Competition and Shrouded Attributes: Evidence from the Indirect Auto Loan Market*

Morteza Momeni
University of Kentucky

July 10, 2023

Abstract

I estimate the effect of competition among auto dealers on the joint pricing of cars and car loans. I find that increased competition causes dealers to decrease vehicle prices to attract consumers. They, however, offset a large portion of their loss through charging higher prices on a non-salient margin (i.e., loan markups). Furthermore, dealers charge price-inelastic borrowers higher loan markups, suggesting that increased competition benefits price-elastic buyers at the expense of price-inelastic consumers. Consistent with the heuristic budgeting channel, I find that (1) consumers bunch at salient monthly payment amounts, and (2) increased competition does not change consumers' monthly payments.

*I am deeply grateful to my advisors Russell Jame and David Sovich for their guidance and support. I would also like to thank William Gerken, Igor Cunha, Charlie Clarke, Mark Liu, Kristine Hankins, Grant Clayton, and seminar participants at the University of Kentucky for helpful feedback. Morteza.Momeni@uky.edu

1 Introduction

In many markets, sellers tend to make the total cost to purchase a product less transparent and more difficult to process by dividing the total cost into salient and non-salient margins. Hidden fees on credit cards, fine-print shipping and handling charges, and mortgages with complex features are just a few examples.[1] These price partitioning practices or shrouding attributes may help sellers to maximize their profits by setting the price of non-salient margins well above its marginal cost (Ellison 2005, Spiegler 2006, Gabaix and Laibson 2006, Carlin 2009, Piccione and Spiegler 2012, Ellison and Wolitzky 2012, Chioveanu and Zhou 2013). This inefficiency has received substantial attention from regulators, in particular in the U.S. auto market, where auto dealers charge a discretionary loan markup for arranging auto loans.

As an intermediary, an auto dealer provides convenient one-stop shopping by bundling auto purchasing and auto financing, as well as reducing households' search cost through a better search technology.[2] The dealer, however, has significant market power in handling auto loans despite the fact that the auto loan market is highly competitive at the lender level[3], allowing the dealer to charge a discretionary loan markup on top of the lenders' quoted price. The Federal Trade Commission (FTC) and the Consumer Financial Protection Bureau (CFPB) have raised concerns regarding the opacity of the institutional structure of this market and stated that discretionary loan markups can lead to illegal discrimination.

This article seeks to understand if competition among auto dealers could be a potential remedy to eliminate this inefficiency. On the one hand, increased competition could lead auto dealers to reveal non-salient prices to win over consumers and increase their market share. Therefore, in a competitive market, non-salient margins should not exist (Becker 1957, Milgrom 1981, Jovanovic 1982, Laibson and Yariv 2007). Recent theoretical models, however, predict that when consumers

1. See Greenleaf et al. 2016 for an overview of non-salient charges across industries.

2. They may substantially lower households' search cost by submitting their application to more than 1,500 lenders through major dealer management systems (Grunewald et al. 2020)

3. Yannelis and Zhang 2021 document that the average Herfindahl-Hirschman Index in the direct U.S. auto loan market is 0.058, suggesting that this market is highly competitive at the lender level. The indirect auto loan market is even more competitive at the lender level, because a dealer can easily have access to virtually all auto lenders in the United States.

are myopic (or unaware), dealers respond to greater competition with greater efforts to shroud prices (Spiegler 2006, Gabaix and Laibson 2006, Carlin 2009). Therefore, competition-related policies may worsen consumer welfare.

In this paper, I focus on the U.S. auto market for several reasons. First, cars are often one of the largest purchases in a consumer's life, and the total cost charged by auto dealers can be separated into a salient margin (i.e., vehicle prices) and a non-salient margin (i.e., loan markups). Second, a car purchase is a financially complex process that the majority of households go through only a few times in their lives. For example, auto loans are customized depending on the household's creditworthiness and the details of the auto loan (loan size, loan maturity, loan to value ratio, etc.), making the comparison of price quotations very difficult. Third, auto dealers intermediate about 80 percent of auto loans in the United States. In aggregate, auto loan debt is the third largest form of household debt in the United States, behind mortgages and student loans. The total auto debt in the U.S. is more than $1.4 trillion, with over 113 million outstanding loans (FRBNY 2021). Given the economic importance of this market, the extent to which local competition among auto dealers affects the joint pricing of cars and car loans is a first-order question.

Empirical identification of this effect comes with several challenges. First, few data sets have comprehensive information on features of vehicles and characteristics of borrowers. For example, auto loan data from the credit bureaus lack information on vehicle features, making the identification of homogeneous products almost impossible. Second, identifying the effect of competition on consumer welfare is challenging. Naïve regressions of vehicle prices or loan markups on the number of auto dealers are unlikely to provide causal estimates. In particular, reverse causality and omitted variable bias could be problematic. For example, auto dealers are more likely to do business in markets where they have a higher chance of charging substantial markups.

In this paper, I overcome these challenges using a novel loan-level dataset with comprehensive information on features of vehicles and characteristics of borrowers. The granularity of the data allows me not only to better control for the borrower's characteristics at the time of origination, but also to estimate the coefficient of interest for homogeneous vehicles (e.g., new 2018 Toyota Camry).

The data also includes loan performance histories over the entire life of each loan, allowing me to measure ex-post default and paid-off rates. The data also covers major auto lenders in the United States, lessening concerns regarding data representativeness.

To overcome identification issues, I exploit plausibly exogenous variation in the number of potential dealerships selling new cars. The variation stems from the non-linear interaction of the state-level relevant market area and the amount of developable land in a given market. The intuition of my identification strategy is straightforward. Starting in the late 1950's, virtually all states enacted automobile franchise laws to protect car dealerships against car manufacturers' superior bargaining power. Specifically, from the late 1950's to the early 2000's, most states enacted laws prohibiting a car manufacturer from granting a new car dealership selling the same line-make vehicles within the exclusive relevant market area (RMA), measured as a radii of X miles from an existing dealership. For example, the state of Kentucky imposed a relevant market area of 10 miles in 1972 and has not changed it since then.

The number of potential dealerships selling new cars in a market, however, is limited not only by the size of the relevant market area, but also by the amount of developable land in a market. For example, assume two local markets with the same relevant market area of 10 miles, where one is severely land-constrained by its geography, and another is completely flat with no area lost to internal water bodies, wetlands, or lands with slopes above 15%. The land-constrained market should experience less local competition because the number of potential dealerships is limited, which leads to higher market concentration among dealerships selling new cars. In contrast, the local market with a greater amount of developable areas should experience more local competition because entry to this market is easier and the number of dealerships selling new cars is not limited by the predetermined geographic features of the market.

Since the variation in the predetermined geographic features is not fundamentally randomly assigned, I exploit plausibly exogenous variation in the number of potential dealerships that comes from the non-linear interaction of the relevant market area and the amount of developable lands, after including both relevant market area fixed effects and developable land quartile fixed effects.

The key source of variation comes from the non-proportional ratio of the amount of developable land and the state-level relevant market areas imposed about 20 to 70 years ago. In other words, I compare loans originated by the same lender for the same vehicle at the same time in markets with the same relevant market area but with different amounts of developable land, and I compare them with loans originated by the same lender for the same vehicle at the same time in markets with the same amount of developable land, but with different relevant market areas. I provide some evidence to support the validity of my instrumental variable. First, I find that the instrument is strongly correlated with the endogenous number of dealers selling new cars. Next, I find that the instrument does not predict state-level macroeconomic outcomes. This suggests that the instrument is not systematically correlated with time-invariant differences across states. This increases the confidence in supporting the validity of the instrument. Furthermore, I use a unique feature of my instrumental variable, in which it affects only the number of dealerships selling new cars. Using a placebo test, I find in reduced form that the instrument does not statistically or economically predict (1) the number of dealerships that exclusively sell used cars[4], or (2) the number of banks in a market, suggesting that the instrument is not correlated with the general demand for vehicles or auto loans across states. This also suggests that the instrument should be less relevant in predicting the variation in vehicle prices and/or loan markups for older used cars. I find no evidence that the instrument statistically or economically predicts vehicle prices and loan markups for old used cars. Overall, this suggests that the instrument has no direct effect on vehicle prices and loan markups other than through the number of dealerships selling new cars.

I find that on average, an increase in the instrumented number of dealerships is associated with a \$88.6 decrease in vehicle prices. The economic magnitude of this effect is large given that the average markup on new cars is between 2-5%.[5] I also find that on average, an increase in the instrumented number of dealerships is associated with a 16.8 basis point increase in loan markups. This increase offsets the average decline in vehicle prices, resulting in no change in the average

4. Unlike franchise dealerships, these dealerships mainly sell low-quality (high-mileage) used cars.

5. Auto dealers' profit margin for new vehicles is razor thin (Beard and Ford 2016) and is constantly decreasing over time (Levitin 2019). According to The National Automobile Dealers Association (NADA), the average net profit before tax for new vehicles is 2-5% (https://www.nada.org/media/2099/download?inline)

monthly payments and other contract terms. My findings suggest that an average consumer does not benefit from competitive pressure in the indirect auto loan market. Auto dealers, however, offset a big portion of their loss on vehicle prices: the revenue generated from the increase in loan markups is split between auto dealers and auto lenders. Grunewald et al. 2020 show that on average, auto dealers capture around 75% of this revenue.

Next, I investigate potential channels through which local competition among auto dealers affects the joint pricing of cars and car loans. I find that the monthly payment targeting channel is driving my results. Argyle, Nadauld, and Palmer 2020a find that many consumers in the auto loan market target specific monthly payment amounts (e.g., \$200, \$300, and \$400 per month). If increased competition leads to lower vehicle prices, then the corresponding monthly payment amounts mechanically decrease too. Auto dealers may exploit consumers' monthly payment targeting bias by charging higher prices on loan markups such that consumers' monthly payment amounts stay the same across markets. Consistent with this channel, I find (1) bunching at salient monthly payment amounts, and (2) no evidence of the effect of competition on monthly payments.

This paper contributes mainly to three strands of literature. First, a related empirical literature suggests that sellers can gain financial benefits — at least in short-term — by engaging in shrouded pricing strategies (Hossain and Morgan 2006, Ellison and Ellison 2009, Brown, Hossain, and Morgan 2010, Xia and Monroe 2004). My paper complements this literature by studying whether competitive forces may be a remedy to eliminate such exploitation. The closest study to my paper is Agarwal, Song, and Yao 2022, which investigates the effect of banking competition on contract terms in the U.S. mortgage market. My paper is distinct from theirs because I show that increased competition leads to a price adjustment at the intensive margin.

This paper also contributes to the empirical literature on the effects of competition in consumer credit markets, including payday loans (Melzer and Morgan 2015), auto loans (Yannelis and Zhang 2021; Gissler, Ramcharan, and Yu 2020; Argyle, Nadauld, and Palmer 2020b), mortgages (Allen, Clark, and Houde 2014; Buchak and Jørring 2021), and credit cards (Dick and Lehnert 2010). For example, Melzer and Morgan 2015 find that banks and credit unions reduce overdraft credit limits and prices when payday credit is prohibited. Gissler, Ramcharan, and Yu 2020 find that competition changes the composition of borrowers, with a reallocation of credit toward subprime borrowers. Dick and Lehnert 2010 find that increased competition is associated with an improvement in screening technologies, which expand consumer credit to both low- and high-risk borrowers. Buchak and Jørring 2021 find the effects of competition on credit access and pricing. They show that lower competition reduces credit access for all borrowers, in particular for female borrowers and borrowers belonging to racial minorities. Yannelis and Zhang 2021 study the effect of competition in presence of costly lender screening and show that competition among lenders has two opposing effects on interest rates. My paper complements this literature by studying the effect of competition among loan intermediaries not lenders.[6] Unlike many credit markets, lenders in the indirect auto loan market compete for auto dealers' business, not borrowers' business. This distinction highlights the important role of intermediaries in this market and may explain why consumers may not fully benefit from the competitive force characterized by many lenders and consumers in the auto loan market. Furthermore, my paper provides a more complete picture of the overall effect of competition by estimating this effect on the joint pricing of cars and car loans. My findings suggest that by ignoring this joint pricing, we may overestimate the price effect of competition.

The closest study to my paper is Allen, Clark, and Houde 2014, which study the relationship between competition and price dispersion in the Canadian mortgage market. They show that increased competition has a heterogeneous impact on borrowers. They argue that search frictions explain this heterogeneity. My paper is distinct from theirs since the heterogeneity in my findings comes from behavioral biases of consumers (i.e., monthly payment targeting). My findings suggest that auto dealers exploit such biases to maximize their profits.

This paper is related to a growing literature on auto loan markets.[7] A major theme of this

6. Auto dealers are different from many intermediaries in credit markets. They not only sell a product but also finance it. This is not common for other intermediaries in the credit markets, including mortgage brokers (Ambrose and Conklin 2014; Allen, Clark, and Houde 2014; Woodward and Hall 2012; Robles-Garcia 2022), real estate brokers (Yinger 1981; Anglin and Arnott 1999; Elder, Zumpano, and Baryla 1999; Beck, Scott, and Yelowitz 2012), financial advisors (Egan 2019; Egan, Matvos, and Seru 2019; Dimmock, Gerken, and Graham 2018; Gerken and Momeni 2022), and the insurance brokers (Anagol, Cole, and Sarkar 2017).

7. Zinman 2015 mentions that auto loan markets are understudied despite its economic importance. He argues that the main hurdle is lack of granular dataset. To overcome this concern, I use publicly available loan-level data

literature is inherent information asymmetry in the auto lending process. Purchasing a vehicle is a complex and opaque process requiring multiple stages of search (Busse and Silva-Risso 2010). This complexity and opaqueness may result in borrowers' irrational behavior (Grunewald et al. 2020; Argyle, Nadauld, and Palmer 2020a; Argyle, Nadauld, and Palmer 2020b), dealers' exploitation of borrowers (Butler, Mayer, and Weston 2021; Lanning 2021; Cohen 2012; Brown and Jansen 2020; Jansen et al. 2021; Melzer and Schroeder 2017), screening mechanism or technologies to improve quality of borrowers (Einav, Jenkins, and Levin 2012; Jansen, Nguyen, and Shams 2021; Yannelis and Zhang 2021; Jansen, Kruger, and Maturana 2021), and lenders' ability to pass-through costs (Hankins, Momeni, and Sovich 2022; Benneton, Mayordomo, and Paravisini 2022). The closest study to my paper is Grunewald et al. 2020, which find that consumers respond substantially more to vehicle prices than loan prices. My work is distinct from theirs since I investigate how and how much competition among auto dealers affects the joint pricing of cars and car loans.

2 Institutional Details and Identification Strategy

This section first gives an overview of the institutional details of the indirect auto lending market in the United States and then provides details on the identification strategy.

2.1 Institutional Details of Indirect Auto Lending Market

Indirect auto lending refers to auto financing through a car dealership.[8] The majority of auto financing is indirect: about 90% of consumers finance their vehicles through car dealerships. In a typical auto purchase transaction, after a consumer first searches for a make and model of vehicle, a sales agent negotiates with her about vehicle specifics such as vehicle price and available options. Then, she is sent to the dealer's Finance and Insurance (F&I) agent to finalize her purchase by arranging her financing terms. In particular, the F&I agent may submit her credit application

from Regulation AB II. Please see Momeni and Sovich 2022 for more information.

8. Another form of auto financing is commonly referred to as "direct auto lending", in which a consumer directly applies for an auto loan. For new vehicles, only about 10% of auto loans in the United States are financed through direct lending.

to more than 1,500 lenders through major dealer management systems such as *DealerTrack* or *RouteOne* (Grunewald et al. 2020). After receiving the credit application of the consumer, lenders review her information and decide either to deny it or offer a buy rate, which is the minimum interest rate at which the lender will acquire the loan from the dealer.[9] The lender's buy rate is a risk-adjusted rate that captures the credit risk of the consumer. This process varies across consumers' creditworthiness. For prime borrowers, it is fully automated and happens quickly. For subprime borrowers, however, it may take longer due to additional verification steps.

As compensation for processing the paperwork, the lender may allow the dealer to add a markup to the lender's buy rate.[10] The markup is discretionary and does not reflect the credit risk on the loan. While the loan markups are discretionary, some lenders may impose caps to not only avoid potential class-action lawsuits, but also lower the consumer's default and prepayment risk (Cohen 2012). Under pre-specified contracts between dealers and lenders, the revenue generated by markups may be split between them. The dealer's share of revenue is commonly called "dealer reserve" or "dealer participation".

Under the existing institutional structure of this market, the consumer has no information about whether her auto loan is marked up since dealers are not required to disclose the lender's buy rate and the dealer's markup. In other words, the final loan rate offered to the consumer is the sum of the lender's buy rate and the dealer's discretionary markup rate. Furthermore, dealers are not required to disclose all offers a consumer is eligible for. Thus, to learn about the market interest rate available to her, the consumer must visit another dealer and go through a formal application process again. This gives the dealer substantial leverage in handling auto loans.

2.2 Identification Strategy

To provide evidence on the causal effect of competition among auto dealers on vehicle prices and loan markups, I should address the endogeneity concern coming from a naïve regression of vehicle

9. Technically, the dealer originates the loan and then the lender will buy the loan from the dealer at the lowest interest rate. In practice, we can assume that the lender originates the loan since the dealer already knows the buy rate and sells the loan immediately (Grunewald et al. 2020; Levitin 2019).

10. Some lenders may offer a flat fee or a combination of a flat fee and a markup for compensation.

prices or loan markups on the number of auto dealers in a market. Omitted variables and reverse causality are likely to prevent the causal interpretation of the point estimate from a naïve regression. For example, market-specific characteristics and consumer sophistication could affect both demand for vehicles, loan markups, and vehicle prices. To address these concerns, I use an instrumental variable stemming from the interaction of the state-level relevant market areas and the amount of developable land. My identification strategy is designed to exploit the variation in the potential number of dealerships selling new cars as an instrument for the number of dealerships selling new cars in a given market.

The intuition of my identification strategy is straightforward. Historically, auto manufacturers had superior bargaining power over car dealerships (Marx 1985).[11] Federal and state legislators enacted several laws to protect new car dealerships against manufacturers' abuse of their bargaining power (Lafontaine and Scott Morton 2010; Brown 1980). In particular, some states have prohibited an automaker from granting a new car dealership selling the same line-make vehicles within the relevant market area (RMA), measured as a radii of X miles from an existing dealership.[12] Starting in the late 1950's until the early 2000's, almost all states have imposed a dealers' exclusive territory requirement to some extent to limit the number of dealerships selling new cars in a given market.

11. For example, a car manufacturer could terminate the franchise agreement at will and without providing any cause or force car dealers to purchase unwanted vehicles. In an infamous example, during the 1929 Great Depression, Ford Motor Company forced its dealers to buy new, unordered vehicles, despite the fact that dealers had a very small chance of selling them (James Surowiecki, Dealer's Choice, New Yorker (September 4, 2006), https://www.newyorker.com/magazine/2006/09/04/dealers-choice-2).

12. The definition of relevant market area may vary across states. Many states measure relevant market area as a radii of X miles from an existing dealership. Some states, however, may be more specific about it. For example, Massachusetts franchise law defines the relevant market area as "the geographic area surrounding the boundary of a dealership, determined as follows: (1) If all boundaries of a dealership located in the counties of Bristol, Essex, Hampden, Middlesex, Norfolk, Plymouth or Suffolk are 8 or more miles from the border of the counties of Barnstable, Berkshire, Dukes, Franklin, Hampshire, Nantucket and Worcester, then the geographic area shall be the entire land mass encompassed in a circle with a radius of 8 miles from any boundary of the dealership. (2) If all boundaries of a dealership located in the counties of Barnstable, Berkshire, Dukes, Franklin, Hampshire, Nantucket or Worcester are 14 or more miles from the border of the counties of Bristol, Essex, Hampden, Middlesex, Norfolk, Plymouth and Suffolk, then the geographic area shall be the entire land mass encompassed in a circle with a radius of 14 miles from any boundary of the dealership. (3) For all dealerships in the commonwealth which are not included in (1) or (2), inclusive, of this definition, the geographic area shall be a land mass comprised of circular arc segments with a radius of 8 miles from any boundary of the dealership for the arc segments that fall within the counties of Bristol, Essex, Hampden, Middlesex, Norfolk, Plymouth and Suffolk; and with a radius of 14 miles from any boundary of the dealership for the arc segments that fall within the counties of Barnstable, Berkshire, Dukes, Franklin, Hampshire, Nantucket and Worcester."

35 states explicitly imposed a dealers' relevant market area. For example, the relevant market area in Kentucky is 10 miles. To provide an example, I map Toyota dealerships located in Lexington, KY. Figure 1 shows that Toyota dealerships in Kentucky are approximately 10 miles apart from each other.

[Figure 1]

Furthermore, all states have prohibited car manufacturers from selling new vehicles directly to consumers. Virtually all new vehicles in the United States must be sold through only franchise dealerships. This restriction, along with the restriction on the location of new car dealers, provides an ideal setting to examine the effect of local competition among auto dealerships. These restrictions ensure that in a given market, the number of new car dealers selling the same new line-make vehicles is limited by the size of the relevant market area and the amount of developable land in a given market.

State-level relevant market areas vary from 5 to 25 miles, and 54 percent of states have a relevant market area of 10 miles. Figure 2 shows the distribution of relevant market area across states. This variation in the relevant market areas may be driven by state-level differences in the political power of dealership associations, population, economic conditions, or the financial literacy of consumers at the time of franchise law enactment. For example, more (less) populated states may have smaller (larger) relevant market areas. This may mechanically correlate with the number of dealerships selling new cars in a market, ceteris paribus.

[Figure 2]

To address this challenge, I use an instrumental variable similar in spirit to Mian and Sufi 2011, which use housing supply elasticity based on developable lands as an instrument for house price growth. I, however, use the interaction of the state-level relevant market area and the amount of developable land as my instrumental variable. Using satellite-based data on terrain elevation and presence of water bodies, Saiz 2010 precisely estimates the amount of developable land within a 50-km radius of each U.S. metropolitan central city. He first measures the area that is unavailable for residential or commercial real estate development.[13] Using elevation data from the USGS Digital Elevation Model (DEM) at its 90-m resolution, he uses a GIS software to calculate the exact share of the area corresponding to land with a slope above 15% within a 50-km radius of each metropolitan central city. Next, Saiz 2010 uses the 1992 USGS National Land Cover Dataset and contour maps to calculate land forgone to oceans, the Great Lakes, wetlands, lakes, rivers, and other internal water bodies. He then measures the amount of developable land at the MSA level.

To construct my instrumental variable, I use the interaction of the state-level variation in the predetermined developable land and the state-level relevant market area. To illustrate, assume two local markets with the same relevant market area of 10 miles; one is severely land-constrained by its geography, and another is completely flat with no area lost to internal water bodies, wetlands, or lands with slopes above 15%. The land-constrained market should experience less local competition among dealerships because the potential number of dealerships selling new cars is limited, which leads to higher market concentration. In contrast, the local market with more developable areas should experience more local competition because entry to this market is easier and the potential number of dealerships selling new cars is not limited by the predetermined geographic features.

To provide suggestive visual evidence of the effect of the predetermined developable lands on the potential number of dealerships selling new cars, I illustrate two hypothetical markets, in which a market is defined as a 50-kilometer (or 31.07-mile) radius. Figure 3 Panel A shows that Market 1 is a flat land with no area forgone to the sea, internal water bodies and wetlands, and the lands have slopes above 15%. Market 2, however, is land-constrained by its geography. These predetermined geographic features limit the potential number of dealerships selling new cars in Market 2.

[Figure 3 Panel A]

Figure 3 Panel B shows that the maximum number of dealers selling new cars in Market 1 (Market 2) is 7 (5).[14] This variation exclusively comes from the predetermined geographic features

13. Under architectural development guidelines, land with slope above 15% is severely constrained for real estate development.

14. In this example, I assume car dealers have perfect market power within their relevant market area. In other words, I assume there is no overlap between dealers' relevant market areas. This understates the potential number of dealers in a given market. This should have no effect on my main results since I use a relative measure.

of each market. One obvious concern with this instrumental variable is that the amount of the predetermined developable lands may affect vehicle prices and/or loan markups other than through the number of dealerships selling new cars, violating the exclusion restriction condition.

[Figure 3 Panel B]

To address this concern, first, I use developable land quartile fixed effects as well as a set of borrowers and vehicle characteristics to control for potential omitted variables. Second, I use a unique feature of this instrument, in which it affects only car dealerships selling new cars. As a placebo test, I show that the instrument does not predict the number of dealerships selling used cars. This suggests that the results are not driven by unobservable differences across states.

To construct my instrumental variable, I use satellite-based geographic data from Saiz 2010.[15] I first calculate *Developable Areas* at the MSA level by subtracting the areas forgone from total available areas within 31-mile radii (or 961π square miles). Since the granularity level of auto loan data is at the state level, I then construct *Developable Areas* at the state level by calculating a simple arithmetic average of *Developable Areas* at the MSA level using Equation 1:

$$Developable\ Area_s = \frac{\sum_{i=1}^{n} Developable\ Area_{s,i}}{n_s} \tag{1}$$

where n_s is the total number of MSAs in state s. Next, I divide the average developable areas at the state level by the corresponding state-level relevant market area squared (πRMA_s^2) using Equation 2:

$$Potential\ Number\ of\ Dealers_s = \frac{Developable\ Area_s}{\pi\ RMA_s^2} \tag{2}$$

where *Potential Number of Dealers*$_s$ measures the maximum number of new car dealerships selling the same line-make vehicles in state s. Next, using the location of new car dealerships from AtoZ databases, I calculate the number of new car dealerships selling the same line-make vehicle v (e.g., new 2018 Toyota Camry) within a 50-kilometer (31.07-mile) radius from metropolitan central cities. To be consistent with the granularity level of the instrument, I then calculate the number of

15. I thank Albert Saiz for sharing this data.

new car dealers selling the same line-make vehicle v at the state level using Equation 3:

$$Number\ of\ Dealers_{v,s} = \frac{\sum_{i=1}^{n} Number\ of\ Dealers_{i,v,s}}{n_s} \tag{3}$$

where $Number\ of\ Dealers_{v,s}$ measures the endogenous number of new car dealers selling the same line-make vehicles v in state s. $Number\ of\ Dealers_{i,v,s}$ is the number of new car dealerships selling the same line-make vehicles v in the MSA i in the state s, and n_s is the total number of MSAs in state s.

The reverse causality and omitted variables could be a problem in a naïve regression of loan markups on the endogenous number of dealerships selling new cars in a market. For example, the number of dealers selling new cars may be correlated with market-specific characteristics in a way that confound the causal interpretation of my point estimate. To address the endogeneity concerns, I instrument the number of dealerships selling new cars by the potential number of dealerships selling new cars stemming from the relationship between the state-level relevant market area and the amount of developable land in a given market. To formalize the instrumental variable approach, I run the two-stage least squares (2SLS) regression outlined in Equations 4 and 5:

$$Number\ of\ Dealers_{v,s} = \alpha + \beta_1 Potential\ Number\ of\ Dealers_s + \delta_{rma} + \delta_{dl} + \delta_{l,t} + \delta_{v,t} + \delta_{i,t} + \delta_{c,t} + \epsilon \tag{4}$$

$$Loan\ Markups_{v,l,c,i,s,t} = \alpha + \gamma_1 \widehat{Number\ of\ Dealers}_{v,s} + \delta_{rma} + \delta_{dl} + \delta_{l,t} + \delta_{v,t} + \delta_{i,t} + \delta_{c,t} + \epsilon \tag{5}$$

where $Loan\ Markups_{v,l,c,i,s,t}$ is the loan markup for auto loans originated by lender l for borrowers with income i and credit score s, who purchase new vehicle v at time t and state s. $Potential\ Number\ of\ Dealers_s$ is the instrumental variable based on the interaction of the state-level relevant market area and the amount of developable land in a given market. $Number\ of\ Dealers_{v,s}$ is the number of new car dealerships selling the same line-make vehicles v in state s. The key variable of interest, $\widehat{Number\ of\ Dealers}_{v,s}$, is a continuous variable, that captures the instrumented number of new car dealerships selling the same line-make vehicles v in state s. δ_{rma} is relevant market area fixed effects and controls for unobservable differences across relevant market areas. δ_{dl} is developable land quartile fixed effects and ensures that the variation in the amount of developable land is not driven by states with an extreme amount of developable lands. I also control for quality of borrowers by adding income fixed effects ($\delta_{i,t}$) and credit score fixed effects ($\delta_{c,t}$). The income fixed effects are defined as $50,000 income bins and the credit score fixed effects are defined as a 25-point credit bin. Moreover, I include lender fixed effects ($\delta_{l,t}$) to ensure that the variation in loan markups is not driven by variation in the pricing strategies of auto lenders. Finally, I add vehicle fixed effects ($\delta_{v,t}$) to estimate the effect of competition for homogeneous vehicles. Vehicle fixed effects refer to vehicle make-model-model year combinations. This ensures that the variation in loan markups is not driven by variation in quality of vehicles. Standard errors are clustered at the state level.

3 Data and Sample Selection

My main data source comes from Regulation AB II. As part of the Dodd-Frank Act, the Securities and Exchange Commission (SEC) reformed the rules governing the asset-backed securities (ABS) market, which resulted in Regulation AB II (Reg AB II). Under this regulation, issuers of public auto loan asset-backed securities (ABS) are required to report loan-level information to the Securities and Exchange Commission at a monthly frequency (Sweet, 2015). The data includes information on loan, vehicle, and borrower characteristics as of the loan origination date, as well as loan performance histories over the entire life of each loan.

As of May 2020, there are more than 11 million unique loans (183 million loan-month observations) in the dataset. The loans come from 181 distinct ABS and 19 lenders. Fourteen of the top 20 auto lenders in the United States are in the Reg AB II data. The data contains two types of lenders: (1) indirect lenders that mainly originate loans through car dealerships, and (2) lenders that originate both direct and indirect loans. Indirect lenders include AmeriCredit, BMW Financial Services, Ford Motor Credit Company, GM Financial, American Honda Finance Corporation, Hyundai Motor Finance, Mercedes-Benz Financial Services, Nissan Finance, Toyota Financial Services, Volkswagen Financial Service, and World Omni Financial Corporation. Loans from indirect lenders make up 68 percent of the data. Lenders that originate both direct and indirect loans include Ally Bank, Mechanics Banks (California Republic Bank), Capital One Financial Corporation, CarMax Auto Finance, Fifth Third Bank, Santander Bank, and the United Services Automobile Association (USAA).

I restrict the estimation sample to auto loans originated after 2017 and loans originated within the United States. I remove loans with income above $250,000, vehicle values above $100,000, and interest rates above 30 percent. I also restrict my estimation sample to indirect lenders, eliminating concerns regarding different compensation schemes across auto loan brokers. I also drop subvented loans[16] from my estimation sample for two reasons: (1) car dealers are not allowed to mark up interest rate for subvented loans, and (2) subvented loans may add measurement errors in the estimated buy rates and markups.

I also remove loans with credit scores below 620 for two reasons. First, Jansen, Kruger, and Maturana 2021 find that car dealerships may treat prime and subprime borrowers differently. They show that subprime borrowers receive subsidized financing in terms of a discount at which the lender is willing to purchase the loan from the dealer. Car dealers, however, mark up interest rates to borrowers with higher credit scores. This filter ensures that markups for borrowers in my sample are rarely negative. Second, to calculate risk-adjusted interest rates for subprime borrowers, lenders may rely not only on hard information (credit score, loan to value ratio, loan maturity, etc.), but also on soft information (Grunewald et al. 2020). Excluding subprime borrowers increases my confidence that the estimated risk-adjusted interest rates come solely from hard information. This may mitigate the measurement errors in estimated loan markups.

My primary outcome variables are loan markups and vehicle prices. In the indirect auto lending, the interest rate that is offered to a borrower consists of two parts: the lender's buy rate and the dealer's markup. The lender's buy rate is a risk-adjusted rate. The dealer's markup, however, is

16. Subvented loans are commonly referred to auto loans that a car manufacturer reduces the cost of financing through cash back programs or rate rebate programs.

discretionary. In other words, the lender's buy rate is the minimum interest rate that the indirect lender will require for the loan. I use this feature of the indirect auto lending to estimate the dealer's markups. Specifically, I first estimate the lender's buy rate by calculating the minimum interest rate among loans originated from the same lender for similar borrowers for the same vehicle at the same time and state. Then, I calculate estimated markups by subtracting the estimated lender's buy rate from interest rates of similar loans. I construct the loan markup variable using Equation 6.

$$Loan\ Markup_{j,v,l,c,i,s,t} = Interest\ Rate_{j,v,l,c,i,s,t} - Min[Interest\ Rate_{v,l,c,i,s,t}] \tag{6}$$

where the outcome variable, $Loan\ Markup_{j,v,l,c,i,s,t}$, is the difference between interest rate for loan j and the minimum interest rate charged by the same lender (e.g., Toyota Financial Services) for borrowers with the same income and credit score, who buy the same vehicle (e.g., new 2018 Toyota Camry) in the same quarter and state. In the estimation sample, I drop cells with only one observation, ensuring that there is enough variation in each cell.

Since the Regulation AB II data does not include vehicle prices, I use a new dataset from the Texas Department of Motor Vehicles. The data consists of information on the make, model, and model year of the purchased car as well as the car sales price and the time of purchase. Using the average car sales price at the make-model-model year-month of purchase level, I estimate Equation 7:

$$Vehicle\ Price_{v,t} = \alpha + \eta_1 Loan\ Size_{v,t,j} + \eta_2 Car\ Value_{v,t,j} + \delta_t + \delta_{vehicle\ value\ source} + \epsilon \tag{7}$$

where $Vehicle\ Price_{v,t}$ is the average vehicle sales price from the Texas Department of Motor Vehicles, $Loan\ Size_{v,t,j}$ is the loan amount for borrower j who purchased vehicle v at time t, $Car\ Value_{v,t,j}$ is the car value for borrower j who purchased vehicle v at time t, δ_t is a list of dummy variables for each month, $\delta_{vehicle\ value\ source}$ is a list of dummy variables for the source of vehicle value. The R^2 for the above regression is 0.871, suggesting that the explanatory variables in the regression explain the vast majority of the variation in vehicle sales prices from the Texas Department of Motor Vehicles. Next, I estimate vehicle prices in the Regulation AB II data by using estimated coefficients from the above regression.

The second data source I use is AtoZ Databases. The data provides information on both new and used car dealerships, including business name, physical address, website, employees' name and gender, primary SIC number, NAICS number, and year established. I first use the latitude and longitude of dealerships selling new cars to calculate the number of dealerships selling new cars within 50 kilometers (31 miles) of each metropolitan central city. I then repeat this procedure to calculate the number of dealerships selling used cars in a given market. The third data source comes from the Summary of Deposits (SOD) provided by the Federal Deposit Corporation (FDIC). The data provides the physical location of every bank branch in the United States. I use the longitude and latitude of each bank branch to calculate the number of banks within 50 kilometers (31 miles) of each metropolitan central city.

Table 1 presents the summary statistics for the estimation sample as of the origination date. The sample contains of 91,405 unique loans. The average loan in the sample has an interest rate of 449 basis points, a markup of 236 basis points, a scheduled monthly payment of $465, a vehicle price of $24,974, a maturity of 68 months, and an initial principal of $27,250. The average loan to value ratio is 89.63 percent. The average borrower has a credit score of 754 and a household income of $80,412. The average number of dealerships selling new cars in a market is 3.62 and the potential number of dealerships selling new cars is 8.13.

4 Empirical results

In this section, I first provide some empirical evidence to support the validity of my instrumental variable, then I explore how the local competition among dealerships selling new cars affects the joint pricing of cars and car loans. I then discuss potential channels through which this effect can be explained.

4.1 Validity of the instrument

Since the number of dealerships selling new cars, vehicle prices and loan markups are likely to be jointly determined, I use the instrumental variable outlined in Section 2.2 to estimate the causal effect of local competition among dealerships on the joint pricing of cars and car loans. In particular, I instrument the endogenous number of dealerships selling new cars via the potential number of dealers selling new cars stemming from the interaction between the state-level relevant market area and the amount of developable land in a given market. To have unbiased point estimates, a valid instrument should satisfy two conditions: the relevance and exclusion restriction conditions.

4.1.1 Relevance condition

To begin, I first provide evidence to satisfy the relevance condition by estimating Equation 4. Table 2 reports that the instrument statistically and economically predicts the number of dealerships selling new cars. Columns (1) through (3) show that the economic magnitude of the coefficient of interest, (β_1), is stable across different specifications: a one unit increase in the potential number of dealerships selling new cars is associated with a 1.22 unit increase in the number of dealerships selling new cars.[17] This suggests that the instrument is not driven by omitted variables correlated with the quality of borrowers across markets.

In Column (3), I also find that the first-stage f-statistic is 19.74, which exceeds the rule of thumb for strong instruments ($F >= 10$) proposed by Staiger and Stock 1997. This satisfies the relevance condition and confirms that the weak instrument problem is less likely to be a concern. Since my instrumental variable meets the relevance condition of being a valid instrument, we would expect to observe the reduced form relation between the instrument and vehicle prices. In Columns (4) and (5), I find exactly this relation. I find that a one unit increase in the potential number of dealerships selling new cars is associated with a statistically significant decrease in vehicle prices and increase in loan markups.

17. I assume no overlaps between the potential number of dealerships. This leads to the underestimation of the potential number of dealerships.

4.1.2 Exclusion restriction condition

Next, for the causal interpretation of my results, I should satisfy the exclusion restriction condition, in which the potential number of dealerships selling new cars has no direct effect on vehicle prices or loan markups other than through the number of dealerships selling new cars. Although the exclusion restriction cannot be tested directly, I provide some evidence to support its validity.

Since the potential number of dealerships selling new cars in a market is not fundamentally randomly assigned, it is reasonable to be concerned that market-specific characteristics could violate the exclusion restriction condition. For example, the interaction of the state-level relevant market area and the amount of developable land in a market might be systematically correlated with state-level macroeconomic variation in a way that would confound the causal interpretation of my findings. To address this concern, I provide some evidence to support the validity of the instrument.

State-level outcomes: First, I test in the reduced form if the instrument predicts state-level macroeconomic outcomes by estimating Equation 8.[18]

$$Y_{s,t} = \alpha + \beta_1 \textit{Potential Number of Dealers}_s + \delta_{rma} + \delta_{dl} + \delta_t + \epsilon \tag{8}$$

where the outcome variable (Y) is a list of state-level macroeconomic variables. Observations are at the state and quarter level. $\textit{Potential Number of Dealers}_s$ is the potential number of dealers selling new cars in state s. I also include relevant market area fixed effects (δ_{rma}) and developable land quartile fixed effects (δ_{dl}) to ensure that the coefficient of interest (β_1) is estimated from the within variation in the developable land quartiles, similar in spirit to Mian and Sufi 2011. I also include time fixed effects (δ_t) to control for time trends.

Table 3 reports the coefficient of interest (β_1) from Equation 8. In Columns (1) and (2), I find no evidence that the instrument is correlated with state-level GDP per capita and income per capita, suggesting that the instrument does not capture the state-level variation in the economic condition.

18. To be consistent with the weighting scheme of my specifications throughout the paper, I also estimate this equation at the loan level after including lender fixed effects, vehicle fixed effects, income fixed effects, and credit score fixed effects. The results are quantitatively and qualitatively robust.

In Column (3), I find no evidence that the instrument is correlated with the state-level variation in the regional price parity across states. This suggests that my instrumental variable does not capture the differences in price levels across states. In Column (4), I find that the instrument does not statistically or economically predict state-level unemployment rate. In Column (5), I find that the instrument does not statistically or economically predict the fraction of people with a bachelor's degree as a proxy for consumers financial sophistication. In Column (6), I find no evidence that the instrument predicts state-level variation in access to the internet as a proxy for consumers search cost. Finally, in Column (7), I also find that the instrument is not correlated with the state-level sales tax.

Selection on unobservables: Despite finding no evidence that the instrument is correlated with the state-level macroeconomic outcomes, it is still possible that states differ on some unobservable characteristics that may explain my findings. To address this concern, I provide out-of-sample evidence to support the validity of exclusion restriction condition. I exploit a unique feature of my instrumental variable, in which it affects only the number of dealerships selling new cars in a market. In other words, as a placebo test, I test if the instrument is correlated with (1) the number of dealerships that exclusively sell used cars, or (2) the number of banks in a market. I estimate Equation 9:

$$Y_{v,l,c,i,s,t} = \alpha + \beta_1 \textit{Potential Number of Dealers}_s + \delta_{rma} + \delta_{dl} + \delta_{l,t} + \delta_{v,t} + \delta_{i,t} + \delta_{c,t} + \epsilon \tag{9}$$

where $Y_{v,l,c,i,s,t}$ is the number of dealerships selling only used vehicles or the number of banks in a given market. As an additional robustness check, I also re-estimate this equation at the state and quarter level and show that the results are robust. In Table 4 Column (1), I find that the instrument does not statistically or economically predict the number of car dealerships that exclusively sell used cars. In Column (2), I find that the instrument does not statistically or economically predict the number of banks. These results suggest that the instrument is not correlated with the general demand for vehicles or auto loans across states. This also outlines my next tests, in which the instrument should be irrelevant in predicting the variation in vehicle prices and loan markups for old used vehicles. Columns (3) to (4) in Table 4 show that the instrument becomes statistically and economically insignificant in predicting vehicle prices for older used cars. Columns (5) to (6) show the results for loan markups. These results suggest that the instrument is less likely to be correlated with unobservable differences across markets. Overall, my findings suggest that the instrument has no direct effect on vehicle prices and loan markups other than through the number of dealerships selling new cars.

4.2 Baseline results

In this section, I first present the instrumental variable results, then I do a back-of-the-envelope calculation to measure the aggregate cost.

4.2.1 Local competition among auto dealers and prices

To begin, I use the instrument outlined in Section 2.2 to explore the causal effect of local competition among auto dealers on the joint pricing of cars and car loans by simultaneously estimating Equations 4 and 5. Table 5 Columns (1) and (2) present my main findings. The key explanatory variable of interest is the instrumented number of dealerships selling new cars.

In Column (1), I find that a one unit increase in the instrumented number of dealerships selling new vehicles is associated with a \$88.6 decrease in vehicle prices. This effect is statistically and economically important given that the net profit margin on new vehicles is only 2-5%. To be more specific, this translates to a 7.1-17.7% decrease in auto dealers net profit margins.[19] In Column (2), I find that a one unit increase in the instrumented number of dealerships selling new vehicles is associated with a 16.8 basis point increase in loan markups. This effect is statistically and economically important, the unconditional average markup in my estimation sample is 236 basis points. In other words, a one unit increase in the number of dealerships is associated with a 7.2%

19. The average price for new vehicles in my sample is about \$25,000. Thus, the average net profit margin is \$500-\$1250.

increase in loan markups. This increase in loan markups offsets the decline in vehicle prices induced by increased competition. In Column (3), I show that increased competition does not statistically and economically affect monthly payment, suggesting that auto dealers recover their losses on vehicle prices by charging higher prices on loan markups such that consumers' monthly payments do not change.

4.3 Economic channel: Monthly payment targeting

In this section, I examine if monthly payment targeting is the channel through which local competition among auto dealers affects the joint pricing of cars and car loans. Argyle, Nadauld, and Palmer 2020a find that many consumers in the auto loan market target specific monthly payment amounts (e.g., \$200, \$300, and \$400 per month). If increased competition leads to lower vehicle prices, then the corresponding monthly payment amounts mechanically decrease too. Auto dealers may adjust auto loan contract terms such that consumers' monthly payments are the same across markets.

To investigate this prediction in my sample, I first show bunching around salient monthly payments. Figure 4 plots the McCrary bunching test of normalized monthly payments around hundred dollar increments from \$100 to \$600. This is consistent with the monthly payment targeting bias in which consumers in the auto loan market target specific monthly payments. Next, I find no evidence that increased competition affects monthly payments. Table 5 Column (3) shows that increased competition does not statistically or economically affect monthly payments. Furthermore, I find that increased competition has no effect on other contract terms. Table 6 Columns (1) through (3) show that the effect of competition on other contract terms is economically insignificant. Table 6 Columns (4) through (5) show that increased competition has little to no effect on the ex-ante measures of quality of borrowers. Column (6) complements this analysis by showing that the competition has no effect on the 24-month default rate, suggesting that increased competition does not lead to a change in the composition of borrowers.

I also show that the results are stronger among less financially savvy consumers. Table 7 shows that the monthly payment targeting bias is stronger among low credit score borrowers. Table 8 repeats the same analysis across income and shows that low-income borrowers are suffering more from this bias.

4.4 Alternative explanations

In this section, I discuss other potential explanations for my findings. I can rule out adverse selection, costly lender screening, moral hazard, search costs as explanations for my findings.

4.4.1 Adverse selection

A plausible explanation for my findings is adverse selection. Intuitively, if auto dealers charge higher prices on loan markups, price-sensitive borrowers may walk away, resulting in a change in the composition of borrowers. This explanation also implies that increased competition among auto dealers should shrink the pool of borrowers. This, however, is in contrast with the positive relation between the local competition among auto dealers and number of loan originations, suggesting that the adverse selection explanation is less likely to be the main channel through which the competition among auto dealers affects the joint pricing of cars and car loans.

4.4.2 Costly lender screening

Another plausible explanation for my findings is the variation in costly lender screening across markets. Yannelis and Zhang 2021 find that in more competitive markets, lenders have less incentives to monitor borrowers through investing in screening technologies, which can lead to a riskier pool of borrowers and higher interest rates. The intuition of their paper is largely irrelevant in my setting for several reasons.

First, Yannelis and Zhang 2021 investigates the competition effect in the direct auto loan market, in which auto lenders originate loans directly to borrowers. I, however, test the effect of competition among auto dealers in the indirect auto loan market, which is at the national level. Second, Yannelis and Zhang 2021 documents that the positive relation between the level of competition and interest rate is concentrated among subprime borrowers with a credit score of 620 or below. I, however, restrict my estimation sample to prime borrowers with a credit score of 620 or above. Third, all my analyses are within the lender level, suggesting that the lenders' screening costs are irrelevant in my setting. All in all, my findings suggest that the costly lender screening cannot be the channel through which the local competition among auto dealers affects loan markups.

4.4.3 Moral hazard

A change in consumers' behavior could appear to explain the positive relation between the number of dealers selling new cars and loan markups. Borrowers with higher loan markups are more likely to default than borrowers with low loan markups. The implied assumption of this explanation is that the existing borrowers change their behavior through stopping their payments. This assumption is, however, in contrast with my results that increased competition does not change both ex-ante and ex-post measures of the quality of borrowers, suggesting that the moral hazard channel is less likely to be the main channel driving my results.

4.4.4 Search costs

Another plausible explanation for my findings is a change in demand induced by a change in consumers' search cost. An increase in the number of auto dealers may reduce consumers' search cost, leading to higher demand for vehicles. This increases both the number of loan originations and vehicle prices and their financing. This intuition, however, is largely incorrect since in all of my specifications, I control for consumers search costs by adding relevant market area fixed effects. This ensures that my findings are not driven by a change in consumers' search costs.

4.5 Robustness

4.5.1 Intra-brand vs. inter-brand competition

Throughout this paper, I estimate the effect of intra-brand local competition of new car dealers on vehicle prices and loan markups for at least two reasons. First, the state automobile franchise laws directly affect new car dealerships selling the same line-make vehicles. Second, investigating the intra-brand competition for new vehicles ensures that the variation in vehicle prices and loan markup is not driven by differentiated products. After establishing my main findings, a natural question is whether the local competition of auto dealers is limited to the same line-make vehicles or whether it affects vehicles across different models or makes. To answer this question, I estimate the effect across (1) vehicle body types, and (2) car value bins.

To begin, I first estimate the effect of local competition among auto dealers after adding vehicle body types fixed effects. I define vehicle body types as sedan, coupe, sports car, station wagon, hatchback, convertible, sport-utility vehicle (SUV), minivan, and pickup truck. Table A.1 Panel A shows that the results are consistent with my main results, suggesting that my results are not exclusive to intra-brand local competition of dealerships selling new cars.

Next, I estimate the effect of local competition among auto dealers on price of cars and car loans after adding car value fixed effects. I define car value bins as car value quartiles. Consistent with the prior results, Table A.1 Panel B shows that increased competition leads to lower vehicle prices, higher loan markups, and higher default rates.

4.5.2 Standard errors

In this section, I test whether my results are robust to different clustering schemes (Cameron and Miller 2015). In Table A.2, I re-estimate my main specification clustering standard errors at different levels, including state-lender, lender, make-model-model year, and year quarter levels. Overall, I find that my findings do not change when using different clustering schemes.

4.5.3 Alternative bins

As a robustness check, I also re-estimate my main specification using different bins. The purpose of these tests is to examine whether my results are robust to different bin sizes. I test my main findings across four different bin sizes. In *Bin size 1*, I calculate loan markups while conditioning on loan contract terms such as loan to value ratio and loan maturity. Column (2) reports the results for cells with at least two observations. In *Bin size 2*, I test if my findings are still robust if I apply tighter filters such as 5-point credit bins and $10,000 income bins. Columns (3) and (4) show that the results are robust to tighter filters. Column (4) reports the results for cells with at least two observations. In *Bin size 3*, I investigate if my results are robust if I apply more generous filters such as 10-point credit bins and $25,000 income bins. In Columns (5) and (6), I show that the results are robust. In *Bin size 4*, I explore if my findings are robust if I apply more generous filters. In Columns (7) and (8), I show that the results are robust if I calculate loan markups using 50-credit bins, $50,000 income bins, and semi annual bins. Overall, my findings do not change when I use different bin sizes.

4.5.4 Sample filters

Next, I show that my sample filters do not affect my results. In Table A.4, I re-estimate my main specification after adjusting the filters applied in Section 3. In Columns (1) through (3), I find that the results are robust when I relax the credit score thresholds. Column (4) shows that my results are robust when I relax the income threshold. Columns (5) shows that my findings are robust if I limit my sample to non-zero markup loans. Columns (6) shows that my findings are robust if I control for more granular developable land fixed effects. Overall, Table A.4 shows that adjusting for sample filters does not change my main findings.

4.5.5 Measurement error

One may be concerned that the loan markup measurement error is likely to be correlated with the market size in a way that confound the causal interpretation of my point estimate. To address this concern, in Table A.5, I show that the results are robust for cells with at least 5, 20 or 30 observations.

One concern could be that estimated loan markups are a very noisy proxy of actual loan markups. To address this concern, in Figure A.1, I show the kernel density distribution of both my sample and a sample of subvented loans. This result shows that the majority of estimated loan markups for subvented loans are zero, consistent with the idea that auto dealers are not allowed to add a loan markup on top of a lender's baseline interest rate. This suggest that the estimated loan markup is a reliable proxy for the actual loan markup. In Table A.6, I also show that the instrument does not statistically or economically predict the likelihood of subvented loans to address concerns regarding automakers' selling strategies across markets.

5 Conclusion

In this paper, I provide empirical evidence of the causal effect of local competition among auto dealers on the joint pricing of cars and car loans. Similar in spirit to Mian and Sufi 2011, I construct an instrumental variable based on variation in the number of dealers imposed by predetermined geographic features of a market and state-level franchise laws. After supporting the validity of my instrumental variable, I find that increased competition leads auto dealers to decrease vehicle prices to attract consumers and to charge higher prices on loan markups. By doing so, auto dealers offset about 75 percent of their losses on vehicle prices. I also provide evidence that this price adjustment at the intensive margin comes from the monthly payment targeting channel. My findings support that sophisticated sellers such as auto dealers exploit behavioral biases of consumers to maximize their profits.

References

Agarwal, Sumit, Changcheng Song, and Vincent Yao. 2022. "Banking competition and shrouded attributes: Evidence from the US mortgage market." *Available at SSRN 2900287.*

Allen, Jason, Robert Clark, and Jean-François Houde. 2014. "The effect of mergers in search markets: Evidence from the Canadian mortgage industry." *American Economic Review* 104 (10): 3365–96.

Ambrose, Brent W, and James N Conklin. 2014. "Mortgage brokers, origination fees, price transparency and competition." *Real Estate Economics* 42 (2): 363–421.

Anagol, Santosh, Shawn Cole, and Shayak Sarkar. 2017. "Understanding the advice of commissions-motivated agents: Evidence from the Indian life insurance market." *Review of Economics and Statistics* 99 (1): 1–15.

Anglin, Paul, and Richard Arnott. 1999. "Are brokers' commission rates on home sales too high? A conceptual analysis." *Real Estate Economics* 27 (4): 719–749.

Argyle, Bronson, Taylor Nadauld, and Christopher Palmer. 2020a. "Monthly payment targeting and the demand for maturity." *The Review of Financial Studies* 33 (11): 5416–5462.

———. 2020b. "Real effects of search frictions in consumer credit markets." *Working paper.*

Beard, T Randolph, and George S Ford. 2016. "State automobile franchise laws: public or private interests?" *Phoenix Center Perspectives,* 16–06.

Beck, Jason, Frank Scott, and Aaron Yelowitz. 2012. "Concentration and market structure in local real estate markets." *Real Estate Economics* 40 (3): 422–460.

Becker, Gary S. 1957. *The economics of discrimination.* University of Chicago press.

Benneton, Matteo, Sergio Mayordomo, and Daniel Paravisini. 2022. "Credit fire sales: Captive lending as liquidity in distress." Working paper.

Brown, Gary Michael. 1980. "State motor vehicle franchise legislation: A survey and due process challenge to board composition." *Vand. L. Rev.* 33:385.

Brown, Jennifer, Tanjim Hossain, and John Morgan. 2010. "Shrouded attributes and information suppression: Evidence from the field." *The Quarterly Journal of Economics* 125 (2): 859–876.

Brown, Jennifer, and Mark Jansen. 2020. "Consumer protection laws in auto lending." *Working paper.*

Buchak, Greg, and Adam Jørring. 2021. "Do mortgage lenders compete locally? Implications for credit access." *Implications for Credit Access (January 7, 2021).*

Busse, Meghan R, and Jorge M Silva-Risso. 2010. ""One Discriminatory Rent" or" Double Jeopardy": Multicomponent Negotiation for New Car Purchases." *American Economic Review* 100 (2): 470–74.

Butler, Alexander W, Erik J Mayer, and James Weston. 2021. "Racial discrimination in the auto loan market." *Available at SSRN 3301009.*

Cameron, Colin A., and Douglas L. Miller. 2015. "A practitioner's guide to cluster-robust inference." *Journal of Human Resources* 50 (2): 317–372.

Carlin, Bruce I. 2009. "Strategic price complexity in retail financial markets." *Journal of financial Economics* 91 (3): 278–287.

Chioveanu, Ioana, and Jidong Zhou. 2013. "Price competition with consumer confusion." *Management Science* 59 (11): 2450–2469.

Cohen, Mark A. 2012. "Imperfect competition in auto lending: Subjective markup, racial disparity, and class action litigation." *Review of Law and Economics* 8 (1): 21–58.

Dick, Astrid A, and Andreas Lehnert. 2010. "Personal bankruptcy and credit market competition." *The Journal of Finance* 65 (2): 655–686.

Dimmock, Stephen G, William C Gerken, and Nathaniel P Graham. 2018. "Is fraud contagious? Coworker influence on misconduct by financial advisors." *The Journal of Finance* 73 (3): 1417–1450.

Egan, Mark. 2019. "Brokers versus retail investors: Conflicting interests and dominated products." *The Journal of Finance* 74 (3): 1217–1260.

Egan, Mark, Gregor Matvos, and Amit Seru. 2019. "The market for financial adviser misconduct." *Journal of Political Economy* 127 (1): 233–295.

Einav, Liran, Mark Jenkins, and Jonathan Levin. 2012. "Contract pricing in consumer credit markets." *Econometrica* 80 (4): 1387–1432.

Elder, Harold W, Leonard V Zumpano, and Edward A Baryla. 1999. "Buyer search intensity and the role of the residential real estate broker." *The Journal of Real Estate Finance and Economics* 18 (3): 351–368.

Ellison, Glenn. 2005. "A model of add-on pricing." *The Quarterly Journal of Economics* 120 (2): 585–637.

Ellison, Glenn, and Sara Fisher Ellison. 2009. "Search, obfuscation, and price elasticities on the internet." *Econometrica* 77 (2): 427–452.

Ellison, Glenn, and Alexander Wolitzky. 2012. "A search cost model of obfuscation." *The RAND Journal of Economics* 43 (3): 417–441.

Gabaix, Xavier, and David Laibson. 2006. "Shrouded attributes, consumer myopia, and information suppression in competitive markets." *The Quarterly Journal of Economics* 121 (2): 505–540.

Gerken, William, and Morteza Momeni. 2022. "Third party quality certification in the market for financial advice." Working paper.

Gissler, Stefan, Rodney Ramcharan, and Edison Yu. 2020. "The effects of competition in consumer credit markets." *The Review of Financial Studies* 33 (11): 5378–5415.

Greenleaf, Eric A, Eric J Johnson, Vicki G Morwitz, and Edith Shalev. 2016. "The price does not include additional taxes, fees, and surcharges: A review of research on partitioned pricing." *Journal of Consumer Psychology* 26 (1): 105–124.

Grunewald, Andreas, Jonathan A. Lanning, Lowm David C., and Tobias Salz. 2020. "Auto dealer loan intermediation: Consumer behavior and competitive effects." NBER Working Paper No. 28136.

Hankins, Kristine W, Morteza Momeni, and David Sovich. 2022. "Does trade policy affect consumer credit? The role of captive finance."

Hossain, Tanjim, and John Morgan. 2006. "... plus shipping and handling: Revenue (non) equivalence in field experiments on ebay." *The BE Journal of Economic Analysis & Policy* 6 (2).

Jansen, Mark, Samuel Kruger, and Gonzalo Maturana. 2021. "Dealer financing in the subprime auto market: Markups and implicit subsidies." *Available at SSRN 3902847.*

Jansen, Mark, Hieu Nguyen, Lamar Pierce, and Jason Snyder. 2021. "Product sales incentive spillovers to the lending market." *Working paper.*

Jansen, Mark, Hieu Nguyen, and Amin Shams. 2021. "Rise of the machines: The impact of automated underwriting." *Fisher College of Business Working Paper,* nos. 2020-03, 019.

Jovanovic, Boyan. 1982. "Truthful disclosure of information." *The Bell Journal of Economics,* 36–44.

Lafontaine, Francine, and Fiona Scott Morton. 2010. "Markets: State franchise laws, dealer terminations, and the auto crisis." *Journal of Economic Perspectives* 24 (3): 233–50.

Laibson, David I, and Yeeat Yariv. 2007. "Safety in markets: An impossibility theorem for dutch books."

Lanning, Jonathan A. 2021. "Testing models of economic discrimination using the discretionary markup of indirect auto loans."

Levitin, Adam J. 2019. "The Fast and the usurious: Putting the brakes on auto lending abuses." *Geo. LJ* 108:1257.

Marx, Thomas G. 1985. "The development of the franchise distribution system in the US automobile industry." *Business History Review* 59 (3): 465–474.

Melzer, Brian, and Aaron Schroeder. 2017. "Loan contracting in the presence of usury limits: Evidence from automobile lending." *Consumer Financial Protection Bureau Office of Research Working Paper,* nos. 2017-02.

Melzer, Brian T, and Donald P Morgan. 2015. "Competition in a consumer loan market: Payday loans and overdraft credit." *Journal of Financial Intermediation* 24 (1): 25–44.

Mian, Atif, and Amir Sufi. 2011. "House prices, home equity-based borrowing, and the US household leverage crisis." *American Economic Review* 101 (5): 2132–56.

Milgrom, Paul R. 1981. "Good news and bad news: Representation theorems and applications." *The Bell Journal of Economics,* 380–391.

Momeni, Morteza, and David Sovich. 2022. "The marginal propensity to default." Working paper.

Piccione, Michele, and Ran Spiegler. 2012. "Price competition under limited comparability." *The quarterly journal of economics* 127 (1): 97–135.

Robles-Garcia, Claudia. 2022. "Competition and incentives in mortgage markets: The role of brokers." *Working paper.*

Saiz, Albert. 2010. "The geographic determinants of housing supply." *The Quarterly Journal of Economics* 125 (3): 1253–1296.

Spiegler, Ran. 2006. "Competition over agents with boundedly rational expectations." *Theoretical Economics* 1 (2): 207–231.

Staiger, Douglas O, and James H Stock. 1997. "Instrumental variables regression with weak instruments." *Econometrica* 65 (3): 557–586.

Woodward, Susan E, and Robert E Hall. 2012. "Diagnosing consumer confusion and sub-optimal shopping effort: Theory and mortgage-market evidence." *American Economic Review* 102 (7): 3249–76.

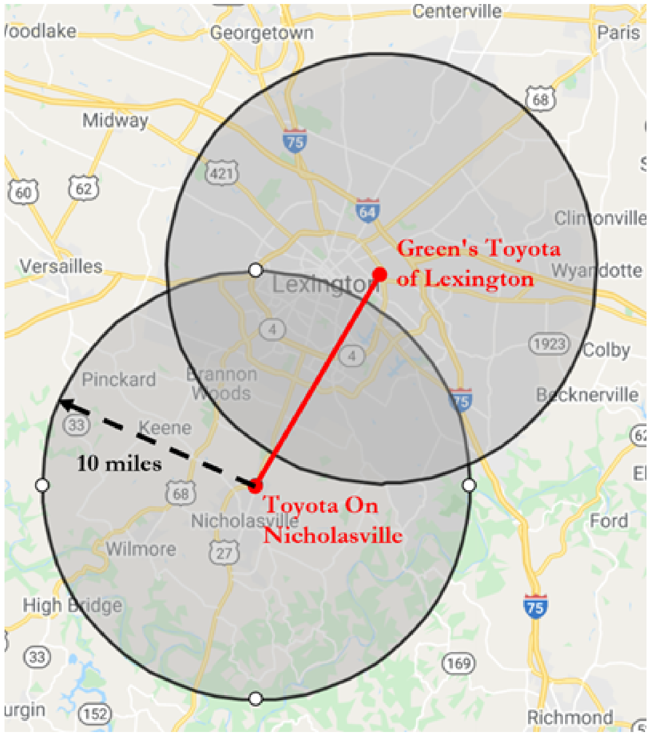
Xia, Lan, and Kent B Monroe. 2004. "Price partitioning on the internet." *Journal of Interactive marketing* 18 (4): 63–73.

Yannelis, Constantine, and Anthony Lee Zhang. 2021. "Competition and selection in credit markets." Working paper.

Yinger, John. 1981. "A search model of real estate broker behavior." *The American Economic Review* 71 (4): 591–605.

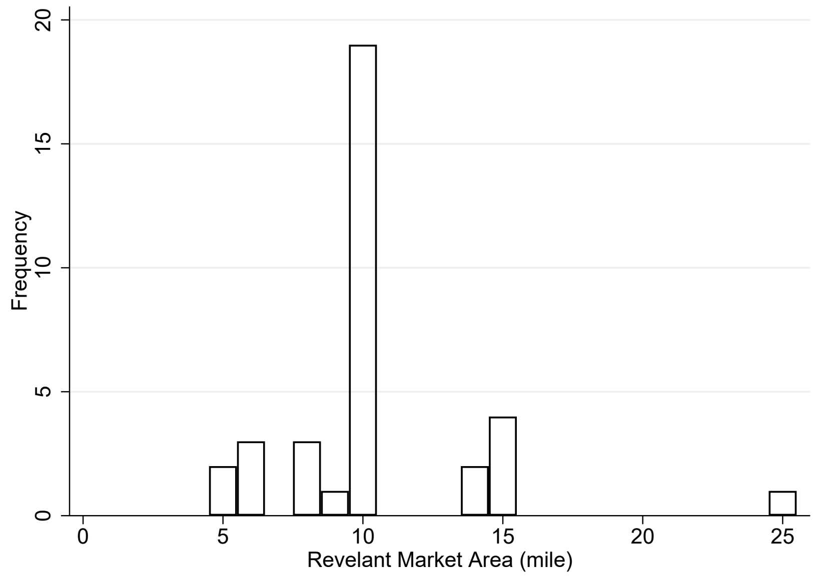
Zinman, Jonathan. 2015. "Household debt: Facts, puzzles, theories, and policies." *Annual Review of Economics* 7:251–276.

Figure 1: Toyota dealerships in Lexington, KY.



NOTE.——This figure plots Toyota dealerships in Lexington, KY. The relevant market area in the state of Kentucky is 10 miles. Each circle corresponds to the relevant market area for each Toyota dealership.

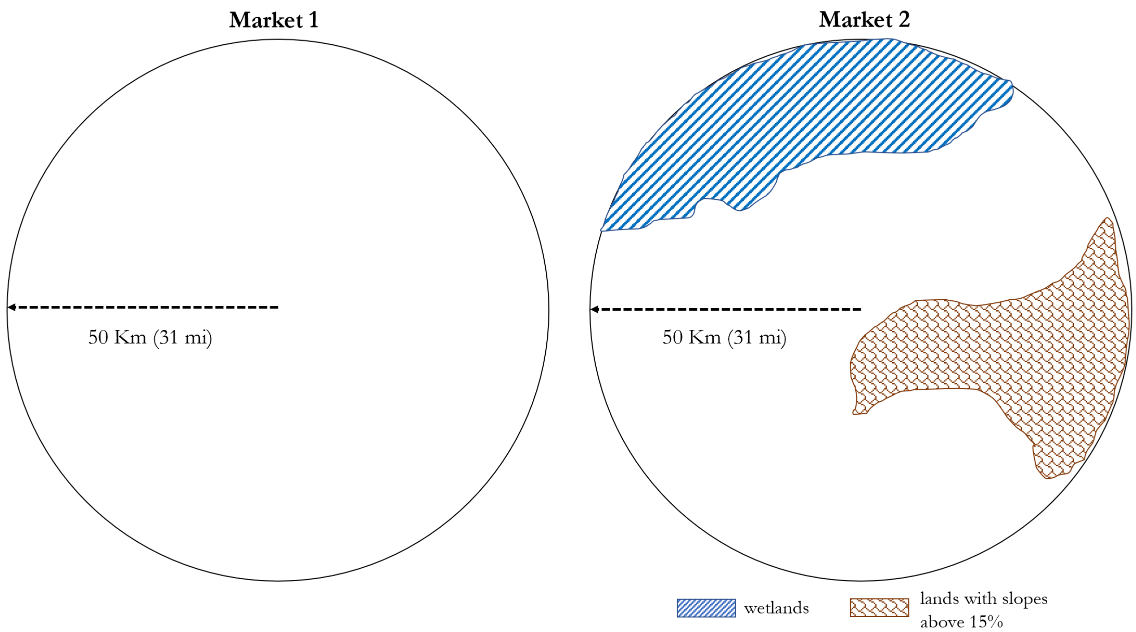
Figure 2: Distribution of relevant market areas across states



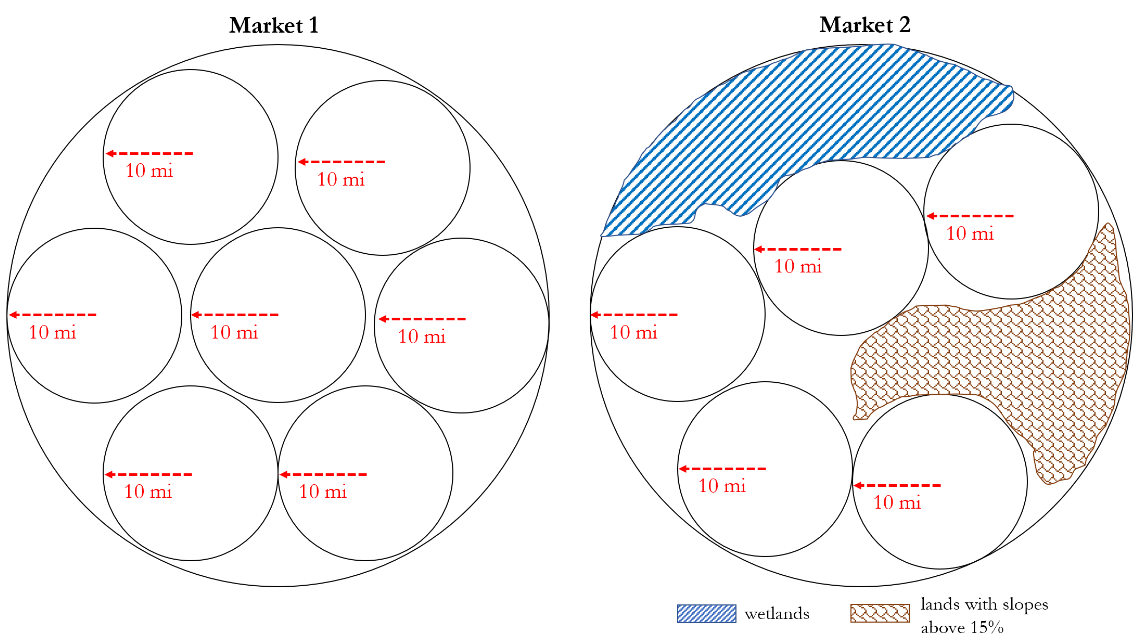
NOTE.——This figure plots the distribution of relevant market areas across states. The x-axis presents the radius of relevant market area in miles.

Figure 3: A hypothetical example

(a) Predetermined developable land

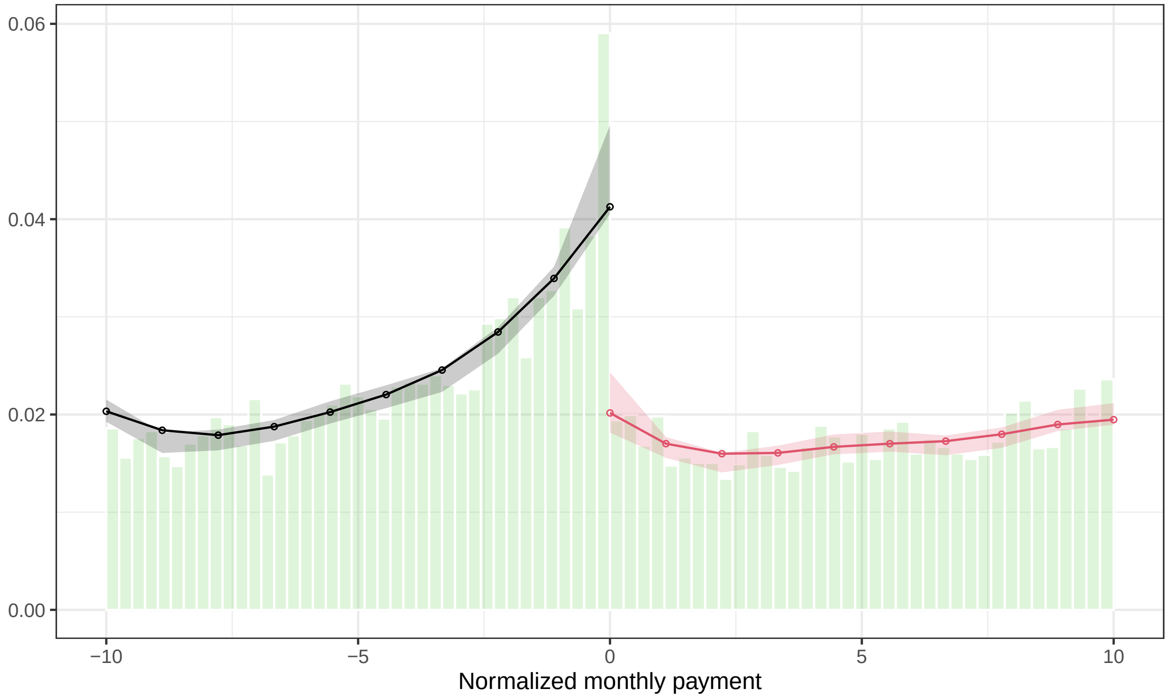


(b) Potential number of dealerships



NOTE.——This figure plots a hypothetical example to clarify the instrumental variable outlined in Section 2.2. Panel A presents the amount of available land in Market 1 and Market 2. The blue shaded area represents wetlands and the brown shaded area represents lands with slope above 15%. Panel B presents the maximum number of new car dealerships in each hypothetical market. The relevant market area (RMA) in each market is 10 miles.

Figure 4: Monthly payment distribution around salient cutoffs



NOTE.——This figure plots McCrary bunching tests of normalized monthly payments around hundred dollar increments from $100 to $600.

Table 1: Descriptive statistics

	Mean	SD	P10	P25	P50	P75	P90
Coobligor (0/1)	0.31	0.46	0.00	0.00	0.00	1.00	1.00
Monthly Payment	465	167	275	352	446	559	674
Credit Score	754	57	675	713	756	803	830
VehiclePrice	24974	6570	17645	20160	23678	29007	34222
Loan Size	27250	10093	15212	20223	26090	33251	40748
Loan Term	68	9	61	62	73	76	77
Income	80412	42420	36000	48996	71477	99996	139574
Loan to value (%)	89.63	24.87	54.73	73.78	91.74	107.53	120.81
Interest rate (%)	4.49	2.02	2.64	3.14	3.99	5.25	6.90
24-month default (%)	0.86	9.23	0.00	0.00	0.00	0.00	0.00
Loan markup (%)	2.36	2.20	0.00	0.31	1.99	3.84	5.19
Number of dealers	3.62	2.16	1.62	1.84	2.76	5.43	8.03
Potential number of dealers	8.13	4.69	4.61	4.61	6.83	12.99	12.99
Developable land (sq. miles)	1998	445	1449	1449	1958	2422	2612
RMA (miles)	9.60	2.08	8.00	8.00	10.00	10.00	10.00
Number of used dealers	24.12	10.75	14.17	14.47	19.02	34.40	41.41
Number of banks	121.77	68.94	41.78	79.08	87.53	187.94	187.94
Internet access (%)	85.20	3.15	80.30	83.70	84.60	89.10	89.10
Personal income per capita	50409	7545	42162	44629	47057	58456	60344
Regional price parities	99.03	7.63	90.29	93.24	95.60	109.75	109.76
Unemployment rate (%)	4.32	0.50	3.90	3.90	4.40	4.80	4.90
PPL with bachelor's degree (%)	32.54	3.77	26.34	30.22	32.50	35.00	35.75
GDP per capita	58.90	10.11	45.00	53.70	56.06	68.61	71.53
Sales tax (%)	5.32	1.92	2.90	3.00	6.25	7.25	7.25

NOTE.—This table describes our sample of 91,405 auto loans originated by indirect lenders from 2017 to 2019. I also require that the loan passes other data quality filters. Descriptive statistics are as of the loan origination date.

Table 2: Validity of the instrument: Relevance condition

	(1) Number of dealers	(2) Number of dealers	(3) Number of dealers	(4) Vehicle price	(5) Loan markup	(6) Monthly payment
Potential number of dealers	1.2788***	1.2244***	1.2196***	-108.0467**	0.2048***	-1.4310
	(4.04)	(4.44)	(4.44)	(-1.99)	(5.90)	(-0.57)
RMA FE	Yes	Yes	Yes	Yes	Yes	Yes
Developable land FE	Yes	Yes	Yes	Yes	Yes	Yes
Vehicle×Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Lender×Time FE		Yes	Yes	Yes	Yes	Yes
Credit Score×Time FE			Yes	Yes	Yes	Yes
Income×Time FE			Yes	Yes	Yes	Yes
R^2	0.799	0.817	0.818	0.769	0.574	0.426
Observations	91,307	91,307	91,307	91,307	91,307	91,307
F-statistics	16.299	19.679	19.740			

NOTE.—Columns (1) through (3) report the results from the first-stage regressions (Equation 4). The dependent variable is the number of dealerships selling new cars in a market. Columns (4) and (5) report the results from the reduced form regressions. In Column (4), the dependent variable is the vehicle prices. In Columna (5) and (6), the dependent variable is the loan markups and monthly payments. The income fixed effects ($\delta_{i,t}$) are defined as \$50,000 income bins and the credit score fixed effects ($\delta_{c,t}$) are defined as a 25-point credit bins. Vehicle fixed effects ($\delta_{v,t}$) refer to vehicle make-model-model year combinations. The developable land fixed effects (δ_{dl}) refer to developable land quartiles. The rma fixed effects (δ_{rma}) refers to the relevant market area defined under state franchise laws. t-statistics, presented below the coefficient estimates, are calculated by clustering at the state level.
* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

Table 3: Validity of the instrument and observables: State-level macroeconomic outcomes

	(1) Log(GDP per capita)	(2) Log(Income per capita)	(3) Log(Regional price parity)	(4) Unemployment rate	(5) Bachelor degree	(6) Internet access	(7) Sales tax
Potential number of dealers	0.0311	0.0375	0.0097	0.0867	0.7809	0.0192	-0.0671
	(0.71)	(1.02)	(0.64)	(0.58)	(0.67)	(0.02)	(-0.13)
RMA FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Developable land FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.430	0.462	0.448	0.342	0.342	0.267	0.166
Observations	270	270	270	270	270	270	270

NOTE.—This Table reports the results for the state-level macroeconomic outcomes. The coefficient of interest is estimated at the state-quarter level. The income fixed effects ($\delta_{i,t}$) are defined as \$50,000 income bins and the credit score fixed effects ($\delta_{c,t}$) are defined as a 25-point credit bins. Vehicle fixed effects ($\delta_{v,t}$) refer to vehicle make-model-model year combinations. The developable land fixed effects (δ_{dl}) refer to developable land quartiles. The rma fixed effects (δ_{rma}) refers to the relevant market area defined under state franchise laws. t-statistics, presented below the coefficient estimates, are calculated by clustering at the state level.

* Significant at the 10% level.

** Significant at the 5% level.

*** Significant at the 1% level.

Table 4: Validity of the instrument and unobservables (placebo tests)

	(1) Number of used dealers	(2) Number of banks	(3) < 4 years old Vehicle price	(4) > 4 years old Vehicle price	(5) < 4 years old Loan markup	(6) > 4 years old Loan markup
Potential number of dealers	-1.0606	-6.9239	-56.4408	-18.3877	0.0233**	0.0079
	(-0.56)	(-0.62)	(-1.06)	(-0.29)	(2.01)	(1.24)
RMA FE	Yes	Yes	Yes	Yes	Yes	Yes
Developable land FE	Yes	Yes	Yes	Yes	Yes	Yes
Lender×Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Vehicle×Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Credit Score×Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Income×Time FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.888	0.808	0.817	0.788	0.078	0.082
Observations	91,307	91,307	78,700	47,858	78,700	47,858

NOTE.—This Table reports the results for the selection on unobservables. In Column (1), the dependent variable is the number of dealerships selling exclusively used cars in a market. In Column (2), the dependent variable is the number of banks in a market. In Columns (3) and (4), the dependent variable is vehicle prices and in Columns (5) and (6), the dependent variable is loan markups. Columns (3) and (5) report the results for used vehicles that are less than 4 years old. Columns (4) and (6) report the results for used vehicles that are more than 4 years old. The income fixed effects ($\delta_{i,t}$) are defined as \$50,000 income bins and the credit score fixed effects ($\delta_{c,t}$) are defined as a 25-point credit bins. Vehicle fixed effects ($\delta_{v,t}$) refer to vehicle make-model-model year combinations. The developable land fixed effects (δ_{dl}) refer to developable land quartiles. The rma fixed effects (δ_{rma}) refers to the relevant market area defined under state franchise laws. t-statistics, presented below the coefficient estimates, are calculated by clustering at the state level.

* Significant at the 10% level.

** Significant at the 5% level.

*** Significant at the 1% level.

Table 5: Price effect of Local competition among auto dealers

	(1) Vehicle price	(2) Loan markup	(3) MonthlyPayment
Number of dealers	-88.5898**	0.1679***	-1.1733
	(-2.07)	(5.45)	(-0.56)
RMA FE	Yes	Yes	Yes
Developable land FE	Yes	Yes	Yes
Lender×Time FE	Yes	Yes	Yes
Vehicle×Time FE	Yes	Yes	Yes
Credit Score×Time FE	Yes	Yes	Yes
Income×Time FE	Yes	Yes	Yes
Observations	91,307	91,307	91,307

NOTE.—This Table reports the effect of local competition among auto dealers on the joint pricing of cars and car loans by simultaneously estimating Equations 4 and 5. In Columns (1) and (2), the dependent variable is vehicle prices and loan markups respectively. In Column (3), the dependent variable is monthly payments. The income fixed effects ($\delta_{i,t}$) are defined as \$50,000 income bins and the credit score fixed effects ($\delta_{c,t}$) are defined as a 25-point credit bins. Vehicle fixed effects ($\delta_{v,t}$) refer to vehicle make-model-model year combinations. The developable land fixed effects (δ_{dl}) refer to developable land quartiles. The rma fixed effects (δ_{rma}) refers to the relevant market area defined under state franchise laws. t-statistics, presented below the coefficient estimates, are calculated by clustering at the state level.

* Significant at the 10% level.

** Significant at the 5% level.

*** Significant at the 1% level.

Table 6: Other contract terms and composition of borrowers

	(1) Loan amount	(2) Maturity	(3) Loan to value	(4) Income	(5) Credit score	(6) 24-month default
Number of dealers	-0.0067	-0.0035*	-0.2042	0.0170**	-0.0028*	0.0246
	(-1.19)	(-1.93)	(-0.38)	(2.12)	(-1.93)	(0.60)
RMA FE	Yes	Yes	Yes	Yes	Yes	Yes
Developable land FE	Yes	Yes	Yes	Yes	Yes	Yes
Lender×Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Vehicle×Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Credit Score×Time FE	Yes	Yes	Yes	Yes		Yes
Income×Time FE	Yes	Yes	Yes		Yes	Yes
Observations	91,307	91,307	91,307	91,307	91,307	66,659

NOTE.—This Table reports the results for other contract terms and borrower characteristics. In Columns (1) through (3), the dependent variable is the logarithm of the loan amount, the logarithm of maturity, and the loan-to-value ratio at the time of origination. In Columns (4) and (5), the dependent variable is the logarithm of income and the logarithm of credit score. In Column (6), the dependent variable is the 24-month default rate. A loan is considered to be in default if it is 90 or more days past due (including charge-offs and repossessions). The income fixed effects ($\delta_{i,t}$) are defined as \$50,000 income bins and the credit score fixed effects ($\delta_{c,t}$) are defined as a 25-point credit bins. Vehicle fixed effects ($\delta_{v,t}$) refer to vehicle make-model-model year combinations. The developable land fixed effects (δ_{dl}) refer to developable land quartiles. The rma fixed effects (δ_{rma}) refers to the relevant market area defined under state franchise laws. t-statistics, presented below the coefficient estimates, are calculated by clustering at the state level.

* Significant at the 10% level.

** Significant at the 5% level.

*** Significant at the 1% level.

Table 7: Cross-sectional test: Credit scores

	(1) Vehicle price	(2) Loan markups	(3) Monthly payment	(4) 24-month default
Number of dealers	-103.5003*	0.0985***	-1.2041	-0.0037
	(-1.80)	(3.84)	(-0.47)	(-0.13)
Number of dealers×Low credit score	47.9191	0.1536***	1.6972	0.0750
	(1.04)	(5.64)	(0.92)	(1.52)
RMA FE	Yes	Yes	Yes	Yes
Developable land FE	Yes	Yes	Yes	Yes
Lender×Time FE	Yes	Yes	Yes	Yes
Vehicle×Time FE	Yes	Yes	Yes	Yes
Income×Time FE	Yes	Yes	Yes	Yes
Observations	91,220	91,220	91,220	66,590

NOTE.—This Table reports the effect of local competition among auto dealers on the joint pricing of cars and car loans across credit scores. *Low credit score* equals one for borrowers with a credit score below median and zero otherwise. In Columns (1) and (2), the dependent variable is vehicle prices and loan markups respectively. In Columns (3) and (4), the dependent variable is monthly payments and the 24-month default rate. A loan is considered to be in default if it is 90 or more days past due (including charge-offs and repossessions). The income fixed effects ($\delta_{i,t}$) are defined as $50,000 income bins. Vehicle fixed effects ($\delta_{v,t}$) refer to vehicle make-model-model year combinations. The developable land fixed effects (δ_{dl}) refer to developable land quartiles. The rma fixed effects (δ_{rma}) refers to the relevant market area defined under state franchise laws. t-statistics, presented below the coefficient estimates, are calculated by clustering at the state level.

* Significant at the 10% level.

** Significant at the 5% level.

*** Significant at the 1% level.

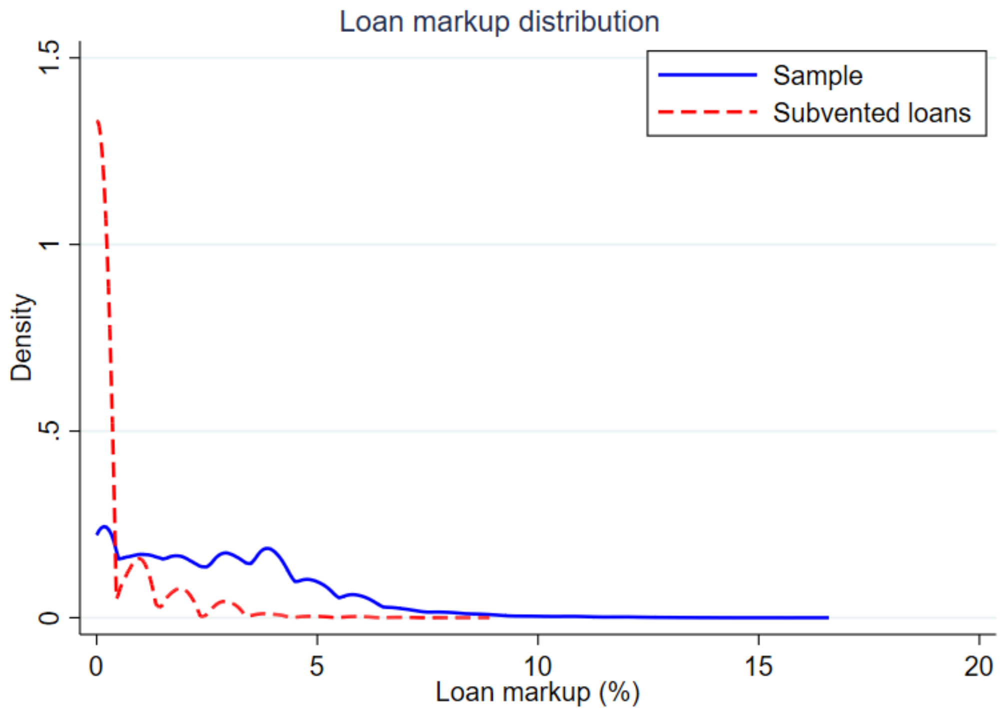
Table 8: Cross-sectional test: Income

	(1) Vehicle price	(2) Loan markups	(3) Monthly payment	(4) 24-month default
Number of dealers	-86.9999*	0.1318***	-1.9686	0.0159
	(-1.79)	(4.15)	(-0.75)	(0.35)
Number of dealers×Low income	-2.0352	0.0654***	1.8102	0.0219
	(-0.09)	(4.39)	(1.01)	(0.44)
RMA FE	Yes	Yes	Yes	Yes
Developable land FE	Yes	Yes	Yes	Yes
Lender×Time FE	Yes	Yes	Yes	Yes
Vehicle×Time FE	Yes	Yes	Yes	Yes
Credit score×Time FE	Yes	Yes	Yes	Yes
Observations	91,195	91,195	91,195	66,555

NOTE.—This Table reports the effect of local competition among auto dealers on the joint pricing of cars and car loans across income. *Low income* equals one for borrowers with an income below the median and zero otherwise.In Columns (1) and (2), the dependent variable is vehicle prices and loan markups respectively. In Columns (3) and (4), the dependent variable is monthly payments and the 24-month default rate. A loan is considered to be in default if it is 90 or more days past due (including charge-offs and repossessions). The credit score fixed effects ($\delta_{c,t}$) are defined as a 25-point credit bins. Vehicle fixed effects ($\delta_{v,t}$) refer to vehicle make-model-model year combinations. The developable land fixed effects (δ_{dl}) refer to developable land quartiles. The rma fixed effects (δ_{rma}) refers to the relevant market area defined under state franchise laws. t-statistics, presented below the coefficient estimates, are calculated by clustering at the state level.
* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

Internet appendix

Figure A.1: Distribution of loan markups



NOTE.——This figure plots the distribution of loan markups for my main sample as well as a sample including subvented loans. The x-axis presents loan markups in percentage. The blue line represents the kernel density distribution of loan markups for my main sample. The dotted red line represents the kernel density distribution of loan markups for a sample including only subvented loans. *subvented loans* refers to loans with cash or rate rebates.

Table A.1: Inter-brand vs. intra-brand competition

Panel A: Vehicle body type	(1) Vehicle price	(2) Loan markup	(3) Monthly payment	(4) 24-month default
Number of dealers	-263.4535***	0.1651***	-4.3872	0.0557
	(-3.01)	(6.59)	(-1.45)	(1.13)
RMA FE	Yes	Yes	Yes	Yes
Developable land FE	Yes	Yes	Yes	Yes
Lender×Time FE	Yes	Yes	Yes	Yes
Vehicle Type×Time FE	Yes	Yes	Yes	Yes
Credit Score×Time FE	Yes	Yes	Yes	Yes
Income×Time FE	Yes	Yes	Yes	Yes
Observations	91,404	91,404	91,404	66,743

Panel B: Car value bins	(1) Vehicle price	(2) Loan markup	(3) Monthly payment	(4) 24-month default
Number of dealers	-90.0919	0.1649***	-1.2608	0.0511
	(-1.36)	(6.34)	(-0.45)	(1.04)
RMA FE	Yes	Yes	Yes	Yes
Developable land FE	Yes	Yes	Yes	Yes
Lender×Time FE	Yes	Yes	Yes	Yes
Car Value×Time FE	Yes	Yes	Yes	Yes
Credit Score×Time FE	Yes	Yes	Yes	Yes
Income×Time FE	Yes	Yes	Yes	Yes
Observations	91,404	91,404	91,404	66,743

NOTE.—This Table reports the effect of inter-brand competition on vehicle prices and loan markups. The effect is simultaneously estimated using Equations 4 and 5. Panel A reports the coefficient of interest after the inclusion of vehicle body type fixed effects ($\delta_{vbt,t}$) instead of vehicle fixed effects ($\delta_{v,t}$). Panel B reports the coefficient of interest after the inclusion of car value fixed effects ($\delta_{cv,t}$) instead of vehicle fixed effects ($\delta_{v,t}$). The dependent variable in Column (1) is vehicle prices. The dependent variable in Column (2) is loan markups. The dependent variable in Column (3) is the 24-month default rate. A loan is considered to be in default if it is 90 or more days past due (including charge-offs and repossessions). The income fixed effects ($\delta_{i,t}$) are defined as $50,000 income bins and the credit score fixed effects ($\delta_{c,t}$) are defined as a 25-point credit bins. The vehicle body type fixed effects ($\delta_{vbt,t}$) refer to sedan, coupe, sports car, station wagon, hatchback, convertible, sport-utility vehicle (SUV), minivan, and pickup truck. The car value fixed effects ($\delta_{cv,t}$) refer to car value quartiles. The developable land fixed effects (δ_{dl}) refer to developable land quartiles. The rma fixed effects (δ_{rma}) refers to the relevant market area defined under state franchise laws. t-statistics, presented below the coefficient estimates, are calculated by clustering at the state level.
* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

Table A.2: Alternative clustering

Panel A: Vehicle prices	(1) Vehicle price	(2) Vehicle price	(3) Vehicle price	(4) Vehicle price
Number of dealers	-88.5898**	-88.5898**	-88.5898***	-88.5898***
	(-2.16)	(-2.36)	(-2.72)	(-3.23)
RMA FE	Yes	Yes	Yes	Yes
Developable land FE	Yes	Yes	Yes	Yes
Lender×Time FE	Yes	Yes	Yes	Yes
Vehicle×Time FE	Yes	Yes	Yes	Yes
Credit Score×Time FE	Yes	Yes	Yes	Yes
Income×Time FE	Yes	Yes	Yes	Yes
Alternative clustering	State lender	Lender	Vehicle	Year quarter
Observations	91,307	91,307	91,307	91,307
Panel B: Loan markups	**(1) Loan markup**	**(2) Loan markup**	**(3) Loan markup**	**(4) Loan markup**
Number of dealers	0.1679***	0.1679***	0.1679***	0.1679***
	(6.78)	(9.54)	(8.57)	(8.96)
RMA FE	Yes	Yes	Yes	Yes
Developable land FE	Yes	Yes	Yes	Yes
Lender×Time FE	Yes	Yes	Yes	Yes
Vehicle×Time FE	Yes	Yes	Yes	Yes
Credit Score×Time FE	Yes	Yes	Yes	Yes
Income×Time FE	Yes	Yes	Yes	Yes
Alternative clustering	State lender	Lender	Vehicle	Year quarter
Observations	91,307	91,307	91,307	91,307
Panel C: Monthly payment	**(1) Monthly payment**	**(2) Monthly payment**	**(3) Monthly payment**	**(4) Monthly payment**
Number of dealers	-1.1733	-1.1733	-1.1733	-1.1733
	(-0.69)	(-1.22)	(-0.82)	(-1.00)
RMA FE	Yes	Yes	Yes	Yes
Developable land FE	Yes	Yes	Yes	Yes
Lender×Time FE	Yes	Yes	Yes	Yes
Vehicle×Time FE	Yes	Yes	Yes	Yes
Credit Score×Time FE	Yes	Yes	Yes	Yes
Income×Time FE	Yes	Yes	Yes	Yes
Alternative clustering	State lender	Lender	Vehicle	Year quarter
Observations	91,307	91,307	91,307	91,307

NOTE.—This Table reports the effect of local competition among auto dealers on vehicle prices and loan markups for different clustering schemes, including state-lender, lender, vehicle, and year-quarter levels. The effect is simultaneously estimated using Equations 4 and 5. In Panel A, the dependent variable is vehicle prices. In Panel B, the dependent variable is loan markups. The income fixed effects ($\delta_{i,t}$) are defined as \$50,000 income bins and the credit score fixed effects ($\delta_{c,t}$) are defined as a 25-point credit bins. Vehicle fixed effects ($\delta_{v,t}$) refer to vehicle make-model-model year combinations. The developable land fixed effects (δ_{dl}) refer to developable land quartiles. The rma fixed effects (δ_{rma}) refers to the relevant market area defined under state franchise laws. t-statistics, presented below the coefficient estimates, are calculated by clustering at the state level.

* Significant at the 10% level.

** Significant at the 5% level.

*** Significant at the 1% level.

Table A.3: Robust to different bin sizes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Bin size 1		Bin size 2		Bin size 3		Bin size 4	
	Loan markup	Loan markup	Loan markup	Loan markup	Loan markup	Loan markup	Loan markup	Loan markup
Number of dealers	0.0085***	0.0312***	0.0219***	0.0623***	0.1115***	0.1130***	0.2795***	0.2179***
	(5.12)	(4.30)	(5.60)	(4.27)	(6.83)	(5.17)	(7.13)	(5.63)
RMA FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Developable land FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender×Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Vehicle×Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Credit Score×Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Income×Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	136,312	19,600	136,306	25,144	137,139	66,825	137,400	119,996
Average cell size	1.152	2.071	1.209	2.143	2.392	3.871	39.334	44.986
Unconditional markup	0.024	0.166	0.050	0.273	0.353	0.728	2.355	2.702

NOTE.—This Table reports the effect of local competition among auto dealers on loan markups for different bin sizes. In *Bin size 1*, I calculate loan markups while conditioning on loan contract terms such as loan to value ratio and loan maturity. In Column (2), I require each cell has at least two observations. In *Bin size 2*, I calculate loan markups after applying tighter filters such as 5-point credit bins and $10,000 income bins. In Column (4), I require each cell has at least two observations. In *Bin size 3*, I calculate loan markups after applying generous filters such as 10-point credit bins and $25,000 income bins. In Column (6), I require each cell has at least two observations. In *Bin size 4*, I calculate loan markups after applying more generous filters such as 50-credit bins, $50,000 income bins, and semi annual-year bins. In Column (8), I require each cell has at least two observations. The income fixed effects ($\delta_{i,t}$) are defined as $50,000 income bins and the credit score fixed effects ($\delta_{c,t}$) are defined as a 25-point credit bins. Vehicle fixed effects ($\delta_{v,t}$) refer to vehicle make-model-model year combinations. The developable land fixed effects (δ_{dl}) refer to developable land quartiles. The rma fixed effects (δ_{rma}) refers to the relevant market area defined under state franchise laws. t-statistics, presented below the coefficient estimates, are calculated by clustering at the state level.

* Significant at the 10% level.

** Significant at the 5% level.

*** Significant at the 1% level.

Table A.4: Adjusted sample filters

Panel A: Vehicle prices	(1) Vehicle price	(2) Vehicle price	(3) Vehicle price	(4) Vehicle price	(5) Vehicle price	(6) Vehicle price
Number of dealers	-89.9997**	-90.2988**	-93.5721**	-79.4367*	-131.5225***	-990.1156
	(-2.04)	(-2.11)	(-1.98)	(-1.85)	(-3.03)	(-0.73)
Sample filter	+500	+650	+700	1*mill*	Non-zero markup	DL decile FE
RMA FE	Yes	Yes	Yes	Yes	Yes	Yes
Developable land FE	Yes	Yes	Yes	Yes	Yes	Yes
Lender×Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Vehicle×Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Credit Score×Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Income×Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	93,643	88,654	75,391	93,116	74,848	92,047

Panel B: Loan markups	(1) Loan markup	(2) Loan markup	(3) Loan markup	(4) Loan markup	(5) Loan markup	(6) Loan markup
Number of dealers	0.2149***	0.1841***	0.1619***	0.2070***	0.1436***	0.0904
	(5.91)	(5.50)	(5.05)	(5.88)	(5.46)	(0.35)
Sample filter	+500	+650	+700	1*mill*	Non-zero markup	DL decile FE
RMA FE	Yes	Yes	Yes	Yes	Yes	Yes
Developable land FE	Yes	Yes	Yes	Yes	Yes	Yes
Lender×Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Vehicle×Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Credit Score×Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Income×Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	93,643	88,654	75,391	93,116	74,848	92,047

NOTE.—This Table reports the effect of local competition among auto dealers on vehicle prices and loan markups after adjusting sample filters. The effect is simultaneously estimated using Equations 4 and 5. In Panel A, the dependent variable is vehicle prices. In Panel B, the dependent variable is loan markups. In Columns (1) through (3), I restrict my sample to auto loans with a credit score of +500, +650, and +700. In Column (4), I restrict my sample to borrowers with an income of $1 million or less. In Column (5), I restrict the estimation sample to auto loans with non-zero markups. In Column (6), I include the developable land decile fixed effects. The income fixed effects ($\delta_{i,t}$) are defined as $50,000 income bins and the credit score fixed effects ($\delta_{c,t}$) are defined as a 25-point credit bins. Vehicle fixed effects ($\delta_{v,t}$) refer to vehicle make-model-model year combinations. The developable land fixed effects (δ_{dl}) refer to developable land quartiles. The rma fixed effects (δ_{rma}) refers to the relevant market area defined under state franchise laws. t-statistics, presented below the coefficient estimates, are calculated by clustering at the state level.

* Significant at the 10% level.

** Significant at the 5% level.

*** Significant at the 1% level.

Table A.5: Robust to different number of observations in each cell

	(1) Loan markup	(2) Loan markup	(3) Loan markup
Number of dealers	0.1328***	0.2783*	0.5200
	(3.49)	(1.88)	(1.81)
Min obs in cell	5	20	30
Unconditional markup	2.823	3.649	3.917
RMA FE	Yes	Yes	Yes
Developable land FE	Yes	Yes	Yes
Lender×Time FE	Yes	Yes	Yes
Vehicle×Time FE	Yes	Yes	Yes
Credit Score×Time FE	Yes	Yes	Yes
Income×Time FE	Yes	Yes	Yes
Observations	58,997	16,593	8,777

NOTE.—This Table reports the effect of local competition among auto dealers on vehicle prices and loan markups conditional on different number of observations in each cell. The income fixed effects ($\delta_{i,t}$) are defined as \$50,000 income bins and the credit score fixed effects ($\delta_{c,t}$) are defined as a 25-point credit bins. Vehicle fixed effects ($\delta_{v,t}$) refer to vehicle make-model-model year combinations. The developable land fixed effects (δ_{dl}) refer to developable land quartiles. The rma fixed effects (δ_{rma}) refers to the relevant market area defined under state franchise laws. t-statistics, presented below the coefficient estimates, are calculated by clustering at the state level.
* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

Table A.6: Subvented loans

	(1) Subvented loan	(2) Subvented loan	(3) Subvented loan
Potential number of dealers	-0.0014	-0.0006	0.0006
	(-0.07)	(-0.16)	(0.15)
RMA FE	Yes	Yes	Yes
Developable land FE	Yes	Yes	Yes
Vehicle×Time FE	Yes	Yes	Yes
Lender×Time FE		Yes	Yes
Credit Score×Time FE			Yes
Income×Time FE			Yes
R^2	0.461	0.524	0.531
Observations	450,108	450,108	450,108

NOTE.—This Table reports the correlation between the instrumental variable and subvented loans. *Subvented loan* is a dummy variable equals to 1 if a loan has either cash or rate rebates and zero otherwise. The income fixed effects ($\delta_{i,t}$) are defined as \$50,000 income bins and the credit score fixed effects ($\delta_{c,t}$) are defined as a 25-point credit bins. Vehicle fixed effects ($\delta_{v,t}$) refer to vehicle make-model-model year combinations. The developable land fixed effects (δ_{dl}) refer to developable land quartiles. The rma fixed effects (δ_{rma}) refers to the relevant market area defined under state franchise laws. t-statistics, presented below the coefficient estimates, are calculated by clustering at the state level.
* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

Table A.7: OLS regressions

	(1) Vehicle price	(2) Loan markup	(3) Monthly payment
Number of dealers	-47.0987**	0.1122***	0.9046
	(-2.14)	(7.36)	(0.82)
RMA FE	Yes	Yes	Yes
Developable land FE	Yes	Yes	Yes
Vehicle×Time FE	Yes	Yes	Yes
Lender×Time FE	Yes	Yes	Yes
Credit Score×Time FE	Yes	Yes	Yes
Income×Time FE	Yes	Yes	Yes
R^2	0.769	0.575	0.426
Observations	91,307	91,307	91,307

NOTE.—This Table reports the effect of local competition among auto dealers on vehicle prices and loan markups using an OLS regression. The income fixed effects ($\delta_{i,t}$) are defined as $50,000 income bins and the credit score fixed effects ($\delta_{c,t}$) are defined as a 25-point credit bins. Vehicle fixed effects ($\delta_{v,t}$) refer to vehicle make-model-model year combinations. The developable land fixed effects (δ_{dl}) refer to developable land quartiles. The rma fixed effects (δ_{rma}) refers to the relevant market area defined under state franchise laws. t-statistics, presented below the coefficient estimates, are calculated by clustering at the state level.
* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

A A brief history of state automobile franchise laws

Historically, auto manufacturers sold vehicles through a wide variety of distribution methods, including direct distribution, mail order, traveling salesmen, wholesale distributors, and retail department stores (Marx 1985). As demand for new vehicles increased, automakers developed an independent franchise distribution system. Under the new system, automakers use their resources on production to make high-quality vehicles, and car dealers make substantial investments in real estate, vehicle and parts inventories, and service facilities to better reach and serve consumers. During the first few decades of the 20th century, this auto dealer-franchise system resulted in unfair conditions for car dealerships. Basically, prior to the late 1950s, the franchise agreement between automakers and car dealerships gave more favorable legal and economic protection to automakers due to their superior bargaining strength. To protect car dealerships against manufacturers' abuse of their bargaining power, federal and state legislators enacted several laws. For example, in 1956, Congress enacted the Automobile Dealer's Day In Court Act (ADDICA), which allows that a car dealership may bring an action in federal court for damages and recovery of cost of lawsuit when the automaker does not use "good faith in performing its obligations under a dealer franchise or in terminating it".[20] Furthermore, many states have enacted laws to impose restrictions on franchise termination, to prohibit coercion and price discrimination, and to provide a system of warranty rate reimbursement (Brown, 1980).

20. 70 Stat. 1125 (1956)