactual, Information, we allow consumers' perceived and actual outside options to differ, and we consider the effects of informing them of their actual outside options. For this counterfactual we assume that consumers' actual outside options are not given by θ but instead are determined by a minimally-competitive first-price auction with just two lenders (see also Section 7.1). This counterfactual helps us understand how effective informational interventions could be if dealer loan price discretion persists.

Our main outcome measures are car prices, interest rates, consumer surplus, dealer profits, and lender profits. To simplify the presentation and to make interest rates comparable across contracts with different term lengths, we calculate total finance charges as a percentage of the principle as if interest accrues in a two-period model.

8.1 No Dealer Discretion Counterfactual

In this counterfactual, as in Baseline, we assume that lenders participate in a first-price auction to issue loans. But unlike in Baseline, now we assume the winning bids in these auctions are the final interest rates that consumers pay. However, unlike dealers, lenders do not observe θ_i directly. They only observe the distribution $F_\theta(\cdot)$. Interest rates are therefore determined via a first-price auction with random reserve prices where the reserve price is given by the draw from $F_\theta(\cdot)$. Dealers know all this when pricing vehicles. We compute the equilibrium via iterative best response. Eliminating dealer discretion over loan prices has two important opposing effects.

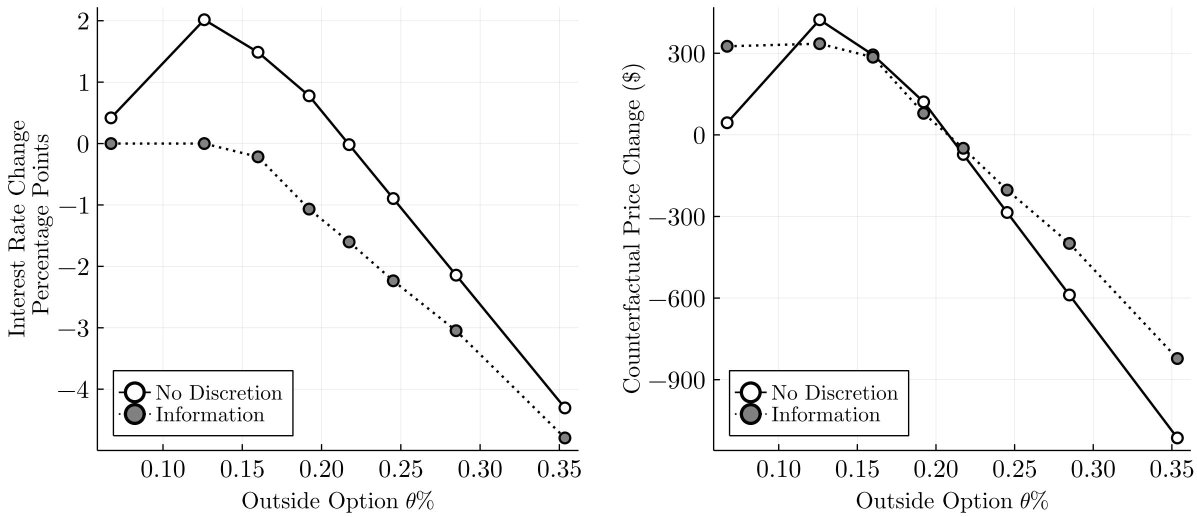
First, lenders have less information about θ than dealers (cp. Section 3.2.1). Eliminating the use of information on θ in loan pricing leads to an *information effect* that reduces price discrimination based on θ. As a consequence, removing dealer discretion eliminates the tight link between loan prices and θ. This change benefits consumers with high θ, i.e. poor outside options. Importantly however, car and loan prices are linked because the price of the car affects the loan amount and hence the price of the loan. Eliminating dealers' ability to set loan prices therefore affects the car prices they post. In Baseline there are two reasons to post higher car prices. First, higher car prices increase profits on car sales directly. Second, higher car prices lead to larger loans, allowing dealers to earn disproportionately large dealer reserves from consumers with poor outside options. *No Discretion* eliminates this second reason so the information effect not only reduces loan price discrimination but also strengthens competition in posted car prices, benefiting all consumers. In Appendix A.5, we present a stylized model with the minimal ingredients to isolate and illustrate these arguments more formally.

Second, eliminating dealer discretion also changes vertical incentives. In Baseline both dealers and lenders profit from dealer loan markups, which effectively aligns their incentives. However, in No Discretion, their interests are no longer aligned. Lenders prefer that surplus be extracted from consumers through high loan prices while dealers prefer low loan prices so that surplus can instead be extracted through higher car prices. This new conflict of interest gives rise to double marginalization. Because there are no more dealer markups in No Discretion lenders increase buy rates relative to Baseline. Dealers then maximize their profits taking these buy rates (which, without dealer markups, are also final interest rates) as given. This double marginalization in turn leads to higher total transaction prices and lower consumer surplus. The size of the *double marginalization effect* depends on the fixed payments β. Recall that we assume that lenders increase the fixed payment β such that the average dealer reserve, conditional on selling, remains identical in Baseline and No Discretion. In Appendix 8.2 we show that the qualitative conclusions from our counterfactual hold for a wide range of counterfactual values of β.

Now we turn towards our quantitative results, structuring the discussion around the two main effects discussed above. We first show how the information effect leads to large changes in the distribution of prices across the population. In a second step, we show that average transaction prices decrease if dealer loan price discretion is eliminated.

No Discretion eliminates the link between loan prices and θ, leading to large changes in interest rates across the population. To illustrate these distributional effects, the left panel of Figure 4 shows the interest rate change from Baseline to No Discretion for different θ-types. Consumers with the lowest θ are almost unaffected by the intervention because they finance at outside lenders in both Baseline and No Discretion. Other consumers finance through dealers. Among this group, eliminating price discrimination benefits those with high θ and hurts those with low θ. Indeed, consumers with the highest 25% of θ obtain interest rates that are 4 percentage points lower, while consumers with the second-lowest 12% of θ obtain interest rates that are 2 percentage points higher. The right panel of Figure 4 shows how these changes in interest rates map to changes in overall transaction prices for different consumer types. Price changes track interest rate changes; relative to Baseline consumers

Figure 4: Distributional Effects



NOTE: This figure shows the interest rate changes from BASELINE to both counterfactuals (left panel) and the counterfactual changes in the overall price (right panel) for the eight different bins of outside options.

with high θ pay lower prices while consumers with low θ pay higher prices.

Table 9: Overview Counterfactual Results

	Baseline	No Discretion	Change ΔRel.	Change ΔAbs.	Not Informed	Informed	Change ΔRel.	Change ΔAbs.
Panel A: Prices (in \$)								
Total Price, $p \cdot (1+r)$ (\$)	27,119	26,972	-0.54	-147.1	27,119	27,063	-0.21	-56
Car Price, p (\$)	24,308	24,249	-0.24	-59.2	24,308	24,614	1.26	306.3
Panel B: Financing (all in %)								
Interest Rate	11.54	11.23	-2.65	-0.31	11.54	9.92	-14	-1.61
Interest, Dealer Financed	11.88	12.06	1.54	0.18	11.83	10.21	-13.65	-1.61
Share, Dealer Financed	91.67	81.25	-11.37	-0.1	0.72	91.66	-0.01	0.0
Panel C: Consumer Surplus (in \$ Billion)								
Total Cons. Surplus,	67.74	68.41	0.98	0.67	67.74	67.93	0.28	0.19
Total Cons. Surplus, $\theta \geq \theta_{50}$	32.77	33.81	3.18	1.04	32.77	33.47	2.14	0.7
Total Cons. Surplus, $\theta < \theta_{50}$	34.97	34.6	-1.08	-0.38	34.97	34.47	-1.45	-0.51
Panel D: Profits (in \$ Billion)								
Total Lender Profits	7.68	7.14	-7.01	-0.54	7.68	6.96	-9.35	-0.72
Total Dealer Profits	83.1	81.88	-1.47	-0.28	83.1	83.57	-0.57	-0.47

NOTE: This table shows results for the two different counterfactual scenarios. In scenario NO DISCRETION lenders set interest rates directly and dealers compete downstream in prices taking them as given. Scenario OUTSIDE OPTION is identical to NO DISCRETION with the only difference that consumer outside options are given by a minimally competitive auction between two lenders. Panel A and B depict averages across all markets. Panel C and D depict totals over all markets.

Next we turn towards aggregate results presented in Table 9. Overall, we find that eliminating dealer discretion decreases average total transaction prices by \$147 or 0.99%. This is the result of two countervailing price effects. First, the double marginalization effect slightly increases interest rates for consumers that finance through dealers. In particular, lenders cannot rely on dealers to mark up loans so they increase their buy rates. Moreover, as discussed above, eliminating dealer discretion increases dealer-intermediated loan prices for consumers with good outside options; it increases these prices so much for consumers with especially good outside options that they stop obtaining loans through dealers and instead get loans themselves. Hence the number of consumers that finance through dealers decreases by about 11%. The second aggregate price effect is that dealers decrease posted car prices because, as discussed under the information effect above, they no longer have an incentive to set high car prices to earn larger dealer reserves from consumers with bad outside options.

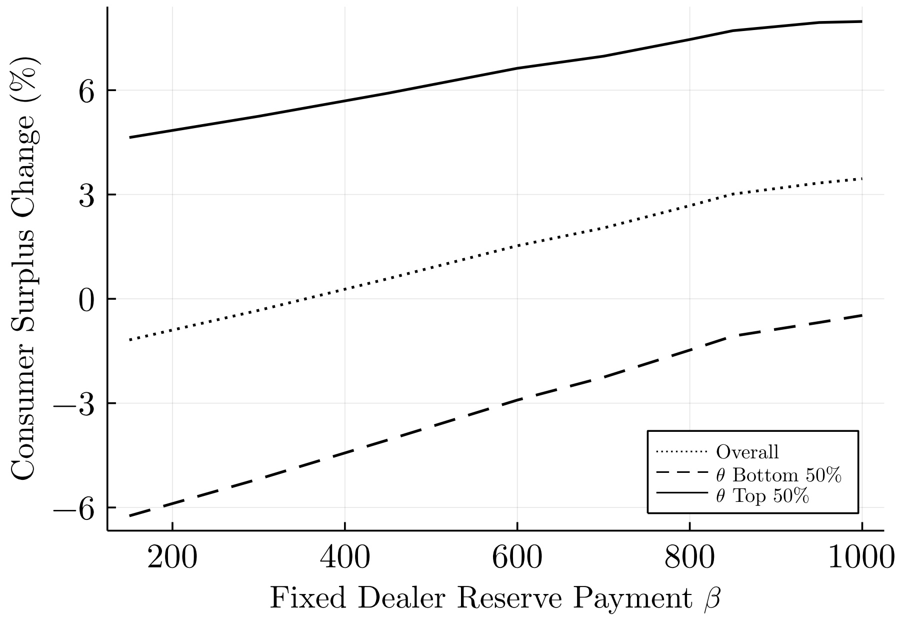
Due to the lower overall transaction prices, consumer surplus increases by 0.98% from Baseline to No Discretion. While the effect on consumer surplus is on average positive, it varies substantially across different subgroups of consumers because of the information effect. The surplus of consumers with θ above the median increases by 3.18 percentage points. The surplus of consumers with θ below the median decreases by 1.08 percentage points.

8.2 No Dealer Discretion under Different Assumptions about β

Figure 5 shows how our estimates for consumer surplus change if we vary the counterfactual dealer reserve, which is now given by the fixed payment β. Two points are worth noting about this robustness check.

First, eliminating dealers' pricing discretion has a positive effect on consumer surplus for a wide range of counterfactual β. However, as the counterfactual β approaches the β from Baseline (about \$100), the effect on consumer surplus becomes negative. This is because the misalignment of incentives between dealers and lenders, and thus the scope for double marginalization, in No Discretion becomes stronger as dealers earn less compensation for intermediating loans. As dealers generate a substantial share of their profits from dealer reserve, however, it seems likely that the counterfactual fixed payments would be higher than in Baseline in order to compensate dealers for the forgone revenues from marking up loans. In particular, the fixed payment constitutes only about 15% of the dealer reserve in Baseline.

Figure 5: Consumer Surplus Effects for Different Fixed Dealer Reserve Payments



NOTE: This figure shows the effect of varying the fixed payment β from what it is in the baseline to the value of the average dealer reserve.

Second, the distributional effects are almost unaffected by β: eliminating dealers' discretion to price loans always reduces the scope for price discrimination and therefore is particularly beneficial for individuals with bad outside options.

8.3 Information Counterfactual

In our main counterfactual NO DISCRETION we assume that consumers' actual and perceived outside options are both equal to θ. However, recall (from Table 3) that there are large differences between θ and a conservative estimate of consumers' actual outside options that we derive from lenders' costs. This evidence suggests that consumers' actual and perceived outside options may differ. We therefore conduct two additional counterfactuals in which we assume that consumers' actual outside options are given not by θ but instead by our estimates from lender costs. In a first step, NOT INFORMED assumes that consumers do not know of these outside options and still behave as if their outside options were given by θ. In a second step, INFORMED, assumes that consumers know their actual outside options.

Results from these two counterfactuals are in Table 9. The results for NOT INFORMED are almost identical to those for BASELINE; in fact average car prices and total transaction costs are literally identical. To understand why, note we can separate consumers into two groups, (1) those that finance at the dealership under BASELINE and (2) those that do not. In NOT INFORMED consumers still bargain with dealers as if their outside options were given by θ, so they achieve the same bargaining outcomes, i.e. the same consumers finance through dealers and obtain the same interest rates. The only change produced by NOT INFORMED is that consumers that do not finance through the dealership are surprised to learn, after visiting lenders, that their outside options were not precisely what they expected. However, only consumers with low θ finance through outside lenders, and recall from Table 3 that for consumers with low θ the difference between actual outside options and θ is quite small. Hence this counterfactual has only small effects on a small number of loans. This demonstrates that, as long as consumers' act as if their perceived outside options are given by θ, the actual relationship between θ and consumers' outside options matters surprisingly little.

Since NOT INFORMED allows θ and actual outside options to differ, it enables us to study the effects of an informational intervention that makes consumers' behavior consistent with their actual outside options. We find that this generally leads to qualitatively similar but quantitatively much smaller effects than eliminating dealer discretion. Overall transaction prices decrease. In particular, interest rates decrease for two reasons. First, consumers know they have better options from outside lenders which improves their bargaining power and therefore lowers interest rates on dealer-intermediated loans. Second, some consumers actually exercise their better outside options and go to outside lenders and get lower interest rates, although this effect is small. However, because dealers anticipate lower loan profits they increase car prices so overall prices decline by only 0.21%, implying an increase of 0.28% in consumer surplus. Furthermore, the intervention harms lenders because it makes them compete against better outside options. Therefore they reduce buy rates and earn lower profits. This reduction in buy rates allows dealers to set higher car prices, which is why dealers earn slightly higher profits in INFORMED than in NOT INFORMED.

9 Conclusion

In this paper we evaluate auto dealer loan intermediation, a key institution at the heart of an important retail market. This institution has recently come under scrutiny; several regulators and consumer advocacy groups have expressed concern that dealer markups may harm consumers by enabling price discrimination. For example, the U.K.'s Financial Conduct

Authority banned dealer markups in 2021 in part because "consumers are not being provided with the right information about [auto loan] commissions at the right time" (FCA, 2019).

To study this institution we use rich and novel administrative data. A unique feature of our data is that we observe both the discretionary markup that dealers add to interest rates as well as all information necessary to recover the incentives under which they do so. This allows us to back out how much information they have relative to lenders, who only have access to standard underwriting variables and do not interact with consumers through a several-hours long sales process. We estimate that removing dealers' discretion to price loans leads to substantial distributional effects that are not driven by variation in risk. Instead, our evidence suggests that discretionary markups may harm consumers with lower income, less education, and those who are less informed. Beyond these distributional effects we find that loan price discretion harms the average consumer because it attenuates competition on posted car prices.

Our results highlight a broader issue in consumer finance markets. To allow for risk adjustment, many financial and insurance markets feature contract-specific pricing. However this allows sellers to price attributes besides risk, to the disadvantage of some consumers. Although the Equal Credit Opportunity Act limits the attributes that can formally be used to price loans, in practice these limits may be less useful in situations in which buyers and sellers negotiate. Our results suggest that consumers' beliefs about their outside options in the auto loan market vary widely and some of these beliefs are inaccurate. Dealers are able to use this dispersion to their advantage. While the considerable size of the auto market makes it a worthy subject of investigation in and of itself, there are many other markets in which products are sold along with financial contracts. For example, durables are often offered with extended warranties and installment plans and flights are sold with travel insurance. How the intermediation of financial contracts by sales agents affects consumer choices and welfare is therefore of broad interest.

Our model combines competition in posted prices with an element of consumer-specific prices through Nash bargaining. Many markets feature both posted prices and additional negotiations about add-ons or discounts. Our modeling strategy therefore can be extended to other settings where the interaction of posted prices and negotiated prices is relevant and may help to shed light on the distributional effects of contract-specific pricing in such markets.

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Appendix

A Proofs and Theoretical Considerations

A.1 Proof of Proposition 1

For the first step, take ρ as given. As stated in the main text, we assume that the observed interest rates r_{ijd} are the outcomes of a Nash Bargaining procedure. They are thus given by:

$$r_{ijd} \in argmax_r[(p_{jd}-\kappa_i)\alpha(r-b_{ijd})+\beta]^\rho \cdot [\gamma_i(p_{jd}-\kappa_i)(\theta_i-r)]^{1-\rho}.$$

The first order conditions yield:

$$\begin{aligned}
&\rho[(p_{jd}-\kappa_i)\alpha(r_{ijd}-b_{ijd})+\beta]^{\rho-1}(p_{jd}-\kappa_i)\alpha[\gamma_i(p_{jd}-\kappa_i)(\theta_i-r_{ijd})]^{1-\rho}\\
&\quad-(1-\rho)[\gamma_i(p_{jd}-\kappa_i)(\theta_i-r_{ijd})]^{-\rho}\gamma_i(p_{jd}-\kappa_i)[(p_{jd}-\kappa_i)\alpha(r_{ijd}-b_{ijd})+\beta]^\rho=0\\
&\Leftrightarrow \rho\alpha\gamma_i(p_{jd}-\kappa_i)\theta_i = r_{ijd}\gamma_i(p_{jd}-\kappa_i)\alpha+(1-\rho)\gamma_i[\beta-(p_{jd}-\kappa_i)\alpha b_{ijd}]\\
&\Leftrightarrow \theta_i = \frac{r_{ijd}}{\rho}+\frac{1-\rho}{\rho}\left[\frac{\beta}{\alpha(p_{jd}-\kappa_i)}-b_{ijd}\right] \qquad (11)
\end{aligned}$$

To derive the marginal type that still finances the car at the dealership, we solve this equation for r_{ijd}:

$$\rho\theta_i-(1-\rho)\left[\frac{\beta}{\alpha(p_{jd}-\kappa_i)}-b_{ijd}\right]=r_{ijd}$$

For the marginal type $\bar{\theta}_i$ this interest rate will be equal to his anticipated outside option. It is thus implicitly defined by:

$$\begin{aligned}
&\rho\bar{\theta}_i-(1-\rho)\left[\frac{\beta}{\alpha(p_{jd}-\kappa_i)}-b_{ijd}\right]=\bar{\theta}_i\\
&\Leftrightarrow b_{ijd}-\frac{\beta}{\alpha(p_{jd}-\kappa_i)}=\bar{\theta}_i
\end{aligned}$$

Hence, for every ρ the joint distribution $F^\rho(\theta,b,\kappa)$ that implies $H(r,b,\kappa)$ to be the equilibrium distribution is identified non-parametrically due to (11). Note that the estimates for θ_i are monotonically decreasing in ρ, while $\bar{\theta}_i$ does not depend on ρ. Hence, the higher is ρ the larger is also the estimated fraction of consumers that finance at outside lenders. To identify ρ, we thus leverage that we observe the fraction of consumers that finance their car at the dealership. Let $\hat{s}^m_{jd}(\mathbf{p}_m, b, \kappa)$ be the observed market share of dealer d for model j among consumers that receive buy rate b and pay downpayment κ. Moreover, let W be the overall fraction of consumers that finance at outside lenders. For a fixed ρ, we get:

$$W = \sum_{m \in \mathcal{M}} \sum_{d \in \mathcal{D}_m} \sum_{j \in \mathcal{J}_d} \int_{b,\kappa,\theta} \hat{s}^m_{jd}(\mathbf{p}_m, b, \kappa)(1 - \mathbb{I}\{\theta_i \geq \underline{\theta}_i\}) dF^\rho(\theta, b, \kappa) \tag{12}$$

This expression monotonically increases with ρ. In particular, the larger is ρ, the lower will be θ_i for all i, which in turn implies that the indicator function $\mathbb{I}\{\theta_i \geq \underline{\theta}_i\}$ will be equal to one for more consumers. Hence, there exist at most one $\rho*$ such that (12) holds together with (11) implying that F^{ρ^*} induces $H(r, b, \kappa)$ to be the equilibrium distribution.

A.2 Estimation of Dealer Costs

In this appendix we show how to transfer the estimation of dealer costs in our setup to the setting of Berry *et al.* (1995). For this purpose, denote the cumulative distribution of θ conditional on b and κ by $F_\theta(\cdot|b, \kappa)$. Consider the profit of dealer d:

$$\begin{aligned}\pi_d(\mathbf{p}_m) = \sum_{j \in \mathcal{J}_d} \int_{b,\kappa} \int_\theta & s^m_{jd}(\mathbf{p}_m, \theta, \kappa) \\ & \cdot \Big(p_{jd} + \mathbb{I}\{\theta_i \geq \underline{\theta}_i\}(\alpha_d \cdot (p_{jd} - \kappa) \cdot (\tilde{r}_{ijd} - b) + \beta) - c^D_{jd}\Big) dF_\theta(\theta|b, \kappa) dF(b, \kappa)\end{aligned}$$

This profit yields a set of $|\mathcal{J}_d| = N_d$ first order conditions for dealer d. Applying Leibnitz' rule, the first order condition with respect to p_{jd} is given by:

$$
\begin{aligned}
\frac{d\pi_d(\mathbf{p}_{dm})}{dp_{jd}} &= \int_{b,\kappa} \left[\alpha(p_{jd}-\kappa)(\bar{\theta}_i - b_{ijd}) + \beta\right] \frac{d\bar{\theta}_i}{dp_{jd}} \\
&+ \int_{\bar{\theta}_i}^{\infty} s^m_{jd}(\mathbf{p}_m, \theta, \kappa) \cdot \alpha_d \left[(\tilde{r}_{ijd} - b) + (p_{jd}-\kappa)\frac{d\tilde{r}_{ijd}}{dp_{jd}}\right] \\
&\qquad + \frac{ds^m_{jd}(\mathbf{p}_m, \theta, \kappa)}{dp_{jd}}(\alpha(p_{jd}-\kappa)(\tilde{r}_{ijd} - b) + \beta) dF_\theta(\theta|b,\kappa) dF(b,\kappa) \\
&+ \int_{\theta,\kappa,b} s^m_{jd}(\mathbf{p}_m, \theta, \kappa) + \frac{ds^m_{jd}(\mathbf{p}_m, \theta, \kappa)}{dp_{jd}} \left[p_{jd} - c^D_{jd}\right] dF_\theta(\theta|b,\kappa) dF(b,\kappa) \\
&+ \sum_{k\neq j} \int_{b,\kappa} \int_{\bar{\theta}_i}^{\infty} \frac{ds^m_{kd}(\mathbf{p}_m, \theta, \kappa)}{dp_{jd}}(\alpha(p_{jd}-\kappa)(\tilde{r}_{ijd} - b) + \beta) dF_\theta(\theta|b,\kappa) dF(b,\kappa) \\
&\sum_{k\neq j} \int_{\theta,b,\kappa} \frac{ds^m_{kd}(\mathbf{p}_m, \theta, \kappa)}{dp_{jd}} \left[p_{kd} - c^D_{kd}\right] dF_\theta(\theta|b,\kappa) dF(b,\kappa)
\end{aligned}
$$

Exploiting (4) to substitute $\bar{\theta}_i$ and collecting terms yields that this expression is identical to:

$$
\begin{aligned}
&\int_{b,\kappa} \int_{\bar{\theta}_i}^{\infty} s^m_{jd}(\mathbf{p}_m, \theta, \kappa) \cdot \alpha_d \left[(\tilde{r}_{ijd} - b) + \frac{(1-\rho)\beta}{p_{jd}-\kappa}\right] dF_\theta(\theta|b,\kappa) dF(b,\kappa) \\
&+ \sum_{k} \int_{b,\kappa} \int_{\bar{\theta}_i}^{\infty} \frac{ds^m_{kd}(\mathbf{p}_m, \theta, \kappa)}{dp_{jd}}(\alpha(p_{kd}-\kappa)(\tilde{r}_{ijd} - b) + \beta) dF_\theta(\theta|b,\kappa) dF(b,\kappa) \\
&+ \int_{\theta,b,\kappa} s^m_{jd}(\mathbf{p}_m, \theta, \kappa) dF(\theta, b, \kappa) \\
&+ \sum_{k} \int_{\theta,b,\kappa} \frac{ds^m_{jd}(\mathbf{p}_m, \theta, \kappa)}{dp_{jd}} \left[p_{kd} - c^D_{kd}\right] dF(\theta, b, \kappa)
\end{aligned}
$$

To simplify notation and exemplify how we can retrieve dealers' costs denote by $Q_{jd}(\mathbf{p}_m)$ the first three lines of the equation above:

$$
\begin{aligned}
Q_{jd}(\mathbf{p}_m) &= \int_{b,\kappa} \int_{\bar{\theta}_i}^{\infty} s^m_{jd}(\mathbf{p}_m, \theta, \kappa) \cdot \alpha_d \left[(\tilde{r}_{ijd} - b) + \frac{(1-\rho)\beta}{p_{jd}-\kappa}\right] dF_\theta(\theta|b,\kappa) dF(b,\kappa) \\
&+ \sum_{k} \int_{b,\kappa} \int_{\bar{\theta}_i}^{\infty} \frac{ds^m_{kd}(\mathbf{p}_m, \theta, \kappa)}{dp_{jd}}(\alpha(p_{kd}-\kappa)(\tilde{r}_{ijd} - b) + \beta) dF_\theta(\theta|b,\kappa) dF(b,\kappa) \\
&+ \int_{\theta,b,\kappa} s^m_{jd}(\mathbf{p}_m, \theta, \kappa) dF(\theta, b, \kappa). \qquad (13)
\end{aligned}
$$

Denoting the aggregate market share of dealer d for model j by $\mathbf{s}_{jd}$, the first order condition thus simplifies to:

$$Q_{jd}(\mathbf{p}_m) + \sum_k \frac{d\mathbf{s}_{kd}(\mathbf{p}_m)}{dp_{jd}} \left[p_{kd} - c^D_{kd}\right] = 0$$

We can thus represent the set of all first order conditions for dealer d in matrix notation. For this purpose, let $Q(\mathbf{p}_m) = (Q_{1d}, \ldots, Q_{N_d d})$ be the vector of all Q_{jd} and let $\nabla_p s(\mathbf{p}_m)$ be the $N_d \times N_d$ Jacobian of the market shares:

$$\nabla_p s(\mathbf{p}_m) = \begin{pmatrix} \frac{d\mathbf{s}_{1d}(\mathbf{p}_m)}{dp_{1d}} & \ldots & \frac{d\mathbf{s}_{N_d d}(\mathbf{p}_m)}{dp_{1d}} \\ \vdots & \ldots & \vdots \\ \frac{d\mathbf{s}_{1d}(\mathbf{p}_m)}{dp_{N_d d}} & \ldots & \frac{d\mathbf{s}_{N_d d}(\mathbf{p}_m)}{dp_{N_d d}} \end{pmatrix}$$

Then the set of first order conditions is given by:

$$Q(\mathbf{p}_m) + \nabla_p s(\mathbf{p}_m) \begin{pmatrix} p_{1d} - c^D_{1d} \\ \vdots \\ p_{N_d d} - c^D_{N_d d} \end{pmatrix} = 0$$

By inverting the matrix $[\nabla_p s(\mathbf{p}_m)]'$, we can thus retrieve dealer costs in an identical manner as in Berry *et al.* (1995).

A.3 Derivation of Lenders' First Order Conditions

From the perspective of the lender the first price auction has a random reserve price. In particular, the lender will only be able to originate the loan if the buy rate is low enough such that the dealer's offer is below the consumers belief about the outside option. Recall that (4) specifies the marginal consumer type that still finances at the dealership $\bar{\theta}_i(b_{ijd}) = b_{ijd} - \frac{\beta}{\alpha(p_{jd}-\kappa_i)}$, where we make its dependency on b_{ijd} explicit in this appendix. To derive the identification of lender costs, we consider symmetric Bayesian Nash Equilibria of the auction and assume that lender strategies $\delta(c^L_l, p_{jd}, \kappa_i) = b^l_{ijd}$, which map the costs of lender l into a buyrate offer b^l_{ijd} for the respective car purchase, are monotone functions in c^l for each tuple (p, κ), which is the information set $\mathcal{I}$ of the lender. The maximization problem of lender l is given by:

$$\max_{b^{\ell}_{ijd}} E[(1-\alpha)(\tilde{r}_{ijd}-b^l_{ijd})(p_{jd}-\kappa_i)+(b^l_{ijd}-c^L_l)(p_{jd}-\kappa_i)-\beta|p_{jd},\kappa_i]Pr(b^l_{ijd}\leq b^{l'}_{ijd}, l'\neq l, b^l_{ijd}\leq\theta_i)$$

Since lender costs and consumer beliefs are mutually independent, we can write this expression as:

$$\begin{aligned}&E[(1-\alpha)(\tilde{r}_{ijd}-b^l_{ijd})(p_{jd}-\kappa_i)+(b^l_{ijd}-c^L_l)(p_{jd}-\kappa_i)-\beta|p_{jd},\kappa_i]\\ &\qquad\cdot(1-\mathcal{F}_l(\delta^{-1}(b^l_{ijd},p_{jd},\kappa_i)|p_{jd},\kappa_i))^{n_d-1}(1-F_\theta(\bar{\theta}_i(b^l_{ijd})|p_{jd},\kappa_i))\end{aligned}$$

Maximizing this expression with respect to b^l_{ijd} and requiring that $\delta(c^L_l,p_{jd},\kappa_i)=b^l_{ijd}$ yields the following differential equation.

$$\begin{aligned}&\alpha(p_{jd}-\kappa_i)(1-\mathcal{F}_l(c^L_l|p_{jd},\kappa_i))(1-F_\theta(\bar{\theta}_i(b^l_{ijd})|p_{jd},\kappa_i))\delta'(c^L_l,p_{jd},\kappa_i)\\ &=E[(1-\alpha)(\tilde{r}_{ijd}-b^l_{ijd})(p_{jd}-\kappa_i)+(b^l_{ijd}-c^L_l)(p_{jd}-\kappa_i)-\beta|p_{jd},\kappa_i]\\ &\cdot\left[(n_d-1)f_l(c^L_l|p_{jd},\kappa_i)(1-F_\theta(\bar{\theta}_i(b^l_{ijd})|p_{jd},\kappa_i))+(1-\mathcal{F}_l(c^L_l|p_{jd},\kappa_i))f_\theta(\bar{\theta}_i(b^l_{ijd})|p_{jd},\kappa_i)\delta'(c^L_l,p_{jd},\kappa_i)\right],\end{aligned} \tag{14}$$

where δ' denotes the partial derivative of δ with respect to c^L. To derive the identification of lender costs, denote by $G(b|p_{jd},\kappa_i)$ and $g(b|p_{jd},\kappa_i)$ the conditional cumulative distribution and the conditional density of observed bids. Following Guerre *et al.* (2000) and Li and Perrigne (2003) it can be shown that $G(b|p_{jd},\kappa_i)=\mathcal{F}_l(\delta^{-1}(b,p_{jd},\kappa_i)|p_{jd},\kappa_i)$ as well as $g(b|p_{jd},\kappa_i)=\frac{f_l(\delta^{-1}(b,p_{jd},\kappa_i)|p_{jd},\kappa_i)}{\delta'(\delta^{-1}(b,p_{jd},\kappa_i),p_{jd},\kappa_i)}$ for all $b\in[\underline{c}^L(p_{jd},\kappa_i),\delta(\bar{c}^L,p_{jd},\kappa_i)]$. We, therefore, obtain:

$$\begin{aligned}&\alpha(p_{jd}-\kappa_i)(1-G(b^l_{ijd}|p_{jd},\kappa_i))(1-F_\theta(\bar{\theta}_i(b^l_{ijd})|p_{jd},\kappa_i))=\\ &E[(1-\alpha)(\tilde{r}_{ijd}-b^l_{ijd})(p_{jd}-\kappa_i)+(b^l_{ijd}-c^L_l)(p_{jd}-\kappa_i)-\beta|p_{jd},\kappa_i]\\ &\cdot\left[(n_d-1)g(b^l_{ijd}|p_{jd},\kappa_i)(1-F_\theta(\bar{\theta}_i(b^l_{ijd})|p_{jd},\kappa_i))+(1-G(b^l_{ijd}|p_{jd},\kappa_i))f_\theta(\bar{\theta}_i(b^l_{ijd})|p_{jd},\kappa_i)\right]\end{aligned}$$

Solving this equation for c^L, yields:

$$
\begin{aligned}
\alpha(p_{jd}-\kappa_i) = E[(1-\alpha)(\tilde{r}_{ijd}-b^l_{ijd})(p_{jd}-\kappa_i) + (b^l_{ijd}-c^L_l)(p_{jd}-\kappa_i) - \beta | p_{jd},\kappa_i] \\
\cdot \left[(n_d-1)\frac{g(b^l_{ijd}|p_{jd},\kappa_i)}{1-G(b^l_{ijd}|p_{jd},\kappa_i)} + \frac{f_\theta(\bar{\theta}_i(b^l_{ijd})|p_{jd},\kappa_i)}{(1-F_\theta(\bar{\theta}_i(b^l_{ijd})|p_{jd},\kappa_i))} \right] \\
\Leftrightarrow \alpha = \left\{ (1-\alpha)E[\tilde{r}_{ijd}-b^l_{ijd}|p_{jd},\kappa_i] + (b^l_{ijd}-c^L_l) - \frac{\beta}{p_{jd}-\kappa_i} \right\} \\
\cdot \left[(n_d-1)\frac{g(b^l_{ijd}|p_{jd},\kappa_i)}{1-G(b^l_{ijd}|p_{jd},\kappa_i)} + \frac{f_\theta(\bar{\theta}_i(b^l_{ijd})|p_{jd},\kappa_i)}{(1-F_\theta(\bar{\theta}_i(b^l_{ijd})|p_{jd},\kappa_i))} \right] \\
\Leftrightarrow c^L_l = \left\{ (1-\alpha)E[\tilde{r}_{ijd}-b^l_{ijd}|p_{jd},\kappa_i] + b^l_{ijd} - \frac{\beta}{p_{jd}-\kappa_i} \right\} \\
- \frac{\alpha}{(n_d-1)\frac{g(b^l_{ijd}|p_{jd},\kappa_i)}{1-G(b^l_{ijd}|p_{jd},\kappa_i)} + \frac{f_\theta(\bar{\theta}_i(b^l_{ijd})|p_{jd},\kappa_i)}{(1-F_\theta(\bar{\theta}_i(b^l_{ijd})|p_{jd},\kappa_i))}}.
\end{aligned}
$$

Note that this condition is well behaved, because of Assumption 1 and equivalent to equation (8) in the main text.

A.4 Proof of Proposition 2

The proof follows in large parts the proof of Theorem 1 in Guerre *et al.* (2000). We start by proving that the two conditions are necessary for $\mathcal{F}_l$ to rationalize G_{n_d}. Since the bids b_i stem from strategy $\delta(c^L, p_{jd}, \kappa_i)$ and the c^L are i.i.d, the b_i's are i.i.d conditional on p_{jd}, κ_i, which implies the first condition in the proposition. To show that the second condition needs to hold, let $\delta(c^L, p_{jd}, \kappa_i)$ be the strictly increasing and differentiable Bayesian Nash equilibrium strategy and define $G(b|p_{jd}, \kappa_i) = \mathcal{F}_l\left(\delta^{-1}(b, p_{jd}, \kappa_i)|p_{jd}, \kappa_i\right)$ for all $b \in [\underline{b}, \bar{b}]$. Since δ is the equilibrium strategy, G must be the distribution of observed equilibrium bids. Since δ must solve (14), it also holds that $\lambda(\delta(c^L, p_{jd}, \kappa_i), G, F_\theta, p_{jd}, \kappa_i) = c^L$ for all $c^L \in [\underline{c}^L(p_{jd}, \kappa_i), \bar{c}^L(p_{jd}, \kappa_i)]$ and $\lambda(b, G, F_\theta, p_{jd}, \kappa_i) = \delta^{-1}(b, p_{jd}, \kappa_i)$ for all $b \in [\underline{b}, \bar{b}]$. Hence, the second condition must hold, because δ^{-1} is strictly increasing on $b \in [\underline{b}, \bar{b}]$ and δ is differentiable on $[\underline{c}^L(p_{jd}, \kappa_i), \bar{c}^L(p_{jd}, \kappa_i)] = [\lambda(\underline{b}, G, F_\theta, p_{jd}, \kappa_i), \lambda(\bar{b}, G, F_\theta, p_{jd}, \kappa_i)]$ for all tuples (p, κ).

Next, we prove sufficiency of the two conditions imposed by the proposition. For this purpose, define $\mathcal{F}_l(\cdot|p_{jd}, \kappa_i) = G(\lambda^{-1}(\cdot, G, F_\theta, p_{jd}, \kappa_i)|p_{jd}, \kappa_i)$ on $[\underline{c}^L(p_{jd}, \kappa_i), \bar{c}^L(p_{jd}, \kappa_i)]$, where we have that $\underline{c}^L(p_{jd}, \kappa_i) = \lambda(\underline{b}, G, F_\theta, p_{jd}, \kappa_i)$ and $\bar{c}^L(p_{jd}, \kappa_i) = \lambda(\bar{b}, G, F_\theta, p_{jd}, \kappa_i)$. Note first that

$\lambda(\underline{b}, G, F_\theta, p_{jd}, \kappa_i)$ and $\lambda(\bar{b}, G, F_\theta, p_{jd}, \kappa_i)$ are finite. In particular, $lim_{b\to\underline{b}}\ \lambda(b, G, F_\theta, p_{jd}, \kappa_i)$ is finite because of Assumption 1. Additionally, $lim_{b\to\bar{b}}\ \lambda(b, G, F_\theta, p_{jd}, \kappa_i)$ is finite due to $\lim_{b\to\bar{b}} \frac{g(b|p_{jd},\kappa_i)}{1-G(b|p_{jd},\kappa_i)} = +\infty$ as well as Assumption 1. Since, $\lambda(b, G, F_\theta, p_{jd}, \kappa_i)$ is strictly increasing on $[\underline{b}, \bar{b}]$ by the second condition and G is strictly increasing as well, $\mathcal{F}_l$ is also strictly increasing. Hence, $\mathcal{F}_l$ is a valid distribution the support of which is $[\underline{c}^L(p_{jd}, \kappa_i), \bar{c}^L(p_{jd}, \kappa_i)]$. Finally, $\mathcal{F}_l$ is absolutely continuous, because G is absolutely continuous and λ^{-1} is differentiable.

It remains to be shown that the distribution of lender costs $\mathcal{F}_l$ rationalizes the distribution G, i.e., $G(b|p_{jd}, \kappa_i) = \mathcal{F}_l\left(\delta^{-1}(b, p_{jd}, \kappa_i)|p_{jd}, \kappa_i\right)$ on $[\underline{b}, \bar{b}]$, where $\delta(\cdot, p_{jd}, \kappa_i)$ solves (14), with boundary condition $\delta(\underline{c}^L(p_{jd}, \kappa_i), p_{jd}, \kappa_i) = \underline{b}$. By construction of $\mathcal{F}_l$ we have that $\mathcal{F}_l(\lambda(\cdot, G, F_\theta, p_{jd}, \kappa_i)|p_{jd}, \kappa_i) = G(\cdot|p_{jd}, \kappa_i)$. Thus it suffices to show that $\lambda^{-1}(\cdot, G, F_\theta, p_{jd}, \kappa_i)$ is identical to the Bayesian Nash equilibrium strategy solving (14) with boundary condition $\lambda^{-1}(\underline{c}^L(p_{jd}, \kappa_i), G, F_\theta, p_{jd}, \kappa_i) = \underline{b}$. The boundary condition holds by construction. Note that the hazard rate of the cost distribution $f_l(\cdot|p_{jd}, \kappa_i)/1 - \mathcal{F}_l(\cdot|p_{jd}, \kappa_i)$ can be expressed as: $\lambda^{-1\prime}(\cdot, G, F_\theta, p_{jd}, \kappa_i) g(\lambda^{-1}(\cdot, G, F_\theta, p_{jd}, \kappa_i)|p_{jd}, \kappa_i)/1 - G(\lambda^{-1}(\cdot, G, F_\theta, p_{jd}, \kappa_i)|p_{jd}, \kappa_i)$. Therefore, λ^{-1} solves (14) if:

$$
\begin{aligned}
&\alpha \\
&= E\left[(1-\alpha)(\tilde{r}_{ijd} - \lambda^{-1}(\cdot, G, F_\theta, p_{jd}, \kappa_i)) + (\lambda^{-1}(\cdot, G, F_\theta, p_{jd}, \kappa_i) - c_l^L) - \frac{\beta}{(p_{jd} - \kappa_i)} \Big| p_{jd}, \kappa_i\right] \\
&\cdot \left[(n_d - 1)\frac{g(\lambda^{-1}(\cdot, G, F_\theta, p_{jd}, \kappa_i)|p_{jd}, \kappa_i)}{1 - G(\lambda^{-1}(\cdot, G, F_\theta, p_{jd}, \kappa_i)|p_{jd}, \kappa_i)} + \frac{f_\theta(\bar{\theta}_i(b_{ijd}^l)|p_{jd}, \kappa_i)}{(1 - F_\theta(\bar{\theta}_i(b_{ijd}^l)|p_{jd}, \kappa_i))}\right],
\end{aligned}
$$

which holds by construction of λ. Hence the two conditions are jointly sufficient.

Next, we show the last part of Proposition 2. From above, we know that $\lambda(\cdot, G, F_\theta, p_{jd}, \kappa_i) = \delta^{-1}(\cdot, p_{jd}, \kappa_i)$ holds. Since $\mathcal{F}_l(\cdot|p_{jd}, \kappa_i) = G(\delta(\cdot, p_{jd}, \kappa_i)|p_{jd}, \kappa_i)$, it holds that $\mathcal{F}_l(\cdot|p_{jd}, \kappa_i) = G(\lambda^{-1}(\cdot, G, F_\theta, p_{jd}, \kappa_i)|p_{jd}, \kappa_i)$. Because λ is unique given G so is $\mathcal{F}_l$ given G.

A.5 Illustrating the Information Effect

In this appendix, we provide intuition for how overall prices are affected by removing dealer reserve. For this purpose, we use a simplistic model with the minimal ingredients necessary to discuss the information effect in isolation.

Suppose there is only one dealer, one lender, and two types of consumers H and L. In the population both consumer types have equal shares and their outside options when obtaining credit at an outside lender are given by θ_L and θ_H, respectively. Moreover, each consumer has outside option u for not obtaining a car. These outside options are distributed according to cdfs F_u^J, with $J \in \{L, H\}$. We assume that the dealer learns (θ, u) once the consumer visits the dealership but that the lender only knows the distribution of types. In analogy to our main model, the dealer first commits to car prices anticipating the distribution of consumers that visit the store. At a second stage, the dealer makes an interest rate offer to consumers. To keep the setting simple, we (i) assume in this section that the dealer presents a take-it-or-leave-it offer and (ii) consider only situations in which it is optimal for the dealer and the lender to extend loans to all consumers and not only to those of type H.

In analogy to the Baseline scenario, we first analyze what happens if the dealer can mark up loan prices. In this case, she offers an interest rate $r = \theta_J$ at the second stage to make the consumer indifferent between financing the loan at the dealership and at an outside lender. When deciding whether to visit the dealer, consumers anticipate this offer. Hence, the dealer sets the price of the car to solve:

$$\max_p \left[1 - F_u^L\Big((1+\theta_L)\cdot p\Big)\right]\cdot(1+\theta_L)\cdot p + \left[1 - F_u^H\Big((1+\theta_H)\cdot p\Big)\right]\cdot(1+\theta_H)\cdot p$$

Because the price of the car determines the principal of the loan, loan prices and car prices are complements in the dealer's decision problem. Larger θ_H, therefore generate an additional incentive to post high car prices.

In a counterfactual scenario without dealer markups, as in No Discretion, lenders set interest rates so both consumer types face the same car price and the same interest rate. This is because lenders cannot condition interest rates on consumer types. Since we consider only situations in which all consumer types finance at the dealership, the lender chooses interest rates such that $r = \theta_L$. To isolate, the information effect, we hold vertical incentives constant. The dealer would then solve

$$\max_p \left[1 - F_u^L\Big((1+\theta_L)\cdot p\Big)\right]\cdot(1+\theta_L)\cdot p + \left[1 - F_u^H\Big((1+\theta_L)\cdot p\Big)\right]\cdot(1+\theta_L)\cdot p$$

Hence, removing the ability to price discriminate reduces marginal incentives to increase the loan amount and thus p. As consumers also anticipate lower interest rates, dealers might, however, be inclined to increase car prices. Which of the two forces dominates in this simple model depends on the shape of F_u^L and F_u^H.

In the main text, we argue that the information effect can reduce overall transaction prices from BASELINE to NO DISCRETION. To illustrate this, consider one particularly easy example in which F_u^H and F_u^L are singular such that all consumers with θ_L face outside option u_L and all consumers with θ_H face outside option u_H. To ensure that all consumers buy a car, with dealer discretion, p satisfies $p(1+\theta_L) \leq u_L$ and $p(1+\theta_H) \leq u_H$. The price will thus be given by $p = \min\{\frac{u_H}{1+\theta_H}, \frac{u_L}{1+\theta_L}\}$. Suppose for this example that $\frac{u_H}{1+\theta_H} > \frac{u_L}{1+\theta_L}$. As a consequence, the overall price for consumer type L is u_L and for type H it is $\frac{u_L}{1+\theta_L}(1+\theta_H) > u_L$.

If in contrast the dealer does not know the type of the consumer, all consumers face the same price and interest rate. At the first stage, the dealer will then select the price such that $p = \min\{\frac{u_H}{1+\theta_L}, \frac{u_L}{1+\theta_L}\}$. With the assumption above, we get: $\frac{u_H}{1+\theta_L} > \frac{u_L}{1+\theta_L}$. Hence, all consumers pay u_L as an overall price. In other words, the information effect, in this example, leads to lower prices in NO DISCRETION than in BASELINE.

A.6 Nash Bargaining over both prices

In this section, we demonstrate that interest rates would equal buy rates if loan prices r and car prices p, (with $r \geq b_{ijd}$ and $p_{ijd} \geq 0$) were determined simultaneously by Nash Bargaining. We assume that the consumer's outside option is to not buy the car from the dealership. To solve the Nash-Bargaining problem, we impose the following additional assumptions. First, $\alpha(1+b_{ijd}) < 1 \; \forall \alpha, b_{ijd}$. This assumption ensures that dealers' revenue share is sufficiently small; this assumption is satisfied by 99.99% of contracts in our data. Second, we assume the consumer's utility from buying the car is greater than the dealer costs of supplying the vehicle, i.e., $\zeta z_j + \psi_j + \xi_{jd} + \epsilon_{ijd} > \gamma_i(c_{jd} + (c_{jd} - \kappa_i)b_{ijd})$. This ensures there are immediate gains from trade. Finally, we assume that $\kappa_i + \beta < c_{jd}$, which ensures that dealers and consumers will never agree on a price below or at the downpayment. Denoting consumer's utility from buying the car by $\omega_{ijd} = \zeta z_j + \psi_j + \xi_{jd} + \epsilon_{ijd}$, we get the following Nash-Bargaining problem:

$$r_{ijd}, p_{jd} \in argmax_{r,p}[p + (p - \kappa_i)\alpha(r - b_{ijd}) + \beta - c_{jd}]^{\rho} \cdot [\omega_i - \gamma_i[p + (p - \kappa_i)r]^{1-\rho}.$$

Note first that every optimal tuple r, p will have $p \in (\kappa_i, \infty)$, because otherwise the expression above is negative. The derivative with respect to r is smaller or equal to zero if:

$$
\begin{aligned}
&\rho[p + (p - \kappa_i)\alpha(r - b_{ijd}) + \beta - c_{jd}]^{\rho-1}(p_{jd} - \kappa_i)\alpha[\omega_i - \gamma_i[p + (p - \kappa_i)r]^{1-\rho} \\
&\quad - (1 - \rho)[\omega_i - \gamma_i[p + (p - \kappa_i)r]^{-\rho}\gamma_i(p_{jd} - \kappa_i)[p + (p - \kappa_i)\alpha(r - b_{ijd}) + \beta - c_{jd}]^{\rho} \leq 0 \\
\Leftrightarrow\ &\rho\alpha[\omega_i - \gamma_i[p + (p - \kappa_i)r] = (1 - \rho)\gamma_i[p + (p - \kappa_i)\alpha(r - b_{ijd}) + \beta] \\
\Leftrightarrow\ &\frac{[p + (p - \kappa_i)\alpha(r - b_{ijd}) + \beta - c_{jd}]}{[\omega_i - \gamma_i[p + (p - \kappa_i)r]} \leq \frac{\rho\alpha}{(1 - \rho)\gamma_i}
\end{aligned}
$$

The derivative with respect to p is equal to zero if:

$$
\begin{aligned}
&\rho[p + (p - \kappa_i)\alpha(r - b_{ijd}) + \beta - c_{jd}]^{\rho-1}(1 + \alpha(r_{ijd} - b_{ijd}))[\omega_i - \gamma_i[p + (p - \kappa_i)r]^{1-\rho} \\
&\quad - (1 - \rho)[\omega_i - \gamma_i[p + (p - \kappa_i)r]^{-\rho}\gamma_i(1 + r_{ijd})[p + (p - \kappa_i)\alpha(r - b_{ijd}) + \beta - c_{jd}]^{\rho} = 0 \\
\Leftrightarrow\ &\frac{\rho(1 + \alpha(r_{ijd} - b_{ijd}))}{(1 - \rho)\gamma_i(1 + r_{ijd})}[\omega_i - \gamma_i[p + (p - \kappa_i)r] = [p + (p - \kappa_i)\alpha(r - b_{ijd}) + \beta - c_{jd}]
\end{aligned}
$$

In any optimum, the derivative with respect to p is zero since the optimal p is interior. Hence,

$$
\frac{\rho(1 + \alpha(r_{ijd} - b_{ijd}))}{(1 - \rho)\gamma_i(1 + r_{ijd})} = \frac{[p + (p - \kappa_i)\alpha(r - b_{ijd}) + \beta - c_{jd}]}{[\omega_i - \gamma_i[p + (p - \kappa_i)r]},
$$

which implies for the derivative with respect to r that:

$$
\begin{aligned}
&\frac{[p + (p - \kappa_i)\alpha(r - b_{ijd}) + \beta - c_{jd}]}{[\omega_i - \gamma_i[p + (p - \kappa_i)r]} \leq \frac{\rho\alpha}{(1 - \rho)\gamma_i} \\
\Leftrightarrow\ &\frac{\rho(1 + \alpha(r_{ijd} - b_{ijd}))}{(1 - \rho)\gamma_i(1 + r_{ijd})} \leq \frac{\rho\alpha}{(1 - \rho)\gamma_i} \\
\Leftrightarrow\ &\alpha(1 + b_{ijd}) < 1,
\end{aligned}
$$

which is true due to the assumptions above. Hence, in any optimum, the derivative with respect to r is negative, which implies that $r_{ijd} = b_{ijd}$. We conclude that bargaining over both prices simultaneously would lead to zero mark ups, which is in stark contrast to the observed mark ups in the data. As discussed in Grunewald *et al.* (2020), one approach to rationalize positive mark ups in a model in which dealers set both prices simultaneously is to allow consumers' utility to be more sensitive to changes in the car price than in the loan price.

B Additional Facts, Estimations, and Figures

B.1 Dealer Issued Loans

This section explains our procedure to estimate the fraction of purchase 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.[33] Let $P_{\mathrm{d}}(i)$ denote the probability that a loan is originated within a short time window of i hard credit inquiries from dealers, and let $P_{\mathrm{do}}(i)$ 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 $P_{\mathrm{d}}(0)$, and have the following equation:

$$P_{\mathrm{do}}(i) = \sum_{n=i}^{N} P_{\mathrm{d}}(n) \cdot \binom{n}{i} \cdot P_{\mathrm{o}}^{i} \cdot (1 - P_{\mathrm{o}})^{n-i} \tag{15}$$

First, we set $N = 3$. The next step is to estimate $P_{\mathrm{do}}(i)$ 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

[33] In 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.

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.[34]

For a given guess of the vector $P_{\mathrm{d}}(n)$, Equation 15 yields implied values of the vector $P_{\mathrm{do}}(i)$. We take as our estimate of $P_{\mathrm{d}}(n)$ the vector that minimizes the sum of squared deviations between implied and estimated values of $P_{\mathrm{do}}(i)$. Using data for the U.S. as a whole, this yields an estimate of $P_{\mathrm{d}}(0) = 0.158$. This implies that an estimated 84.2 percent 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 percent of auto loans are indirect. However, note this estimate will include both purchase and refinanced auto loans. To our knowledge precise estimates of the percent of auto loans that are refinance does not exist, but van Rijn *et al.* (2021) note that less than 10% of all auto loans are refinance. Assuming that 5% of auto loans are refinances yields that roughly 88.6% of purchase auto loans are indirect.

B.2 Car Price and Loan Rate Markups

In our model car prices are posted, while in reality they are sometimes negotiated. A potential concern with our model is that car price markups could be correlated with loan price markups, which are a focus of our paper.

To address this concern, we first construct a proxy for vehicle price markups. We regress log vehicle prices on model fixed effects, month fixed effects, state fixed effects, lender fixed effects, and dummies for vehicle age. We run this regression separately for new and used vehicles, and include mileage as a control for used vehicles. Results are in Table A1. We take the residuals from these regressions as a proxy for vehicle price markups. This proxy is almost unrelated to loan markups. The correlation between the two is only .027. A linear regression of our vehicle markup proxy on loan markups yields that a 100 basis point increase in loan markups predicts an increase in our vehicle log price markup proxy by .011; the R^2 from this regression is just .0007.

[34] Lenders 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.

Figure A1: MEM Questions on Consumers' Views of Financial Markets

43. Do you think the following statements are mostly true or mostly false?

	Mostly True	Mostly False
All lenders give about the same rates for the same type of loan	☐	☐
It's easy to shop around for the best loan terms	☐	☐
I'm comfortable interacting with banks and other lenders	☐	☐
The COVID-19 pandemic has had a large impact on my financial life	☐	☐
Auto dealers give the best loan interest rates people qualify for	☐	☐

B.3 More Details on the MEM Surveys

MEM is a rich and unique data source consisting of a series of surveys funded by the CFPB and matched to the CCP. The MEM surveys have rich information on many topics. Some are not the focus of this paper, such as the experiences of financially-distressed households before and during the COVID pandemic. However, in the third MEM survey several questions were included to understand consumers' views on lending markets and how those views interact with auto loan outcomes. Figure A1 shows the question. The full survey instrument can be found here.

B.4 Markup Proxies in the MEM for the full sample

In subsection 7.1 we investigated the relationship between our markup proxy and MEM responses. In that section, we focused on loans from banks and credit unions, and therefore excluded loans from captives and other finance companies.[35] We made these choices to align the empirical sample with our model, but they could impact the interpretation of other coefficients. In this section, we briefly study how including loans from captives and finance

[35] We excluded loans from captives because they have different incentives than banks and credit unions; in particular they often limit markups or even subsidize interest rates to increase vehicle demand. We excluded loans from finance companies because they typically focus on subprime borrowers with significant default risk we wish to abstract away from.

companies changes our race coefficients, a particular focus of previous work.

We reconstruct our markup proxy in the CCP, as described in subsection 7.1, this time including loans from captives and finance companies. Then we regress this markup proxy on MEM variables as before, except this time we again include loans from captives and finance companies. Results are in Table A2.

In contrast with our results in subsection 7.1, once we include loans from finance companies we find in Table A2 that black borrowers have significantly higher markup proxies than white borrowers. This is consistent with evidence from Charles *et al.* (2008) that a large portion of the black-white gap in auto loan interest rates comes from black-white differences in the propensity to have loans from finance companies, and from black-white differences in the interest rate markups from finance company loans.

B.5 Additional Tables and Figures

Table A1: Proxying for Vehicle Price Markups

	New Vehicles	Used Vehicles
Mileage (in thousands)		-.004***
		(0.000)
Model Age Fixed Effects		
(Zero omitted)		
-1	.021***	
	(.001)	
1	-0.048***	-0.066***
	(.001)	(.001)
2		-0.129***
		(.001)
3		-0.184***
		(.001)
4		-0.260***
		(.001)
5		-0.362***
		(.001)
6		-0.460***
		(.001)
7		-0.569***
		(.002)
8		-0.666***
		(.002)
9		-0.761***
		(.002)
10		-0.841***
		(.003)
11 or more		-0.982***
		(.003)
R^2	0.79	0.82
Model Fixed Effects	✓	✓
State Fixed Effects	✓	✓
Month Fixed Effects	✓	✓
Lender Fixed Effects	✓	✓

NOTE: Table displays coefficient estimates from a regression of log vehicle price. Model, state, month, and lender fixed effects are included but not shown. Model age is defined as the year of the vehicle transaction minus the model year of the vehicle. Note that for new cars model age will almost always be either -1, 0, or 1, while for used cars it will usually be positive. For new and used vehicles model age is winsorized at the .5th and 99.5th percentiles. Regression for used vehicles does not use data from one lender that did not provide mileage information. *** denotes statistical significance at the 1 percent level.

Table A2: Conditional Correlations of Markup Proxy with MEM Survey Responses

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Shopping Proxies							
All Lenders Give Same Rates	0.118	0.147					0.162
	(0.236)	(0.244)					(0.240)
Dealers Give Best Rates			-0.027	-0.026			-0.049
			(0.243)	(0.240)			(0.240)
Comfortable Making Decisions					-0.396*	-0.191	-0.192
					(0.238)	(0.239)	(0.247)
Borrower Finances							
80k< Income < 125k		-1.071**		-1.068**		-1.043**	-1.052**
		(0.491)		(0.485)		(0.468)	(0.462)
Income > 125k		-0.764**		-0.767**		-0.725**	-0.723**
		(0.313)		(0.316)		(0.295)	(0.293)
Variable Monthly Income		0.347		0.340		0.336	0.344
		(0.278)		(0.286)		(0.285)	(0.278)
Small Financial Buffer		-0.057		-0.068		-0.064	-0.052
		(0.291)		(0.299)		(0.293)	(0.287)
Borrower Race							
(white omitted)							
Black		0.664**		0.639**		0.635**	0.659**
		(0.296)		(0.291)		(0.290)	(0.296)
Hispanic		0.203		0.211		0.186	0.178
		(0.319)		(0.324)		(0.309)	(0.304)
Other		0.610*		0.628*		0.591*	0.573*
		(0.335)		(0.341)		(0.331)	(0.325)
Borrower Education							
(≤ high school omitted)							
> High School		-0.192		-0.191		-0.202	-0.206
		(0.436)		(0.445)		(0.430)	(0.427)
≥ College		-0.131		-0.141		-0.146	-0.135
		(0.427)		(0.420)		(0.412)	(0.420)
N	1689	1537	1689	1537	1689	1537	1537

NOTE: The table shows estimates from OLS regressions. The markup proxy is defined as the residual from segment- (prime or nonprime) and year-specific regressions of interest rates on month, credit score, loan term, coborrower, and lender type dummies. Monthly income is defined to be "variable" if respondents report that it varies "somewhat" or "a lot" from month to month. Respondents' financial buffer is defined to be "small" if they report they could cover expenses for one month or less after losing their main source of income. Columns (1), (2), and (5) regress markup proxies on survey responses related to loan shopping behavior. Columns (2), (4), and (6) add survey controls for borrower finances, race, and education. To avoid subvented loans and outliers, loans with interest rates below one percent are dropped, as are loans with markup proxies below the 2nd or above the 98th percentile. Loans originated before 2015 are also dropped. Regression is weighted by sampling weights. Some consumers have multiple loans, so robust standard errors are clustered at the consumer level. *, **, and *** denotes statistical significance at the 10, 5, and 1 percent level respectively.

Table A3: Summary Statistics in the Commercial and Administrative Data

	25th Pctile	50th Pctile	75th Pctile	Mean
Monthly Payment				
Administrative	283	364	470	399
Commercial	300	382	481	409
Loan Amount				
Administrative	15805	21185	27790	22922
Commercial	16193	21504	27361	22555
Loan Term				
Administrative	60.0	63.0	72.0	64.0
Commercial	58.0	60.0	69.0	60.7
Interest Rate				
Administrative	2.99	3.95	4.79	4.09
Commercial	2.85	3.85	4.95	3.94

Note: This table provides summary statistics for monthly payment, loan amount, loan term, and interest rate in the administrative data and in the commercial data from 2011. Both samples are restricted to consumers with credit scores above 720.

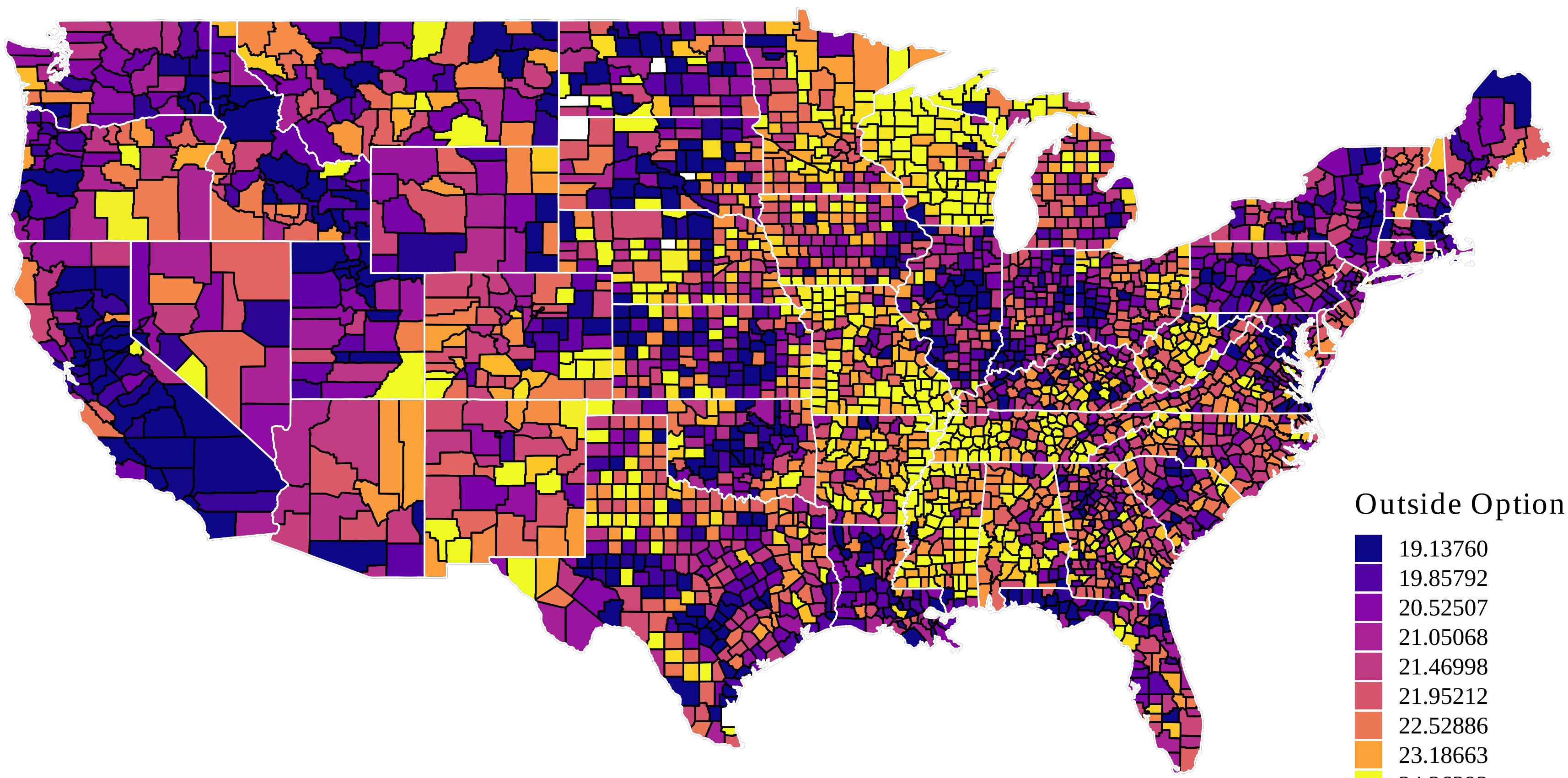


Figure A2: Geographic Distribution of Outside Options

Table A4: Demand Model Coefficients

Make	Mean Utility Shift	Standard Error of Mean Utility Shift	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 makes, the standard errors of those mean shifts, as well as own-price elasticities for different makes.

B.6 Prepayment of Auto Loans

This section investigates how auto loan prepayment may affect our estimates of consumers' outside options θ_i. We proceed in three steps. First, we provide institutional details on how dealers and lenders share prepayment risk. Second, we provide empirical evidence that unlike for some other credit products (e.g. mortgages) for auto loans the relationship between interest rates and prepayment rates is weak. Third, we show theoretically that our estimates for outside options are not affected by prepayment risk as long as the probability of prepayment does not depend on interest rates.

B.6.1 Institutional Details on Prepayment

Consumers often prepay auto loans. They can do so by trading in their vehicle for a new one, by prepaying in cash (or with an insurance payment after the vehicle is totaled), or through refinancing. Prepayment risk is usually shared between dealers and lenders. Contracts between dealers and lenders typically include a "clawback" period, often the first three to six months of the loan, during which the dealer bears all prepayment risk. If the consumer prepays during the clawback period, the dealer refunds the entire dealer reserve to the lender. Afterwards, the lender bears all prepayment risk. In particular, if the borrower has not defaulted or prepaid the loan by the end of the clawback period, the dealer keeps the entire dealer reserve no matter what happens to the loan thereafter. We define "early" prepayment as prepayment that occurs during the clawback period and "late" prepayment as prepayment that occurs after it.

We examine prepayment in the CCP. Auto loan prepayment risk is substantial; in our CCP sample 7% of auto loans are prepaid within the first 120 days, while another 30% are prepaid after the first 120 days but within the first two years. While prepayment risk is substantial, we show in this section that it has little relationship with interest rates or markups and instead seems to reflect consumer "types".

B.6.2 Time Series Evidence on Prepayment and Interest Rates

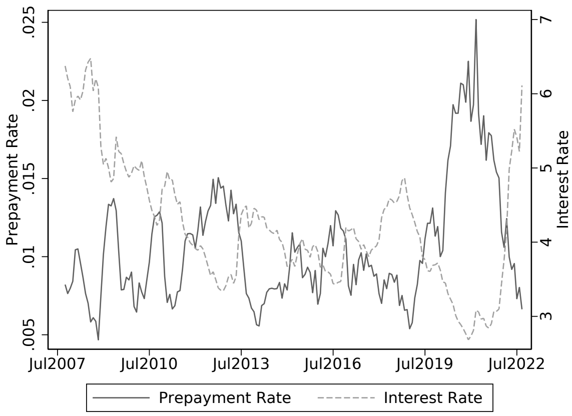
First, we consider time series evidence on auto loan prepayment rates and interest rates. Because we expect that many readers will be more familiar with the large literature on mortgage prepayment, as a useful comparison we also investigate the time series relationship between mortgage prepayment rates and interest rates.

We begin by calculating monthly prepayment rates for both auto loans and mortgages in the CCP. In each month we consider only open and "active" loans, i.e. those most recently reported to the NCRA during or after that month. We define an open and active loan as "prepaid" during that month if it is paid in full more than 60 days before the scheduled end date of the loan. We also calculate monthly interest rates on auto loans from the CCP. To avoid contaminating our measure of the auto loan interest rates available to borrowers with seasonal variation in the creditworthiness of new borrowers, when calculating auto loan interest rates we restrict our attention to new auto loans with loan terms between 3 and 8 years originated to borrowers with credit scores above 720. We cannot calculate mortgage interest rates from the CCP, because mortgage payments typically include escrow payments for property taxes and insurance. Therefore, we take the interest rates on new 30-year fixed rate mortgages from FRED as our proxy for mortgage interest rates.

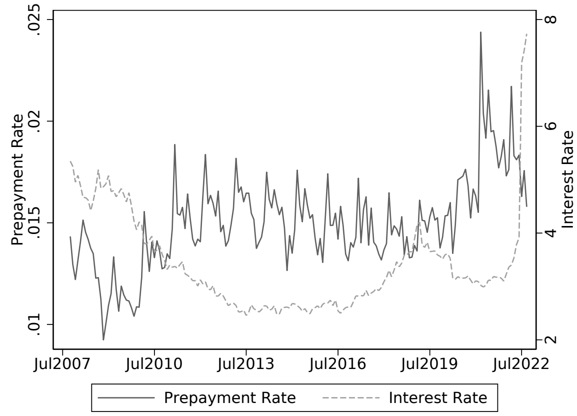
Figure A3a plots prepayment rates and interest rates for mortgages; Figure A3b does the same for auto loans. Comparing the figures suggests that the relationship between prepay-

Figure A3: Time Series of Loan Prepayments and Interest Rates

(a) Mortgages



(b) Auto Loans



Note: Left (right) panel displays prepayment rates and interest rates for mortgages (auto loans) over time. Prepayment rates for both mortgages and auto loans are calculated from the CCP. Interest rates for mortgages are for 30-year fixed rate mortgages and are taken from FRED. We calculate interest rates for auto loans ourselves from the CCP, restricting attention to newly-originated auto loans for consumers with credit scores above 720 with loan terms between 3 and 8 years.

ment rates and interest rates is much weaker for auto loans than it is for mortgages. This may not be surprising. A large literature (e.g. Andersen *et al.*, 2020, Fisher *et al.*, 2021) documents that even mortgage refinance rates are surprisingly insensitive to interest rate changes, and so models of mortgage refinancing typically need refinancing costs to be on the order of thousands of dollars to explain why mortgage rate refinances are so rare. The savings borrowers could obtain by refinancing auto loans, while often significant, are typically less than thousands of dollars. Thus evidence from the mortgage refinance literature on borrowers' refinancing costs might explain why auto loan rate refinances appear to be rare. This is compounded by the fact that vehicles, unlike homes, almost always depreciate, which could make auto loan rate refinances less appealing for both borrowers and lenders than mortgage rate refinances.

While auto loan prepayment rates are only weakly related to interest rates, they have a strong seasonal component. They peak in March, when many consumers receive tax refunds and use them to buy cars,[36] remain high through the summer, and fall in the winter. This

[36]The arrival of tax refunds coincides with a well-known seasonal peak in car purchases. For example, see this article.

coincides with seasonality in vehicle retail sales.[37] The strong seasonality of auto loan prepayments, combined with the weak relationship between auto loan prepayments and interest rates, suggests that demand for vehicle tradeins is a significantly more important factor for auto loan prepayments than interest rate considerations.

We consider this evidence more formally with linear regressions of prepayment rates on (1) interest rates and (2) month fixed effects. Results are in Table A5. In a regression of prepayment rates on interest rates, the coefficient on interest rates for auto loans is less than one-third that for mortgages; the R^2 is .11 for auto loans and .45 for mortgages. Thus auto loan prepayment rates are indeed much less related to interest rates than mortgage prepayment rates are. Instead they are much more seasonal; in a regression of prepayment rates on month fixed effects, the R^2 is .24 for auto loans and only .03 for mortgages. Overall, we conclude that auto loan prepayments are frequently driven by vehicle tradeins and rarely driven by interest rate considerations.

B.6.3 How do our Estimates depend on Prepayment Risk?

In this section we introduce prepayment risk into our model of Nash Bargaining. Motivated by the evidence in Section B.6.2 that borrower prepayment decisions are mostly unrelated to interest rates and instead driven by other factors (e.g. vehicle tradeins) that are outside our model, we model prepayment risk as an ex-ante consumer type. With this modeling assumption, we show that for both early and late prepayment our estimates of θ do not depend on borrower prepayment risk. This implication of the model is empirically testable; we validate it in Section B.6.4.

Early Prepayment Risk

First, we explore the role of early prepayment by adding a consumer-specific early repayment probability ϕ_i to our baseline model. In the case of early prepayment, the dealer returns the entire dealer reserve to the lender and the consumer reverts to outside option θ_i. The Nash Bargaining problem from Section 4 then becomes:

$$r_{ijd} \in argmax_r \left\{(1-\phi_i)[(p_{jd}-\kappa_i)\alpha(r-b_{ijd})+\beta]\right\}^{\rho} \cdot \left\{\gamma_i(p_{jd}-\kappa_i)[\theta_i-(1-\phi_i)r_i-\phi_i\theta_i]\right\}^{1-\rho}.$$
$$\Leftrightarrow r_{ijd} \in argmax_r[1-\phi_i]\left\{(p_{jd}-\kappa_i)\alpha(r-b_{ijd})+\beta\right\}^{\rho} \cdot [\gamma_i(p_{jd}-\kappa_i)(\theta_i-r_i)]^{1-\rho}.$$

[37] See for example, here.

Table A5: Regressions of Aggregate Prepayment Rates on Interest Rates and Month

	Auto Loans			Mortgages		
	(1)	(2)	(3)	(4)	(5)	(6)
Interest Rate	-0.000801***		-0.000816***	-0.00295***		-0.00297***
	(0.000)		(0.000)	(0.000)		(0.000)
February		0.000774	0.000776		0.000239	0.000367
		(0.001)	(0.001)		(0.001)	(0.001)
March		0.00370***	0.00367***		0.00222	0.00250**
		(0.001)	(0.001)		(0.001)	(0.001)
April		0.00149**	0.00139**		0.00123	0.00149
		(0.001)	(0.001)		(0.001)	(0.001)
May		0.00140*	0.00133*		0.00156	0.00179*
		(0.001)	(0.001)		(0.001)	(0.001)
June		0.00203***	0.00200***		0.00195	0.00235**
		(0.001)	(0.001)		(0.001)	(0.001)
July		0.00126*	0.00133*		0.00119	0.00149
		(0.001)	(0.001)		(0.001)	(0.001)
August		0.00176**	0.00185***		0.00165	0.00177*
		(0.001)	(0.001)		(0.001)	(0.001)
September		0.000990	0.00117*		0.00150	0.00163
		(0.001)	(0.001)		(0.001)	(0.001)
October		0.000366	0.000368		0.00172	0.00186*
		(0.001)	(0.001)		(0.001)	(0.001)
November		-0.000550	-0.000583		0.00100	0.00115
		(0.001)	(0.001)		(0.001)	(0.001)
December		-0.0000119	-0.0000982		0.00151	0.00162
		(0.001)	(0.001)		(0.001)	(0.001)
R^2	0.107	0.238	0.348	0.447	0.027	0.480

Note: Table reports results from OLS regressions of loan prepayment rates on interest rates and/or month fixed effects. Loan prepayment rates and auto loan interest rates are from the CCP. Mortgage interest rates are from FRED. *, **, and *** denote statistical significance at the 10, 5, and 1 percent level, respectively.

This maximization problem is identical to that from the main model, so the first order conditions are identical and (7) still identifies θ_i. Intuitively, we obtain this equivalence result because early prepayment probability ϕ_i modifies both consumer and dealer utility in a multiplicative way. Because of Nash bargaining, it therefore affects only total surplus and not how the surplus is split.

Late Prepayment Risk

Lenders bear all prepayment risk after the end of the clawback period. To understand how late prepayment risk affects the model, in this section we assume that after obtaining a loan with interest rate r from a dealer, consumer i actually pays $(1-\phi_i)r+\phi_i\theta$ in interest. Hence, the consumer-specific $\phi_i > 0$ represents, in reduced form, the point in time that the dealer and consumer expect prepayment to occur (or, equivalently, the probability of prepayment). The Nash Bargaining problem in Section 4 then becomes:

$$r_{ijd} \in argmax_r \left\{(p_{jd}-\kappa_i)\alpha(r-b_{ijd})+\beta\right\}^{\rho} \cdot \left\{\gamma_i(p_{jd}-\kappa_i)[\theta_i-(1-\phi_i)r_i-\phi_i\theta_i]\right\}^{1-\rho}.$$
$$\Leftrightarrow r_{ijd} \in argmax_r[1-\phi_i]^{1-\rho}\left\{(p_{jd}-\kappa_i)\alpha(r-b_{ijd})+\beta\right\}^{\rho} \cdot [\gamma_i(p_{jd}-\kappa_i)(\theta_i-r_i)]^{1-\rho}.$$

Again, this maximization problem is identical to that from the main model, so again the first order conditions are identical and (7) still identifies θ_i. Intuitively, we obtain this equivalence result because late prepayment probability ϕ_i does not affect dealer utility but, like early prepayment, it modifies consumer utility in a multiplicative way. Again because of Nash bargaining, it therefore affects only total surplus and not how the surplus is split.

B.6.4 Correlation Between Prepayment and Estimate for θ

Section B.6.3 shows that, if consumer prepayment is exogenous to the model, then prepayment does not affect our estimates of θ and so prepayment risk and θ should be unrelated. This theoretical implication can be tested empirically. We do so in this section, providing further evidence that loan prepayments and interest rates are essentially unrelated.

The challenge is that we observe θ only in our supervisory data, while we observe prepayment only in the CCP. Therefore to create a proxy for prepayment risk in our supervisory data, we run a logit regression predicting prepayment in the CCP, using credit score, log loan amount, loan length, and state fixed effects.[38] We use the coefficients, which are reported

[38]Note that, to align with our supervisory data, we examine prepayment in the CCP for auto loans

in Table A6, to impute prepayment risk in the supervisory data. The information we use to predict prepayment is clearly a limited subset of the information available to both the borrower and the dealer, and yet it is remarkably predictive. 26 percent of those in the bottom decile of predicted risk prepay within two years, while 56 percent in the top decile do.

Table A7 provides percentiles of markup conditional on percentiles of predicted prepayment risk. Table A8, Table A9, Table A10 provides estimates from regressions of prepayment risk, late prepayment risk, and early prepayment risk (respectively) with a large number of controls. The tables show that the conditional correlation between observable prepayment risk and θ is quite weak. For example, Table A8 shows that moving from below the 10th percentile of prepayment risk to above the 90th percentile of prepayment risk leads to a predicted decrease in θ by just .076, and to a predicted increase in total markup costs over the life of the loan, expressed as a present of the original loan amount, of just 27 basis points.

B.7 Robustness to Price Elasticity

Recent work (Grieco *et al.*, 2022) studies the evolution of market power in the U.S. automobile industry and finds larger price elasticities than we do. We therefore briefly discuss how our main counterfactual results change if we double the price coefficient. Doubling the price coefficient changes the price elasticity from -3.05 to -6.38, which is closer to what Grieco *et al.* (2022) estimate.

Moving from Baseline to No Discretion, the average increase in consumer surplus is 0.7% instead of 0.98%. While the average change in consumer surplus is slightly smaller, the distributional effects are larger. The surplus of consumers with worse than median outside options ($\theta > \theta_{50}$) increases by 5.5% instead of 3.5%. The surplus of other consumers falls by 3.5% instead of 1.1%. Dealer profits fall by 1.48% instead of 1.47%. Lender profits fall by 9.8% instead of 7.01%. While larger elasticity estimates change the levels of consumer and producer surplus, they do not lead to qualitatively different conclusions from our main counterfactual.

originated between 2011 and 2013. The fact that we observe so many prepayments when interest rates were so stable (see Figure A3b) provides further evidence that few auto loan prepayments are driven by interest rate considerations.

Table A6: Logit Regression of Prepayment Risk

	Prepayment	Early Prepayment	Late Prepayment
$730 \leq$ Credit score ≤ 749	-0.0113	0.0602**	-0.0283**
	(0.012)	(0.024)	(0.013)
$750 \leq$ Credit score ≤ 769	0.0000673	0.136***	-0.0375***
	(0.012)	(0.024)	(0.012)
$770 \leq$ Credit score ≤ 789	0.0194	0.265***	-0.0559***
	(0.012)	(0.023)	(0.012)
$790 \leq$ Credit score ≤ 809	0.0158	0.359***	-0.0917***
	(0.012)	(0.023)	(0.012)
$810 \leq$ Credit score ≤ 829	-0.0262**	0.370***	-0.143***
	(0.012)	(0.024)	(0.013)
$830 \leq$ Credit score ≤ 849	-0.157***	0.234***	-0.243***
	(0.013)	(0.026)	(0.014)
Log loan size	-0.352***	-0.342***	-0.271***
	(0.006)	(0.011)	(0.006)
$42 \leq$ Loan term ≤ 53	-0.366***	-0.348***	-0.268***
	(0.012)	(0.021)	(0.012)
$54 \leq$ Loan term ≤ 65	-0.562***	-0.172***	-0.540***
	(0.010)	(0.017)	(0.010)
$66 \leq$ Loan term ≤ 77	-0.481***	-0.133***	-0.462***
	(0.011)	(0.019)	(0.011)
$78 \leq$ Loan term ≤ 89	-0.361***	-0.158***	-0.326***
	(0.019)	(0.037)	(0.020)

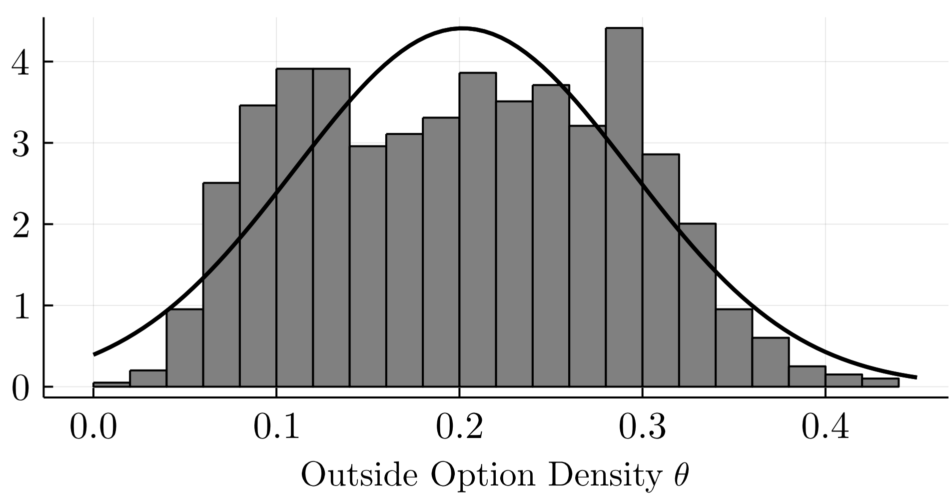
NOTE: Table reports coefficients from a logit regression of prepayment risk on borrower observables in the CCP. Here, "prepayment" is defined as prepayment within the first two years of the loan. "Early" prepayment is defined as prepayment within the first 120 days. "Late" prepayment is defined as prepayment after the first 120 days. Loans with length less than three years or more than ten years are dropped. Otherwise, loan lengths above six years are winsorized. *, **, and *** denote statistical significance at the 10, 5, and 1 percent level, respectively.

Table A7: Joint Distribution of Prepayment and θ

	P10	P25	P50	P75	P90
θ					
$<$ 10th percentile prepayment risk	7.62	11.88	17.92	24.47	29.29
$10 - 25$th percentile prepayment risk	8.4	12.62	19.23	26.37	30.66
$25 - 50$th percentile prepayment risk	8.9	13.39	20.41	27.47	31.42
$50 - 75$th percentile prepayment risk	9.17	13.92	21.53	28.44	32.1
$75 - 90$th percentile prepayment risk	9.53	14.75	22.79	29.69	34.53
$>$ 90th percentile prepayment risk	7.88	12.54	19.18	26.91	32.98

NOTE: Table shows conditional percentiles of θ conditional on prepayment risk.

Figure A4: Histogram of θ



NOTE: The figure shows a histogran of the estimates for θ, including the estimated parametric approximation.

Table A8: Regressions of θ and Markups on Prepayment Risk

	θ	Markups
Log Monthly Income	-0.182***	-0.0278***
	(0.013)	(0.004)
Credit Score, 100 points	-2.029***	-0.225***
	(0.020)	(0.006)
Mileage, Tens of Thousands	0.729***	0.0449***
	(0.004)	(0.001)
New Car	-0.433***	-0.310***
	(0.023)	(0.007)
Log Loan Amount	-3.377***	-0.320***
	(0.037)	(0.010)
Average Years of Education in County	-0.131***	-0.0241***
	(0.023)	(0.007)
Fraction with Internet Access in Census Tract	-1.646***	-0.398***
	(0.095)	(0.028)
10-25th Percentile Prepayment Risk	-0.236***	0.0884***
	(0.032)	(0.010)
25th-50th Percentile Prepayment Risk	-0.0845**	0.176***
	(0.039)	(0.011)
50th-75th Percentile Prepayment Risk	-0.107**	0.249***
	(0.050)	(0.014)
75th-90th Percentile Prepayment Risk	0.0198	0.312***
	(0.060)	(0.017)
>90th Percentile Prepayment Risk	0.0764	0.266***
	(0.079)	(0.023)

NOTE: Table presents coefficients from OLS regression of θ and markups (expressed as a percent of the original loan amount) on observables including prepayment risk. Loan term fixed effects are also included, but not shown. Standard errors are clustered at zip code level. Prepayment is defined as prepayment within the first 2 years. Estimated prepayment probabilities in the supervisory data are imputed using coefficient estimates from the CCP. *** denotes statistical significance at the 1 percent level.

Table A9: Regressions of θ and Markups on Early Prepayment Risk

	θ	Markups
Log Monthly Income	-0.178***	-0.0282***
	(0.013)	(0.004)
Credit Score, 100 points	-1.698***	-0.206***
	(0.021)	(0.006)
Mileage, Tens of Thousands	0.727***	0.0429***
	(0.004)	(0.001)
New Car	-0.448***	-0.322***
	(0.023)	(0.007)
Log Loan Amount	-4.006***	-0.487***
	(0.033)	(0.009)
Average Years of Education in County	-0.130***	-0.0243***
	(0.023)	(0.007)
Fraction with Internet Access in Census Tract	-1.653***	-0.400***
	(0.095)	(0.028)
10-25th Percentile Prepayment Risk	-0.508***	-0.0562***
	(0.030)	(0.009)
25th-50th Percentile Prepayment Risk	-0.820***	-0.0858***
	(0.033)	(0.010)
50th-75th Percentile Prepayment Risk	-1.264***	-0.127***
	(0.039)	(0.011)
75th-90th Percentile Prepayment Risk	-1.602***	-0.164***
	(0.045)	(0.013)
>90th Percentile Prepayment Risk	-1.758***	-0.211***
	(0.056)	(0.017)

Note: Table presents coefficients from OLS regression of θ and markups (expressed as a percent of the original loan amount) on observables including early prepayment risk. Loan term fixed effects also included, but not shown. Standard errors clustered at zip code level. Early prepayment is defined as prepayment in the first 120 days. Estimated prepayment probabilities in the supervisory data are imputed using coefficient estimates from the CCP. *** denotes statistical significance at the 1 percent level.

Table A10: Regressions of θ and Markups on Late Prepayment Risk

	θ	Markups
Log Monthly Income	-0.181***	-0.0278***
	(0.013)	(0.004)
Credit Score, 100 points	-1.886***	-0.188***
	(0.021)	(0.006)
Mileage, Tens of Thousands	0.731***	0.0450***
	(0.004)	(0.001)
New Car	-0.418***	-0.310***
	(0.023)	(0.007)
Log Loan Amount	-3.111***	-0.312***
	(0.033)	(0.010)
Average Years of Education in County	-0.131***	-0.0241***
	(0.023)	(0.007)
Fraction with Internet Access in Census Tract	-1.644***	-0.398***
	(0.095)	(0.028)
10-25th Percentile Prepayment Risk	-0.0362	0.0980***
	(0.031)	(0.009)
25th-50th Percentile Prepayment Risk	0.255***	0.195***
	(0.036)	(0.010)
50th-75th Percentile Prepayment Risk	0.469***	0.290***
	(0.045)	(0.013)
75th-90th Percentile Prepayment Risk	0.797***	0.364***
	(0.055)	(0.016)
>90th Percentile Prepayment Risk	1.023***	0.333***
	(0.074)	(0.021)

NOTE: Table presents coefficients from OLS regression of θ and markups (expressed as a percent of the original loan amount) on observables including late prepayment risk. Loan term fixed effects also included, but not shown. Standard errors clustered at zip code level. 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. *** denotes statistical significance at the 1 percent level.