Conspicuous Consumption: Vehicle Purchases by Non-Prime Consumers

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Working Paper 2107 **June 2021**

Research Department

https://doi.org/10.24149/wp2107

Conspicuous Consumption: Vehicle Purchases by Non-Prime Consumers*

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May 2021

Abstract

Consumers with higher income often spend more on luxury goods. As a result, lower-income consumers who seek to increase their perceived income and social status may be motivated to purchase conspicuous luxury goods. Lower-income consumers may also desire to emulate the visible consumption displayed by their wealthier peers. Using a unique vehicle financing dataset, we find that consumers with lower credit scores value vehicle brand prestige more than average consumers. The stronger preferences for prestige lead non-prime consumers to purchase more expensive vehicles than they otherwise would have. We find evidence that the preferences for prestige are driven both by status signaling and peer emulation motives. Furthermore, we show that larger vehicle purchases financed by auto loans lead to worse loan performance and credit standing for non-prime consumers.

Keywords: Conspicuous Consumption, Status, Emulation, Automobile, Show Off, Vehicles, Auto Loan, Creditworthiness, Non-Prime

JEL Classifications: D12, G51, L62

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* The views expressed in this article are those of the authors and do not necessarily represent the views of the Federal Reserve Bank of Dallas or the Federal Reserve System.

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1 Introduction

Consumers with higher income and net worth often spend disproportionately more on luxury goods. As a result, owning luxury goods visible to others could signal one's income or wealth status. If consumers find satisfaction from being perceived as higher status than they actually are, they would purchase more luxury goods than they otherwise would have (Corneo and Jeanne, 1997). Moreover, consumers with lower income or wealth may also desire to emulate their richer peers' consumption of visible luxury goods so that they can "keep up with the Joneses." The motivations of status signaling and peer emulation could lead individuals to purchase conspicuous luxury goods more than what the goods' inherent functionality warrants. Large spending on luxury goods could be concerning for low-income consumers with low credit scores because more spending on conspicuous luxury goods implies cutting back on consumption of inconspicuous and often necessity goods, reducing savings, or accumulating additional debts that are financially costly.[1]

Our paper studies the extent to which the pursuit of prestige affects automobile vehicle purchases by the non-prime consumers.[2] Automobile vehicle is a highly visible conspicuous commodity. Thus, consumers may be motivated to purchase luxury vehicles to enhance their income and wealth status compared to their peers (Charles et al., 2009). Prestigious vehicles belonging to friends and neighbors could also become the target of emulation if consumers have a strong tendency for upward social comparison. Compared with other visible consumer goods, vehicles are among the largest purchases in the lifetime of most consumers and are often financed by loans.[3] The underwriting standard for auto loans was relaxed more than that of mortgages after the Great Recession (Haughwout et al., 2019).[4] Financed by relatively easy loans, vehicle purchases fueled by conspicuous consumption could be a potential contributor to the delinquency and defaults of lower-income and non-prime consumers.

Using a unique vehicle financing dataset, we demonstrate that such a desire for prestige has indeed led

[1]Status signaling and peer emulation often go beyond the consumption of luxury goods (Roussanov, 2010). Bursztyn and Jensen (2017) review a range of costly behaviors out of conspicuous motives in consumption, education, investment, work efforts, voting, and charity for social image that lead to undesirable outcomes.

[2]Non-prime consumers are defined as consumers with the Vantage Score between 280 and 660. Prime consumers are defined as consumers with scores between 661 and 850. We use Vantage Score 3.0. Vantage Score is a credit scoring model maintained by VantageScore company, which was founded in 2006 by the three national credit reporting companies (Equifax, Experian, and TransUnion) – https://vantagescore.com/company/about-vantagescore.

[3]In March 2020, at least 55.8% of the transactions were financed with loans, based on AutoCount Data.

[4]For lenders, vehicle repossession is much less costly than foreclosing a home. Table A2 shows that auto loans are more prevalent among consumers with non-prime credit scores. Among the 32% of these consumers with an Equifax risk score lower than 660, about 44% held auto loan debt, versus only 13% held mortgage debt as of December 2019 based on the Federal Reserve Bank of New York Consumer Credit Panel (CCP)/Equifax. Lending competition contributed to the loosening of the underwriting of auto loans. See also https://occ.gov/publications-and-resources/publications/semiannual-risk-perspective/files/semiannual-risk-perspective-spring-2014.html

non-prime consumers to purchase more expensive vehicles. To show that, we analyze and compare the demand for vehicles by consumers with different credit scores. We find that non-prime consumers have a markedly stronger demand for vehicles with prestigious brands (makes) than average consumers, holding the price of the vehicle model constant. Vehicles with higher brand prestige tend to be more pricey; therefore, the demand for vehicle prestige raises the average demand for expensive vehicles by non-prime consumers.

Furthermore, we demonstrate that the demand for prestige in vehicles by non-prime consumers is driven both by 1) the desire to signal income status to others through displaying vehicle prestige and 2) the desire to emulate peers' visible vehicle prestige to "keep up with the Joneses."

First, to capture and test the status signaling motive, we present a model in which consumers desire being perceived higher income than his/her peers, and the vehicle prestige signals owners' income level. We derive two empirical predictions from the status signaling model. The first prediction of the model is that consumers with lower-income peer groups (social comparison reference group) should have a stronger demand for prestige because the marginal gain in relative income status with respect to higher prestige is larger if the income level of the group that the consumer compares against is lower (Charles et al., 2009). Second, consumers who are visibly "tagged" as belonging to a group with higher income inequality should also have a stronger demand for prestige. This is because vehicle prestige as a signal of owners' income is more likely to reflect income differences as opposed to "noises" in unobserved preferences for prestige if the underlying income inequality of the consumers' group is larger.

To take these predictions to data, we further assume that consumers' social comparison reference groups consist of their neighbors and the neighborhood characteristics are also signals to "tag" consumers when society infers one's income. We find both predictions validated by data. The demand for vehicle prestige is particularly strong among non-prime consumers living in low-income neighborhoods and non-prime consumers living in neighborhoods with high income inequality.[5]

We next test for the peer emulation mechanism — the consumers' desire to "keep up with the Joneses." We rationalize such a mechanism in a model where consumers' marginal utility of prestige depends on the prestige level demonstrated by their peers' consumption. The model predicts that non-prime consumers whose peers are more likely to purchase prestigious vehicles would be more likely to have stronger preferences for prestige. We test the prediction by examining whether non-prime consumers living in neighborhoods where

[5]We also find strong relative demand for prestigious brands among consumers living in upper-income neighborhoods, regardless of credit scores. But since few consumers with low credit scores live in upper-income neighborhoods, the aggregate results for non-prime consumers are primarily driven by non-prime consumers living in low-income neighborhoods.

their prime neighbors purchase more prestigious vehicles also tend to do so, all else equal. We exploit detailed ZIP Code-level purchase information and show with strong statistical significance that non-prime consumers have a stronger demand for prestige when the average prime neighbors in the same ZIP Code purchase more prestigious vehicles.

After showing that preferences for prestige push up non-prime consumers' spending on vehicles, we proceed to demonstrate that borrowing large amounts to finance high vehicle spendings leads to adverse financial consequences for non-prime consumers. Using the panel structure of the loan performance data provided by the Federal Reserve Bank of New York Consumer Credit Panel (CCP)/Equifax data, we show that borrowing 10% higher initial auto loan debt at least leads to a 0.28 percentage-point increase in auto loan delinquency among the non-prime borrowers, which is around 3% higher than average. In comparison, larger borrowing on vehicles does not raise delinquency rates for the prime borrowers. Moreover, non-prime borrowers with higher initial auto loan debt pay down the debt slower and have a higher chance of vehicles being repossessed. Poor loan performance also leads to a drop in these borrowers' credit scores further down the road. Finally, non-prime consumers taking out larger auto loans are also more likely to miss payments on other consumer loans such as mortgages and credit cards. In comparison, the effect of borrowing large amounts of auto loan debt on loan performance and credit standing is minimal for prime consumers. These findings suggest that higher auto loan debt has an adverse impact on those who may have borrowed beyond their repayment capacity. Since the impaired credit scores and missed payments can lead to further financial malaise, borrowing a large amount of auto loan debt by non-prime consumers can increase the probability of rolling into a vicious cycle of financial distress and limited credit access in the future.

Our paper contributes to several strands of literature. First and foremost, we contribute to the literature that studies the role of conspicuous consumption in household spending. We provide evidence that the desire for conspicuous vehicle prestige incentivizes non-prime consumers to purchase more expensive vehicles. A large number of papers have studied the role of conspicuous consumption in triggering expenditure cascades through society and how income inequality interacts with it (Chao and Schor, 1998; Hopkins and Kornienko, 2004; Rayo and Becker, 2006; Charles et al., 2009; Frank et al., 2014; Bertrand and Morse, 2016; Coibion et al., 2016; Agarwal et al., 2016, 2021). The study of conspicuous consumption is also complemented by the research on how individuals' relative economic positions within society or groups affect their well-beings.[6] Luttmer (2005) shows that higher earnings of neighbors are associated with less happiness. Card et al. (2012)

[6] Duesenberry (1949) proposes that consumer preferences are likely inter-dependent and one's relative position plays an important role in consumption and savings decisions.

show that employees report lower well-being when informed that their income level ranks below the median.

Our paper further unpacks the desire for conspicuous vehicle prestige among the non-prime consumers by showing that such a desire is driven by both a *status signaling* motive and a *peer emulation* motive – "Keeping Up With the Joneses." Our paper makes the point that status signaling and peer emulation are theoretically distinct, as the purpose of status signaling requires the visibility of consumers' own consumption to increase perceived status from others while peer emulation requires peers' consumption to be visible.

Many papers have hypothesized and analyzed status signaling as a powerful motivation for prestige spending. As far back as more than a century ago, Veblen (1899) famously dubbed the term "conspicuous consumption" and highlighted that the display of consumption items could convey information about ones' economic status through social interactions. More recently, a number of papers have provided empirical evidence that status signaling motive drives up conspicuous consumption (Bloch et al., 2004; Charles et al., 2009; Bursztyn et al., 2018; Bricker et al., 2020). A few other papers show evidence for status signaling motive in charitable giving (Glazer and Konrad, 1996; DellaVigna and Gentzkow, 2019).

Another large literature also has examined the peer emulation motive, popularly known as "Keeping Up with the Joneses" and its role in affecting consumption choices (Corneo and Jeanne, 1997; Dupor and Liu, 2003; Christen and Morgan, 2005; Grinblatt et al., 2008; De Giorgi et al., 2020). A number of macroeconomic and asset pricing models have famously included the ingredients in peer emulation in their household utility specifications (Abel, 1990; Gali, 1994; Ljungqvist and Uhlig, 2000; Chan and Kogan, 2002). Aside from peer comparison's impact on consumption, a few papers study the role of social and peer pressure on other general economic outcomes and empirical methodologies for identifying such mechanisms (Manski, 2000; Bursztyn and Jensen, 2017). Others have provided empirical evidence of peer pressure on other important household decisions, such as financial portfolio positions (Roussanov, 2010; Bursztyn et al., 2014).

Our paper also contributes to the literature that studies the role of brands in automobile demand. Our results highlight the role of brands in shaping non-prime and low-income consumers' demand for vehicles. The literature on automobiles is extremely large, both in terms of method and empirical work (Berry, 1994; Berry et al., 1995). The analysis on consumer demand for brands is also very large (Bronnenberg et al., 2012; Anderson et al., 2015; Train and Winston, 2007).

Finally, our paper sheds light on the financial consequences of taking on large auto loans by non-prime consumers. We highlight that as a result, consumers may roll into a vicious cycle. Zinman (2015) provides a review of how easy access to auto loan debt can have an adverse impact on consumers. Bernheim et al.

(2015) present a model where low initial assets can reduce self-control and spur borrowing even at a high interest rate, trapping people in poverty. Some papers have documented that substantial population with low education levels and financial literacy borrow beyond optimal levels (Lusardi and Tufano, 2015; Brown et al., 2016). Using a field experiment, Bertrand and Morse (2011) demonstrate that a lack of information and the cognitive bias about the financial consequences of borrowing have also contributed to overborrowing. Adams et al. (2009) also find that loan size in subprime auto loan market increases default rate both within and across borrowers. They cite the within-borrower effect as moral hazard. We cannot disentangle the financial consequences of excessive borrowing from moral hazard. Some other papers show that despite the risk of overborrowing, restricting access to credit can be harmful to consumers on net Karlan and Zinman (2010); Zinman (2010).

The rest of the paper is organized as the following: Section 2 presents a model of vehicle demand featuring conspicuous consumption; Section 3 discusses the data; Section 4 presents the empirical framework and how we test our hypotheses empirically; Section 5 analyzes the financial consequences of large spending on vehicles; Section 6 concludes.

2 Model of Conspicuous Consumption in Vehicle Demand

We begin our analysis by presenting and analyzing a vehicle demand model where consumers derive additional utility gain from vehicle prestige. In the model, we show that the preference for vehicle prestige could lead consumers to buy more expensive vehicles.

We assume consumer types are indexed by k. For now, we divide consumers into two types: prime and non-prime consumers, denoted by h and l, respectively. Prime consumers are those with high credit scores or creditworthiness. On average, prime consumers have a higher income than non-prime consumers, type h consumer is endowed with income Y^h, and type l consumer is endowed with income Y^l, where $Y^h > Y^l$ (Beer et al., 2018). Since we do not explicitly model the consumption dynamics over the lifetime, we can think of Y^k as the present value of consumer type k's lifetime income.

Each consumer of type k decides on which vehicle to buy. A vehicle is characterized by its price P, quality X, and prestige c associated with the vehicle. The consumer chooses a vehicle by maximizing the following utility function over P, X, and c:

$$u\left(Y^k - \lambda^k P\right) + \eta_k F(X) + s(c, k)$$

We can think of $Y^k - \lambda^k P$ as the present value of lifetime non-vehicle consumption. λ^k captures the present value of the cost of financing each dollar of the vehicle, which we assume could differ by consumer type due to liquidity constraints. Non-prime consumers could potentially face a higher financing cost for each dollar of vehicle purchased, and thus have a larger λ^k.[7]

Consumers generally desire higher-quality vehicles, as $\eta_k > 0$ and $F^{'}(X) > 0$. We allow the marginal utility of quality to also differ potentially by consumer type. As long as vehicle quality is not inferior, η_k should be higher among consumers with higher lifetime income.

$s(c, k)$ is the additional term that captures the utility coming from the consumption of vehicle prestige level c. We allow high- and low-type consumers to value vehicle prestige differently, namely the marginal utility of prestige $s_c(c, h)$ being potentially different from $s_c(c, l)$. The marginal utility of prestige is the key aspect of the model through which the status-signaling motive and the peer-emulation motive drive up the demand for prestige vehicles. We discuss the motives in detail in the next subsection.

The equilibrium vehicle price is a linearly increasing function of its quality X and prestige c:

$$P = \alpha_0 + \alpha_x X + \alpha_c c \quad \text{where } \alpha_x > 0 \text{ and } \alpha_c > 0$$

α_x captures the quality premium and α_c the prestige premium of each vehicle. Each consumer will choose a vehicle by searching along the quality and prestige space to maximize utility. Hence, in the equilibrium, the following first-order conditions are satisfied for consumers of each type k:

$$-\alpha_x \lambda^k u^{'}\left(Y^k - \lambda^k P\right) + \eta_k F^{'}(X) = 0$$
$$-\alpha_c \lambda^k u^{'}\left(Y^k - \lambda^k P\right) + s_c(c, k) = 0$$

Without explicitly specifying the functional forms of $u(.)$, $F(.)$, or $s_c(., .)$, we cannot solve for the analytical solutions from the first-order conditions. But we use these conditions to derive key comparative statics

[7] If a consumer gets into a large amount of debt for an expensive vehicle, the present value of the future cost of financing the one-time purchase would be internalized in this term.

that predicts how the preferences for prestige affect vehicle demand for consumers of each type. To proceed, we assume u and F are strictly concave, i.e., $u^{''} < 0$ and $F^{''} < 0$.

Income Effect First, let us examine how the demand for vehicles changes with income levels, all else equal. Assuming that the marginal utility s_c is a constant with respect to c, we can easily derive the comparative static for the price of vehicle P using implicit function theorem on the second first-order condition:

$$\frac{\partial P^*}{\partial Y^k} = \frac{1}{\lambda^k} > 0$$

The model implies that higher-income consumers generally choose more expensive vehicles. This result is driven by the assumption that the marginal utility of non-vehicle consumption being strictly concave. A higher income diminishes the consumers' sensitivity to vehicle spending.

Furthermore, with the help of the two-equation version of the implicit function theorem, the model implies that a higher income generally leads to a higher demand for prestige, with the marginal utility of prestige held constant:

$$\frac{\partial c^*}{\partial Y^k} = \frac{1}{\alpha_c \lambda^k} > 0$$

This means that without accounting for the potential difference in utility return to prestige from the additional utility term, higher income would generally lead to higher demand for prestige, which is consistent with prestige being a normal good.

The Effect of the Marginal Utility of Prestige Next, we explore how the additional term of vehicle prestige affects vehicle demand.

If $s_c(c, k)$ is a constant with respect to c, i.e., $s_c(c, k) = s_c$, by applying the implicit function theorem to the second first-order condition, we derive

$$\frac{\partial P^*}{\partial s_c} = -\frac{1}{\alpha_c (\lambda^k)^2 u''} > 0.$$

This means that higher marginal utility of prestige will drive up the price of vehicles that consumers are willing to purchase. In the appendix, we use a two-equation version of implicit function theorem to further derive the comparative statics for optimal quality X and prestige c with respect to s_c:

$$\frac{\partial c^*}{\partial s_c} = -\frac{(\alpha_x \lambda^k)^2 u'' + \eta_k F''}{(\alpha_c \lambda^k)^2 \eta_x F'' u''} > 0$$
$$\frac{\partial X^*}{\partial s_c} = \frac{\alpha_x}{\alpha_c \eta_x F''} < 0.$$

The demand for prestige c^* increases with the marginal utility of prestige, while the demand for quality X^{k*} decreases with the increase in the marginal utility of prestige. In other words, consumers with a higher marginal utility of prestige would choose more prestigious but lower quality vehicles, all else equal. This highlights that even without considering the effect on non-vehicle consumption, the pursuit of prestige could potentially cut into vehicle quality consumers choose to have.

We have previously shown that the demand for prestige c is generally higher among higher-income consumers. On top of that, a larger marginal utility of prestige would further drive up the demand for prestige. In light of previous literature (Charles et al., 2009), low-income consumers may have a higher marginal utility s_c for prestige than higher-income groups due to higher return in terms of social status gain and therefore may be more likely to buy higher-prestige and more expensive vehicles than they would have otherwise.

However, we are cautious to note that strong preferences for prestige by itself may not necessarily reflect a desire for conspicuous consumption. Instead, such preference may reflect a desire to enhance self-image or self-identity (Bursztyn and Jensen, 2017), in which case such demand for prestige would be sustained even if prestige were not visible to outsiders.

To further test whether the preferences for prestige by non-prime consumers reflect conspicuous consumption driven by social comparison, we provide further micro-foundations for the marginal utility of prestige $s_c(c, k)$. We hypothesize that the marginal utility of prestige can potentially be driven by two distinct mechanisms: 1. a desire to signal one's own income status relative to a reference social group; 2. a desire to emulate the consumption of visible prestige goods of their peers in the neighborhood or friend circle, popularly coined as the desire to "keep up with the Joneses."

2.1 The Status Signaling Model

First, to provide the micro-foundation for the status-signaling mechanism, we follow Charles et al. (2009) and assume consumers value their relative income status, which is the ratio between the society's *perceived* income of the consumer and the mean income of the consumer's social reference group. The term reference group is used to denote the group of people that the consumer compares him or herself with.[8] Although reference groups can be arbitrary on an individual basis, here we assume that consumers compare within their type. We can think of the collection of consumers in group k as the reference group for each of the consumers inside the group. Thus, the social status utility reflects the society's perceived income of consumer i relative to the mean income of the reference group that the consumer belongs to.

The consumer's choice of vehicle prestige serves as a visible signal of his/her true income level, which the society does not observe directly. Therefore, the higher the prestige of the consumer i' vehicle, the higher the owner's income perceived by the society.

We define consumer i's perceived income to be the expected income conditional on the noisy signal of consumer i's choice of vehicle prestige and the group k that consumer i visibly belongs to: $E(y_i|c_i, k)$. We can think of consumer i's group k as a "tag" of consumer i such that society knows that you belong to. This could be a neighborhood that one belongs to, the school that one has gone to, or the social circle that one surrounds oneself with. In our paper, we use neighborhood as the "tag."[9] To proceed, we call $s(c, k)$ the social status utility in this subsection. It can be written as:

$$s(c_i, k) = \frac{E(y_i|c_i, k)}{\mu_k}$$

The society does not observe individual i's income level but does observe the income distribution of consumer's tag k and the statistics associated with k: μ_k, σ_k^2, as well as the prestige of individual i's chosen vehicle c_i. Conditional on the observed prestige chosen by consumer i and the consumer's tag k, $E(y_i|c_i, k)$ is the perceived income for individual i. Society takes the observed prestige of consumers' vehicle choice as a signal and infers the consumer's income based on such signal and the income distribution of the consumer's tag.

To solve for the expected income, we assume that an individual's prestige choice c_i is a linear function of the underlying log income of the consumer i plus some idiosyncratic preference "noise" ξ_i specific to consumer i:

$$c_i = \theta_0 + \theta y_i + \xi_i$$

[8] In theory, a reference group can be any arbitrary group of people that the consumer cares about in social comparison. However, empirically it is not possible to precisely pinpoint whom the consumers are comparing themselves against. Thus, in practice, researchers often make assumptions about the structure of these reference groups. For example, many papers have considered geographic units such as neighborhoods or states and/or racial groups as natural frames of comparisons.

[9] In our case, neighborhood serves both as the group for social comparison and the "tag."

θ_0 captures the base level of prestige consumption. θ is the marginal propensity to consume prestige. To ensure a closed-form solution, we further assume that the income distribution of the consumer's type k is normally distributed: $y_i \sim N(\mu_k, \sigma_k^2)$. The distribution of the noise term is also normally distributed: $\xi_i \sim N(0, \sigma_\xi^2)$. We assume that the noise is uncorrelated with the income distribution. Hence, the joint distribution of the prestige of consumer's vehicle consumption c_i and consumer's income level is $(y_i, c_i) \sim N\left((\mu_k, \theta\mu_k), \begin{pmatrix} \sigma_k^2 & \theta\sigma_k^2 \\ \theta\sigma_k^2 & \theta^2\sigma_k^2 + \sigma_\xi^2 \end{pmatrix}\right)$.

Exploiting the parametric normal distribution of reference group k, we can compute the perceived income as the following:

$$E(y_i|c_i, k) = \mu_k + \frac{\theta^2\sigma_k^2}{\theta^2\sigma_k^2 + \sigma_\xi^2}\left(\frac{c_i - \theta_0}{\theta} - \mu_k\right)$$

We can see that perceived income depends on the consumers' reference group/tagged type's mean income. It also depends on the consumer's choice of prestige, scaled by the marginal propensity for prestige θ. By choosing a vehicle with higher prestige, the consumer "strengthens" the signal to society that he/she has a higher income. Importantly, the effectiveness of the signal depends on the relative size of the degree of income inequality (represented by the income variance σ_k^2) of type k and the size of the preference noise: σ_ξ^2. This is intuitive because if preference noise is large and income inequality is low, buying more expensive vehicles would be more likely interpreted by society as an idiosyncratic preference shock and not the consumer's own income level. In contrast, if income inequality is high in a reference group and the preference noise is small, buying more expensive vehicles is a cleaner signal of higher income relative to the consumer's peers.

Given the perceived income, we arrive at the social status utility by dividing it by the mean income of the reference group. We define $e(\theta, \sigma_k, \sigma_\xi, \mu_k) = \frac{\theta\sigma_k^2/\mu_k}{\theta^2\sigma_k^2+\sigma_\xi^2}$. We can thus write the social status utility as the following:

$$s(c_i, k) = (1 - e(\theta, \sigma_k, \sigma_\xi, \mu_k)\mu_k) + e(\theta, \sigma_k, \sigma_\xi, \mu_k)c_i$$

Based on the final form of the social status utility, the marginal utility of prestige is $s_c(c_i, k) = e(\theta, \sigma_k, \sigma_\xi, \mu_k)$, which is a *decreasing* function of the mean income of consumer i's reference group μ_k, an *increasing* function of the income inequality within consumer i's type σ_k^2, a decreasing function of the noisiness of the signal σ_ξ^2, and an increasing function of the marginal propensity for prestige θ.[10] Thus, based on the derived social status utility, consumers living in lower-income neighborhoods should have a stronger preference for prestige. Con-

[10] The prediction that consumers living in lower-income neighborhoods demand more prestige is consistent with the prediction in Charles et al. (2009).

sumers living in neighborhoods with higher income inequality are also predicted to have stronger preferences for prestige.

2.2 Emulation Model - "Keeping Up with the Joneses"

Alternatively, consumers may gain utility from consuming prestige due to their desire for social emulation. Because conspicuous consumption by neighbors is often visible, even if consumers do not have any desire to signal their status to outsiders, they may be tempted to "keep up with the Joneses" to avoid feeling left out. A number of papers have introduced some varieties of utility specifications to capture this "emulation" mechanism (Gali, 1994; Ljungqvist and Uhlig, 2000; De Giorgi et al., 2020). The basic requirement of the functional form is that the marginal utility of prestige needs to be an increasing function of peers' prestige consumption. In this subsection, we call the $s(c, k)$ as the emulation utility. We define the emulation utility as the following:

$$s(c, k) = g_0 c \bar{c}_k^{\rho}.$$

In this case, consumers gain additional utility from consuming a higher level of prestige c, and the marginal utility of prestige depends on the average level of prestige of peers that type-k consumers compare themselves to, $\bar{c}_k$. g_0 captures the marginal utility of prestige without social comparison. ρ captures the intensity of social comparison against their targeted peers.

Based on the emulation model, consumers who face a higher level of $\bar{c}_k$ will have a higher marginal utility with respect to prestige:

$$s_c(c, k) = g_0 \bar{c}_k^{\rho}.$$

As we have shown previously, a higher $s_c(c, k)$ drives up both the prestige demand and the price of the vehicles chosen. Therefore, the model predicts that consumers whose peers have a higher level of prestige consumption are likely to have a stronger demand for prestige and expensive vehicles.

In the next part of the paper, we turn to the data and study consumers' preferences for vehicle prestige empirically and test whether some of the preferences for prestige by consumers with low credit scores are driven by the status signaling motivation and/or the desire to keep up with their peers.

3 Data and Summary Statistics

3.1 AutoCount

We use detailed automobile purchasing data to study the preferences for prestige for consumers with different credit scores. The main data we use are from AutoCount monthly reports, an Experian database on auto loan underwriting. The market share reports break down vehicle sales volume by transaction type (loans, leases, no lender), vehicle type (new or used), title state, lender type (bank, captive, finance, credit union, buy-here-pay-there), dealer types (franchised/independent), make (brand), model, segment, body, and vehicle year by consumers' residential ZIP Code. The risk reports add to the above information also loan amounts, terms, interest rate, loan-to-value ratios for consumers with different credit score categories. The majority of the transactions are loans.[11]

We use the five-year (2015-2019) aggregate AutoCount reports to construct vehicle choice probabilities for our empirical study of vehicle demand. We construct the vehicle model choices made by consumers of different credit scores living in different counties and ZIP Codes. We use the average value of each vehicle model computed from the vehicle transaction records to approximate the vehicle price for each model faced by consumers. Importantly, each vehicle model belongs to a vehicle brand (make).[12] Using the linkage, we construct our measures of vehicle prestige based on information at the brand level. Vehicles that belong to a brand with a high share categorized as luxury are assumed to be more prestigious. We describe our measurement procedure in detail in the later sections.

We limit our analysis to brands with more than 500 transactions across the nation during the 2015-2019 period and vehicle models with a vehicle identification number (VIN).

3.1.1 Vehicle Models, Brands, and Value by Credit Score

Consumers choose from 54 brands and 1,243 models in our studied sample; the models also belong to 29 segments. Among the 41% non-prime consumers of all buyers who finance their vehicle purchases, a substantial fraction purchase expensive vehicles. We plot the share of purchases by the value of vehicles sold to consumers with non-prime and prime credit scores (Figure 1). Unsurprisingly, the share of non-prime pur-

[11] For example, in March 2020, at least 55.8% of the transactions were financed with loans, 34.9% did not have lender information (some are cash transactions) and 9.4% were leases. We do not have access to the transaction level data of leases. Leases account for 30% of new vehicle transactions (29.6% of all purchases) and only 0.6% of used sales and concentrate on borrowers with prime credit scores.

[12] For the rare cases that the same model names are used across brands, we exclude the models in our analysis.

chases relative to prime purchases decreases as vehicle value increases. Still, for vehicles valued at more than $35,000, around 12% of buyers are non-prime buyers and nearly a third of their share of all borrowers. For new vehicles, non-prime buyers account for 15-20% of vehicles valued at more than $35,000, a sizable share considering these consumers only account for 30% of all new vehicle buyers.[13]

3.1.2 Vehicle Brands and Model Market Shares

Consumer demand for brands, indicated by vehicle market share, rank similarly between the two types of consumers with several exceptions (Figure 2). Each vehicle brand typically has multiple models. For example, Figure 3 shows the aggregate model market of Jeep and Dodge. In our analysis, we calculate for each ZIP Code the model market shares for non-prime and prime borrowers and use the shares to measure the differential demand between the two groups. The average zip code model market share is about 0.3% for new vehicles and 0.8% for used vehicles, regardless of prime or non-prime. We calculate the average value for each model and new/used status. We use the model value as a proxy for the price of vehicles that buyers pay.[14]

A key variable in our analysis is vehicle prestige. We use the information at the brand level to capture variation in prestige. Our primary measure is the brand-specific share of new vehicles sold that are luxury models. This measure is designed to capture the luxury content associated with each brand. The idea is that if a brand mainly sells luxury-type vehicles, it would carry the reputation of higher prestige. In our main analysis, we define luxury models that those whose segments contain key words “luxury”, “upscale”, or “premium.” For robustness, we also define luxury models based on the average value of new models (threshold – $30,000). To demonstrate the contrasting luxury content across brands, Figure 4 plots the luxury share by brands based on both definitions of luxury.

It is also important to note that luxury brands are, on average, more expensive than non-luxury brands, thus carrying a “luxury brand premium.” Figure 5a and Figure 5b show binned scatterplot between the average model value and the luxury share of each brand. We can see that across both definitions of luxuries, higher luxury content is associated with more expensive vehicles. Specifically, compared with non-luxury vehicles,

[13]Despite the higher repayment risk, non-prime consumers, especially those taking out loans to finance high-priced new vehicles, may have an optimistic view of their future ability to repay the loans.

[14]Within a brand, values of different models vary because the models differ in many ways such as size, fuel efficiency, mechanics, horsepower, segments, etc. For example, the average new model value of Toyota, the most popular brand, ranges from $16,529 of its subcompact Yaris to $83,404 of its luxury Sport Utility Vehicle (SUV) Land Cruiser. We expect the model value to pick up the variation in functionality of the vehicles.

luxury vehicles are around 30% – 60% more expensive on average (luxury brand premiums).

3.1.3 Vehicle Purchases by Credit Score

During the five-year period (2015 – 2019) we examine, about 27 million (or 41%) transactions were made to non-prime borrowers with the Vantage Score between 280 and 660 and 40 million (or 59%) to prime borrowers with scores between 661 and 850. New vehicles accounted for 39% of the transactions, and 61% are used ones. As shown in Table 1, new vehicles are generally much more expensive and financed with larger loans than used ones, but with lower loan-to-value (LTV) ratios, longer terms, and lower interest rate.[15]

3.2 IPUMS/NHGIS/ACS

We compile demographic variables on income, income inequality, race, and ethnicity shares in the geographies that can be associated with AutoCount and CCP/Equifax from recent five-year American Community Surveys (ACS) obtained through the IPUMS National Historical Geographic Information System (NHGIS).[16]

3.3 FRBNY Consumer Credit Panel/Equifax

To understand the financial implications for auto loan borrowers who make expensive vehicle purchases, we supplement the analysis with the Federal Reserve Bank of New York Consumer Credit Panel (CCP)/Equifax.[17]

The CCP/Equifax trade-line data provide a quarterly panel of financial outcomes such as loan balances, status including length past due, repossession, charge-offs, etc. For each trade line of loans originated in the same month to the same consumer, we are also able to observe the credit score of the linked consumer and his/her residential location by quarter. The consumer panel of CCP/Equifax provides the quarterly loan balance and performance data from different consumer loan types. We use both the trade-line and consumer panels to estimate the impact of the initial auto loan balance on the financial outcomes from borrowing. Trade-line/consumer level panel data allow us to include consumer fixed effects and a variety of controls based on location characteristics of consumers' current ZIP Code.

[15] According to AucoCount, LTVs are calculated based on resale values instead of the market value and therefore can be higher than one. Non-prime consumers, on average, have a much larger LTV and pay much a higher interest rate than prime consumers. Their average monthly payment is therefore comparable or even higher despite a lower average debt and a slightly longer term.

[16] We use the Center for the Advancement of Data and Research in Economics (CADRE) at the Federal Reserve Bank of Kansas City to process the main analysis of this study (Lougee et al. (2018)).

[17] The CCP/Equifax provides consumer and loan-level credit data of US consumers with a credit report. We use the panel of consumers whose social security numbers were used to draw a random sample—the primary consumers. The CCP/Equifax also includes both vehicle purchases and leases and can be used to supplement our analysis using the purchase data from AutoCount being subscribed.

According to the CCP/Equifax data, as of the end of 2020, the total outstanding auto loan balance is $1.37 trillion. It accounts for 9.4% of all outstanding consumer loan debt in the US and ranked next to mortgages and student loans. Auto loan delinquency by non-prime borrowers far exceeded that of prime borrowers. In particular, the amount serious delinquent, or 90-plus day past due, reached 20% in mid-2020 for auto loans borrowed by subprime consumers with an Equifax risk score lower than 620, exceeding the highest level coming out of the Great Recession (Figure 6).

4 Empirical Framework and Tests for Conspicuous Consumption

To test for these conspicuous consumption motives using vehicle choice, we enhance the model and tailor it to allow for discrete vehicle choices observed in the data. Instead of modeling vehicle demand along a simplified continuous space of quality and prestige, we now assume that each consumer chooses to purchase a vehicle of model m out of all the available choices of model $1, ..., M$ to maximize his/her utility. On top of the previously specified consumer utility, we add a type-specific idiosyncratic taste shifter for each model ζ_m^k and an individual-specific Type-I Extreme Value preference shifter for each model:

$$U_{ikm} = u\left(Y^k - \lambda^k P_m\right) + \eta_k F(X_m) + s(c_m, k) + \zeta_m^k + \sigma\varepsilon_{ikm}.$$

This specification allows us to derive a vehicle demand equation (choice probability) as a function of vehicle characteristics and consumers' own characteristics such as income Y^K, financing cost λ^k, and preference parameters.

We first use first-order Taylor approximation to linearize the utility function:

$$\begin{aligned} U_{ikm} \approx\; & u\left(Y^k - \lambda^k \exp(\overline{\log(P)})\right) - \lambda^k \exp(\overline{\log(P)}) u^{'}\left(Y^k - \lambda^k \exp(\overline{\log(P)})\right)\left(\log(P_m) - \overline{\log(P)}\right) \\ & + \eta_k \log(X_m) + s(\bar{c}, k) + s_c(\bar{c}, k)(c_m - \bar{c}) + \zeta_m^k + \sigma\varepsilon_{ikm} \end{aligned}$$

We then normalize the utility function by dividing it by the standard deviation of the individual idiosyncratic component σ. We abuse the notations a bit by keeping the existing unknown parameters in the utility function intact after the normalization. The normalized utility function is the following:

$$U_{ikm} = \alpha_k - \beta_k \log(P_m) + \eta_k F(X_m) + \gamma_k c_m + \zeta_m^k + \varepsilon_{ikm}$$

where,

$$\beta_k = \lambda^k \exp(\overline{\log(P)}) u' \left(Y^k - \lambda^k \exp(\overline{\log(P)}) \right)$$
$$\gamma_k = \frac{s_c(\bar{c}, k)}{\sigma}$$

Consumer utility is thus approximated by a linear function of log vehicle price, quality, prestige, and taste shifters. The marginal utility of lower price β_k is decreasing in consumer's income level. Therefore, $\beta_h < \beta_l$. In other words, non-prime consumers should be more sensitive to vehicle prices, consistent with intuition discussed earlier.

The marginal utility of prestige is given by the first-order derivative of the prestige term $s(\bar{c}, k)/\sigma$, which differs by k. If low-income consumers are more sensitive to prestige, then it should be the case that $\gamma_l > \gamma_h$. However, we do not set any a priori restrictions and let the data determine the relative sizes of these parameters in the empirical part.

Due to the assumption of Type-I Extreme Value distribution for the individual taste shifter ε_{ikm}, type k consumer's choice probability of vehicle model m, s_m^k, admits the following functional form:

$$s_m^k = \frac{\exp\left(\alpha_k - \beta_k \log(P_m) + \eta_k F(X_m) + \gamma_k c_m + \zeta_m^k\right)}{\sum_{m'} \exp\left(\alpha_k - \beta_k \log(P_{m'}) + \eta_k F(X_{m'}) + \gamma_k c_{m'} + \zeta_{m'}^k\right)}$$

The key parameters of interest are β_k and γ_k. β_k governs consumers' sensitivity to the vehicle price, and γ_k governs how much consumers value vehicle prestige. We need to know the magnitude of these parameters to gauge the importance of the demand for prestige is.

4.1 Identification

To identify the model parameters, we compute the log choice probability of model m by each consumer type k:

$$\log(s_m^k) = \alpha_k - \beta_k \log(P_m) + \eta_k F(X_m) + \gamma_k c_m + \zeta_m^k - \delta^k$$

The type fixed effect captures the expected utility for each consumer type:

$$\delta^k = \log\left(\sum_{m'} \exp\left(\alpha_k - \beta_k \log(P_{m'}) + \eta_k \log(X_{m'}) + \gamma_k c_{m'} + \zeta_{m'}^k\right)\right)$$

The log choice probability equation can then be taken to the data. Despite its clean linear form, a simple OLS regression does not achieve the identifications of β_k or γ_k. Since the model choice probability resembles a standard demand equation, the price of vehicle $\log(P_m)$ is an endogenous object determined by both demand and supply shifters. If there are any quality characteristics that the consumers observe and value but are unobserved in the data and thus not included in the equation, a severe bias would arise for both β_k and γ_k.

To illustrate, suppose there is a variable that captures unobserved vehicle quality Z_m, which would shift the demand curve outward but are unobserved and excluded from the equation.[18] This would lead to two sources of biases. First, if the supply curve is upward sloping, the price would be driven up by the unobserved vehicle quality Z_m.[19] Meanwhile, the unobserved high quality would drive up consumer's choice probability. This would create a positive association between the choice probability and the price, leading to a downward bias for β_k. The second source of bias is that unobserved Z_m is likely correlated with vehicles' prestige c_m. Therefore, γ_k will pick up the consumer demand for Z_m, leading to an upward bias for γ_k.

Identifying the absolute sizes of β_k and γ_k requires random variations in price and prestige uncorrelated with any unobserved quality Z_m.[20]

4.1.1 Identification of Relative Demand

Fortunately, although the absolute sizes of the preference parameters cannot be identified by an OLS regression, we are able to identify the group-specific preference parameters *relative to* the parameters for the average consumer. For example, although we cannot identify the absolute sizes of γ_k for each consumer type k, we can identify the size of γ_k relative to the average demand for prestige $\bar{\gamma}$ with an OLS regression.

To illustrate how, we first take the difference between the choice probability made by type k consumers and the one made by the average consumer:

$$\log(s_m^k) - \log(\bar{s}_m) = \alpha_k - \bar{\alpha} - (\beta_k - \bar{\beta})\log(P_m) + (\eta_k - \bar{\eta})F(X_m) + (\gamma_k - \bar{\gamma})c_m + \delta^k - \bar{\delta} + \zeta_m^k - \bar{\zeta}_m$$

Note that the determinants of the *relative* demand equation are the type-specific preference parameters relative to those of the average consumer. Identification of the relative preference parameters relies on weaker assumptions than the identification of the absolute sizes of these parameters. Even if some unobserved vehicle

[18]The demand equation would have an extra term: $\log(s_m^k) = \alpha_k - \beta_k \log(P_m) + \eta_k F(X_m)) + \gamma_k c_m + \eta_{k,Z} Z_m + \zeta_m^k - \delta^k$.

[19]This could be captured by the equilibrium price function: $P = \alpha_0 + \alpha_x X + \alpha_c c + \alpha_z Z$.

[20]Bursztyn et al. (2018) actually uses random variation in prestige (the prestige of premium credit card) to identify the demand for prestige).

qualities Z_m are positively correlated with vehicle price and prestige, the aforementioned biases on the relative parameters $\beta_k - \bar{\beta}$ and $\gamma_k - \bar{\gamma}$ would not show up if consumers of each type value Z_m the same. Intuitively, since the outcome variable is the relative vehicle choice, not the choice itself, as long as the type-specific valuation for Z_m does not deviate much from the valuation by the average consumer, Z_m would not have an impact on the *relative* choice, even though it might have a sizable impact on vehicle choice by each type of consumers separately.

If we allow for the type-specific valuation for Z_m to potentially differ by type, some bias may indeed arise. But since our focus is on low-score consumers, under the normal good assumption, the demand for the unobserved quality Z_m is likely lower by the l type consumers relative to the average consumer. Having an omitted Z_m will likely lead to a downward bias for $\beta_k - \bar{\beta}$ and a downward bias for $\gamma_k - \bar{\gamma}$. Therefore, if we find that l type consumers have a large positive $\gamma_k - \bar{\gamma}$, the true value is likely even larger than the estimate.

4.2 Identifying Conspicuous Consumption Motives

By identifying the type-specific preference parameters for vehicle price and prestige relative to the average consumer, we are able to see whether and to what extent the relative preferences for prestige is a driving force behind non-prime consumers' purchasing of expensive vehicles. That being said, non-prime consumers' relatively strong preference for prestige by itself could simply reflects a stronger intrinsic preference for prestige vehicles and may not necessarily result from the conspicuous consumption motive that is externally motivated (Bursztyn and Jensen, 2017).

To further identify whether the relative demand for prestige by the non-prime consumers reflects their intrinsic preferences for prestige or a conspicuous consumption motive, we test the predictions of the status signaling model and the peer emulation model discussed earlier.

Tests for Status Signaling The status signaling model has two empirical predictions. The first predicts that consumers with lower-income reference groups should have a stronger preference for prestige because they have a higher marginal return of social status with respect to acquiring a higher level of prestige. The second prediction is that consumers tagged with an identifiable group with higher income inequality should have a stronger preference for prestige.

To evaluate the predictions empirically, we dissect non-prime consumers into finer geographic groups and estimate their relative preferences for prestige separately.

We evaluate the first prediction by examining whether the $\gamma_k - \bar{\gamma}$ is larger for non-prime consumers living in low-income neighborhoods. We assume that consumers, if engaging in social comparison, are more likely to compare with their neighbors. Thus, if the relative preferences for prestige are driven by status signaling motive, non-prime consumers living in low-income neighborhoods should see stronger preferences for prestige. We also examine whether $\gamma_k - \bar{\gamma}$ is larger in different minority neighborhoods. If consumers tend to engage in social comparison within their racial groups, then consumers in minority neighborhoods with low group-specific mean income should exhibit stronger preferences for prestige.

To evaluate the second prediction, we examine whether consumers living in neighborhoods with higher income inequality should see a higher preference for prestige.

Tests for Peer Emulation The peer emulation model predicts that consumers whose peers are more likely to own visibly prestigious vehicles should be more likely to have a higher level of preferences for prestige, all else being equal. If consumers tend to compare themselves upward with others living in the same ZIP Code, we can test the peer emulation model by examining whether non-prime consumers whose prime neighbors living in the same ZIP Code tend to have higher preferences for prestige, controlling for other neighborhood characteristics.

4.3 Empirical Specification

To simplify notations in the discussion of the empirical specification, from now on, we let $\tilde{\beta}_k = \beta_k - \bar{\beta}$, $\tilde{\eta}_k = \eta_k - \bar{\eta}$, $\tilde{\gamma}_k = \gamma_k - \bar{\gamma}$, $\tilde{\delta}^k = \delta^k - \bar{\delta}$, $\tilde{\zeta}^k_m = \zeta^k_m - \bar{\zeta}_m$, and $\widetilde{\log(s^k_m)} = \log(s^k_m) - \log(\bar{s}_m)$. We can re-write the estimating equation as the following:

$$\widetilde{\log(s^k_m)} = \tilde{\alpha}_k - \tilde{\beta}_k \log(P_m) + \tilde{\eta}_k F(X_m) + \tilde{\gamma}_k c_m + \tilde{\delta}^k + \tilde{\zeta}^k_m.$$

The outcome variable is the relative demand for vehicle models made by consumers of each type k. The relative demand coefficients are driven by how much each consumer type's vehicle choices depend on vehicle prices, observed qualities, and prestige compared to the average consumer. The key parameters of interest are: $\tilde{\beta}_k = \beta_k - \bar{\beta}$ and $\tilde{\gamma}_k = \gamma_k - \bar{\gamma}$, which are the relative demand coefficients with respect to vehicle prices and levels of prestige.

4.3.1 Measuring Model Prices, Quality Characteristics, and Prestige

For estimation, we treat the model category m as given by the vehicle model and the new/used status of the vehicle. In other words, the new and used vehicles that belong to the same vehicle model would be categorized as different model category m. We measure the vehicle model price P_m by taking the average value for each m observed in the national transaction record in the AutoCount. Note that the prices of vehicles that are new or used are computed separately.

We use the AutoCount segment categories to account for vehicle quality in the equation. There are around 30 segments associated with vehicle models in AutoCount. Vehicle types such as vehicle ranges, sizes, and tiers are captured by the classification.

To construct the prestige variable for each vehicle model, we rely on the brand-level (make) information. We assume that vehicle prestige varies by brand – a model has a higher level of prestige if it belongs to a brand that has the reputation of carrying more upscale and luxury vehicle models. For each brand, we calculate the share of luxury models that belong to segments labeled as "upscale", "luxury" or "premium" and use the luxury share as the proxy for prestige level. We then assign the prestige measurement (brand luxury share) to each vehicle model based on the brand it belongs to. A non-luxury model is assumed to have high "prestige" if it belongs to a brand that has a large luxury share. For robustness, we also calculate the luxury share by using the share of new vehicles that have prices higher than a certain threshold ($30,000 in our main estimation).

4.3.2 Vehicle Choice Sets and Geographic Level of Analysis

To construct the vehicle demand for each group and the average consumers, we need to specify the level of analysis for the demand equation. A seemingly straightforward way is to conduct the analysis at the national level by constructing $\log(s_m^k)$ and $\log(\bar{s}_m)$ at the national level and compute the relative demand $\widetilde{\log(s_m^k)}$ for consumers of each credit-score group nationally with respect to the aggregate national demand for each model. The issue with this approach is that a national analysis could be confounded by the spatial variation in vehicle supply. If non-prime consumers disproportionately reside in places where they have limited vehicle choices, the national-level analysis would erroneously attribute them not choosing these missing vehicles as their choices, when in fact such observations are driven by spatial variation in choice sets. Dealers and lenders may also target marketing efforts in certain communities to sell specific models or brands.[21]

[21] One potential confounding factor for identifying consumer's demand for prestige is that dealers and lenders may target specifically target communities with a large number of non-prime consumers. If non-prime buyers are targeted into buying higher-end brands due to marketing, then we could wrongly attribute their purchases to their demand for brand prestige. One way such targeting

We can address this by conducting the analysis at relatively local level, where the population are more or less facing the same vehicle pool to choose from. We construct the type-specific demand and the average demand for vehicle models at county level: $\log(s^k_{m,j})$ and $\log(\bar{s}_{m,j})$, where j denotes county.[22] We construct our relative demand across subgroups k of consumers within each county j: $\widetilde{\log(s^k_{m,j})} = \log(s^k_{m,j}) - \log(\bar{s}_{m,j})$. Thus the final estimating equation is:

$$\widetilde{\log(s^k_{m,j})} = \tilde{\alpha}_k - \tilde{\beta}_k \log(P_m) + \tilde{\eta}_k F(X_m) + \tilde{\gamma}_k c_m + \tilde{\delta}^k_j + \tilde{\zeta}^k_{m,j}. \tag{1}$$

The indicator variables $\tilde{\delta}^k_j$ varies by county j and consumer type k. The county-type fixed effects capture the variation in the denominators of the Logit choice probability for each consumer type in each county.

4.4 Estimation Results

4.4.1 Baseline – Desire for Prestige

Table 3 presents the baseline estimates of the parameters in the relative demand equation 1. We focus on the vehicle demand by non-prime consumers relative to the average consumer. β_k estimates are negative and statistically significant, which means that low-score consumers are more sensitive to vehicle price compared with the average consumer. However, γ_k estimates are positive in all three columns, indicating that holding vehicle model price constant, non-prime consumers are more likely to purchase vehicles that belong to brands with higher prestige (higher brand luxury content). Column 3 presents the results where we add the shares of pick-up trucks and shares of alternative-energy vehicles within brands as additional brand-level characteristics. The coefficient on brand luxury share continues to be positive and significant. For robustness, in column 4, we use the alternative definition of brand luxury share by defining luxury models as models higher than \$30,000 of value. The results are similar to column 1. The positive estimates provide evidence that the

can be done is through offering financing options through captives–the financing arms of auto manufacturers, Buy Here Pay Here (BHPH) option at dealers, and other finance companies. Figure A1 and Figure A2 show the lender market share by luxury and non-luxury brands, respectively. Traditional lenders, such as banks and credit unions, lend to buyers of all brands and of different creditworthiness. Although captives sell vehicles of their own brands, most large brands have captives regardless of the prestige level. Further evidence can be found by regressing market shares on luxury dummies for captives (See Table A6, column 1). In addition, if we regress the credit standard of captives (relative to all lenders) on luxury dummies for each lender type (Table A7. We do not find captives' average credit standard relative to all lenders differ between higher-end and lower-end brands. Also suggested, despite that auto finance companies and BHPH lenders generally lend to borrowers with lower credit scores, and finance companies do target lower-end vehicles (column 2 in Table A6), they do not differentiate brands in underwriting. This alleviates our concern for identification driven by lender behavior.

[22] Credit constraint and financial capability can of course deter some consumers from choosing certain high-end vehicles. But these factors affect the *cost* of purchase, not the choice set per se.

preferences for prestige are stronger among non-prime consumers than the average consumer.[23]

4.5 The Importance of Prestige in Vehicle Purchases

With the preference parameters estimated, we proceed to conduct a few simple calculations to evaluate how much the preferences for prestige drives up the demand for pricey vehicles by non-prime consumers.

First, let's consider a vehicle not belonging to a luxury brand (brand luxury share = 0%), which non-prime consumers have the same initial demand for it relative to the population average, namely $s_m^k = \bar{s}_m$. If we increase the prestige level by making it a luxury brand (brand luxury share = 100%), all else being equal, non-prime consumers' demand for the vehicle would increase by $0.0536 \times (1 - \bar{s}_m)$ log point more than the population, based on the estimate in Table 3 column 1. Such an increase in relative demand is equivalent to dropping the vehicle price by 7.8%, which is equivalent to roughly $1,506 if we take the average vehicle price as $19,310. This first exercise suggests that the non-prime consumers' preference for prestige is quite sizable and considerably stronger than that of the average consumer.

We know that since non-prime consumers are more sensitive to vehicle prices, their demand for luxury vehicles must be lower compared to the average consumers if their preferences for prestige were taken out of the equation. However, since non-prime consumers have stronger preferences for prestige and prestigious vehicles, on average, are more expensive, once preferences for prestige are fully accounted for, the demand gap for prestigious vehicles would be smaller.

To measure how much the relative demand for luxury vehicles by non-prime consumers is driven up by preferences for prestige, we conduct the following exercise. We first measure the price premium of luxury brands relative to non-luxury brands, and the premium is about 70%. Therefore, if we do not take the demand for prestige γ_k into account, non-prime consumers' demand for prestigious vehicles with 100% brand luxury share should be $0.684 \times 36.8\% \times (1 - \bar{s}_m)$ or $0.2517 \times (1 - \bar{s}_m)$ lower than the average consumers' demand for such vehicles. This is a natural result of non-prime consumers being more sensitive to vehicle prices, and luxury branded vehicles are more expensive. However, by taking into non-prime consumers' stronger

[23] We further explore if consumers distinguish the brand prestige between new and used vehicles. To do so, we allow the relative preference coefficients to differ based on vehicles' new/used status, as consumers may be deferentially sensitive to vehicle price and prestige between new vs. used vehicles. If used prestige vehicles cannot be easily recognized as used, or vehicle age matters little in vehicles' prestige value, non-prime consumers may be more drawn to the used vehicles to acquire prestige, and thus the preference coefficient on prestige would be larger for used vehicles. Alternatively, if the used status of vehicles is clearly visible to outsiders or vehicles' prestige depreciates sharply with age, the preference coefficients may be higher among new vehicles. Table A1 presents the results based on this more flexible specification. We can see that the demand for prestige is actually lower among new vehicles but stronger within used ones. This suggests that used vehicles may be a cheaper way to acquire prestige vehicles.

preference for prestige, the resulting demand by non-prime consumers for such luxury-branded vehicle would have been only $(0.684 \times 36.8\% - 0.0536) \times (1 - \bar{s}_m)$ lower than the demand by the average population. The demand gap shrinks by 21.3% due to the preferences for prestige. This means that the non-prime consumers' preference for prestige is likely a sizable driving force behind their purchasing pricey vehicles.[24]

These findings show that non-prime consumers' demand for prestige is likely a strong propellant behind their spending on expensive vehicles.

4.6 Evidence for Status Signaling

Next, we test whether non-prime consumers' desire for luxury brands is driven by their trying to signal their income status relative to their reference group. Recall that the first prediction of the status signaling model is that the marginal utility of the prestige and thus the demand for prestige should be higher if the mean income of the reference group is lower. The second prediction is that the marginal utility of prestige and thus the demand for prestige should be higher if the consumer is "tagged" by a community group that has a higher level of income inequality. We assume the consumers' reference group (the group that the consumers are comparing themselves against) is the neighbors living in the same ZIP Code. We further assume that consumers are "tagged" by their neighborhood characteristics.[25]

To test the model, we run the same regression to estimate the relative demand equation for prestige for non-prime consumers, but allowing the relative demand coefficients to potentially differ not only by credit score but also by consumers' neighborhood characteristics. We classify neighborhoods by race, income, and Gini coefficient. We categorize each neighborhood as to whether they are majority black, Hispanic, Asian, or neither. We also categorize neighborhoods into three groups based on median income: <40K, >=40K and <120K, or >=120K. Finally, we categorize neighborhoods into four groups based on Gini coefficient: <0.3783, 0.3783 - 0.4174, 0.4174 – 0.4576, or >0.4576.

Table 4 presents the results. Base results denote coefficients for consumers living in the neighborhoods in which all included indicator categories are zeros (base level). Columns 1, 2, 3 presents the results of regressions in which race, income, and Gini indicators are included one at a time. Column 4 includes all indicators simultaneously.

[24]Alternatively, we can conduct the calculation using the other definition of brand luxury share – using model value. Using the model value ($30,000 as luxury threshold), we calculate that the luxury brand premium is 63.19%, considerably larger than the premium estimated using our main luxury share measure. However, the γ_k coefficient is 0.0902, also much larger. Based on this definition, the demand gap shrinks by 20.97% due to preferences for prestige, which is quite similar to our main number.

[25]Consumers' place of residence is clearly highly visible to outsiders.

First, compared with non-prime consumers in mid-income neighborhoods ($40K – $120K), non-prime consumers in low-income neighborhoods are more sensitive to vehicle price, and non-prime consumers in high-income neighborhoods are less sensitive to vehicle price. Importantly, non-prime consumers in low-income neighborhoods have a stronger preference coefficient for brand luxury share (vehicle prestige), all else equal. This is consistent with the first prediction of the model, which states that consumers with a lower-income reference group should have stronger preferences for prestige.

Secondly, compared with non-prime consumers in neighborhoods with low Gini (<0.3783), non-prime consumers in neighborhoods with the very high Gini coefficients have much stronger preferences for vehicle prestige, consistent with the second prediction of the model, which states that consumers whose "tagged" groups have higher income inequality should exhibit stronger preferences for prestige.

In addition, our result by race is consistent with the finding in Charles et al. (2009), in that non-prime consumers in black-majority neighborhoods have the strongest demand for vehicle prestige, even though they tend to be more sensitive to vehicle price. Charles et al. demonstrates that the racial difference in the demand for visible conspicuous consumption could be due to the different mean incomes of the race-specific reference groups.

4.6.1 Importance of Prestige in Low-income And Minority Neighborhoods

If we look at non-prime consumers in our subsamples, such as those who live in low-income or minority neighborhoods, the role of prestige in driving up demand for luxury vehicles is much more stark than for non-prime consumers in general. Based on the estimates for non-prime consumers in low-income neighborhoods in Table 4, the gap between their demand for luxury branded vehicle and that by the average consumers would be offset by 45.79%, which means that prestige plays a much bigger role in driving consumers toward expensive vehicles in low-income neighborhoods. If we look at non-prime consumers living in low-income black-majority neighborhoods, the gap between their demand for luxury branded vehicles and the average consumers not only is entirely offset by preferences for prestige, the demand for luxury branded vehicle is actually higher among these consumers relative to the average consumers. This shows that brand prestige is a major driving force behind vehicle spending in these communities, and status signaling is likely the mechanism driving the pursuit of prestige.

4.7 Evidence for "Keeping Up with the Joneses"

Next, we proceed to test whether non-prime consumers' demand for prestige is also driven by a peer emulation motive – the story of "Keeping Up With the Joneses." Recall that the prediction of the peer emulation model is that consumers should have a larger marginal utility of prestige and thus a stronger demand for prestige if the peers in their comparison group purchase more prestigious vehicles. We further assume that the peers who are potentially in non-prime consumers' comparison groups are the prime neighbors who live in the same ZIP Code as these non-prime consumers we study.

To test the peer emulation model, we need to examine whether the non-prime consumers who live in ZIP Codes where their prime neighbors purchase more prestigious vehicles tend to have stronger preferences for prestige. For each ZIP Code, we compute the average luxury share of the vehicle brands purchased by the prime consumers. We then examine whether non-prime consumers' preference for brand luxury share is an increasing function of their prime neighbors' luxury shares.

Table 5 presents the results. We allow the demand coefficients to differ by prime neighbors' average luxury share. We do so by interacting the Log(Model Value) and Log(Brand Luxury Share) with prime neighbors' average luxury share. Column 1 shows the results without the controls for neighborhood characteristics. Column 2 includes further interaction terms, where Log(Model Value) and Log(Brand Luxury Share) are interacted with indicator variables of race, income, and Gini indicators of the neighborhoods.

We can see that the coefficient on the interaction term between non-prime consumers' own preference for prestige and their prime neighbors' average luxury share is positive with strong statistical significance in both columns 1 and 2. This indicates that non-prime consumers are more likely to buy luxury brands, holding vehicle prices constant, if their prime neighbors buy more of them. Note that in column 2, after we control for the interaction between Log(Brand Luxury Share) and Log (Model Value) with neighborhood controls, the coefficient on the interaction term between Log(Brand Luxury Share) and prime neighbors' luxury share remain large. This shows that, even between neighborhoods with similar racial composition, income, and inequality, non-prime consumers' preference for prestige is higher when their prime neighbors purchase more prestigious vehicles. This result validates the prediction of the peer emulation model.

The primary empirical concern for drawing this inference is that due to spatial sorting by income, race, or taste for consumer goods, consumers who live next to neighbors who have strong taste in luxury brands may themselves have strong taste in luxury brands. In that case, the correlation of taste may not be driven by emulation. In column 1, indeed, non-prime consumers who live next to neighbors who buy more luxury brands tend to be less sensitive to vehicle prices, which indicates a possibility of taste homophily due to spatial sorting. However, in column 2, once we control for the interaction terms with race, income, and Gini, the dependence of price sensitivity on neighbors' average luxury share becomes considerably weaker. Importantly, in column 2, with the controls, the coefficient on the interaction term between Log(Brand Luxury Share) and prime neighbors' luxury share actually becomes much *larger* than that without the controls. If the homophily of taste for luxury is indeed driven by spatial sorting, it is likely the spatial variation in the controls would *reduce* the size of the dependence of taste for luxury on neighbors' luxury shares. The coefficient becoming larger indicates that the primary driving force behind the positive estimate for the taste homophily is not likely spatial sorting.

5 Financial Consequences of Higher Auto Loan Debt for Non-prime Consumers

Since automobile purchases are often funded by auto loan debt, especially for those who are cash-constrained, higher spending on vehicles driven by the conspicuous consumption of prestige would often lead to higher amount of auto loan. We now turn the page to study the extent to which borrowing a larger amount of auto loan debt affects non-prime consumers' financial well-being.

We examine the trade-line panel data from CCP/Equifax for auto loans originated between 2015 and 2019.[26] We use the 20% of the primary sample (a randomized sample of 5% of the US consumers with a credit report) or 1% of the 1.14 million US auto loan trade lines. The data record the dates of loan performances and origination of each trade-line account, borrowers' credit profiles, and lender information.

Table 6 presents the summary of the loan characteristics and performance observed in the fourth quarter of 2019. Non-prime borrowers are younger, less likely to lease a vehicle, take out lower amounts of debt but tend to hold a higher level of the remaining balance.[27] They are also less likely than prime borrowers to borrow from banks, credit unions or captives (financial subsidiaries of automobile manufacturers), and more likely to borrow from auto finance companies. On average, non-prime consumers who have paid down less of the original debt are more likely to fall behind their payments or have their vehicles repossessed than prime consumers. The credit scores (Equifax risk score) of prime borrowers are 15 points higher on average from

[26]Borrowing a large amount of consumer loans does not always lead to adverse financial outcomes. For example, consumers who take out a large amount of student loans are less likely to be delinquent than those who borrow less (Looney and Yannelis (2015)).

[27]Initial balance and remaining balance are adjusted for joint ownership

the time they take out the loan, but for non-prime borrowers, the average score is 30 points lower. We also see a much larger share of auto loans borrowed by non-prime borrowers involves bankruptcy filings, payment plan arrangements, or charge-offs.

5.1 Auto Loan Debt Size and Loan Performance

We run a linear probability model to examine if these financial outcomes for non-prime consumers are at least partly the result of borrowing a higher amount of auto loan debt.

$$Outcome_{ijt} = \beta_0 + \beta_1 log(Balance)_{ij0} + \beta_2 Score_{ij0} + \delta_i + \tau_t + \epsilon_{ijt} \quad (2)$$

i indexes borrowers; j denotes trade-line account; t denotes month. $Outcome_{ijt}$ denotes any account outcome variable over time. $log(Balance)_{ij0}$ denotes the initial balance of the trade-line account owned by borrower i's account j. $Score_{ij0}$ denotes the initial credit score the borrower i has at the initial month of the account j. The regressions control for consumer fixed effects δ_i and time fixed effects τ_t.

Table 7 shows how amounts borrowed affect the probability of delinquency past due between 30-150 days. As column 1 indicates, the likelihood of auto loan delinquency increases as borrowers' initial balance goes up. Doubling the loan amount is associated with a 1.1 percentage-point (or about a third) increase in auto loan delinquency (from the overall 3.2%), controlling for credit scores (Equifax risk score), leasing type, lender type, consumer, and time fixed effects. As expected, a higher credit score at loan origination offsets the negative impact of the initial balance on loan performance. Auto loan delinquency decreases by 0.43 percentage points if the borrower's credit score increases by 100 points. We then run regressions for each credit risk range of consumers at loan origination. As shown in Columns 2-4, for prime borrowers whose credit scores are greater than or equal to 660, holding a higher level of auto loan debt has a minimal impact on loan performance. Doubling the debt amount is associated with only a 0.12 percentage-point increase in delinquency. For subprime borrowers with a credit score lower than 620, though, the average increase in delinquency would be 3.8 percentage points, a much larger effect.[28]

To see how non-prime borrowers fare over time, we also calculate whether loans have been delinquent at different loan ages. As Table 8 shows, delinquency typically occurs within the first two years following loan origination for non-prime borrowers if they take out larger loans. After that, loan amounts no longer

[28] If we include near-prime borrowers (scores between 620 and 660), the increase in delinquency would be 2.8 percentage points.

contribute to delinquencies.

If auto loan borrowers miss payments consecutively, lenders may choose to repossess the vehicle to sell and recoup the loan loss instead of doing further debt collection. Repossession is a low-cost process for lenders but can have a great negative impact on the borrowers' life and credit standing. Table 9 shows the results of regressing the probability of repossession on the initial loan balance. Repossessions are much more likely to happen with a larger auto loan debt. For non-prime borrowers, doubling the initial loan amount is associated with a 0.37 percentage point increase in the chance of vehicle repossession, a 28% increase from the overall percentage of vehicles repossessed from non-prime borrowers (1.3%). Table 10 compares the probability of vehicles being repossessed from non-prime borrowers for different loan ages. Repossession is more likely to happen in the first two years following loan origination if the non-prime borrower takes out a large amount of debt.

In general, on-time repayment helps consumers build credit and access future loans with better terms. However, delinquencies and repossessions can lead to severe damages to borrows' credit. We now examine how auto loan borrowers' credit score changes as the result of a large loan balance, controlling for loan age and other factors. Table 11 shows that the changes in borrowers' credit scores from the loan origination can also be partially explained by the amounts borrowed. Excessive borrowing can be detrimental to borrowers' credit standing. Non-prime borrowers' credit scores decline if they take out a larger amount of auto loan debt, while prime borrowers' score generally increases, holding other things constant.

We further test the impact of auto loan borrowing on the growth in auto loan debt measured by the change in log remaining balance from quarter to quarter. Table 12 presents the results. Across consumers with different credit profiles, there is a positive relationship between the amounts initially borrowed and the increase in the auto loan remaining balance; that is, larger loans are not paid down as much as smaller loans. Prime borrowers paid down slower than non-prime borrower as the originated amount increases.[29]

These findings that larger loans lead to worse loan performance is consistent with Adams et al. (2009), who find that larger loans lead to higher default in the subprime auto loan market. They explain that larger loans create the incentive of moral hazard for the borrowers because the larger the loans are, the larger share of the default costs would be pushed onto the lenders. This would lead to a higher default rate. Moral hazard could certainly explain part of our results. We cannot empirically disentangle moral hazard from borrowers' genuine financial distress from these set of regressions alone. But in the rest of the section, we proceed to

[29]It is possible that non-prime borrowers are getting shorter terms for larger loans, but we do not observe complete term information in CCP/Equifax

show that larger auto loans also lead to worse loan performance in other non-auto loan accounts of the same borrowers. This provides a hint that the negative effect of larger loans may partly reflect consumers' genuine financial distress, in addition to moral hazard.

5.2 Other Consumer Loan Performance

Consumers who have trouble paying down auto loan debt may also struggle to repay other debt. We examine how auto loan borrowing can affect other consumer loan performance. Instead of using the trade-line panel that includes only auto loans, we use the consumer panel data from the CCP/Equifax for this new set of regressions. The consumer-panel data allow us to see consumers' debt portfolio and the performance of other loan types.[30][31]

The results are reported in Table 13. For non-prime borrowers, a higher auto loan balance results in higher delinquencies in bank-issued credit card and mortgage delinquencies; and not surprisingly, higher overall delinquencies of consumer loans (also including student loans, home equity loans, consumer loans, and retail loans, etc.). Taking out large auto loan debt can create repayment woes that spread to other loan types.

For non-prime consumers, borrowing auto loan debt beyond the capacity to repay can lead to a vicious cycle of financial struggles. Non-prime borrowers of larger auto loan debt are more likely to be delinquent, have vehicles repossessed, unable to build credit, pay down debt slowly, and miss payments on other consumer loans.

6 Conclusion

In this paper, we unpack the driving forces behind the purchase of expensive vehicles by non-prime consumers. We use detailed automobile purchase data from AutoCount to analyze vehicle demand and the consumers' preference prestige. We find that non-prime consumers' demand for expensive vehicles is partially driven by their pursuit of vehicle brand prestige. Non-prime consumers have stronger preferences for brand prestige than average consumers.

We further demonstrate that such relatively strong preferences for prestige is driven by a desire to use

[30]Consumers' borrowing and loan performance are listed in Table A2 in the Appendix

[31]Because consumers can purchase multiple vehicles and take out more than one auto loans, instead of defining the borrower risk categories based on the credit score at loan origination month, we use the credit ranges based on the current scores in the analysis.

the conspicuous consumption of prestige to signal ones' own income status to others and/or to emulate the conspicuous consumption of prestigious vehicles by their peers. Using a status signaling model and peer emulation model, we derive a few empirical predictions of these hypotheses. We find evidence that the predictions of both the status signaling model and the peer emulation are supported by the data.

Finally, we show that larger borrowing of auto loans comes at a cost, especially for non-prime consumers. Borrowing a larger amount of auto loans would increase delinquency, reduce credit scores of the borrower, increase the probability of bankruptcies, and decrease the performance of other loans such as credit card loans. This implies that borrowing to finance conspicuous vehicle consumption could create challenges for non-prime consumers.

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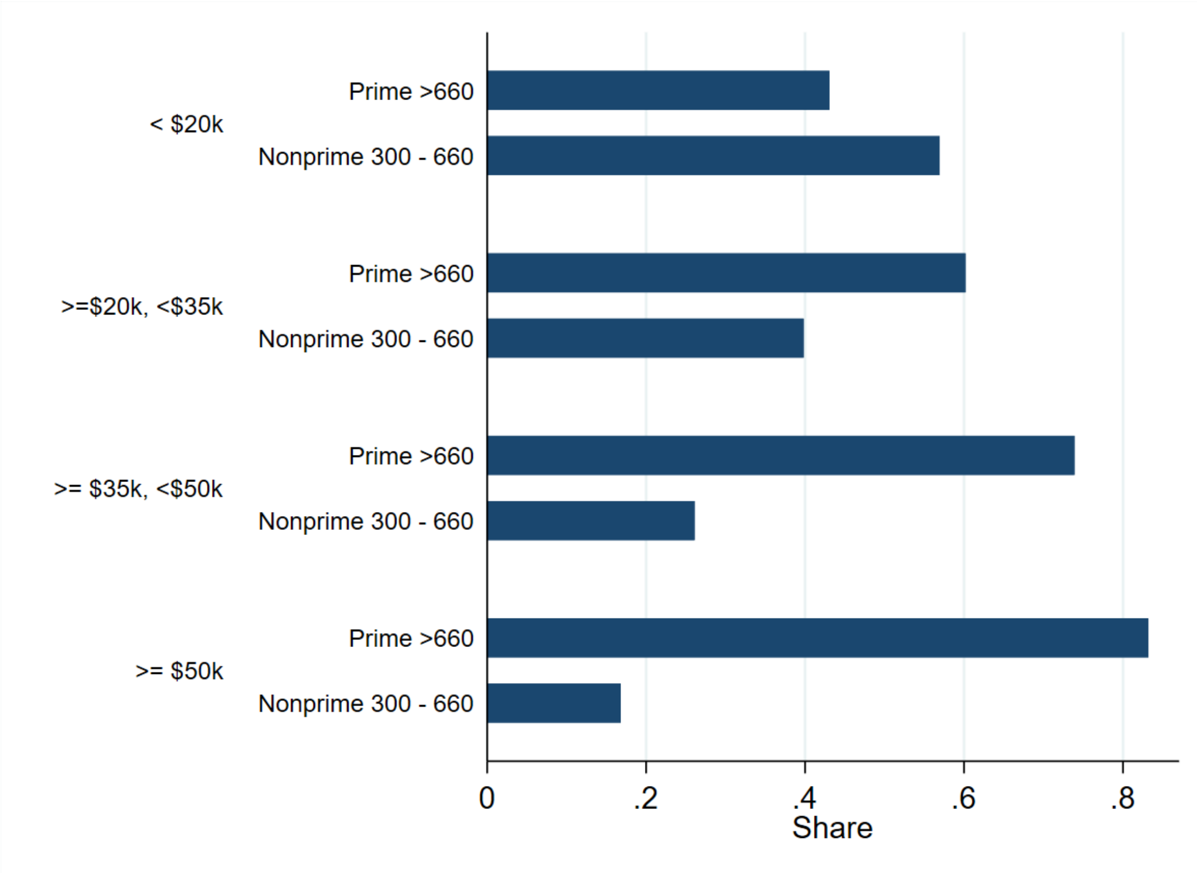
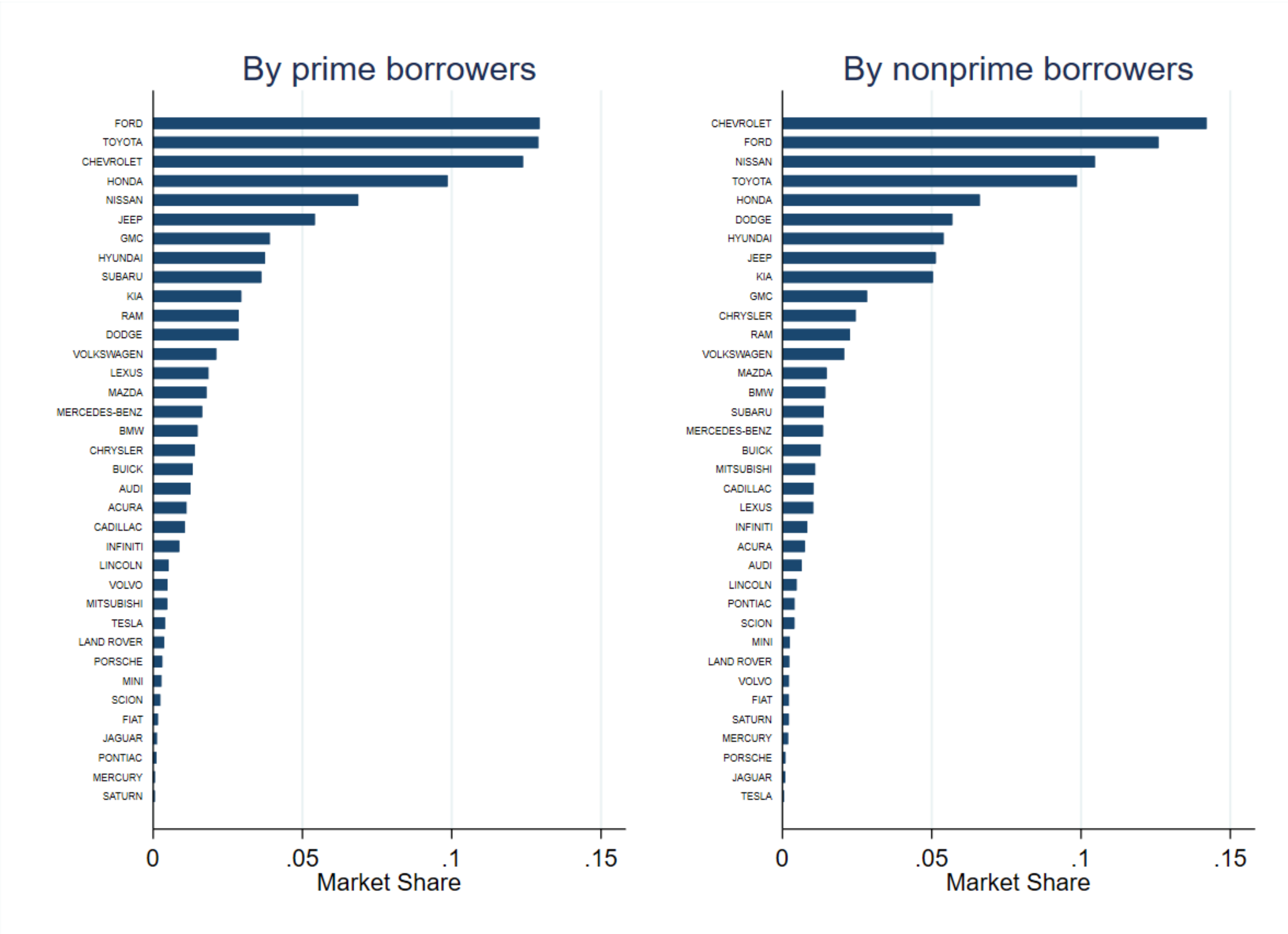
Figure 1: Non-prime borrowers also buy expensive vehicles



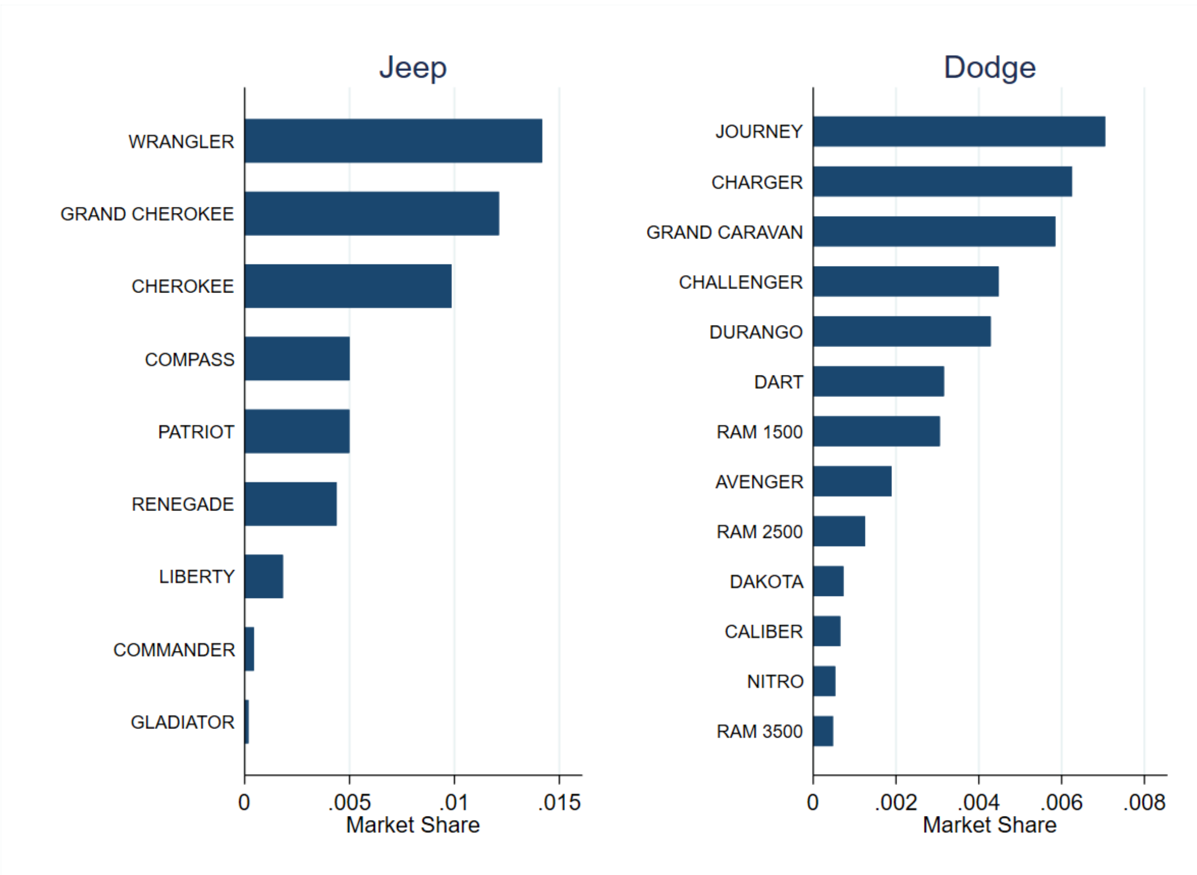
Note: For each price category, we compute the share of vehicles purchased by prime and non-prime consumers, respectively. We use the count of vehicle purchases by vehicle model, new/used status, and the credit scores of the buyers during 2015-2019 in the AutoCount data. We assign the value of the vehicle based on the average vehicle value by vehicle model and new/used status calculated with the national sample. Prime and non-prime statuses of consumers are defined based on Vantage Scores provided by Experian Automotive.

Figure 2: Brand Market Shares Vary by Prime Status



Note: We compute the market share of each brand (make) by dividing the total number of sales per brand by total number of sales. We compute the market shares separately for prime and non-prime consumers. We use the vehicle purchase data during 2015-2019 in the AutoCount data. Prime and non-prime statuses of consumers are defined based on Vantage Scores provided by Experian Automotive.

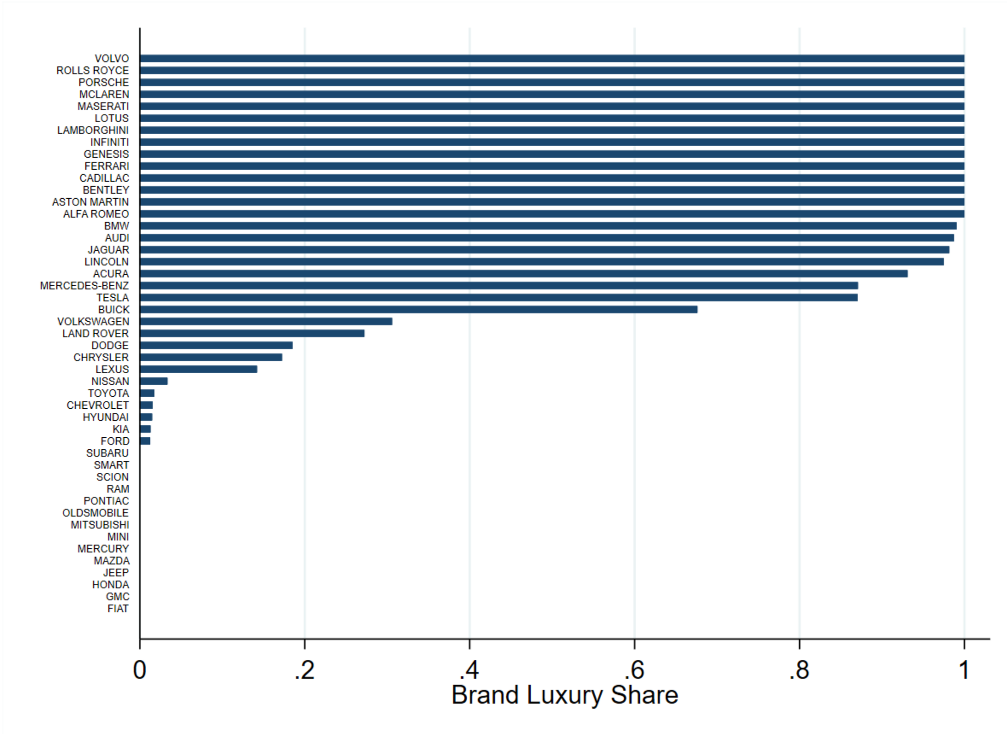
Figure 3: Examples of Vehicle Models within Brands



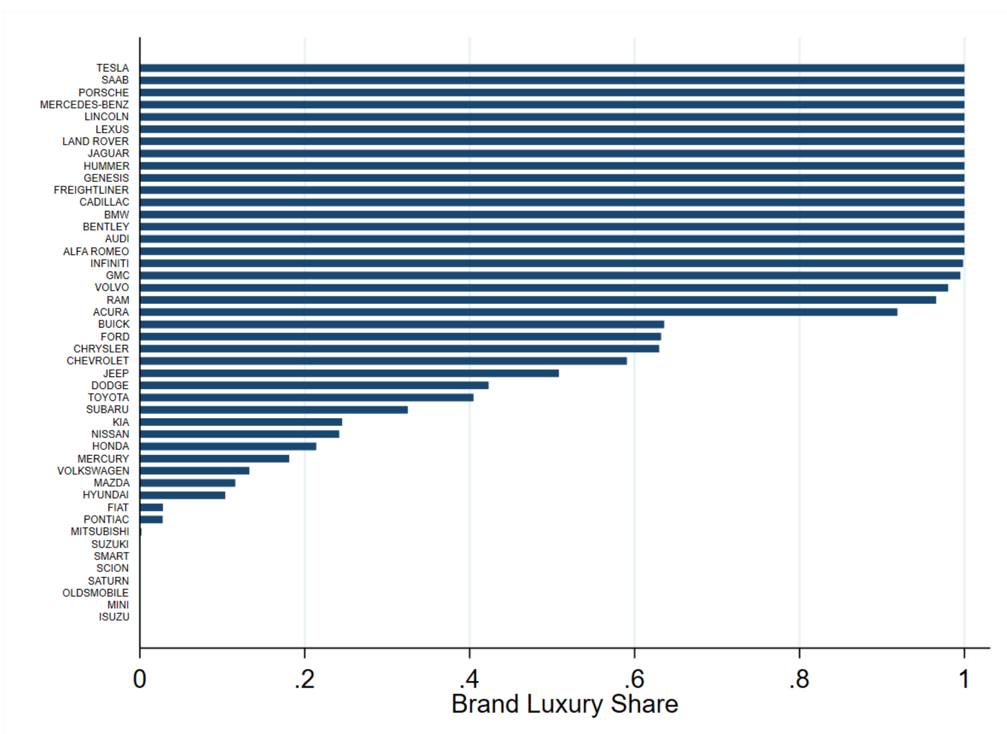
Note: We compute the market share of Jeep and Dodge brands (makes) by dividing the total number of sales per brand by total number of sales for these two brands separately. We use the vehicle purchase data during 2015-2019 in the AutoCount data.

Figure 4: Luxury Share By Brand

(a) Luxury Model Defined Based on Segments (Luxury, Upscale, or Premium)



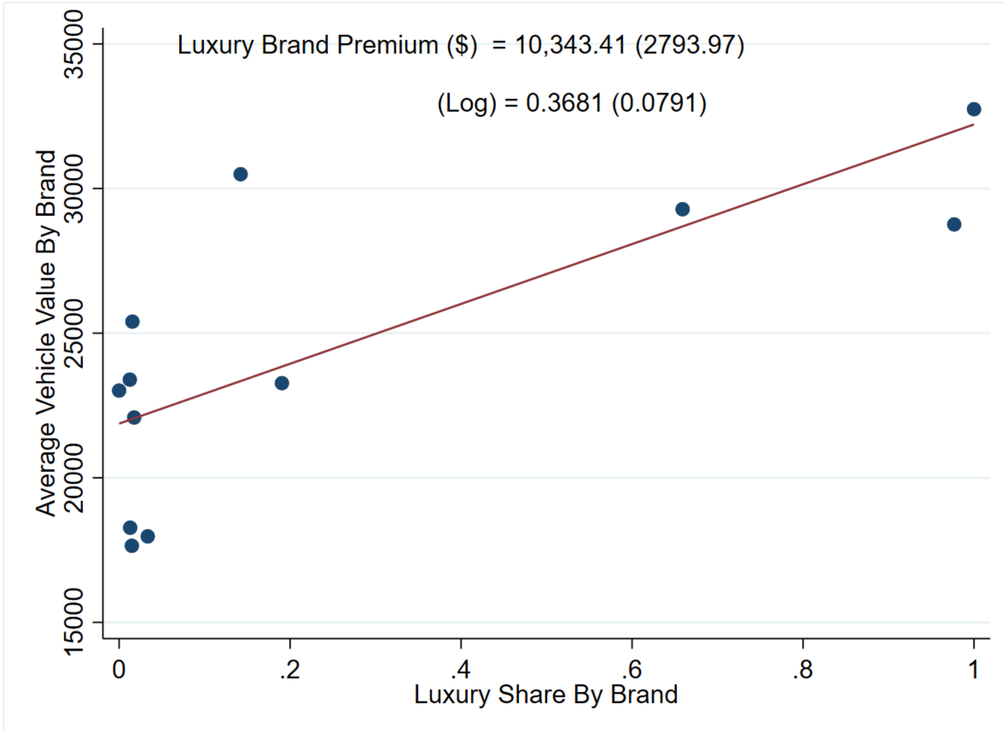
(b) Luxury Model Defined By New Model Value ($\geq$\$30,000)



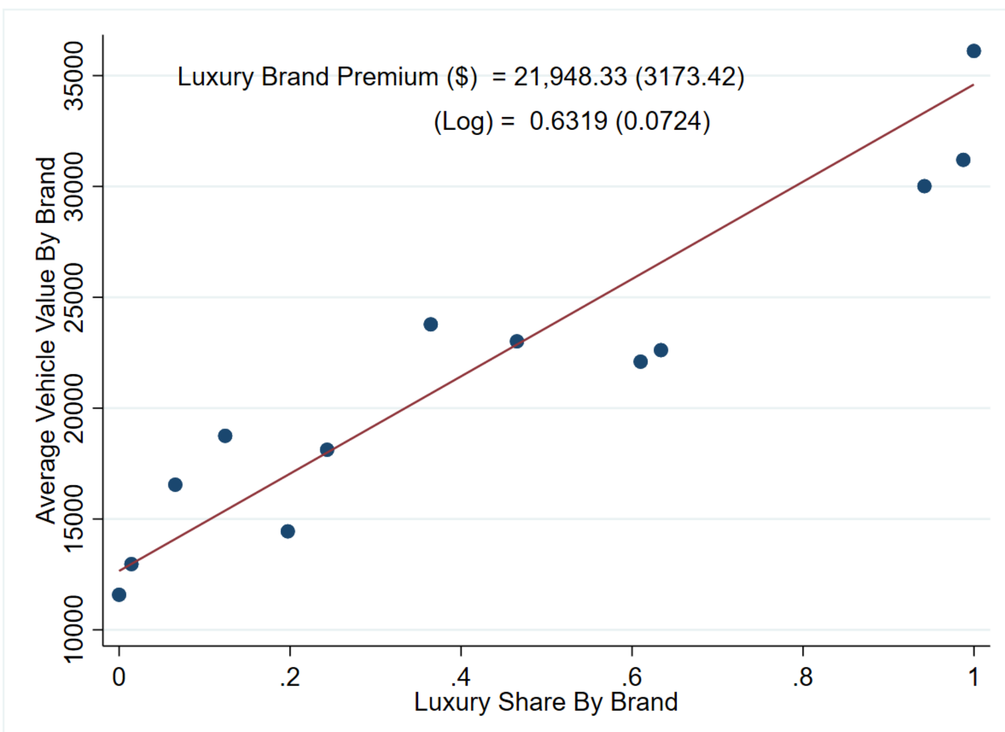
Note: For Figure 4a, we define a model as luxury if the model segment contains the word “luxury”, “upscale”, or “premium”. We calculate the fraction of the new vehicle sales by each brand (make) that belong to luxury models. For Figure 4b, we define a model as luxury if the new model’s average value is greater than \$30,000. We then calculate the fraction of new vehicle sales by each brand (make) that belong to luxury models.

Figure 5: Luxury Brand Premium in Vehicle Price

(a) Luxury Model Defined Based on Segments (Luxury, Upscale, or Premium)

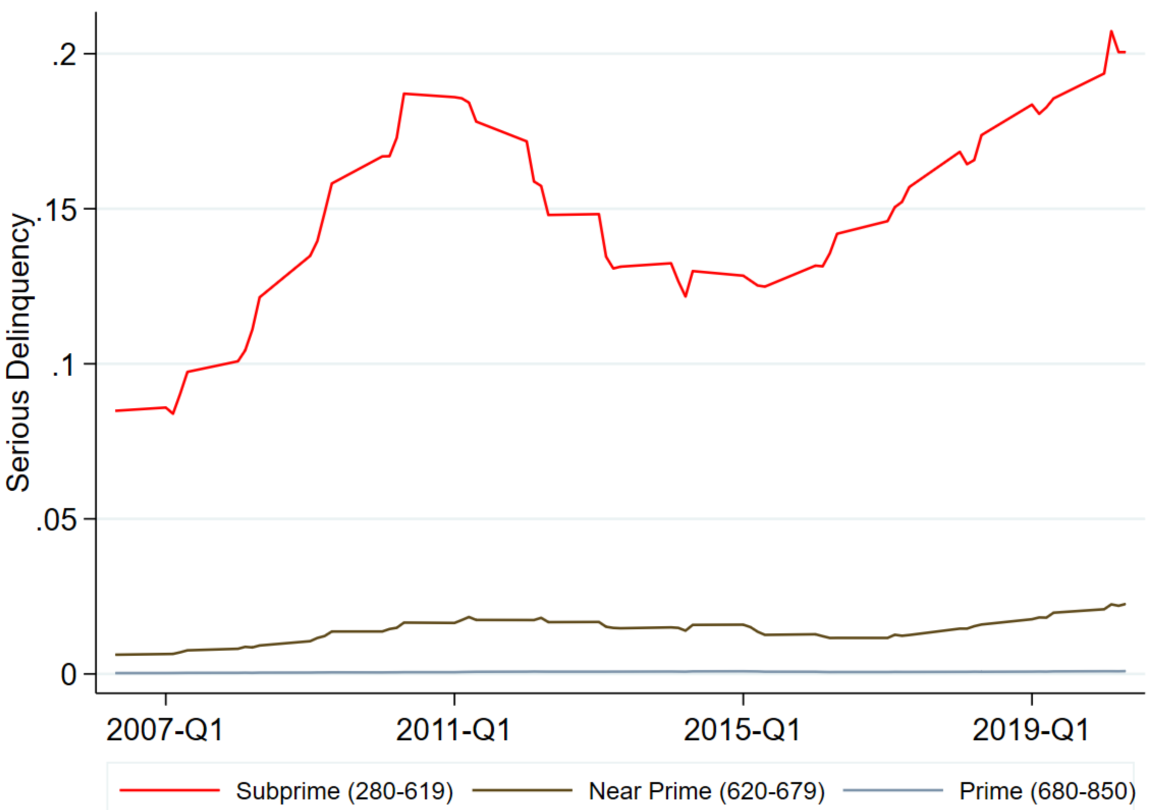


(b) Luxury Model Defined By New Model Value (≥$30,000)



Note: In these figures, we plot the average vehicle value by brand against the brand luxury shares in a binned scatterplot. The average vehicle value for each brand is calculated with both new and used sample with the national data. To calculate the brand luxury share, Figure 5a uses the luxury definition based on model segment and Figure 5b uses the luxury definition based on model value.

Figure 6: Auto Loan Serious Delinquency by Borrower Risk



Note: Data are from the New York Fed Consumer Credit Panel (CCP)/Equifax, a representative sample of 5% adults in the U.S. with a credit history or public-record information. Consumers in the plotted sample all have a credit score. Data are quarterly snapshots taken at 12/1, 3/1, 6/1, 9/1 of each year. First quarter is represented by the snapshots taken on 3/1 of each year. Serious delinquency is calculated based on balance 90+ day past due in all outstanding balance.

Table 1: Average characteristics of auto loans

Transaction type	New	Used	All	All	New	Used	New	Used
Prime status	All	All	Y	N	Y	Y	N	N
Amount financed ($)	30,618	19,483	25,426	21,556	30,638	20,907	30,569	17,915
Vehicle value ($)	31,280	18,658	26,550	19,310	32,970	20,988	27,287	16,095
Loan-to-value ratio	1.12	1.49	1.21	1.54	1.05	1.34	1.27	1.65
Interest rate (%)	5.25	9.15	4.54	12.13	3.78	5.20	8.72	13.51
Maturity term (months)	69	64	66	66	67	65	73	64
Monthly payment ($)	517	373	432	426	509	365	535	381
Total (million)	26	40	40	27	18	21	7.8	19

Source: AutoCount 2015-2019 vehicles financed with a Vehicle Identification Number (VIN) and a minimum of 500 transactions for each brand. Prime status is based on Vantage score 3.0 greater than or equal to 660.

Table 2: Average market share and lending practice by lender type

			Average ratio relative to all lender types			
Lender type	N	Market share	Loan size	Credit score	Interest rate	Term
Captives	36	18%	1.18	1.02	0.89	1.01
Finance company	32	11%	0.70	0.85	2.44	0.94
Bank	44	46%	1.03	1.02	0.90	1.03
Credit union	37	23%	0.93	1.02	0.75	1.01
Buy here pay here	28	3%	0.77	0.95	1.33	0.92
Luxury brands						
Captives	19	17%	1.18	1.02	0.90	1.03
Finance company	18	14%	0.75	0.86	2.31	0.94
Bank	20	38%	1.03	1.03	0.83	1.03
Credit union	19	23%	0.95	1.03	0.68	1.00
Buy here pay here	17	3%	0.76	0.94	1.35	0.88
Non-luxury brands						
Captives	17	19%	1.18	1.02	0.89	0.99
Finance company	14	8%	0.63	0.85	2.61	0.93
Bank	24	52%	1.03	1.01	0.96	1.02
Credit union	18	22%	0.92	1.00	0.83	1.02
Buy here pay here	11	3%	0.79	0.96	1.30	0.96

Note: Average market share is the average share of the lender type in each of the major brands. Average ratios relative to all lender types are derived by dividing the average value of the variable of interest of the particular lender type to the average of all lender types. For example, to calculate the credit score ratio for captives, we divide the average borrower credit score of loans originated by captives by the average borrower credit score of all loans. The ratio 1.02 indicates that the average credit score of captives is slightly higher than average. Finance companies have a much looser standard than the average, because the ratio is 0.85, much smaller than 1. Luxury brands are brands with average loan amount exceeding $27,000. Data are based on popular brands from AutoCount Q4 of 2019.

Table 3: Vehicle Demand by Non-Prime Consumers: Brand Effect Relative to County Average

	Dep Var: Relative Log (Model Market Share)			
	(1)	(2)	(3)	(4)
Log (Model Value)	-0.6840***	-0.6836***	-0.6819***	-0.6868***
	(0.0098)	(0.0098)	(0.0098)	(0.0010)
Brand Luxury Share	0.0536***	0.0753***	0.0547***	0.0902***
	(0.0102)	(0.0104)	(0.0116)	(0.0075)
Brand Pick-up Share		0.1219***	0.1127***	
		(0.0101)	(0.0101)	
Brand Alt-Energy Share			-0.1303***	
			(0.0219)	
Luxury Definition	Segment	Segment	Segment	Model Value
Observations	99,913	99,913	99,913	99,913

Note: Log(Model Value) is the mean value of vehicles based on vehicle model and new/used status. Luxury share, pick-up share, and alternative energy share are brand-specific measures. Luxury share is the share of vehicles sold that are luxury models for each brand. Pick-up share is the share of vehicles that are categorized as pick-up truck segment for each brand. For column 1, 2, and 3, brand luxury share is defined based on model segment. For column 4, the brand luxury share is defined based on model value (luxury model if average value of new models is greater than $30,000). Sample includes counties with population 500,000 or above. Standard errors are clustered at county level and displayed in the parentheses. *** $p < 0.01$, ** $p < 0.05$, *$p < 0.1$.

Table 4: Vehicle Demand by Non-Prime Consumers: Neighborhood Heterogeneity

		Dep Var: Relative Log (Model Market Share)				
		(1)	(2)	(3)	(4)	(5)
Log (Model Value)	Base	-0.6167***	-0.6392***	-0.4581***	-0.444***	-0.444***
		(0.0116)	(0.0114)	(0.0235)	(0.0239)	(0.0249)
	Black	-0.1869***			-0.0606*	-0.0632*
		(0.0572)			(0.0367)	(0.0379)
	Hispanic	-0.1845***			-0.0783**	-0.106***
		(0.0461)			(0.0315)	(0.0351)
	Asian	0.2314***			0.1895**	0.219**
		(0.0920)			(0.0749)	(0.0863)
	Income <\$40K		-0.2731***		-0.1756***	-0.175***
			(0.0422)		(0.0320)	(0.0332)
	Income >\$120K		0.4805***		0.4008***	0.428***
			(0.0479)		(0.0463)	(0.0504)
	Gini - 0.3783 - 0.4174			-0.1703***	-0.1204***	-0.1299***
				(0.0290)	(0.0274)	(0.0291)
	Gini - 0.4174 - 0.4576			-0.2140***	-0.1290***	-0.1338***
				(0.0262)	(0.0279)	(0.0293)
	Gini >0.4576			-0.1880***	-0.0784***	-0.0499*
				(0.0290)	(0.0289)	(0.0303)
Brand Luxury Share	Base	0.0685***	0.0284***	0.0680**	0.0518**	0.0294
		(0.0138)	(0.0101)	(0.0272)	(0.0240)	(0.0219)
	Black	0.3678***			0.2339***	0.2508***
		(0.0394)			(0.0261)	(0.0223)
	Hispanic	-0.1780***			-0.1546***	-0.0587***
		(0.0518)			(0.0281)	(0.0171)
	Asian	0.1363***			0.0786*	-0.0105
		(0.0480)			(0.0414)	(0.0414)
	Income <\$40K		0.2030***		0.0781***	0.0749***
			(0.0435)		(0.0247)	(0.0192)
	Income >\$120K		0.3414***		0.2681***	0.1906***
			(0.0376)		(0.0300)	(0.0214)
	Gini - 0.3783 - 0.4174			-0.0669*	-0.0203	0.0092
				(0.0355)	(0.0283)	(0.0248)
	Gini - 0.4174 - 0.4576			-0.0137	0.0333	0.0496**
				(0.0326)	(0.0266)	(0.0238)
	Gini >0.4576			0.2103***	0.2030***	0.1155***
				(0.0313)	(0.0288)	(0.0253)
Luxury Definition		Segment	Segment	Segment	Segment	Model Value
Observation		178,335	190,897	316,583	610,088	610,088

Note: Log(Model Value) is the mean value of vehicles based on vehicle model and new/used status. Luxury share is the share of vehicles sold that are luxury models for each brand. We divide consumers within counties by consumers' home ZIP Codes. In Column 1, we further categorize consumers by the racial composition of the residing ZIP Codes. The racial indicators denote neighborhoods in which the mentioned race is the majority in the consumers' ZIP Code. The base group denotes consumers living in neighborhoods in which none of the mentioned racial groups are the majority. In Column 2, we further categorize consumers by the income level of the residing ZIP Codes. The base group for the income indicator is consumers living in neighborhoods with median income that falls \$40K - \$120K. In Column 3, we further categorize consumers by the Gini coefficients of the residing ZIP Codes. The base group for the Gini is the consumers living in neighborhoods with Gini lower than 0.3783. In Column 4, we categorize consumers by the intersection of all the above-mentioned categories based on the residing ZIP Codes. For column 1 – 4, brand luxury share is defined based on model segment. For column 5, the brand luxury share is defined based on model value (luxury model if average value of new models is greater than \$30,000). Sample includes counties with population 500,000 or above. Standard errors are clustered at the county $\times$ racial group $\times$ income level $\times$ Gini level and displayed in the parentheses. *** $p < 0.01$, ** $p < 0.05$, *$p < 0.1$.

Table 5: Vehicle Demand by Non-Prime Buyers: By Prime Neighbors' Luxury Share

	Dep Var: Relative Log (Model Market Share)		
	(1)	(2)	(3)
Log (Model Value)	-0.8872***	-0.8347***	-2.3892***
	(0.0401)	(0.1800)	(0.3017)
Log (Model Value) $\times$ Prime Neighbors' Luxury Share	2.817***	1.4875	3.8768***
	(0.3515)	(0.9545)	(0.6518)
Brand Luxury Share	-0.1005	0.2940*	-1.2083***
	(0.0878)	(0.1575)	(0.2195)
Brand Luxury Share $\times$ Prime Neighbors' Luxury Share	2.8690***	3.9279***	2.6861***
	(0.6473)	(0.5287)	(0.5696)
Control for Neighborhood Chars $\times$ Log (Model Value) and X Brand Luxury Share	No	Yes	Yes
Luxury Definition	Segment	Segment	Model Value
	319,345	318,649	318,649

Note: Log(Model Value) is the mean value of vehicles based on vehicle model and new/used status. Luxury share is the share of vehicles sold that are luxury models for each brand. Each observation is the empirical choice probability made by consumers in each ZIP Code. Prime neighbors' luxury share is the average luxury share of the brands of the vehicles that prime consumers in the local ZIP Code purchase. All regressions include fixed effect for county, vehicle segment, and zero share indicator. For column 1 and 2, brand luxury share is defined based on model segment. For column 3, the brand luxury share is defined based on model value (luxury model if average value of new models is greater than $30,000). Sample includes counties with population 500,000 or above. Standard errors are clustered at county level and displayed in the parentheses. *** $p < 0.01$, ** $p < 0.05$, *$p < 0.1$.

Table 6: Summary Statistics of Auto Loan Trade Lines, Q4, 2019

VARIABLES	**Prime**	**Non Prime**	**All**
Share in the sample	68%	32%	100%
No. of observations (million)	0.77	0.36	1.14
Average borrower characteristics			
Equifax risk score at origination	744	595	696
Borrower age	48	41	46
Average loan characteristics			
Lease	14%	7%	12%
Adjusted initial balance ($)	18,728	16,139	17,891
Adjusted remaining balance ($)	11,159	11,248	11,176
Adjusted monthly payment ($)	306	290	301
Lender types			
Credit union	30%	19%	26%
Bank	26%	13%	22%
Auto finance company	43%	62%	49%
Captive	27%	18%	25%
Borrowing consequences			
Percent paid down	43%	34%	39%
Past due	0.2%	16.4%	5.4%
Delinquent less than 5 months	0.2%	9.8%	3.2%
Seriously delinquent	0.01%	1.9%	0.6%
Vehicle repossessed	0.004%	1.3%	0.4%
Change in risk score	15	-30	0.7
Bankruptcy activities	0.4%	3.9%	1.6%
Charged off	0.1%	6.4%	2.1%
In modified payment plan	0.002%	0.11%	0.04%

Note: Sample is 20% of Federal Reserve Bank of New York Consumer Credit Panel/Equifax, Q4 2019; 1.14 million auto loan trade lines. Risk categories (subprime 280-659, prime 660-850) are based on Equifax Risk Score.

Table 7: Borrowing Consequence: Auto Loan Delinquency

	Dep Var: auto loan delinquent less than 5 months			
VARIABLES	(1)	(2)	(3)	(4)
log (Initial Balance)	0.0110***	0.00117***	0.0379***	0.0280***
	(0.000207)	(0.000122)	(0.000746)	(0.000521)
Initial Risk Score	-4.31e-05***			
	(4.60e-06)			
Constant	-0.0550***	-0.00670***	-0.293***	-0.216***
	(0.00366)	(0.00118)	(0.00703)	(0.00495)
Sample	All	Prime (660-850)	Subprime (280-619)	Non-prime (280-659)
Observations	7,627,802	5,001,179	1,656,404	2,624,374
R-squared	0.244	0.203	0.261	0.249

Notes: Accounts past due between 30 and 150 days are considered delinquent. Initial balance is the combined amounts taken out at auto loan origination. Initial score is the Equifax Risk score of the borrower at origination. Lease is the dummy variable indicating that the transaction type of the vehicle is a lease. Consumer, quarter and year, lender type (captive, finance company, credit union and banks), transaction type (lease or purchase) and ZIP Code fixed effects are included. Data are from Federal Reserve Bank of New York/Consumer Credit Panel on loans originated between 2015 and 2019. Robust standard errors clustered at ZIP Code level. *** p<0.01, ** p<0.05, * p<0.1.

Table 8: Borrowing Consequence: Auto Loan Delinquency by Non-prime

	Dep Var: auto loan delinquent less than 5 months by non-prime				
	(1)	(2)	(3)	(4)	(5)
Loan age	0-1yr	1-2yr	2-3yr	3-4yr	4-5yr
Log (Initial Balance)	0.0207***	0.0139***	-0.00317	-0.0169***	-0.0162
	(0.00118)	(0.00202)	(0.00333)	(0.00588)	(0.0166)
Constant	-0.121***	0.0215	0.242***	0.413***	0.466***
	(0.0112)	(0.0191)	(0.0316)	(0.0560)	(0.161)
Observations	1,044,224	820,614	480,534	184,923	40,805
R-squared	0.616	0.740	0.861	0.932	0.966

Notes: Accounts past due between 30 and 150 days are considered delinquent. Initial balance is the combined amounts taken out at auto loan origination. Initial score is the Equifax Risk score of the borrower at origination. Lease is the dummy variable indicating that the transaction type of the vehicle is a lease. Consumer, quarter and year, lender type (captive, finance company, credit union and banks), transaction type (lease or purchase) and ZIP Code fixed effects are included. Data are from Federal Reserve Bank of New York/Consumer Credit Panel on loans originated between 2015 and 2019. Robust standard errors clustered at ZIP Code level. *** p<0.01, ** p<0.05, * p<0.1.

Table 9: Borrowing Consequence: Vehicle Repossession

	Dep Var: vehicle repossessed			
VARIABLES	(1)	(2)	(3)	(4)
Log (Initial Balance)	0.00138***	0.000238***	0.00556***	0.00369***
	(8.29e-05)	(3.39e-05)	(0.000351)	(0.000230)
Initial Risk Score	-1.22e-05***			
	(2.29e-06)			
Constant	-0.00102	-0.00189***	-0.0360***	-0.0242***
	(0.00172)	(0.000327)	(0.00327)	(0.00217)
Sample	All	Prime (660-850)	Subprime (280-619)	Non-prime (280-659)
Observations	7,627,802	5,001,179	1,656,404	2,624,374
R-squared	0.300	0.271	0.327	0.313

Notes: Repossession is one of the account statuses that do not overlap with delinquencies. Initial balance is the combined amounts taken out at auto loan origination. Initial score is the Equifax Risk score of the borrower at origination. Consumer, quarter and year, lender type (captive, finance company, credit union and banks), transaction type (lease or purchase) and ZIP Code fixed effects are included. Data are from Federal Reserve Bank of New York/Consumer Credit Panel on loans originated between 2015 and 2019. Robust standard errors clustered at ZIP Code level. *** p<0.01, ** p<0.05, * p<0.1.

Table 10: Borrowing Consequence: Repossession for the Non-prime

	Dep Var: Vehicle repossessed for the non-prime				
	(1)	(2)	(3)	(4)	(5)
Loan age	0-1yr	1-2yr	2-3yr	3-4yr	4-5yr
Log (Loan Balance)	0.00191***	0.00146*	2.22e-05	-0.00683**	-0.00429
	(0.000407)	(0.000880)	(0.00156)	(0.00288)	(0.00660)
Constant	-0.00865**	0.0109	0.0329**	0.0929***	0.0599
	(0.00384)	(0.00830)	(0.0148)	(0.0274)	(0.0629)
Observations	1,044,224	820,614	480,534	184,923	40,805
R-squared	0.579	0.690	0.812	0.906	0.958

Notes: Accounts past due between 30 and 150 days are considered delinquent. Initial balance is the combined amounts taken out at auto loan origination. Initial score is the Equifax Risk score of the borrower at origination. Lease is the dummy variable indicating that the transaction type of the vehicle is lease. Consumer, quarter and year, lender type (captive, finance company, credit union and banks), transaction type (lease or purchase) and ZIP Code fixed effects are included. Data are from Federal Reserve Bank of New York/Consumer Credit Panel on loans originated between 2015 and 2019. Robust standard errors clustered at ZIP Code level. *** p<0.01, ** p<0.05, * p<0.1.

Table 11: Borrowing Consequence: Change in Risk Score

	Dep Var: change from initial score			
VARIABLES	(1)	(2)	(3)	(4)
Log (Initial Balance)	0.551***	0.527***	-0.982***	-1.047***
	(0.0440)	(0.0640)	(0.210)	(0.161)
Initial Risk Score	-0.707***			
	(0.00125)			
Loan Age	0.00283***	0.0114***	0.00461***	0.00371***
	(6.91e-05)	(0.000103)	(0.000376)	(0.000290)
Constant	485.0***	-10.40***	10.44***	8.364***
	(0.976)	(0.625)	(2.024)	(1.554)
Sample	All	Prime (660-850)	Subprime (280-619)	Non-prime (280-659)
Observations	7,619,970	4,993,168	1,652,479	2,619,291
R-squared	0.543	0.505	0.474	0.459

Notes: Initial balance is the combined amounts taken out at auto loan origination. Initial score is the Equifax Risk score of the borrower at origination. Consumer, quarter and year, lender type (captive, finance company, credit union and banks), transaction type (lease or purchase) and ZIP Code fixed effects are included. Data are from Federal Reserve Bank of New York/Consumer Credit Panel on loans originated between 2015 and 2019. Robust standard errors clustered at ZIP Code level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 12: Borrowing Consequence: Balance Growth

	Dep Var: Change in Log Balance			
VARIABLES	(1)	(2)	(3)	(4)
Log (Initial Balance)	0.0476***	0.0499***	0.0376***	0.0427***
	(0.000478)	(0.000539)	(0.00132)	(0.00100)
Initial Risk Score	0.000154***			
	(6.20e-06)			
Constant	-0.656***	-0.577***	-0.443***	-0.493***
	(0.00624)	(0.00525)	(0.0125)	(0.00955)
Sample	All	Prime (660-850)	Subprime (280-619)	Non-prime (280-659)
Observations	5,925,067	3,866,812	1,301,671	2,051,914
R-squared	0.168	0.203	0.155	0.153

Notes: Change in log balance from quarter to quarter shows the growth in debt. Initial balance is the combined amounts taken out at auto loan origination. Initial score is the Equifax Risk score of the borrower at origination. Consumer, quarter and year, lender type (captive, finance company, credit union and banks), transaction type (lease or purchase) and ZIP Code fixed effects are included. Data are from Federal Reserve Bank of New York/Consumer Credit Panel on loans originated between 2015 and 2019. Robust standard errors clustered at ZIP Code level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 13: Auto Loan Borrowing Consequence: Other Consumer Loan Delinquency

	Dep Var: delinquency in					
	Any Loan	Any Loan	Mortgage	Mortgage	Credit card	Credit card
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Log (Initial Auto Loan Balance)	0.000306***	0.0179***	1.91e-06	0.000776***	-7.61e-05***	0.00399***
	(1.58e-05)	(0.000121)	(3.65e-06)	(3.38e-05)	(9.89e-06)	(8.17e-05)
Constant	0.00858***	0.261***	0.000598***	0.0183***	0.00541***	0.125***
	(4.38e-05)	(0.000325)	(1.01e-05)	(9.05e-05)	(2.73e-05)	(0.000219)
Sample	Prime	Non-prime	Prime	Non-prime	Prime	Non-prime
Observations	18,817,166	10,417,767	18,817,166	10,417,767	18,817,166	10,417,767
R-squared	0.469	0.610	0.247	0.494	0.531	0.562

Notes: Account is considered delinquent if it is past due or severely derogatory. Loans balance is the current balance and not the amount initiated at loan origination. Risk score is the current Equifax Risk score of the borrower. Consumer, quarter and year, ZIP Code fixed effects are included. Bank card is credit card issued by banks. Prime borrowers are borrowers with Equifax Risk score higher than or equal to 660, non-prime borrowers are those between 280 and 659. Data are from Federal Reserve Bank of New York/Consumer Credit Panel on loans originated between 2015-2019. Robust standard errors clustered at ZIP Code level. *** p<0.01, ** p<0.05, * p<0.1.

Appendices

A1 Comparative Statics

We use implicit function theorem to derive the comparative statics of the vehicle demand with respect to income level and the marginal utility of prestige.

We start with the two first-order conditions:

$$-\alpha_x \lambda^k u' \left(Y^k - \lambda^k P\right) + \eta_k F'(X) = 0$$
$$-\alpha_c \lambda^k u' \left(Y^k - \lambda^k P\right) + s_c(c,k) = 0$$

We define $\mathbf{G}(X, c, s_c) = \begin{pmatrix} -\alpha_x \lambda^k u' \left(Y^k - \lambda^k P\right) + \eta_k F'(X) \\ -\alpha_c \lambda^k u' \left(Y^k - \lambda^k P\right) + s_c \end{pmatrix}$. We employ the multivariate implicit function theorem to derive $\begin{pmatrix} \frac{\partial X^*}{\partial Y^k} \\ \frac{\partial c^*}{\partial Y^k} \end{pmatrix}$ and $\begin{pmatrix} \frac{\partial X^*}{\partial s_c} \\ \frac{\partial c^*}{\partial s_c} \end{pmatrix}$. Based on the two-equation version of the implicit function theorem,

$$\begin{pmatrix} \frac{\partial X^*}{\partial Y^k} \\ \frac{\partial c^*}{\partial Y^k} \end{pmatrix} = -\begin{pmatrix} \mathbf{G_1}_X & \mathbf{G_1}_c \\ \mathbf{G_2}_X & \mathbf{G_2}_c \end{pmatrix}^{-1} \begin{pmatrix} \mathbf{G_1}_{Y^k} \\ \mathbf{G_2}_{Y^k} \end{pmatrix}.$$

$$\begin{pmatrix} \frac{\partial X^*}{\partial s_c} \\ \frac{\partial c^*}{\partial s_c} \end{pmatrix} = -\begin{pmatrix} \mathbf{G_1}_X & \mathbf{G_1}_c \\ \mathbf{G_2}_X & \mathbf{G_2}_c \end{pmatrix}^{-1} \begin{pmatrix} \mathbf{G_1}_{s_c} \\ \mathbf{G_2}_{s_c} \end{pmatrix}.$$

Plugging in all the algebraic derivations, the comparative statics would become:

$$\begin{pmatrix} \frac{\partial X^*}{\partial Y^k} \\ \frac{\partial c^*}{\partial Y^k} \end{pmatrix} = \begin{pmatrix} 0 \\ \frac{1}{\alpha_c \lambda^k} \end{pmatrix}$$

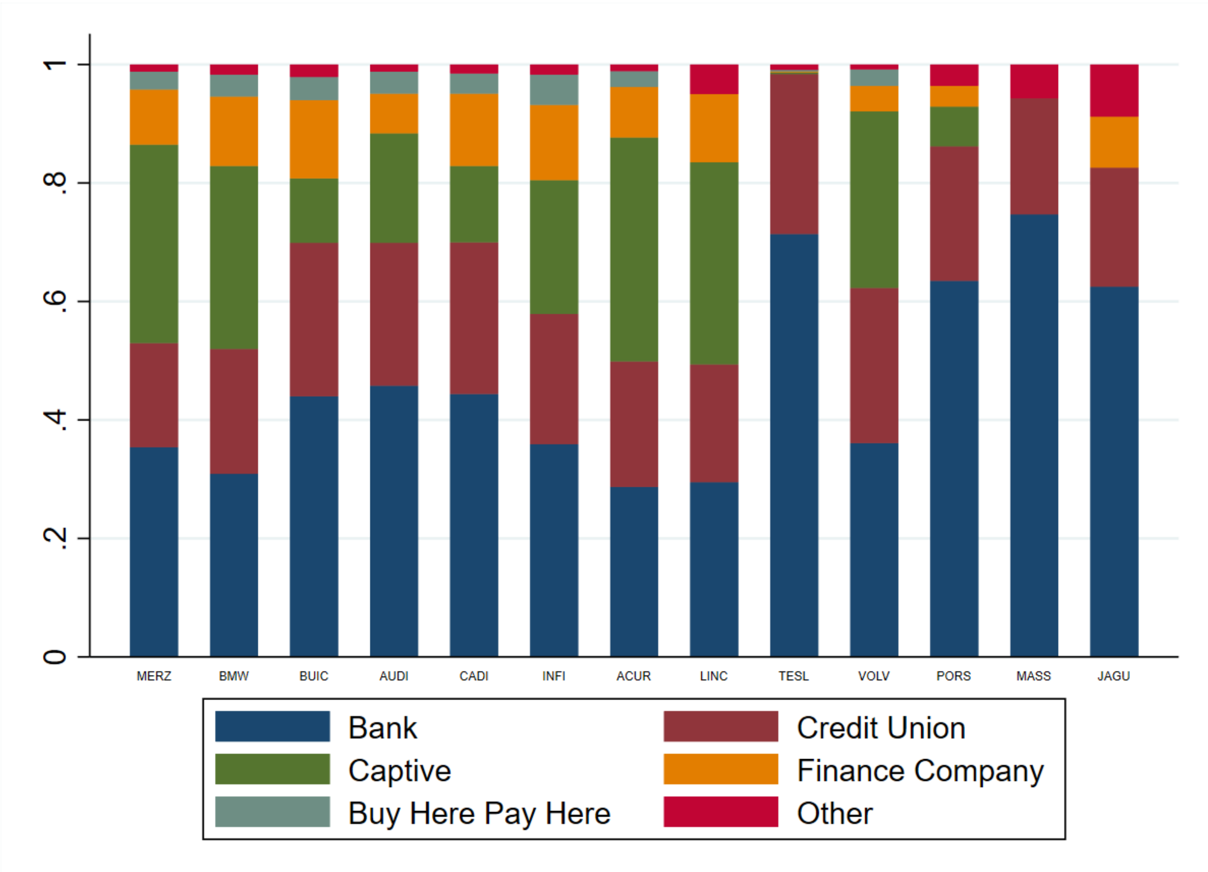
$$\begin{pmatrix} \frac{\partial X^*}{\partial s_c} \\ \frac{\partial c^*}{\partial s_c} \end{pmatrix} = \begin{pmatrix} \frac{\alpha_x}{\alpha_c \eta_x F''} \\ -\frac{(\alpha_x \lambda^k)^2 u'' + \eta_k F''}{(\alpha_c \lambda^k)^2 \eta_x F'' u''} \end{pmatrix}$$

Since $\alpha_x > 0$, $\alpha_c > 0$, $u'' < 0$, and $F'' < 0$,

$$\frac{\partial c^*}{\partial Y^k} > 0$$
$$\frac{\partial X^*}{\partial s_c} < 0$$
$$\frac{\partial c^*}{\partial s_c} > 0$$

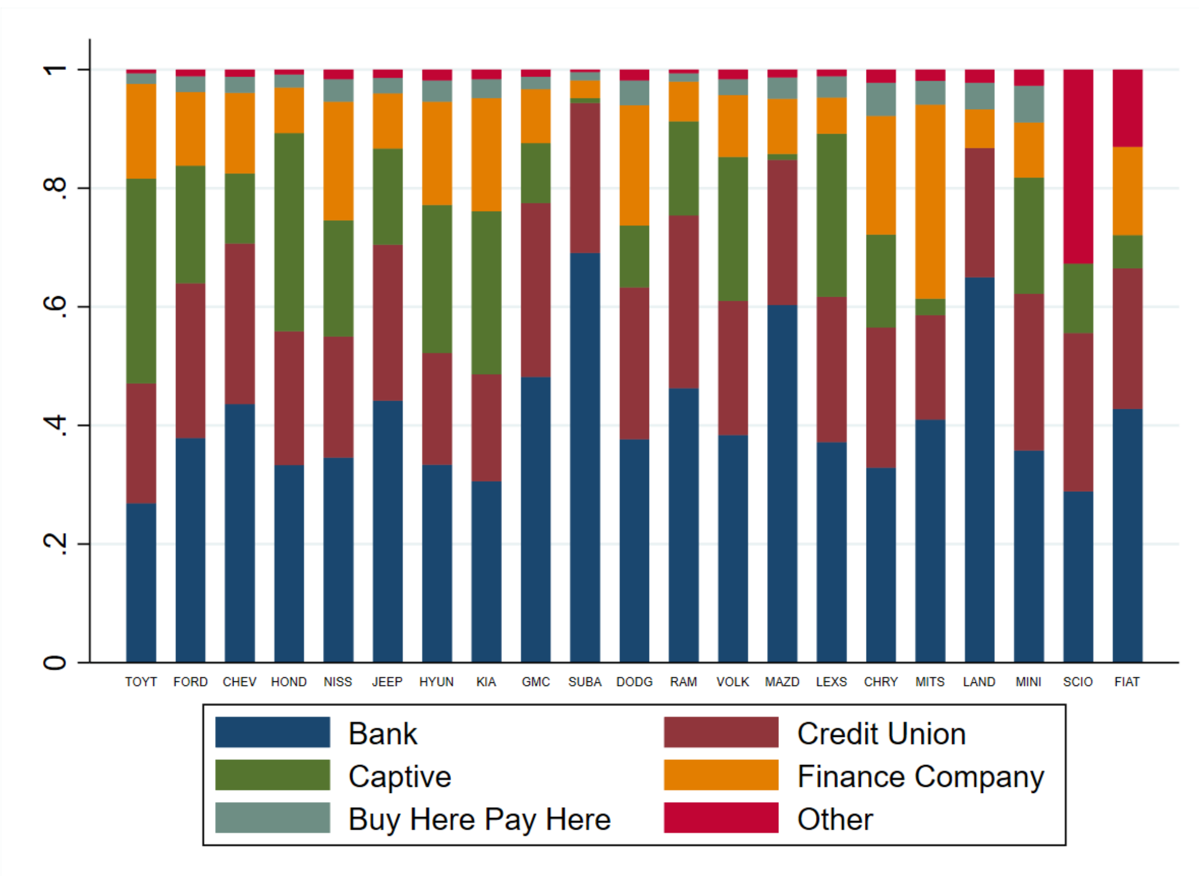
A2 Figures

Figure A1: Lender Market Share by Luxury Brand



Notes: Brands are in the order of overall market share. Brands with market share smaller than 0.05% are not included. For smaller brands with not enough transactions to aggregate for certain lender types in AutoCount, the lender types are combined with "Others." Luxury brands are defined with share of luxury segments greater than half of the transactions.

Figure A2: Lender Market Share by Non-Luxury Brand



Notes: Brands are in the order of overall market share. Brands with market share smaller than 0.05% are not included. For smaller brands with not enough transactions to aggregate for certain lender types in AutoCount, the lender types are combined with "Others." Non luxury brands are defined with share of luxury segments lower than half of the transactions.

A3 Tables

Table A1: Vehicle Demand by Non-Prime Buyers: Brand Effect Relative to County Average by New/Used

		Dep Var: Relative Log (Model Market Share)		
		(1)	(2)	(3)
Log (Model Value)	New	-0.5174***	-0.5291***	-0.5080***
		(0.0180)	(0.0184)	(0.0186)
	Used	-0.3928***	-0.3893***	-0.3944***
		(0.0105)	(0.0104)	(0.0104)
Brand Luxury Share	New	-0.0760***	-0.0352**	-0.0785**
		(0.0137)	(0.0147)	(0.0166)
	Used	0.1008***	0.1038***	0.0856***
		(0.0100)	(0.0100)	(0.0101)
Brand Pick-up Share	New		0.1818***	0.1509***
			(0.0145)	(0.0145)
	Used		0.0494***	0.0544***
			(0.0088)	(0.0089)
Brand Alt-Energy Share	New			-0.3281***
				(0.0314)
	Used			-0.0351*
				(0.0187)
Observations		99,913	99,913	99,913

Note: The sample is sliced by model, brand (make), county, prime status, and new/used status. We allow the coefficients for brand characteristics to differ potentially by new/used status of the vehicles. Log(Model Value) is the mean value of vehicles based on vehicle model and new/used status. Luxury share and pick-up share are brand-specific measures. Luxury share is the share of vehicles that are luxury. Pick-up share is the share of vehicles that are categorized as pick-up truck segment for each brand. Alt-Energy share is the share of alternative-fuel vehicles for each brand. All regressions include fixed effect for county, vehicle segment, and zero share indicator. Sample includes counties with population 500,000 or above. Standard errors are clustered at county level and displayed in the parentheses. *** $p < 0.01$, ** $p < 0.05$, *$p < 0.1$.

Table A2: Consumer Debt and Loan Performance, Q4, 2019

VARIABLES	**Prime**	**Non Prime**	**All**
Share in the sample	69%	31%	100%
Risk score	765	570	705
Consumers with auto loans (million)	0.58	0.31	0.89
Initial auto loan balance ($)	23,442	19,558	22,080
ZIP Code median income ($)	67,597	56,130	63,213
ZIP Code minority share	35%	44%	38%
Percent borrowing			
Auto loan	37%	44%	33%
Bank card	73%	59%	58%
Mortgage	36%	13%	25%
Loan Balance ($)			
Auto loan ($)	14,877	14,050	14,587
Bank card ($)	5,807	5,728	5,786
Mortgage ($)	144,368	112,652	140,014
Monthly Payment			
Auto loan ($)	422	442	429
Bank card ($)	365	295	346
Mortgage ($)	1,174	973	1,147
Delinquency			
Auto loan	0.2%	14.0%	3.8%
Bank card	0.7%	24.8%	6.9%
Mortgage	0.1%	2.6%	0.7%

Source: 20% of Federal Reserve Bank of New York Consumer Credit Panel/Equifax, Q4 2019; 2.7 million consumers. Risk categories (subprime 280-659, prime 660-850) are based on Equifax Risk Score.

Table A3: Borrowing Consequence: Bankruptcy

	Dep Var: having bankruptcy activities			
VARIABLES	(1)	(2)	(3)	(4)
Log (Initial Balance)_auto_hi	-0.000717***	-0.000312***	-0.000400	-0.00109***
	(7.20e-05)	(4.12e-05)	(0.000245)	(0.000183)
Initial Risk Score	-1.20e-05***			
	(2.38e-06)			
Constant	0.0264***	0.00546***	0.0361***	0.0379***
	(0.00182)	(0.000399)	(0.00231)	(0.00173)
Sample	All	Prime (660-850)	Subprime (280-619)	Non-prime (280-659)
Observations	7,628,649	5,001,265	1,657,096	2,625,137
R-squared	0.846	0.818	0.867	0.867

Notes: Loans balance is the current balance and not the amount initiated at loan origination. Risk score is the current Equifax Risk score of the borrower. Consumer, quarter and year, ZIP Code fixed effects are included. Bank card is credit card issued by banks. Prime borrowers are borrowers with Equifax Risk score higher than or equal to 660, non-prime borrowers are those between 280 and 659. Data are from Federal Reserve Bank of New York/Consumer Credit Panel on loans originated between 2015-2019. Loans bankruptcy activities also originated between 2015-2019. Robust standard errors clustered at ZIP Code level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A4: Borrowing Consequence: Charge-offs

	Dep Var: loan charged off			
VARIABLES	(1)	(2)	(3)	(4)
Log (Initial Balance)	-0.0441***	-0.0130***	-0.136***	-0.104***
	(0.000528)	(0.000350)	(0.00142)	(0.00107)
Initial Risk Score	7.71e-05***			
	(5.28e-06)			
Constant	0.383***	0.128***	1.309***	1.006***
	(0.00566)	(0.00339)	(0.0133)	(0.0101)
Sample	All	Prime (660-850)	Subprime (280-619)	Non-prime (280-659)
Observations	7,628,649	5,001,265	1,657,096	2,625,137
R-squared	0.374	0.401	0.440	0.413

Notes: Loans balance is the current balance and not the amount initiated at loan origination. Risk score is the current Equifax Risk score of the borrower. Consumer, quarter and year, ZIP Code fixed effects are included. Bank card is credit card issued by banks. Prime borrowers are borrowers with Equifax Risk score higher than or equal to 660, non-prime borrowers are those between 280 and 659. Data are from Federal Reserve Bank of New York/Consumer Credit Panel on loans originated between 2015-2019. Robust standard errors clustered at ZIP Code level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A5: Borrowing Consequence: Modified Payment Plan

	Dep Var: having a payment plan			
VARIABLES	(1)	(2)	(3)	(4)
Log (Initial Balance)	5.66e-05***	-9.47e-06	0.000213***	0.000138***
	(1.56e-05)	(6.87e-06)	(5.90e-05)	(3.97e-05)
Initial Risk Score	-2.46e-06***			
Constant	0.00135***	0.000125*	-0.00143**	-0.000879**
	(0.000335)	(6.76e-05)	(0.000563)	(0.000381)
Sample	All	Prime (660-850)	Subprime (280-619)	Non-prime (280-659)
Observations	7,627,802	5,001,179	1,656,404	2,624,374
R-squared	0.427	0.485	0.486	0.449

Notes: Robust standard errors clustered at ZIP Code level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Loans balance is the current balance and not the amount initiated at loan origination. Risk score is the current Equifax Risk score of the borrower. Robust standard errors clustered at ZIP Code level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Consumer, quarter and year, ZIP Code fixed effects are included. Bank card is credit card issued by banks. Prime borrowers are borrowers with Equifax Risk score higher than or equal to 660, non-prime borrowers are those between 280 and 659. Data are from Federal Reserve Bank of New York/Consumer Credit Panel on loans originated between 2015-2019.

Table A6: Market share and brand targeting

	Dep Var: market share				
	(1)	(2)	(3)	(4)	(5)
Lender type	Captive	Finance Company	Bank	Credit Union	BHPH
luxury brand	-0.0153	-0.0626**	0.0558	0.0198	0.00180
	(0.0396)	(0.0257)	(0.0410)	(0.0140)	(0.00483)
Constant	0.257***	0.155***	0.400***	0.237***	0.0303***
	(0.0157)	(0.00858)	(0.0180)	(0.00597)	(0.00193)
Observations	36	32	44	37	28
R-squared	0.004	0.165	0.042	0.054	0.005

Notes: Brand market share is the share of transactions in each lender type. Luxury brands are brands with average loan amount exceeding $27,000. Regressions are weighted for by lender market share for each lender type. Robust standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1. Data are based on popular brands from AutoCount Q4 of 2019.

Table A7: Credit standard and brand targeting

	Dep Var: credit score relative to all				
	(1)	(2)	(3)	(4)	(5)
Lender type	Captive	Finance Company	Bank	Credit Union	BHPH
Luxury Brand	0.00566	-0.0242	-0.00861*	-0.0175***	0.0224*
	(0.0105)	(0.0173)	(0.00434)	(0.00513)	(0.0126)
Constant	1.029***	0.870***	1.022***	1.028***	0.940***
	(0.00417)	(0.00577)	(0.00191)	(0.00219)	(0.00502)
Observations	36	32	44	37	28
R-squared	0.009	0.061	0.086	0.249	0.109

Notes: Credit score relative to all is the ratio between average credit score of loans originated by the lender type to the average credit score of all lender types of the brand.Luxury brands are brands with average loan amount exceeding $27,000. Regressions are weighted for by lender market share for each lender type. Robust standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1. Data are based on popular brands from AutoCount Q4 of 2019.