Behavioral Skimming: Theory and Evidence from Resale Markets

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A large body of research shows that even when information is accessible, consumers often fail to attend to it. To what extent and under what conditions can firms profit from such consumer inattention? We study this question theoretically and empirically in the used car market, focusing on the widely documented left-digit bias. Theoretically, firms can profit from targeting the most inattentive consumers. Leveraging a detailed dataset of millions of automobile transactions from a seven-year period, we find that consumers exhibit inattention in the form of left-digit bias to the odometer, and such inattention is estimated to be significantly more for consumers who buy from firms. Compared to private sellers, car dealerships transact with ex-post significantly more left-digit biased consumers. Dealerships sell more vehicles whose odometers are below round numbers, sell them faster, and extract higher margins from these vehicles. Our results imply that intermediaries can "skim" consumers with specific behavioral biases and extract surplus from selling to them.

Keywords: Behavioral Industrial Organization, Consumer Inattention, Game Theory

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1 Introduction

Evaluating relevant product features is a crucial part of any significant purchasing decision. Growing evidence indicates that consumers are frequently inattentive, even to information that is readily observable at the point of purchase, including critical information like prices (Clerides and Courty, 2017), product ingredients (Bronnenberg et al., 2015), and taxes (Chetty et al., 2009). Such inattention could sometimes arise due to inattention to non-leftmost digits of prices (Strulov-Shlain, 2021; List et al., 2022; Jiang, 2021), and product attributes (Lacetera et al., 2012; Englmaier et al., 2018).

Not surprisingly, there are individual differences in how much consumers are affected by such biases arising from inattention. It is well understood that consumers have individual differences in many other dimensions in standard decision-making domains. For example, they have a heterogeneous willingness to pay or differential responses to advertising. Profit-maximizing firms react strategically to such heterogeneity in numerous ways, such as offering personalized pricing or targeted advertising, Although the importance of consumer heterogeneity for understanding firm behaviors is well understood in marketing, surprisingly, little work explicitly considers how firms react to consumers that differ in how behaviorally biased they are. Previous work on behavioral consumers has generally abstracted away from firms specifically reacting to heterogeneously inattentive consumers or strategically affecting their behavioral biases[1].

In this paper, we consider a firm selling to heterogeneously inattentive consumers. We leverage a unique setting where left-digit biased consumers can buy a product from firms (i.e., intermediaries) or directly from individual sellers. This setting allows us to explore the following research questions. Do intermediaries sell to more inattentive buyers than buyers who buy directly from other consumers? What are potential mechanisms that allow firms to serve relatively more biased consumers? Do intermediaries benefit more from consumer inattention than private sellers?

We do so by building on previous literature that has documented inattention in the context of passenger vehicles (Lacetera et al., 2012; Englmaier et al., 2018). We consider the role of intermediaries in markets where heterogeneous consumer inattention might create behavioral frictions. We present theory and provide empirical evidence that shows: (i) Inattention affects resale markets in

[1]Notable exceptions are (Gurun et al., 2016; Ru and Schoar, 2017), who find present evidence of credit card firms advertise to relatively less sophisticated consumers

an economically meaningful way and (ii) that intermediaries (i.e., car dealerships) react strategically to benefit from inattentive consumers. We present supplementary evidence of the effects of other important considerations, such as competition and inventory levels.

Our theory considers a resale market in which consumers can trade in a decentralized consumer-to-consumer market and via a centralized intermediary. The model assumes that friction arises due to inattention, wherein consumers do not fully attend to a negative attribute. We allow consumers to use a "default value" in lieu of paying attention. We furthermore assume that consumers are not aware of their own (or others' inattention). Inattention to a negative attribute thus increases willingness to pay if consumers default to a lower level and decreases otherwise. This can affect consumption because some consumers overestimate or underestimate the expected utility of the product relative to the price. Our model shows that inattention can also affect *where* consumers purchase a product. More specifically, we show that when a consumer first visits a centralized intermediary, the intermediary can use pricing to benefit from the heterogeneity in expected utility induced by inattention.

To see the intuition of our model, consider the following highly simplified example. Imagine a consumer visiting a dealership to buy a used car. Suppose she inspects a car with an odometer reading of 9,850 miles. If she is inattentive and focuses primarily on the left digit, she perceives the car to be closer to 9,000 miles than 10,000 miles. A perceptive dealership could foresee an arbitrage opportunity here: She could price this car such that it is perceived as being lower than what a consumer would expect to pay for a 9,000-mile car but is higher than what a 9,850-mile vehicle would fetch in the marketplace. With such pricing, an inattentive buyer is less likely to search in the secondary market as they perceive the price to be a (fictitious) deal and, thus, more likely to buy. On the other hand, an attentive buyer would be able to discern the price arbitrage by the seller and is more likely to go elsewhere to buy such a car. We hasten to add that this example is a somewhat extreme illustration of how consumers might become biased on the basis of inattention to exact attribute values. However, this simple insight allows us to construct and test a formal model within large transaction data with multiple specifications and controls.

In such a setting, the intermediary benefits from being consumers' first stop because inattentive consumers overestimate the utility of the product and the price they would pay for it elsewhere. However, the degree of inattention, if it exists at all, is likely to vary among consumers, and so

the effects are likely to be more nuanced than in the above example. Capturing such nuances is precisely the goal of our paper. Furthermore, our detailed dataset allows us to formalize the underlying mechanism and test for other alternative explanations.

We show that in a market without an intermediary, the opportunity cost of missing out on transactions from consumers with a low willingness to pay can mute the ability of individual sellers to take advantage of this heterogeneity. Consumers with a low willingness to pay protect the other consumers because the seller cannot distinguish between the two. This protection disappears in markets that include both an intermediary and a decentralized consumer market. We find that the presence of an intermediary hurts consumer welfare precisely because consumers mistakenly overestimate the price they would have paid in the consumer market and purchase instead at the *more expensive* intermediary. The prices and the ensuing profits of the intermediary increase if the population is (on average) more inattentive. Product owners looking to sell benefit from the presence of the intermediary because the intermediary's higher purchasing price enables the seller in the consumer market to set a higher price. In equilibrium, however, when inattention in the consumer market is sufficiently low, it does not affect the price. As a result, whether product owners are aware of consumer inattention is irrelevant because they are not able to cater to the inattentive consumers in equilibrium.

Our empirical analysis considers a source of inattention that applies to most resale markets. Durable goods generally depreciate continuously, and ample evidence shows that many consumers exhibit left-digit bias and (partially) ignore the depreciation until it exceeds a discrete threshold (Lacetera et al., 2012; Englmaier et al., 2018; Allcott and Knittel, 2019). For example, when evaluating a house with a 9-year-old roof versus another with a 10-year-old one, a buyer might perceive the former as significantly newer than the latter. Similar perceptions might be in play when comparing an airplane that has logged 9,900 miles in the air versus one with 10,000 miles or a car with an odometer reading of 9,9992 miles versus another with 10,020 miles. To validate the theoretical model, we derive several testable predictions about inattention and its effect on prices (intermediary sales and purchase prices, consumer market price) and on the number of transactions. We assembled a comprehensive dataset of all the used vehicle transactions in the state of Texas over a period of seven years, containing millions of consumer-to-consumer transactions as well as dealership purchases and sales. Leveraging an identification strategy based on discontinuity for

left-digit-biased consumers in the perceived mileage around the 10,000-mile cutoff, we find the following:

1. Consistent with our proposed skimming, consumers buying from an intermediary are twice as inattentive to the exact digits of mileage between 10,000-mile thresholds. For example, a vehicle with an odometer reading of 58,000 miles sells in the intermediary market as if it has a (perceived) reading of 54,800 miles. On the other hand, in the consumer market, the same vehicle is perceived by consumers as if it has an average (perceived) reading of 55,752 miles[2].
2. Vehicles just below a 10,000-mile threshold (e.g., 49,999 miles vs. 50,000 miles) are up to $170 more profitable for car dealerships than vehicles immediately above such a threshold.
3. Intermediaries offer product owners significantly higher purchase prices for vehicles just below a 10,000-mile threshold.
4. Vehicles below a 10,000-mile threshold are up to 4% more likely to be sold through a dealership than in a consumer market.
5. Intermediaries sell vehicles below a 10,000-mile threshold up to 6% faster than cars above.

These findings are consistent with our proposed theory and provide novel evidence of how marketing intermediaries strategically react to consumer inattention. Our estimated effects are both statistically and economically significant. For example, in our data, total dealership profits from buying and selling vehicles with odometer readings between 99,000 and 99,999 miles are about $13 million (or 36%) higher than the operating profits from the vehicles between 100,000 and 100,999 [3].

Additionally, we consider how the observed level of inattention differs by market scenarios and present a number of additional results that probe factors affecting the level of inattention.

1. There seems to be no "safety in markets," as inattention in dealership transactions is 40% higher in the highest quantile of competition versus the lowest quantile.
2. Inattention is largely uncorrelated by the inventory levels.
3. Vehicle depreciation and prices are largely uncorrelated with the estimated inattention.

[2] Lacetera et al. (2012) and Englmaier et al. (2018) estimate inattention parameters of 0.31 and 0.39, respectively.
[3] The drop is particularly steep at 100,000 miles but is 10.8%, on average, for all cutoffs between 20,000 miles and 150,000 miles.

4. Controlling for a vehicle's price, depreciation, and model, the level of estimated inattention is greater at relatively higher odometer readings.

The remainder of the paper proceeds as follows. Section 2 introduces the literature relevant to our study. Section 3 presents a theoretical model to motivate our empirical analysis in Section 4. Section 5 presents results relating to the heterogeneity of inattention. Section 6 concludes with a discussion of our findings, limitations, and possible avenues for future research.

2 Literature Review

Our paper broadly contributes to two streams of literature. First, we provide marketplace evidence for heterogeneity of inattention across different channels. Second, we investigate firm behavior resulting from this heterogeneity and the ensuing effects on market outcomes, such as prices and quantity traded.

The specific type of inattention that we consider in our empirical application is left-digit bias. This bias has been studied extensively in the laboratory and in field settings (Poltrock and Schwartz, 1984; Thomas and Morwitz, 2005; Sokolova et al., 2020). For example, several papers investigate the common practice of prices ending in 9 (Anderson and Simester, 2003; Kalyanam and Shively, 1998). Jiang (2021) finds evidence of left-digit bias in the bargaining process for auto loans. Repetto and Solís (2020) find that apartments listed at prices right below round numbers (e.g., $499,999) sell at a price approximately $13,000 higher because more consumers bid on such apartments. A small number of papers examine left-digit bias within non-price attributes. Allen et al. (2017) show that marathon runners use round numbers as targets, and Luca (2016) shows that consumers use discrete changes in star ratings on Yelp to inform their consumption decisions. In a context similar to ours, Lacetera et al. (2012) find evidence of incomplete attention to odometer readings in the wholesale vehicle market. Subsequent work shows similar patterns in retail transactions (Busse et al., 2013) and in posted prices in the online marketplaces (Englmaier et al., 2018). While we also provide another estimate of inattention parameters in an economically significant market, our primary contribution is in providing evidence of heterogeneity in equilibrium across different channels.

At a broad level, We add to a broad stream of papers in the behavioral IO literature that

studies firm reactions to consumer biases (see Ellison (2006); Grubb (2015); Heidhues and Kőszegi (2018) for excellent surveys) and, more specifically, to the work that considers firm reactions to inattentive consumers. This literature is primarily theoretical (e.g., De Clippel et al. (2014)) and has identified several firm strategies. Gabaix and Laibson (2006) shows that firms can "shroud" attributes and use hidden add-on prices to profit from inattentive consumers, and this effect persists even in competitive settings. Similarly, firms benefit from left-digit bias by using prices ending in 9 (e.g., \$3.99) (Levy et al., 2010; Anderson and Simester, 2003) because consumers perceive them to be lower than they objectively are. Strulov-Shlain (2021) presents empirical evidence, in the context of retail markets, of firms reacting to left-digit bias in their pricing and shows that they do not fully optimize to take advantage of this bias. Our contribution is to consider a firm's strategy when facing consumers who are heterogeneously inattentive. We identify an equilibrium mechanism and provide evidence wherein firms set prices that allows them to skim inattentive consumers.

Another strand of literature relevant to our work studies the role of intermediaries in resale markets. Akerlof (1970) points out that asymmetric information can introduce trade frictions when sellers have informational advantages over buyers. A large stream of papers provided nuance to this insight and extended it to more general settings (Hendel and Lizzeri, 1999; Peterson and Schneider, 2014, 2017). Several other papers consider how intermediaries can strategically react to benefit from such informational frictions. Various firm strategies, such as leasing (Hendel and Lizzeri, 2002; Gilligan, 2004; Gavazza, 2011), buybacks (Johnson and Waldman, 2003), and trade-ins (Rao et al., 2009), have been rationalized as strategic responses to asymmetric information. Similarly, starting with Rubinstein and Wolinsky (1987), researchers have studied how intermediaries can benefit from (relatively) high transaction costs in consumer-to-consumer transactions. Others consider the interaction of transaction costs and asymmetric information (e.g., Waldman (2003)) and find that the effect of transaction costs can vary greatly, depending on the level of asymmetric information. However, only a limited amount of work directly incorporates the effects of inattention on resale markets (Lacetera et al., 2012; Englmaier et al., 2018; Repetto and Solís, 2020). Furthermore, to the best of our knowledge, no paper has explicitly incorporated inattention to study how strategic sellers or intermediaries would react to asymmetric information induced via inattention. We aim to fill this gap.

3 Theoretical Model

We present a simple analytical model to analyze the role of a centralized intermediary in a market with consumer inattention. Although the empirical context of our paper involves data on used passenger vehicles and left-digit bias, our model is quite general and can be applied to study other forms of inattention and markets. To isolate the effect of inattention, we abstract away from several other elements that could be present in such markets, including adverse selection[4]. We begin by describing the modeling of inattention in our model, followed by the game details and the equilibrium analysis. Finally, we apply our model to the specific context of left-digit bias and derive several testable predictions.

3.1 Inattention

Starting with Simon (1955), researchers began relaxing the assumption that consumers process all information perfectly. To formalize this notion, we follow Strulov-Shlain (2021); Gabaix (2019) and assume that consumers use a heuristic and thus imperfectly process information about an attribute. Our theoretical model is agnostic to the source of inattention. For simplicity, we assume that utility from each product can be separated into an additive combination of two attributes, where the first attribute (v) is easily observed while the second attribute (z) requires attention to be processed accurately[5]. In our empirical application, we consider that depreciation is measured by z and that it requires attention from consumers to be observed. Additionally, in the absence of being attentive to z, we allow consumers to impute some arbitrary level of z, which is given by Γ_z and assume it to be exogenously given. Γ_z can be zero if consumers are oblivious to the attribute or positive if consumers are inattentive but default to using Γ_z in lieu of the true z. In our application, this allows us to accommodate a fully inattentive consumer perceiving, e.g., 46,000 mi as 40,000 mi or 50,000 mi . To model the level of inattention, we define $\theta \in [0, 1]$ as the exogenously

[4]The empirical results we present are not plausibly explainable by adverse selection. Nonetheless, we want to emphasize that we are not arguing that adverse selection is not present in this market.

[5]In practice, we might see inattention to multiple attributes, stemming from multiple biases. In this case, inattention in our model can be interpreted as net total inattention. If a consumer's inattention stemming from different biases is negatively correlated, the net effect could be less than the sum of the effects. We restrict our analysis to attributes z that decrease the utility from consuming such a product (i.e., $\frac{\partial u}{\partial z} < 0$). We do so because, in our context, potential sellers would always disclose positive values and make them easy to observe. For example, a firm might not advertise minor product defects but certainly would promote hard-to-observe positive attributes, such as a shirt's being made of high-quality fabric.

given inattention parameter, wherein the fully attentive consumers are captured by $\theta = 0$, fully inattentive consumers by $\theta = 1$, and partially inattentive consumers by $0 < \theta < 1$. A consumer with inattention parameter θ, perceives attribute z as a mix of the actual value of z and the imputed value Γ_z.

$$\hat{z}(\theta) = (1 - \theta)z + \theta\Gamma_z. \tag{1}$$

Consistent with the past evidence that ownership increases attention (Hartzmark et al., 2021), we assume that inattention primarily affects buyers during the purchasing process. This is likely since durable goods buyers potentially evaluate a large number of options and have limited time to fully process all the product-related information. However, as consumers use the product, we assume that the misperceptions resulting from inattention eventually get eliminated, and as eventual sellers, they are unbiased.[6]

3.2 Supply, Demand, and the Intermediary

Consider a resale market consisting of three types of players. A unit mass of risk-neutral owners is exogenously endowed with an (indivisible) homogeneous product and a unit mass of risk-neutral buyers with a potentially positive willingness to pay for the product.[7] Finally, a risk-neutral intermediary receives no utility from owning the product but can purchase it from the owners and sell it to the buyers.

Buyers' expected utility from consuming the product is given by $u_B(\theta) = v_B - \hat{z}(\theta)$. Buyers are unaware of their own (and other consumers') inattention and treat their inattentively observed product attribute as the actual product attribute[8]. Owners' expected utility is given by $u_S = v_S - z$. In the specification, v_B and v_S are the valuations of buyers and sellers for the product attribute that is easily observable, and θ is the extent of inattention. To ease the exposition and without a loss of generality, we define $V = v_B - v_S$ and fix $v_S = 1$. To ensure that the product always

[6] One could alternatively assume that even consumption does not lead to fully attentive evaluations. No party in the transaction "accurately" evaluates the product, and the perceived value is part of the consumption utility. In this case, one could think of the inattention parameter in our model as the level of inattention of buyers relative to sellers.

[7] We assume exogenous endowment to focus on the resale market. However, the market setup is consistent with several papers that study used goods markets (e.g., Hendel and Lizzeri (1999)), where consumers with a high willingness to pay for quality prefer to buy new vehicles and then sell them in the next period because they prefer to purchase a new vehicle again.

[8] We define this equilibrium concept fully in Online Appendix A.1.

gives positive utility and that there are positive gains to trade, we assume a bound on attribute $z \in (0,1)$, $\Gamma_z \in (0,1)$ and $V \in (0,\infty)$. The expected utilities for the buyers and the sellers can then be written as:

$$u_S = 1 - z, \tag{2}$$

$$u_B(\theta) = u_S + \underbrace{\underbrace{V}_{\text{actual gains of trade}} + \underbrace{\theta(z - \Gamma_z)}_{\text{inattention wedge}}}_{\text{Perceived gains of trade}}. \tag{3}$$

Buyers with $\theta = 0$ accurately evaluate the attribute, while the consumers with $\theta = 1$ completely ignore the value of attribute z and default to Γ_z. Consumers vary in their level of inattention, which we capture by letting $\theta \sim U[0, \bar{\theta}]$, where $\bar{\theta} \in (0,1]$ is the upper bound on the distribution of inattention, and $E[\theta] = \bar{\theta}/2$. As $\bar{\theta}$ increases, consumers are (on average) less attentive. On the supply side, current product owners vary in their transaction cost to supply to the consumer market, given as $k \sim U[0, \bar{k}]$, and $\bar{k} \in (0,\infty)$ is the upper bound on this cost. This transaction cost captures the costs associated with a sale in the decentralized consumer market, which could include the hassle costs of travel to where the potential buyers reside and demonstrating and explaining the product, as well as the opportunity cost of using the product in that time period, and potential legal liability after the sale. These costs could be higher for high-earning individuals who face more significant opportunity costs and are likely lower for owners geographically close to potential buyers. We assume that an owner trying to sell her asset directly in the consumer market incurs this transaction cost (k), meets one buyer at random, and makes a take-it-or-leave-it offer.

The final player is a centralized, profit-maximizing intermediary. The intermediary sets a purchasing price p^S (i.e., the price it offers the product owner sellers) and a sales price p^I. The intermediary incurs a small fixed cost of c (e.g., cleaning and repackaging the product, salesperson effort) for each transaction. Several papers consider similar settings in which intermediaries are more efficient at matching buyers to sellers. For example, Hendel et al. (2009) show that the time required to sell in the real estate market is faster if an intermediary is used. We capture this improved efficiency by assuming that some owners have higher transaction costs than the intermediary. $c < \bar{k}$[9] The timing of the game is as follows:

[9]In addition, we assume that this cost is sufficiently low, $c < V - z\bar{\theta}$, such that the intermediary never shuts down.

t=1: The intermediary offers a purchase price p^S to all owners[10]. Owners accept or decline, conditional on transaction cost k. If an owner accepts the offer, the transaction occurs, and the owner exits the game.

All buyers visit the intermediary first and observe the intermediary sales price p^I. Buyers who purchase the product exit the game. Buyers who decline the offer enter the decentralized consumer market in the next time period.

t=2: Owners who did not sell the product in stage 1 can choose to enter the consumer market or exit. All sellers who enter the market incur a transaction cost of k, meet one buyer at random, and make an offer p^D. If the offer is accepted, the transaction occurs.

(t=3): Consumption occurs.

The assumption that buyers start their search at the intermediary is common in the literature (Biglaiser et al., 2020), and we believe this assumption is appropriate in our setting for the following reasons. First, finding trading opportunities in the decentralized consumer markets is time-consuming, while the intermediary is prominent and typically carries an assortment of items, thus acting as a convenient one-stop destination. Second, intermediaries proactively use marketing strategies like advertising to find buyers, while such marketing investments are typically harder for individual sellers.

3.3 Analysis

We solve the game by backward induction.[11]. In the second period, each seller that enters the consumer market is randomly matched with a potential buyer and makes one take-it-or-leave-it offer. The offer is conditional on the distribution of inattention among the consumers. Although the actual offer is conditional on the sellers' belief about the distribution of inattention, all players need to form an expectation about that offer, which is conditional on each player's belief about the sellers' beliefs. Also, in the second period, sellers take all actions from the first period as given and

[10]Throughout the paper, we use the terms *owners* and *sellers* interchangeably.

[11]To facilitate tractability and exposition, we focus on the case of relatively significant gains of trade ($V \geq 2$) In addition, we assume that the intermediary's cost is sufficiently low, such that the intermediary never shuts down.

maximize their profit function.

$$\begin{aligned} p^{D*} &= \arg\max_{p^D} E[\pi_O(p^D)] = P(\text{accept}|p^D) \times p^D + (1 - P(\text{accept}|p^D)) \times (1 - z), \\ &\text{s.t. } 0 \leq P(\text{accept}|p^D) \leq 1, \end{aligned} \tag{4}$$

where $P(\text{accept}|p^D)$ depends on the (perceived) distribution of θ for consumers who remain on the market because they did not buy in the first period.

A consumer needs to form an expectation of the price in the decentralized market to choose whether or not to buy from the intermediary. Because the inattention leads them to perceive the value of attribute z as $\hat{z}$, they expect private sellers to set the price conditional on this inaccurate value:

$$P(\text{accept}|p^D, \theta) = \begin{cases} 1, & \text{for } p^D \leq u_B(\theta) \\ 0, & \text{otherwise.} \end{cases} \tag{5}$$

Solving the perceived profit maximization problem, buyers' expectation about the price in the decentralized market[12] is given by $E[p^{D*}|\theta] = u_B(\theta) = 1 - z + V + \theta(z - \Gamma_z)$. Depending on the sign of the inattention wedge $(z - \Gamma_z)$, consumers with the highest or lowest level of inattention have the highest price expectation. Accordingly, consumers with the highest expectations purchase from the intermediary, while the remaining consumers enter the private market. This results in market segmentation as follows: Whenever $\Gamma_z < z$, only consumers with a sufficiently high level of inattention (i.e., $\theta > \hat{\theta}$) purchase from the intermediary in the first period. Whenever $\Gamma_z > z$, consumers with a sufficiently low level of inattention purchase from the intermediary.

However, in the second time period, sellers with accurate beliefs about the distribution of inattention set the price, conditional on the probability of acceptance of an offer, given by

$$P(\text{accept}|p^D) = \begin{cases} \int_{\frac{z-1-V+p^D}{z-\Gamma_z}}^{\hat{\theta}} \frac{\hat{\theta}}{\theta} f(\theta) d\theta & \text{for } \Gamma_z \leq z \\ \int_{\hat{\theta}}^{\frac{z-1-V+p^D}{z-\Gamma_z}} \frac{\hat{\theta}}{\theta} f(\theta) d\theta & \text{for } \Gamma_z > z \end{cases} \tag{6}$$

Individual sellers set the price that maximizes profit, subject to the actual distribution of

[12] We are assuming a homogenous product, but in reality a consumer would likely need to form an expectation about the *actual* level of z as well.

consumers[13]. Thus, the actual equilibrium price in the decentralized market is given by the solution to equation 4. Because we assume sufficiently high gains of trade, sellers prefer to set a price that is accepted by the consumer with the lowest willingness to pay. :

$$p^{D*} = \begin{cases} 1 + V - z & \text{for } \Gamma_z \leq z \\ 1 + V - \hat{z}(\hat{\theta}) & \text{for } z < \Gamma_z \end{cases} \tag{7}$$

Now, we can easily solve the first period by backward induction. In the first period, the marginal consumer, who is indifferent between buying the product or waiting to buy it in the consumer market, is given by: $\hat{\theta} = \frac{p^I - V + z - 1}{z - \Gamma_z}$, and demand for the intermediary is given by: $D(p^I) = \begin{cases} \int_{\hat{\theta}}^{\bar{\theta}} f(\theta) d\theta & \text{for } \Gamma_z \leq z \\ \int_0^{\hat{\theta}} f(\theta) d\theta & \text{for } z > \Gamma_z \end{cases}$. Similarly, the seller, who is indifferent between selling to the intermediary or selling directly, is given by: $\hat{k} = E[\pi_O] - p^S$. Total supply for the intermediary is given by: $S(p^S) = \int_{\hat{k}}^{\bar{k}} f(k) dk$. The intermediary firm's profit-maximizing prices are the solution to the following maximization problem:

$$\begin{aligned} &(p^{I*}, p^{S*}) = \arg \max_{(p^I, p^S)} E[\pi] = D(p^I) \times (p^I - p^S - c) \\ &\text{s.t. } 0 \leq D(p^I) \leq S(p^S) \leq 1 \end{aligned} \tag{8}$$

We present the benchmark results without inattention (i.e., $\bar{\theta} \to 0$) in Lemma 1 in Online Appendix A.2. The only role of the intermediary in a market without inattention is to facilitate transactions for owners who have sufficiently high transaction costs, similar to Biglaiser (1993). Prices in both markets are equal, and whenever individual sellers' transaction costs are sufficiently low, the intermediary's transaction quantity is zero. This outcome is consistent with other models in which the intermediaries' primary role is reducing transaction costs (Rubinstein and Wolinsky, 1987). However, when consumers are inattentive, the intermediary can capture inattentive consumers (with a higher willingness to pay), and the market gBiglaiser (1993)ets segmented. This equilibrium outcome is formally presented below:

[13]Note that the intermediary cannot sell more products than it purchases. Therefore, the number of buyers cannot exceed the number of sellers in the decentralized market. Sellers with a high k might endogenously choose not to make an offer or sell to the intermediary, but this decision does not affect the buyer's expected payoff because the expected offer gives them zero utility.

Proposition 1 *Whenever consumers are inattentive, intermediary prices are higher than the prices in the decentralized market ($p^{I*} > p^{D*}$). Consumers with high perceived gains of trade purchase from the intermediary and consumers with low perceived gains of trade purchase in the decentralized market.*

Consumers visit the intermediary first and decide between purchasing the product or waiting to (potentially) purchase in the decentralized market. If inattention leads to an overestimation of utility, fully attentive consumers correctly estimate the product's value and realize that the price in the decentralized market is lower. Inattentive consumers overestimate the product's value and, therefore, overestimate the price of such a product in the consumer market.[14] Because inattentive consumers overestimate the price in the consumer market, the intermediary's price has to be below the (estimated) expected price to be accepted. The optimal strategy for the intermediary is to set a price that is acceptable only to the inattentive segment. As a result, consumers with high inattention purchase from the intermediary and exit the market. More attentive consumers anticipate a lower price in the decentralized market and thus enter it. When sellers set the price in the consumer market, they face a trade-off between the increased payoff from a higher price and the increased probability of an offer's being declined. Because the consumer base in the decentralized market is relatively more attentive, the decentralized market price gets pushed down. In the case of inattention leading to an underestimation of the utility, the mechanism is very similar. Because consumers are not aware of their own (or others) inattention, the most attentive consumers estimate a price that would be correct absent the presence of inattentive consumers. However, because other consumers are inattentive and have a lower willingness to pay, individual sellers are better off lowering the prices to sell to all consumers. Because attentive consumers do not anticipate that, they overestimate the price. Interestingly, this leads to an outcome wherein the most inattentive consumers have an accurate estimate of the price in the decentralized market, even though they misperceive the seller's profit maximization problem. As a result, more attentive consumers purchase at the intermediary at higher prices, while inattentive consumers purchase in

[14] Note that inattention, rather than heterogeneity in the reservation price, drives these results. In Appendix A.5, we derive results for the same model under the assumption that consumers are fully attentive but are heterogeneous in their willingness to pay for attribute z. Our analysis shows that competition between the centralized and decentralized markets drives prices down and that there is only one price in the market. The consumer surplus fully absorbs an increase in willingness to pay, and the supply side cannot benefit from this heterogeneous increase in average willingness to pay.

the decentralized market.

These results are formally stated in the following result:

Proposition 2 *For sufficiently high gains of trade:*
The quantity of decentralized transactions decreases ($\partial Q^{D*}/\partial\bar{\theta} < 0$), and the quantity of intermediary transactions increases ($\partial Q^{I*}/\partial\bar{\theta} > 0$), as inattention goes up.
For a positive inattention wedge ($\theta(z - \Gamma_z) > 0$), transaction prices in the decentralized market are constant ($\partial p^{D*}/\partial\bar{\theta} = 0$), intermediary sell prices ($\partial p^{I*}/\partial\bar{\theta} > 0$) and purchase prices increase ($\partial p^{S*}/\partial\bar{\theta} > 0$), as inattention increases.
For a negative inattention wedge($\theta(z - \Gamma_z) < 0$), transaction prices in the decentralized market decrease ($\partial p^{D*}/\partial\bar{\theta} < 0$), intermediary sell prices ($\partial p^{I*}/\partial\bar{\theta} < 0$) and purchase prices decrease ($\partial p^{S*}/\partial\bar{\theta} < 0$), with the rise in inattention.

These results showcase the role of an intermediary in a market with inattentive consumers. To understand the intuition of the equilibrium, note that an increase in inattention leads to greater heterogeneity in consumers' misperceptions of prices in the consumer market, which allows the intermediary to skim consumers with the highest willingness to pay. The intermediary reacts to the increased demand by raising sales prices and improving supply by setting a higher purchasing price. The remaining consumers who enter the decentralized market are the subset of consumers with the lowest willingness to pay. For the sellers, the potential gains from setting a higher price to benefit from the heterogeneity of buyers is dominated by the opportunity cost of missing out on potential transactions. In equilibrium, the prices charged in the consumer market are set to induce purchases by buyers with the lowest willingness to pay. In the case of a positive inattention wedge, this is the price a fully attentive buyer would pay. In the case of a negative wedge, it is the price the consumer with the highest level of inattention is willing to pay. In equilibrium, we observe two prices for identical products. Consumers who overestimate the price in the decentralized market pay a higher price (to the intermediary), while the remaining consumers pay a lower price (in decentralized transactions). This difference between the two prices increases as the level of inattention increases.

3.4 Effect of Intermediary

We next analyze the impact of the intermediary more explicitly by comparing the market outcomes when only consumer-to-consumer trade occurs against a setting where both intermediary and consumer trade is possible. Without the intermediary, each owner-seller sets a price that maximizes their utility. Setting a higher price reduces the probability of a sale because only consumers who overestimate their utility purchase the product. Specifically, when the gains from trade (V) are more significant, the opportunity cost from a declined offer becomes large enough that sellers prefer to set a price accepted by all buyers, regardless of the level of inattention. Since sellers cannot observe individual consumer attention, the opportunity cost of missing out on transactions from consumers with lower perceived gains of trade protects consumers with the highest perceived gains of trade from facing a higher price. In Online Appendix A.3.1, we derive these results formally and show in Lemma 2 that for sufficiently high gains of trade, the price is set at such a level that all consumers purchase the product.

The situation undergoes a fundamental change when an intermediary is present. The intermediary sets a higher price and sells to consumers with relatively high perceived gains of trade.
The impact of the intermediary can be summarized via three key points. First, consumers can purchase either from the intermediary or directly from an individual owner, creating competition. Second, the intermediary purchases products from owners who would not have entered the market in the absence of an intermediary due to high transaction costs, thereby increasing the quantity supplied. Third, by virtue of being the first stop for consumers, the intermediary is able to skim consumers with higher perceived gains of trade from the market, as previously described. Combining all these effects, we can derive the following formal result:

Proposition 3 *In the presence of consumer inattention, the introduction of an intermediary reduces buyer surplus and increases owner-seller surplus.*

Other studies show that producer competition does not always eliminate excess producer surplus arising from behavioral biases (Gabaix and Laibson, 2006). Offering a different perspective, our result is noteworthy in that it shows how adding an intermediary decreases consumer surplus. In most market contexts, competition improves outcomes for consumers through an increase in welfare arising from price reduction, which typically reduces firm profits. For example, the classic Bertrand

paradox implies that the entry of a single other firm in a monopoly could eliminate all potential profits in the market. This intuition does not hold in our context, even when the product is modeled as homogeneous. In the absence of an intermediary, sellers need to balance the incentive to set prices that exploit consumers' high willingness to pay due to inattention with the opportunity cost of serving consumers with relatively low perceived gains. In a market with an intermediary and decentralized trade, this opportunity cost is not an issue because the intermediary can "skim" consumers with the highest willingness to pay while the remaining consumers can purchase the good in the consumer market.

3.5 Left-Digit Bias and Testable Predictions

So far, we have considered a general model in which z could capture any one of several attributes that consumers might not be attending to. To empirically test predictions from this model, we require variation in the level of consumer inattention while keeping other variables constant. Finding such variation in observational data is difficult, which makes the identification of inattention and its effects non-trivial.

Instead of relying on variation in the level of inattention (which is usually unobserved), we leverage the observed variation in the attribute z. In our empirical application, we use a well-documented finding that consumers in many market interactions are left-digit biased. More specifically, in the resale markets for passenger vehicles, left-digit-biased consumers might overweight the leftmost digits of an odometer reading. This tendency implies significant discontinuities in expected quality whenever mileage increases above a round threshold. In this section, we link the model directly to our empirical context of left-digit bias and derive several testable predictions from the theoretical model. We model left-digit bias similar to Lacetera et al. (2012) and let $\hat{z}(\theta) = \alpha\hat{M}(\theta)$, where α denotes the depreciation rate and $\hat{M}(\theta)$ is the perceived mileage of a vehicle. Consistent with prior empirical findings (Lacetera et al., 2012; Englmaier et al., 2018), we assume that consumers imperfectly process continuous attributes and pay full attention only to the leftmost digit. In our model, utility decreases in magnitude of the continuous attribute $M \in [0, 10)$.[15]

[15] Of course, continuous values have an infinite number of digits that a consumer could take into account at varying levels. In this model, we assume that consumers pay full attention to the first digit and give lower but equal attention to all the remaining digits. M could, as in our empirical application, refer to miles, with 1 corresponding to 10,000 miles, 2 corresponding to 20,000 miles, and so on.

For a consumer with an inattention parameter θ, the perceived value of attribute M is given by

$$\hat{M}(\theta) = \lfloor M \rfloor + (1-\theta)(M - \lfloor M \rfloor) + \theta\Gamma_M, \tag{9}$$

where $\lfloor \cdot \rfloor$ is the floor operator.[16] For example, if $\theta = 1/3$, $\Gamma_M = 0$, and $M = 4.92$, the perceived attribute value is given by $\hat{M} = 4 + (1 - 1/3)(0.92) = 4.61$.

Seller and buyer product utilities are:

$$u_S = v_S - \alpha M. \tag{10}$$

$$u_B = v_B - \alpha\hat{M}(\theta). \tag{11}$$

In the specification, v_B and v_S are the baseline valuations of buyers and sellers for the product, and θ is the value of inattention.[17]

Discontinuities arise in utility whenever the mileage M crosses a round number. Inattentive buyers perceive a product whose attribute falls right below or above a round cutoff differently. Similar to regression discontinuity estimators, we can leverage these cutoffs and derive empirically testable predictions. It is important to note that Γ_M is not directly identified from the discontinuities, but the theoretical model makes sharply different predictions for consumers "rounding down" versus "rounding up."). We carefully derive and test these predictions in B and find evidence consistent with "rounding down" ($\Gamma_M = 0$). For the sake of brevity and to maintain a focus on the core implications of our findings, the subsequent discussion is confined to theoretical considerations derived on the assumption that $\Gamma_M = 0$, while the case for $\Gamma_M = 1$ is derived in Online Appendix B

We denote $\Delta x = \lim_{M \to \lfloor M \rfloor^-} x(\lfloor M \rfloor) - x(M)$, which estimates the discrete change in some variable x as M crosses a round number (from below). We characterize predictions for equilibrium inattention, prices, and equilibrium quantities.

Proposition 4 *If consumers exhibit inattention (i.e., $\bar{\theta} > 0$):*

[16] Strulov-Shlain (2021) uses a similar functional form to study left-digit bias with respect to retailer data. We define $\lfloor M \rfloor = M - M \bmod 1$. In our empirical context (and with a slight abuse of notation), we use the floor at each 10,000-mile cutoff: $\lfloor M \rfloor = M - M \bmod 10,000$.

[17] We assume that there are moderate gains of trade ($v_B - v_S > 1$) and that the depreciation rate is relatively low ($0 < \alpha < 1$).

1. *Average inattention is lower in decentralized transactions than in intermediary transactions.*
2. *There is a negative discontinuity in intermediary sales prices ($\Delta p^{I*} < 0$). In other words, there is a sharp drop in price once mileage crosses a round number.*
3. *The discontinuity in intermediary sales prices is larger in absolute terms than the discontinuity in purchase prices and the discontinuity in consumer market prices ($|\Delta p^{I*}| > |\Delta p^{D*}|$ and $|\Delta p^{I*}| > |\Delta p^{S*}|$).*
4. *The discontinuity in the dealership purchase price is (weakly) larger in absolute terms than the discontinuity in consumer market prices ($|\Delta p^{S*}| \geq |\Delta p^{D*}|$).*
5. *The discontinuity in the number of intermediary transactions is (weakly) negative ($\Delta Q^{I*} \leq 0$).*
6. *The discontinuity in the number of intermediary transactions is (weakly) larger in absolute terms than the discontinuity in the number of decentralized transactions ($|\Delta Q^{I*}| \geq |\Delta Q^{D*}|$).*

The proposition derives six empirically testable predictions involving consumer inattention (θ), prices (p^I, p^D, and p^S), and the quantities in the consumer market (Q^D) and intermediary (Q^I) transactions. In equilibrium, the intermediary charges a higher price and serves relatively inattentive consumers. This skimming of inattentive consumers leaves relatively attentive consumers in the decentralized market. Because the intermediary can charge a higher price when consumers are inattentive, it has an incentive to sell a higher quantity at that higher price. In order to obtain a higher quantity to sell, the intermediary increases the purchase price offered to individual owners looking to sell. As noted, because the intermediary skims inattentive consumers from the market, owners are left with relatively attentive consumers who do not accept higher prices. Thus, an increase in the purchase price offer leads to more owners selling to the intermediary and fewer owners selling directly in the decentralized market. Interestingly, two outcomes follow from prediction 3 and prediction 6 for vehicles with odometer readings below round thresholds: (i) that inattention increases intermediary prices relative to consumer market prices, and (ii) that inattention increases the number of transactions for the intermediary relative to the quantity in the consumer market. This seemingly counterintuitive increase in both the price charged and the quantity supplied follows from the intermediary catering to the relatively inattentive segment. Rationalizing the simultaneous increase in quantity and price is difficult without this proposed behavioral segmentation.[18] The result thus provides a particularly strong test of our proposed theory.

[18] For example, if the intermediary and individual sellers face the same distribution of inattentive consumers, one would expect that an increase in the price of the intermediary would lead to a decrease in market share.

4 Empirical Analysis

In this section, we test the main predictions of our proposed theory. We first describe the context and data in greater detail and then proceed to test the main analysis.

4.1 Empirical Context

Our empirical context is the U.S. passenger vehicle resale market. Passenger vehicles are actively traded between consumers and through intermediaries (i.e., used car dealerships). Despite this market's complexity, it shares many of the key elements of our analytical model. In the model, we assume that consumers start their search for vehicles at the intermediary. Although we cannot directly test this assumption in our data, we can think of many intuitive reasons why consumers might first visit a dealership in search of a used car. First, vehicles traded through a dealershipgenerally require a less thorough inspection by the customer (Biglaiser et al., 2020) because dealerships offer warranties and have instituted mechanisms to reduce asymmetric information (Rao et al., 2009; Johnson and Waldman, 2003). Second, dealerships act as a one-stop destination where consumers can often view and compare vehicles on its website and inspect and test-drive multiple vehicles during a single visit to a dealership. Third, dealerships offer additional services, such as accepting trade-ins or financing options that further reduce transaction costs. To closely match the analytical model, we focus on consumer-to-consumer transactions and transactions where the same dealership buys and sells a vehicle.

Our data provides detailed information on vehicle transactions, including the price a dealership paid to procure a vehicle (which we refer to as the dealership purchase price) and the price at which the dealership sold the vehicle[19]. We also observe the prices at which vehicles are sold in the consumer markets. The analytical model maps our empirical context quite well. However, we also want to highlight a few important differences. First, we consider one intermediary in the model, but in the empirical setup, the data obviously involve numerous dealerships. Second, used car dealerships often bundle used car purchases with used or new car sales (referred to as "trade-ins"), which we do not explicitly consider. Third, for simplicity, we consider homogenous goods in our

[19] Used car dealerships purchase vehicles from consumers in the form of trade-in transactions. Throughout the paper, we use the term "purchase price" to denote the price the dealerships pay individual owners in trade-in transactions.

model, but the vehicle market clearly is vertically and horizontally differentiated. Despite these differences, our data include many useful features of durable goods resale markets to allow our model to assess the role of inattention.

4.2 Data

Our primary dataset consists of all vehicle transactions (consumer-to-consumer and dealership transactions) in the state of Texas between September 2014 and December 2021, which comprises approximately 10% of vehicle transactions in the United States (FHA, 2018). Our data source is the title forms (see Figure A1), which the transacting parties are required to file and which are submitted to the Department of Motor Vehicles for registration and tax purposes. For each transaction, we observe the transaction price and details about the vehicle, including the exact vehicle identification number (VIN) and the buyer's zip code. For vehicles not older than ten years on the date of a transaction, we also observe the odometer reading on the transaction date[20]. For dealership transactions, we also observe detailed information about the dealership and information about vehicles that are traded in, including the VIN and purchase price. We use the National Highway Traffic Safety Administration database to get detailed vehicle information and to collect detailed information for each observed VIN. One difficulty is that we do not observe the odometer reading of vehicles sold to the dealership; however, we observe the odometer reading when the vehicle is subsequently sold, which allows us to impute the odometer reading. We restrict our sample to: (i) vehicles traded directly between two consumers and (ii) vehicles purchased by a dealership as a trade-in and subsequently sold by the same dealership[21]. In Table 2, we present summary statistics of the data. Figure A4 in the Online Appendix shows histograms for key numerical variables.

[20] Until December 31, 2020, vehicles older than ten years were exempt from disclosing the odometer reading in transactions. Starting January 1, 2021, a new law began to be phased in so that only vehicles of model years 2010 and older are exempt from disclosing the odometer reading. Starting January 31, 2030, only vehicles older than 20 years will be exempt from disclosing the odometer reading.

[21] We conduct robustness checks that include vehicles that were purchased and sold by different dealerships and the results are qualitatively identical to the results with the restricted sample.

4.3 Empirical Predictions

If the car buyers are left-digit biased, there should be discontinuities in how they perceive the odometer reading at every 10-, 100-, 1,000-, and 10,000-mile mark. Our visual examination of prices shows a consistent drop in prices at the 10,000-mile mark, while such discontinuities at the smaller cutoffs are smaller and more difficult to measure precisely. We thus follow Englmaier et al. (2018) and Lacetera et al. (2012) and assume that consumers are inattentive to digits between 10,000-mile cutoffs. We can thus define the perceived mileage of a vehicle as

$$\hat{M}(\theta) = \lfloor M_i \rfloor_{10k} + (1-\theta)(M_i - \lfloor M_i \rfloor_{10k}), \tag{12}$$

where $\lfloor M_i \rfloor_{10k} = 10,000 \times \lfloor \frac{M_i}{10,000} \rfloor$ denotes the floor operator, and where the floor is the nearest multiple of 10,000. For example, a moderately inattentive consumer ($\theta = 0.4$) perceives a vehicle with 50,000 miles as $50,000 + (1-0.4) \times (0) = 50,000$ but perceives a vehicle with 49,999 miles as $40,000 + (1-0.4) \times (9,999) = 45,999$.

Our theoretical framework derived several predictions from the model. The predictions concern three elements: (i) the level of inattention of consumers transacting at dealers versus consumer markets; (ii) the impact of inattention on prices; and (iii) the impact of inattention on the number of transactions. We test the three sets of predictions separately. First, we directly use the observed transaction prices to estimate the inattention parameter. Second, we test the key prediction from our theoretical model: that more inattentive consumers are more likely to purchase the car through an intermediary. Third, we consider the effect of inattention on marketplace outcomes like pricing and quantities.

4.4 Estimation of Inattention Parameter

The critical insight from the equilibrium described in the theoretical model is the presence of skimming by the intermediary. The intermediary sells to consumers having a higher level of inattention, implying that only relatively attentive consumers purchase in the decentralized market. Based on Proposition 2, we can test the following prediction.

Prediction 1: The average buyer inattention is lower in decentralized transactions than in dealership transactions.

To accurately estimate the inattention parameter, we need to jointly account for the continuous, potentially nonlinear depreciation, as well as the discontinuous drops at 10,000-mile marks. To do so, we follow an approach similar to Lacetera et al. (2012). That is, we include a polynomial that captures the continuous depreciation and jointly estimates the inattention parameter.[22] We estimate the model separately for dealership transactions and decentralized transactions. The estimator is given by: $price_i = \beta_0 + f(\hat{M}(\theta)) + \psi X_i + u_i$. We use a polynomial of order K to capture the potentially nonlinear depreciation, and we rearrange the formula to get the following:

$$price_i = \beta_0 + \sum_{k=1}^{K} \alpha_k (\underbrace{M_i - \theta(M_i - \lfloor M_i \rfloor)}_{\text{Perceived Mileage}})^k + \psi X_i + u_i, \tag{13}$$

where X_i denotes a vector of the fixed effects we describe below. In this specification, we consider the case with no inattention (i.e., $\theta = 0$). Then, we fit a continuous K dimensional polynomial function to capture the relationship between mileage and price. At the other extreme, if consumers are completely inattentive (i.e., $\theta = 1$) to the right-most digits, the continuous M_i in Equation 18 cancels out, and all depreciation happens at the 10,000-mile marks. To account for potential changes in time, we include fixed effects for each of the 381 observed weeks. We also include fixed effects for each zip code.[23] We include fixed effects for each of the 43,459 combinations of the make, model, year, and trim. For the dealership transactions, we also include the dealership fixed effects. A large number of fixed effects makes it computationally infeasible to estimate the nonlinear model directly, so we estimate it in two stages. First, we run a regression with the full set of fixed effects but omit the odometer variables and store the residual. Then, using the residual as the outcome variable, we estimate the nonlinear model and estimate the α_k and θ coefficients. We estimate the model separately for dealership transactions and decentralized transactions.

The results are presented in Table 3. Vehicles sold directly in the consumer market are presumably different from those sold in dealerships, and we aim to control for these differences by using several fixed effects. In addition, vehicles sold by car dealerships have a different distribution of

[22] The estimate of the inattention parameter relies on prices. Thus, the estimated coefficient can be interpreted as the level of inattention that corresponds to the pricing.

[23] In total, we observe 10,041 zip codes. There are 1,930 zip codes in Texas, but in our dataset, we also observe some out-of-state locations (fewer than 4% total). Some observations (fewer than 0.2%) presumably have typos because the zip codes do not correspond to any location. Our results remain virtually identical if the data is restricted to observations in Texas.

odometer readings and generally are less depreciated (see Figure A4 in the Online Appendix). Thus, one potential issue might be that vehicles sold by intermediaries are generally newer and consumers may have different levels of attention when purchasing these vehicles. To account for this difference, we also estimate the models using a weighted nonlinear least squared estimate, in which we assign each odometer reading $m_j \in M = \{5,000; 5,001; ...; 150,000\}$ the same weight. The weight for each observation i with odometer reading m_i is given by: $W_i = \frac{1}{\sum_j m_j} \left(\sum_{n=1}^{N} \mathbf{1}[m_i = m_n] \right)^{-1}$, where N is the total number of observations. We estimate the average inattention by weighing each odometer reading equally. This approach mutes any potential difference that might arise if inattention varies across odometer readings. The results under both these specifications support our hypothesis. The estimate for the inattention parameter is given by $\theta = 0.4$ for dealership transactions and $\theta = 0.28$ for decentralized transactions. In the weighted least squares estimate, the difference between the two estimates is even larger; the inattention parameter is $\theta = 0.456$ for dealership transactions and $\theta = 0.205$ for decentralized transactions. Buyers in dealership transactions exhibit significantly higher levels of inattention than buyers in decentralized transactions. For example, a vehicle with an odometer reading of 69,000 mi is perceived as having 64,896 mi by consumers at dealerships and 67,155 mi by consumers in decentralized transactions.

4.4.1 Equilibrium Pricing Effects

We have derived several predictions from the model regarding the equilibrium sales price (p^{I*}) and purchase price (p^{S*}) of the intermediary and the price in decentralized transactions (p^{D*}) in the consumer market. We formalized these predictions in Proposition 6 and can test whether the pricing behavior is consistent with the proposed theory. As before, we use the discrete cutoff around 10,000-mile increments, where the perceived mileage of left-digit biased consumers exhibits a discrete drop. The discontinuity around the 10,000-mile cutoff thus allows us to identify the effect of inattentive consumers on the market outcomes described in Predictions 2-5.

Prediction 2: Dealership sales prices drop discontinuously at 10,000-mile marks ($\Delta p^{I*} < 0$).

Prediction 3: The discontinuity in dealership sales prices is greater than the discontinuity in dealership purchase prices at 10,000-mile marks ($|\Delta p^{I*}| > |\Delta p^{S*}|$).

Prediction 4: The discontinuity in dealership prices is greater than the discontinuity

in consumer market prices at 10,000-mile marks ($|\Delta p^{I*}| > |\Delta p^{D*}|$).

Prediction 5: The discontinuity in the dealership purchase price is (weakly) greater than the discontinuity in consumer prices at 10,000-mile marks ($|\Delta p^{S*}| \geq |\Delta p^{D*}|$).

The model predicts that the intermediary sets prices that are attractive only to relatively inattentive consumers while more attentive consumers purchase in the decentralized consumer market. The intermediary sells to inattentive consumers, and the equilibrium price increases due to inattention (Prediction 2). Prediction 3 implies that inattention increases intermediaries' per-vehicle profit. Prediction 4 implies that inattention increases the "dealership premium" and allows intermediaries to charge a higher price relative to the price in the decentralized market. Finally, Prediction 5 reflects that inattention leads a strategic intermediary to increase the purchase price to increase supply and to take advantage of the inattention on the demand side.

Predictions (2) and (3) are readily observable in the data for vehicles that are purchased and subsequently sold by the dealer. To show potential discontinuities in purchasing price and sales price, Figure 2 graphically shows the change in the average purchase price, the average subsequent sales price, and average profit (i.e., the difference between observed purchase price and sales price)[24] in. Here, we restrict the sample to vehicles between 5,000 miles and 150,000 miles and aggregate the vehicle price for each 1,000-mile bucket. For example, the rightmost dot in the sales price plot represents the average sales price for all vehicles sold that have an odometer reading between 149,000 and 149,999 miles. We add a linear fit line within each 10,000-mile observation window to highlight the potential discontinuities at the 10,000-mile marks. The plots for the average purchase price and average sales price show a strong discontinuity at the 100,000-mile mark. Clear declines in the average sales price are visible at the majority of the 10,000-mile marks. Similarly, a small but visible discontinuity occurs at several 10,000-mile marks in the purchasing price. Finally, looking at the difference between the two, significant discontinuities emerge, particularly for the cutoffs between 60,000 miles and 100,000 miles[25].

Although the plot is based on millions of observations, the raw data remain noisy. To get more

[24]Figure A12 presents the residuals, net of fixed effects for the dealership, customer zip code, make/model/trim/year/week, as the outcome variable and shows similar, but more pronounced discontinuities

[25]The average profit increases as odometer numbers go up. Biglaiser et al. (2020) argue that the "dealership premium," which is the price difference between dealership and decentralized market transactions, results from potential lemon problems and assortative matching. The higher profit could result from similar phenomena or might be attributed to potential investments by dealers to refurbish vehicles with higher mileage. However, in testing for inattention, our identification of it relies on the differences around mileage cutoffs.

accurate estimates and to formally test our hypotheses, we next consider a regression, similar to Lacetera et al. (2012):

$$y_i = \beta_0 + \sum_{k=1}^{K} \alpha_k miles_i^k + \sum_{j=1}^{14} \beta_j \mathbf{1}\left[miles_i \geq j \times (10,000)\right] + \gamma X_i + u_i, \tag{14}$$

where y_i is our outcome variable of interest (sales price, purchase price, and profit). We fit a high-ordered polynomial function of the mileage's effect on the outcome variable, which captures the continuous portion of the relationship between the outcome variable and the mileage. In addition, we include an indicator variable for all 10,000-mile thresholds in our model, which is 1 for odometer readings that exceed it and 0 otherwise. The coefficient on the indicator variable captures the discrete change in the outcome variable, above and beyond the effect attributable to the continuous effect[26]. Finally, we again include several fixed effects for the vehicle model-make-year-trim combination, the dealer, the customer zip code, and the date (in weeks). Identification in the model comes from the variation in each trim-year, dealer, week, and zip code effect around the cut-off.

We present the results for the outcome variables of the sales price, the purchase price, and the difference between the two (i.e., profit) in Table 4. The coefficients of interest $\{\beta_1, \beta_2, ..., \beta_{14}\}$ are precisely estimated for most cutoffs, and the standard errors incrase for larger cutoffs because there are fewer observations. Dealership sales prices show sizable and statistically significant drops at all discontinuities (except at 110,000 miles). Similarly, the average purchase price shows sizable and statistically significant drops for values below 100,000 miles. Finally, the difference between the purchase price and the sales price is estimated in the third column and is negative for most values. The cutoffs at 60,000 miles to 100,000 miles, where the most considerable portion of intermediary transactions occur, are significant and range between -$69 and -$179.[27]

The interpretation of the coefficients is that dealerships charge a significantly higher price for

[26]The polynomial is of order seven or higher in all our specifications, but we use the AIC to choose the model with the optimal polynomial order. We present results using different odometer readings in figures A5,A6, and A7. In addition, because odometers of vehicles in the United States show the mileage in imperial units, we conduct a type of placebo test for all our models, in which we use odometer readings in kilometers instead of miles, expecting all effects to be muted.

[27]Note that when we estimated the difference in a separate regression, the fixed effects have a slightly different interpretation. For example, the dealership fixed effect now controls for the dealer-specific idiosyncratic profit deviation per vehicle. In the regression with the purchase price, the dealership fixed effect controls for the dealer-specific idiosyncratic purchase price deviation.

vehicles immediately below the 10,000-mile cutoffs. From these higher prices, a proportion is passed through to product owners in the form of a higher purchase price. However, the dealership also earns a higher margin on vehicles immediately under a 10,000-mile cutoff.

Predictions (4) and (5) focus on the differences in the predicted drops between dealership transaction prices and prices in decentralized transactions. We estimate a regression that allows us to test for the difference in the discontinuity at each 10,000-mile mark between decentralized transaction prices and dealership sales and purchase prices, respectively. The model we estimate is given by:

$$y_i = (1 + \mathbf{1}\left[\mathrm{D}_i\right]) \left(\beta_0 + \sum_{k=1}^{K} \alpha_k miles_i^k + \sum_{j=3}^{14} \beta_j \mathbf{1}[miles \geq j \times (10,000)] \right) + \gamma X_i + u_i, \tag{15}$$

where $\mathbf{1}\left[\mathrm{D}_i\right]$ is 1 for dealership transactions and 0 otherwise; y_i is the transaction price or purchasing price, and the remaining variables are as defined in Equation 15.

We present the interacted coefficients in Table 5.[28] The differences between decentralized and dealership price drops are significantly negative in the range between 60,000 and 100,000 miles, where most transactions occur. For example, the parameter at 60,000 miles is -$115.17. This estimate implies that, after controlling for all fixed effects and the continuous portion of depreciation, the discontinuous price drop experienced at dealership sale prices is higher relative to the discontinuities measured at the decentralized price by about $115.17. Since these discontinuities arise due to inattention, it provides supplementary evidence of (higher) inattentive buyers being served by dealerships. On the other hand, the difference between the dealerships' purchasing price and the decentralized prices is insignificant throughout. Thus, this discontinuity is not significantly different for intermediary and decentralized transactions.

4.4.2 Number of Transactions

In this section, we examine predictions about the quantity of transactions in intermediary and decentralized markets. We have shown that, compared to vehicles above the threshold, vehicles below round thresholds are relatively more expensive than those in the centralized market. However,

[28] We restricted the sample to vehicles with at least 25,000 miles because there are relatively few decentralized transactions for vehicles under 25,000 miles, and fitting an appropriate polynomial in this case is difficult.

due to the proposed skimming strategy, we expect that the intermediary will sell a larger quantity despite the vehicles being more expensive. We test this directly via the following predictions:

Prediction 6a: The quantity of dealership transactions decreases discontinuously at the 10,000-mile marks ($\Delta Q^{I*} \leq 0$).

Prediction 6b: The discontinuous drop in transactions is larger at at the dealerships than in the consumer markets at the 10,000-mile marks ($\Delta Q^{I*} < \Delta Q^{D*}$).

Figure 3 plots the number of dealership transactions and decentralized transactions, using the same aggregation to 1,000-mile buckets as in Figure 2. The figure shows a clear pattern of discontinuities in the number of dealership transactions at round numbers, particularly for vehicles between the 40,000- and 100,000-mile cutoffs. For decentralized transactions, the discontinuities are less pronounced and are only significant for the cutoffs at 90,000 miles and 100,000 miles.[29]

Next, we look at the universe of all vehicles sold by a vehicle owner, either to the intermediary or in the consumer-to-consumer market. In Figure A2, we plot the percentage of transactions that involve an intermediary. Our theoretical model implies that we should expect drops in this percentage at the 10,000-mile marks. Although the data are somewhat noisy, smaller discontinuities are seen at 10,000-mile marks and a clear discontinuity is visible at the 100,000-mile mark.

To precisely estimate these visual effects, we conduct a regression of the relative quantity of transactions through an intermediary vs. transactions in the decentralized market. We re-estimate the model given in Equation 14, but the outcome variable of interest is an indicator of the transactions being facilitated by a dealership. We continue to use the same set of fixed effects (except the dealership fixed effect), which allows us to interpret the coefficients on each 10,000-mile discontinuity as the discrete jump in the propensity of a vehicle's being sold to the dealership rather than in the decentralized market. The coefficient is again identified by the variation in mileage within each make, model, year, trim, zip code, and week. The results are presented in Table 6, and all estimated coefficients of interest are negative and statistically significant. The coefficients imply that the likelihood of a vehicle transaction being mediated by the dealership drops discontinuously by about 1 to 5 percentage points after crossing a 10,000-mile threshold.

[29] Due to the nature of the data, odometer readings for decentralized transactions are more likely to be rounded. We deal with this problem in several robustness checks in the Online Appendix C.5.3, and conclude that such rounding behavior cannot fully explain the pattern we observe.

5 Additional Analyses and Robustness Checks

We derived a series of predictions from the theoretical model we tested using used car transactions data wherein our identification leveraged the discontinuity in *perceived* mileage around the 10,000-mile mark. Although other explanations could potentially rationalize each prediction in isolation, the combined validity of these predictions makes for a plausible empirical test of our theory. In particular, our theory predicts that the intermediary is in an excellent position to benefit from inattention. It leverages this position by (i) charging higher prices and (ii) engaging in a partial pass-through of this increased price to sellers. Interestingly, the intermediary charges a higher price for vehicles valued by consumers and sells a higher quantity in absolute and relative terms to the decentralized market. We find empirical support for all predictions. Consumers buying from the intermediary are less attentive than consumers in the decentralized market. Consistent with the proposed theory, intermediaries react by acquiring more vehicles on the market by offering a higher purchase price for cars below the 10,000-mile cutoffs. Intermediaries significantly increase the price for vehicles below the 10,000-mile threshold.

We provide the following robustness checks and analysis in Online Appendix C.

1. A placebo test that includes 10,000-kilometer thresholds (figures A8,A9,and A10). The United States uses the imperial measurement system, and consumers never observe kilometers. We expect the kilometer variables to be insignificant, and we largely find insignificant coefficients.
2. A test to separately estimate the effect of warranties and a regression excluding vehicles with active warranties (figure A3). The results are noisy but consistent with the estimates presented above.
3. Analysis that estimates the residual of prices within each 10,000 mi bucket (figure A16). We find results generally consistent with left-digit bias, with some smaller discontinuities at 5,000 thresholds.
4. Estimation using alternative functional forms of prices and profits (table A2). The results hold under this assumption.
5. Alternative sample selection procedures to account for rounding (table A1) and different inclusion criteria for vehicles not purchased and sold by the same dealership. The results are similar but generally show larger effect sizes.

6. Estimates of the heterogeneity of the inattention parameter are consistent, with inattention being larger for intermediary transactions (table A5).

So far, we have focused on testing the proposed theory. We now consider some additional analyses for which our theoretical model did not allow us to make predictions.

5.1 Time on Lot

We have presented evidence that dealerships sell vehicles immediately before crossing round thresholds at higher prices and margins. If these vehicles remain on the lot longer, the increase in inventory costs resulting from this could reduce or completely outweigh the increase in margin. To see if vehicles above and below round thresholds differ systematically in how long they are held, we re-estimate the model presented in equation 14, specifying the time on the lot as the outcome variable.

Table 7 presents the results and shows that vehicles below round thresholds, in fact, sell slightly *faster*[30], compared to vehicles immediately above thresholds. For example, vehicles with mileages just above 90,000 miles are approximately 1.74 days longer on the lot than vehicles with mileages immediately below 90,000 miles. Evaluated at the median value of 29 days, this is an economically significant difference of 6This implies that intermediaries incur lower inventory costs for vehicles below round thresholds in addition to higher margins and higher quantities sold.

5.2 Dealership Inventory

In the theoretical model, we made the simplifying assumption of considering one firm and one decentralized market, assuming that consumers first visit dealerships. The empirical exercise has largely been focused on testing the predictions from the model. We now present some additional data that presumably shows variation in the proportion of consumers who first visit a dealership in the decentralized market. To do so, we construct a measure of available vehicles at dealerships[31]. We then estimate how the level of observed inattention varies by the level of availability at dealerships.

[30] We also see this as potential evidence that car dealerships do not make higher investments in quality of vehicles below round thresholds, as these investments would potentially increase the time before a vehicle becomes available.

[31] Ideally, we would also like to obtain the number of cars available in the decentralized market. However, because of the decentralized nature of the market, such data are unavailable to us.

The intuition of this test is that if there are fewer vehicles available at dealerships, a more significant proportion of consumers presumably directly shop in the decentralized market.

To create a valid measure of the availability of a particular model, we follow (Israeli et al., 2022) and define the designated market area (DMA) of each vehicle dealership as the region of consideration. Within each DMA, we measure availability by the current level of inventory of a particular model across all dealerships. Then, we use quantiles to categorize the level of competition and estimate a baseline level of inattention for the lowest quantile and the marginal effect of moving into a different quantile. The specification is given by:

$$price_i = \beta_0 + \sum_{k=1}^{K}((\sum_{q=1}^{4}\alpha_{kq}\mathbf{1_q})(M_i - ((\theta + \sum_{q=2}^{4}\theta_q\mathbf{1_q})(M_i - \lfloor M_i \rfloor))^k + \psi X_i + u_i, \tag{16}$$

We run this model separately for vehicles purchased at dealerships and decentralized transactions. In both models, the quantiles are defined by the number of vehicles available at dealerships in a particular DMA.

We present the results in Table 8. We find that the observed level of inattention in dealership transactions is significantly higher when there are more vehicles available, which is consistent with dealerships' increased ability to skim inattentive consumers due to higher inventory levels across dealerships. On the other hand, we find that dealership availability has a minimal impact on inattention in consumer markets.

6 Conclusion

This paper considers equilibrium outcomes in a market where firms sell to heterogeneously left-digit biased consumers. We explored the consequences of this inattention, which has been identified (Lacetera et al., 2012) in resale markets of durable goods, theoretically and empirically.

Our theoretical model proposes that an intermediary can use pricing to skim inattentive consumers. Using several novel theoretical predictions and data from millions of used vehicle transactions, we tested the key predictions of the model and find evidence of intermediaries benefitting from being able to sell to (relatively) inattentive consumers via behavioral segmentation.

Our paper has several limitations. The theoretical model is designed to be parsimonious to

capture the key elements of the proposed mechanism, but it abstracts away several important considerations. For example, horizontal and vertical differentiation are omnipresent in durable goods markets, but we do not simultaneously model them in this study. Furthermore, we assume the exogenous endowment of the goods. Thus, future research should also consider how inattention and awareness of inattention can affect consumers' choice of purchasing a new or used vehicle.

In addition, we abstract away sources of asymmetric information, such as the lemon problem. The interplay of asymmetric information and behavioral frictions might lead to additional insights, mainly because disclosing more information allows sellers to benefit from inattentive consumers. In the most extreme case, the benefit of selling to inattentive consumers could be a sufficient incentive for sellers to disclose quality information.

Future research should examine how much segmentation by inattention occurs in other markets. Based on our results, which shed light on how competition leads to and influences segmentation in the used car market, the research could examine how firm channel management decisions might differ when consumers are inattentive to specific attributes. Another avenue worth investigating is the link between inattention to product attributes and other explanations for consumers' failure to choose to purchase at the lowest price. Our work implies a link between consumers' difficulty evaluating a product and inattention.

Our paper has several implications for policymakers, managers, and researchers. First, we document that inattention has a moderate yet significant effect on numerous equilibrium outcomes in the market for durable goods. Disclosing information has traditionally been thought to improve consumer outcomes, but the effect is moderated by consumer attention to such disclosures. A second implication is that estimating inattention parameters for the population based on a subset of consumers can be misleading because inattentive consumers can make systematically different choices about where to purchase the product. In our setting, the inattention of comnsumers who purchased from an intermediary was significantly higher than that of the population in general.

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Tables

Table 1: Description of notation used in theoretical model

Symbol	Description
θ	Inattention Parameter
$\bar{\theta}$	Upper bound on distribution of inattention
v	Value of easily observable attribute
z	Value of difficult to observe attribute
k	Owners transaction cost
$\bar{k}$	Upper bound on distribution of transaction cost
M	Mileage of product
m	Remainder of mileage ($M - \lfloor M \rfloor$)
p^I	Sales price in intermediary transactions
p^S	Purchasing price in intermediary transactions
p^D	Price in decentralized transactions
$\psi_j(g(\theta))$	Player j belief about distribution of Inattention
$\psi_j^{j'}(g(\theta)$	Player j belief about player j' belief about the distribution of Inattention
Q^D	Quantity of decentralized transactions
Q^I	Quantity of intermediary transactions
c	Intermediary transaction cost

Table 2: Summary Statistics

Statistic	N	Mean	St. Dev.	Median
Dealership Transactions				
Sales Price	3,219,973	22,270.800	12,107.410	19,630.000
Purchase Price	3,219,973	19,565.000	13,174.670	17,000.000
Operating Profit	3,219,973	2,705.801	6,655.869	3,464.260
Odometer Reading	3,219,973	54,089.030	31,610.210	49,223
Weeks to sell	3,219,973	5.721	6.531	4.143
Decentralized Transactions				
Sales Price	1,600,988	13,592.450	14,124.110	9,000.000
Odometer Reading	1,600,988	71,826.540	40,741.920	70,809

Table 3: Estimate of the Inattention Parameters

	Dealership	Dealership	Decentralized	Decentralized
Inattention (θ)	0.40***	0.42***	0.28***	0.19***
	(0.01)	(0.02)	(0.04)	(0.04)
Observations	2,483,421	2,483,421	1,138,197	1,138,197
7th order polynomial	Yes	Yes	Yes	Yes
Uniformly Weighted	No	Yes	No	Yes
Fixed Effects	Yes	Yes	Yes	Yes

Notes: Columns (2) and (4) are estimated using weighted nonlinear least squares, giving each odometer reading equal weight. We omitted polynomial coefficients in the table. The sample includes vehicles between 25,000 miles and 125,000 miles. +p<0.1, *p<0.05, **p<0.01, *** p<0.001.

Table 4: Estimated discrete change in prices at 10,000 mile thresholds

	Purchase Price	Sales Price	Dealership Profit
10k miles	−76.023	−147.458***	−73.150
	(58.650)	(27.312)	(55.431)
20k miles	−97.966**	−72.907**	26.831
	(37.323)	(23.235)	(38.722)
30k miles	−86.547**	−108.085***	−22.736
	(32.668)	(14.115)	(31.696)
40k miles	−126.738***	−165.037***	−39.105
	(30.238)	(13.174)	(27.263)
50k miles	−113.599***	−141.334***	−25.329
	(27.165)	(12.069)	(26.325)
60k miles	−146.138***	−192.094***	−45.939+
	(26.867)	(13.265)	(25.074)
70k miles	−109.235***	−238.415***	−132.346***
	(28.663)	(12.915)	(26.991)
80k miles	−101.602***	−185.259***	−83.566**
	(29.693)	(14.455)	(27.923)
90k miles	−159.241***	−278.419***	−114.905***
	(33.841)	(16.788)	(30.940)
100k miles	−45.840	−213.595***	−168.290***
	(40.792)	(20.814)	(37.514)
110k miles	−34.546	−22.487	4.726
	(45.353)	(27.269)	(38.216)
120k miles	−30.281	−131.168***	−98.830*
	(49.969)	(31.824)	(46.173)
130k miles	−64.789	−83.012+	−8.608
	(66.408)	(42.372)	(57.946)
140k miles	−241.756*	−211.323***	14.327
	(94.022)	(58.896)	(77.143)
Observations	3,219,973	3,219,973	3,219,973
R^2	0.783	0.933	0.145
Polynomial Order	11^{th}	11^{th}	9^{th}
Fixed Effects	Yes	Yes	Yes

Notes: We omitted polynomial parameters and intercepts in the table. The outcome variables are (1) the purchase price, (2) the subsequent sales price, and (3) the difference between sales price and purchase price. A high-order polynomial captures the continuous change in price as a function of the odometer reading. The estimated coefficients estimate the discrete change in the outcome variable at the respective 10,000-mile mark. +p<0.1, *p<0.05, **p<0.01, *** p<0.001.

Table 5: Estimated difference in discontinuous change at 10,000 mile thresholds

	Decentralized vs. Dealership Sales Price	Decentralized vs. Dealership Purchase Price
$\mathbf{1}_{\text{Dealer}}\times$30k miles	−47.946	−12.600
	(70.551)	(82.197)
$\mathbf{1}_{\text{Dealer}}\times$40k miles	39.092	63.259
	(55.674)	(63.263)
$\mathbf{1}_{\text{Dealer}}\times$50k miles	45.850	69.187
	(49.825)	(55.221)
$\mathbf{1}_{\text{Dealer}}\times$60k miles	−111.542*	−60.754
	(45.539)	(52.982)
$\mathbf{1}_{\text{Dealer}}\times$70k miles	−67.373	46.741
	(41.056)	(50.893)
$\mathbf{1}_{\text{Dealer}}\times$80k miles	−125.057**	−50.316
	(38.819)	(49.093)
$\mathbf{1}_{\text{Dealer}}\times$90k miles	−141.542***	−38.890
	(39.282)	(52.127)
$\mathbf{1}_{\text{Dealer}}\times$100k miles	−105.273**	41.255
	(39.021)	(54.367)
$\mathbf{1}_{\text{Dealer}}\times$110k miles	64.237	40.517
	(42.155)	(58.122)
$\mathbf{1}_{\text{Dealer}}\times$120k miles	−19.740	70.722
	(45.561)	(62.704)
$\mathbf{1}_{\text{Dealer}}\times$130k miles	26.499	15.426
	(53.623)	(79.280)
$\mathbf{1}_{\text{Dealer}}\times$140k miles	−21.483	8.492
	(68.920)	(102.423)
Observations	3,909,925	3,909,925
R^2	0.906	0.772
Polynomial Order	11^{th}	11^{th}
Fixed Effects	Yes	Yes

Notes: We omitted polynomial, interacted polynomial, un-interacted 10k mile parameters and intercepts in table. (1) includes all decentralized transactions and dealership sales. (2) includes all decentralized transactions and dealership purchases. Both include vehicles between 25,000 mi and 150,000 mi . +p<0.1, *p<0.05, **p<0.01, *** p<0.001.

Table 6: Estimated discrete change in channel choice at 10,000 mile thresholds

	Dependent Variable: $\mathbf{1}_{\text{Intermediary}}$
30K miles	−0.002
	(0.002)
40K miles	−0.002
	(0.002)
50K miles	−0.005**
	(0.002)
60K miles	−0.006***
	(0.002)
70K miles	−0.004*
	(0.002)
80K miles	−0.007***
	(0.002)
90K miles	−0.005*
	(0.002)
100K miles	−0.038***
	(0.003)
110K miles	−0.018***
	(0.003)
120K miles	−0.022***
	(0.003)
130K miles	−0.008*
	(0.004)
140K miles	−0.024***
	(0.005)
Observations	3,741,370
R^2	0.277
Polynomial Order	12^{th}
Fixed Effects	Yes

Notes: We omitted polynomials and intercepts in the table. The table includes all decentralized transactions and intermediary transactions for vehicles between 25,000 mi and 150,000 mi . +p<0.1, *p<0.05, **p<0.01, *** p<0.001.

Table 7: Estimated discrete change in days-to-sell at 10,000-mile thresholds.

	Dependent variable: days on lot
10K miles	0.752**
	(0.296)
20K miles	0.235
	(0.220)
30K miles	0.391**
	(0.197)
40K miles	0.833***
	(0.200)
50K miles	0.259
	(0.200)
60K miles	0.839***
	(0.209)
70K miles	1.855***
	(0.224)
80K miles	0.959***
	(0.242)
90K miles	1.736***
	(0.274)
100K miles	2.660***
	(0.321)
110K miles	0.187
	(0.405)
120K miles	1.120**
	(0.480)
130K miles	0.647
	(0.605)
140K miles	0.424
	(0.827)
Observations	3,219,973
R^2	0.154
Adjusted R^2	0.140
Residual Std. Error	6.057 (df = 3168146)
Note:	*p<0.1; **p<0.05; ***p<0.01

Note: We omitted polynomial and intercept in table. The table includes all intermediary transactions for vehicles between 5,000 mi and 150,000 mi that were purchased and sold at the same dealership.

Table 8: Heterogeneity of the Inattention Parameters

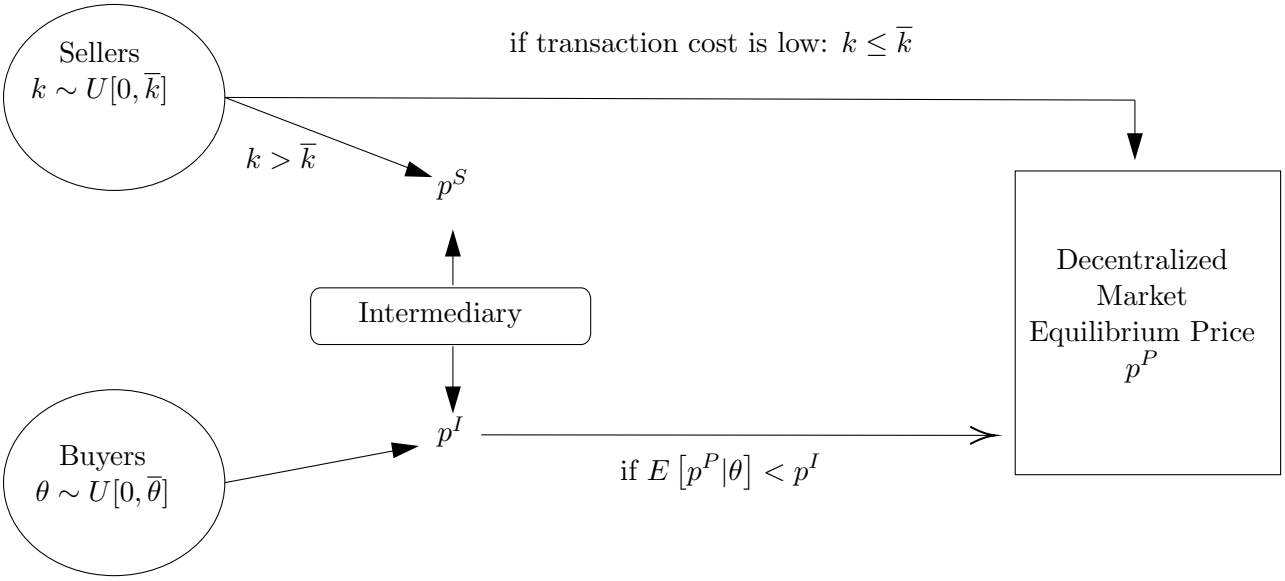
	Sample	
	Dealership	Decentralized
Inattention by dealership inventory		
(θ)	0.321^{***}	0.288^{***}
	(0.026)	(0.016)
$\Delta\theta_{q50}$	$0.082*$	0.065
	(0.038)	(0.043)
$\Delta\theta_{q75}$	0.097^{*}	0.013
	(0.041)	(0.044)
$\Delta\theta_{q1}$	0.136^{**}	-0.090
	(0.042)	(0.038)
Observations	2,483,421	1,128,157
7th order polynomial	Yes	Yes
Fixed Effects	Yes	Yes

*p<0.1; **p<0.05; ***p<0.01

Note: The columns estimate the level of inattention for different quantiles of inventory across dealerships in a particular DMA. The first "Inattention" term is the baseline inattention for the first quantile, and the other three terms are the marginal differences between the level of inattention in the first quantile and the focal quantile. We omitted the polynomial coefficients in the table. The sample includes vehicles between 25,000 miles and 125,000 miles. Omitted vehicles from dealerships without valid DMA code.

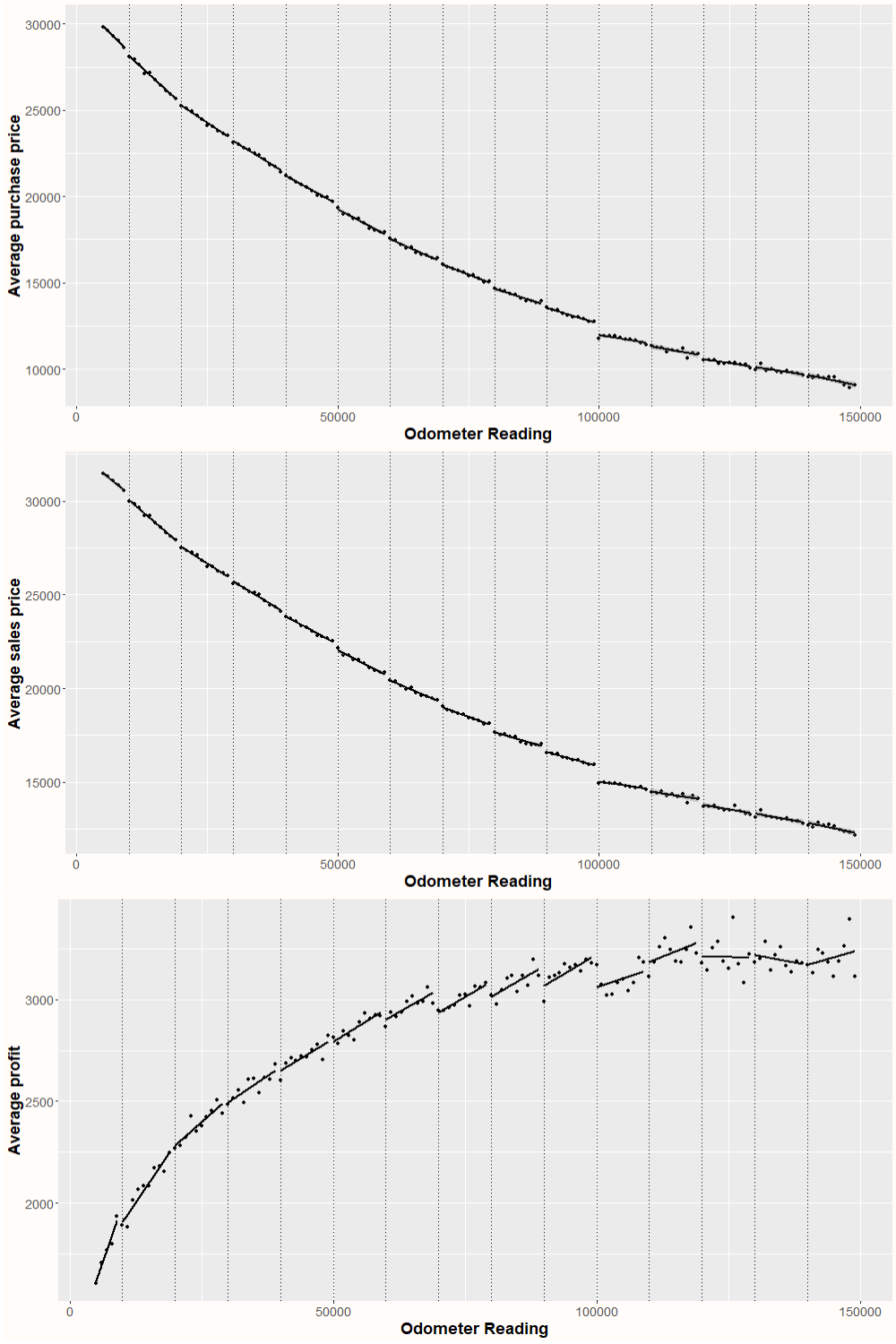
Figures

Figure 1: Market structure



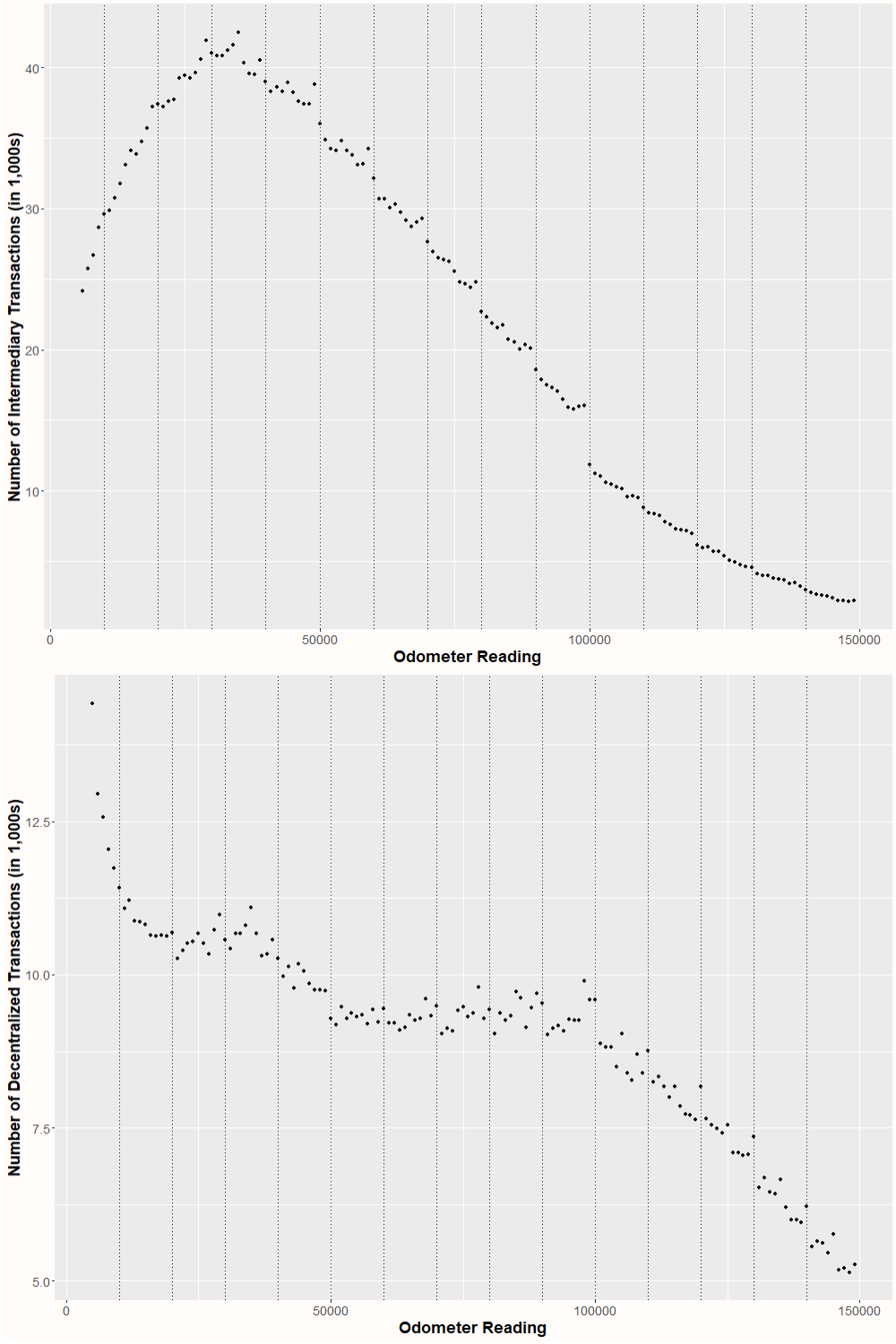
Note: Market structure with an intermediary and decentralized trade. Product owners with high transaction cost sell to the intermediary. Consumers with high levels of inattention buy from the intermediary because they have a higher $E\left[p^P|\theta\right]$. The remaining owners and consumers meet in the decentralized market. The intermediary incurs a transaction fee c for each transaction.

Figure 2: Dealership purchase price, sales price, and profit.



Note: Each dot represents the average purchase price/ sales price/ operating profit for vehicles within a 1,000 mi band.

Figure 3: Quantity of intermediary and decentralized transactions



Note: Each dot represents the quantity of transactions for vehicles within a 1,000 mi band.

Technical Appendix

A Proofs omitted in main text

In this section we present the proofs omitted in the main text for the analytical model.

Proof for Proposition 1

Case with Positive Wedge ($\theta(z - \Gamma_z) > 0$)

By backward induction, we can solve for the decentralized transaction price using the profit maximization problem in equation 4. The solution is given by $p^{D*} = 1 + V - z$ for $V > 1$. To solve the intermediary case in the first period, we consider the case of an interior and corner solution.

Interior solution

Suppose that supply equals demand at the interior solution. In that case, we can calculate the purchase price as a function of the sales price. Supply is given by integrating over the transaction cost k: $S(p^S) = \frac{\bar{k}-1+p^S+z}{\bar{k}}$, and demand is given by integrating over inattention: $D(p^I) = 1 - \frac{p^I-V+z-1}{\bar{\theta}(z-\Gamma_z}$. The solution gives $p^{S*} = 1 + V - z + \frac{\bar{k}(V-p^I-z+1)}{\bar{\theta}(z-\Gamma_z)}$. Then, plugging the purchase price into the profit maximization problem given by equation 8, the optimal sales price is given by: $p^{I*} = \frac{1}{2}\left(2 + c - \Gamma_z\bar{\theta} + 2V + (-2+\bar{\theta})z - \frac{c\bar{k}}{\bar{k}-\Gamma_z\bar{\theta}+\bar{\theta}z}\right)$. This solution is valid whenever the equilibrium purchase price is above the consumption utility of the seller. For a sufficiently small c, $\bar{k} < 2V$ implies $p^{S*} > u_S$. Simple comparison of prices shows that $p^{I*} > p^{D*}$.

Corner solution

Next, we consider the corner solution in which the purchase price is at the lower bound. This bound is given by $p^{S*} = u_S = 1 - z$. At a price lower than this, buyers will never sell the product to the intermediary because consumption gives higher utility. Plugging $p^{S*} = 1 - z$ and equation supply and demand, gives $p^{I*} = 1 + V - z + \frac{\bar{\theta}V(z-\Gamma_z)}{\bar{k}}$. This solution is valid whenever $0 \leq D(p^{I*}) \leq 1$, which holds whenever $\bar{k} > V$. Simple comparison of prices shows that $p^{I*} > p^{D*}$.

Solution

Comparison shows that the profits from the interior solution dominate profits from the corner solution. Thus, the interior price is optimal whenever feasible.

Case with Negative Wedge ($\theta(z - \Gamma_z) < 0$)

Interior solution

Suppose that supply equals demand at the interior solution. In that case, we can calculate the purchase price as a function of the sales price. Supply is given by integrating over the transaction

cost k: $S(p^S) = \frac{\bar{k}-V-1+p^S+\Gamma_z}{\bar{k}}$, and demand is given by integrating over inattention: $D(p^I) = \frac{p^I-V+z-1}{\bar{\theta}(z-\Gamma_z}$. The solution gives $p^{S*} = 1-\Gamma_z+V-\frac{\bar{k}(-1+pI+\Gamma_z\bar{\theta}-V+z-\bar{\theta}z)}{\bar{\theta}(\Gamma_z-z)}$. Then, plugging the purchase price into the profit maximization problem given by equation 8, the optimal sales price is given by: $p^{I*} = \frac{-\bar{\theta}(\Gamma_z-z)(-2-c+\Gamma_z-2V+z)+\bar{k}(2-\Gamma_z\bar{\theta}+2V+(-2+\bar{\theta})z)}{2(\bar{k}+\bar{\theta}(\Gamma_z-z))}$. This solution is valid whenever the equilibrium purchase price is above the consumption utility of the seller. For a sufficiently small c, $\bar{k} < 2V$ implies $p^{S*} > u_S$. Simple comparison of prices shows that $p^{I*} > p^{D*}$.

Corner solution

Next, we consider the corner solution in which the purchase price is at the lower bound. This bound is given by $p^{S*} = u_S = 1-z$. At a price lower than this, buyers will never sell the product to the intermediary because consumption gives higher utility. Plugging $p^{S*} = 1-z$ and equation supply and demand, gives $p^{I*} = 1-\Gamma_z\bar{\theta}+V-\frac{\bar{\theta}(\Gamma_z-z)(\Gamma_z-V-z)}{\bar{k}}-z+\bar{\theta}z$. This solution is valid whenever $0 \leq D(p^{I*}) \leq 1$, which holds whenever $\Gamma_z - z < V < \Gamma_z + \bar{k} - z$ and $V >$. Simple comparison of prices shows that $p^{I*} > p^{D*}$.

Solution

Comparison shows that the profits from the interior solution dominate profits from the corner solution. Thus, the interior price is optimal whenever feasible.

Proof for Proposition 2

The proof follows straightforward differentiation. Prices are derived in Proposition 1 and the derivatives for $\theta(z-\Gamma_z) \leq 0$ are given by: $\frac{\partial p^{D*}}{\partial\bar{\theta}} = 0$, $\frac{\partial p^{I*}}{\partial\bar{\theta}} = \frac{1}{2}\left(z-\Gamma+\frac{c\bar{k}(z-\Gamma)}{(\bar{k}+\bar{\theta}(z-\Gamma))^2}\right)$, $\frac{\partial p^{S*}}{\partial\bar{\theta}} = \frac{c\bar{k}(z-\Gamma)}{2(\bar{k}+\bar{\theta}(z-\Gamma))^2}$, $\frac{\partial Q^{I*}}{\partial\bar{\theta}} = \frac{c(z-\Gamma)}{2(\bar{k}+\bar{\theta}(z-\Gamma))^2}$, and $\frac{\partial Q^{D*}}{\partial\bar{\theta}} = -\frac{\partial Q^{I*}}{\partial\bar{\theta}}$. For the case of $\theta(z-\Gamma_z) > 0$, $\frac{\partial p^{D*}}{\partial\bar{\theta}} = z-\Gamma$, $\frac{\partial p^{I*}}{\partial\bar{\theta}} = \frac{1}{2}\left(\Gamma-\frac{c\bar{k}(\Gamma-z)}{(\bar{k}+\bar{\theta}(\Gamma-z))^2}+z\right)$, $\frac{\partial p^{S*}}{\partial\bar{\theta}} = \frac{c\bar{k}(\Gamma-z)}{2(\bar{k}+\bar{\theta}(\Gamma-z))^2}+z-\Gamma$, $\frac{\partial Q^{I*}}{\partial\bar{\theta}} = \frac{c(\Gamma-z)}{2(\bar{k}+\bar{\theta}(\Gamma-z))^2}$, and $\frac{\partial Q^{D*}}{\partial\bar{\theta}} = -\frac{\partial Q^{I*}}{\partial\bar{\theta}}$.

Proof for Proposition 3

In the case with an intermediary, owner surplus is given by $OS = \int_0^{\hat{k}}(p^{D*}-k)f(k)dk + \int_{\hat{k}}^{\bar{k}} p^{S*}f(k)dk$, where $\hat{k}$ is the owner indifferent between selling directly or to the intermediary. To show $OS > OS^{\text{private trade}}$, recall that p^{D*} is the same in both situations. Therefore, it is sufficient that $p^{S*} \geq p^{D*}-k$ for some k, which always holds. Consumer surplus without intermediary is given by $CS^B = Q^{B*} * (1+V-z-p^{D*})$. Consumer surplus with an intermediary is given by: $CS = Q^{I*}*(1+V-z-p^{I*})+Q^{D*}*(1+V-z-p^{D*})$. It is negative because $p^{D*} < p^{I*}$ and $Q^{B*} \leq Q^{I*}+Q^{D*}$.

Proof for Proposition 4

Note that this case is equivalent to the general case for each $\lfloor M \rfloor \leq M < \lfloor M \rfloor + 1$ because we can make the same substitutions. Thus, the first statement follows from the general case. For the remaining statements, observe that we can rewrite $\Delta x = x(\theta = 0'; z = 1) - x(\theta = \theta'; z = 1)$, and

plug in from the general case. Further, note that $\Delta x < 0 \Leftrightarrow \frac{\partial x}{\partial \bar{\theta}} > 0$. Proposition 2 shows that $\frac{\partial p^{I*}}{\partial \bar{\theta}} > 0$, which thus implies $\Delta p^{I*} < 0$. Similarly, straightforward algebra shows that $\frac{\partial p^{I*}}{\partial \bar{\theta}} > \frac{\partial p^{D*}}{\partial \bar{\theta}}$, $\frac{\partial p^{I*}}{\partial \bar{\theta}} > \frac{\partial p^{S*}}{\partial \bar{\theta}}$, $\frac{\partial p^{S*}}{\partial \bar{\theta}} \geq \frac{\partial p^{D*}}{\partial \bar{\theta}}$, $\frac{\partial Q^{I*}}{\partial \bar{\theta}} \geq 0$, and $\frac{\partial Q^{I*}}{\partial \bar{\theta}} \geq \frac{\partial Q^{I*}}{\partial \bar{\theta}}$, which implies $|\Delta p^{I*}| > |\Delta p^{D*}|$ and $|\Delta p^{I*}| > |\Delta p^{S*}|$ and $|\Delta p^{S*}| \geq |\Delta p^{I*}|$, $\Delta Q^{I*} \leq 0$, and $|\Delta Q^{I*}| \geq |\Delta Q^{D*}|$, which completes the proof.

Online Appendix

A Theory Model Extensions

In this section, we first present results for the omitted case of only intermediary trade. Then, we derive the main model under the assumption of naive owners. Then, we briefly derive results assuming that consumers are not inattentive to the attribute z but rather vary in their willingness to pay for a higher level of the attribute.

A.1 Equilibrium Definition

To define the equilibrium, we need to consider who is aware of inattention. Under standard assumptions (i.e., rational beliefs), we cannot fully capture inattention because it would assume awareness about one's own inattention. To avoid the issue and capture the intuition of inattention, we relax the assumption of common knowledge about the distribution of inattention and let each player have a (potentially correct) belief about the distribution. We then use a solution concept based on (O'Donoghue and Rabin, 1999)[1] and require that all players' actions are perception-perfect strategies. Each player chooses the optimal action given their preferences, their perceptions of what the other players' current action will be, and their perceptions of all players' future actions. In a similar context, Haan and Hauck (2014) and consider higher-level beliefs in games of present biased consumers, which is also consistent with Fedyk (2021), who experimentally shows that individuals are naive about their own and (to a lesser extent) other people's level of present bias. Throughout the model, we focus on the inattention of consumers and assume that the supply is fully aware of the inattention of consumers, but we relax the assumption of full awareness of owners in appendix A.4.

Formally, each player has an exogenously given deterministic belief about the distribution of inattention in the population of buyers. Let $\psi_j(g(\theta)) \in \{0,1\}$ denote probability that player j assigns to the belief that buyers are distributed according to the density function $g(\theta)$. Similarly, let $\psi_j^{j'}(g(\theta)) \in \{0,1\}$ denote the probability that player j beliefs player j' assigns to the belief that buyers are distributed according to $g(\theta)$. For example, these beliefs capture the following:

$$\psi_j(U[0,1])) = 1 \Leftrightarrow I \text{ } (j) \text{ believe } \theta \sim U[0,1].$$
$$\psi_j^{j'}(U[0,1]) = 1 \Leftrightarrow I \text{ } (j) \text{ think that } you \text{ } (j') \text{ believe that } \theta \sim U[0,1].$$

Each buyer is unaware of the inattention problem and beliefs all other buyers are equally inattentive. Coming back to the t-shirt example, this implies that the inattentive consumer who did not observe the stain also thinks everyone is treating the stained shirt as if it is unstained. We let $\psi_{B^{\theta'}}(g(\theta')) = \psi^S_{B^{\theta'}}(g(\theta')) = \psi^I_{B^{\theta'}}(g(\theta')) = 1$, where $g(\theta')$ denotes a degenerate distribution at $\theta = \theta'$. The remaining beliefs and hyper beliefs are assumed to be correct $\psi_j(f(\theta)) = 1 \forall j \neq B$ and $\psi_j^i(h(\theta)) = \psi_i(h(\theta)) \forall j \neq B$, where $f(\theta)$ denotes the true distribution of inattention and $h(\theta)$ denotes any

[1] O'Donoghue and Rabin introduce the concept in a single-player context. We generalize this concept to the multi-player game, similar to Gans and Landry (2019) in the context of present bias.

distribution of inattention. In the presented game, we maintain that the intermediary is (i) fully attentive and (ii) fully aware of the other players' inattention. We focus on the case in which owners are fully attentive and consider the case in which they are naive and wrongly believe there is no consumer inattention and the case in which they correctly anticipate the level of inattention among consumers.

A.2 Omitted Lemma

Here we present the lemma describing the equilibrium outcome under full attention.

Lemma 1 *In the absence of inattention in the population ($\bar{\theta} \to 0$), the equilibrium price in the decentralized market and at the intermediary are equal ($p^{I*} = p^{D*} = V$).*

The purchase price, quantity of intermediary transactions, firm profit, owner surplus and consumer surplus are given by:

$$p^{S*} = \begin{cases} 0, & \text{if } \bar{k} < 2V - c \\ V - (c + \bar{k})/2, & \text{otherwise} \end{cases}, \; Q^{I*} = \begin{cases} \frac{1}{2} - \frac{c}{2\bar{k}}, & \text{if } \bar{k} < 2V - c \\ 1 - \frac{V}{\bar{k}} & \text{otherwise} \end{cases},$$

$$\pi^* = \begin{cases} \frac{(\bar{k}-c)^2}{4\bar{k}}, & \text{if } \bar{k} < 2V - c \\ \frac{(\bar{k}-V)(\bar{k}V-\bar{k}c)}{\bar{k}^2} & \text{otherwise} \end{cases}, \; OS^* = \begin{cases} (\frac{c^2}{\bar{k}} + 8V - 3\bar{k} - 2c)/8, & \text{if } \bar{k} < 2V - c \\ \frac{V^2}{2\bar{k}} & \text{otherwise} \end{cases}, \text{ and}$$

$CS = 0$

Proof. The proof follows from plugging in to proposition 1 and proposition 2. ■

A.3 Omitted Cases of the Game

First, we consider the case with only decentralized trade (i.e., without the first period in the full game) and then present the case with only intermediary trade (i.e., without the second period in the full game).

A.3.1 Case With Only Decentralized Trade

We now consider a market with only consumer-to-consumer transactions. In the first stage, each product owner decides to meet a buyer in the decentralized market and incur a transaction cost of k or exit the game (and consume the product). In the second stage, each participating owner meets one buyer at random and makes one take-it-or-leave-it offer. If the buyer accepts the offer, she receives the product, and the seller receives the offered price. Else, the game ends, and the seller keeps the product and consumes it. We use backward induction to find the optimal price and the cutoff in k below which sellers enter the market to solve the game. The sellers' equilibrium price is given by the following maximization problem:

$$p^{D*} = \underset{p^D}{\text{argmax}} \; E[\pi_O(p^D)] = P(\text{accept}|p^D) \times p^D + (1 - P(\text{accept}|p^D)) \times (1 - z),$$

$$\text{s.t. } 0 \leq P(\text{accept}|p^D) \leq 1,$$

where $P(\text{accept}|p^D) = \int_{\frac{1-z+V-p^D}{\Gamma_z - z}}^{\bar{\theta}} f(\theta)d\theta$ for $\Gamma_z < z$ and $P(\text{accept}|p^D) = \int_0^{\frac{1-z+V-p^D}{\Gamma_z - z}} f(\theta)d\theta$ for $\Gamma_z > z$. Owners with sufficiently low transaction costs are willing to enter the market in period 1 and sell the product. We can find the transaction cost of the owner indifferent between entering the decentralized market or not entering the market: $\hat{k} = E[\pi_O(p^{D*})] - u_S$. The mass of owners that enter the market is given by: $S(p^{D*}) = min\left[1, \int_0^{\hat{k}} f(k)dk\right]$ and the total mass of transactions consists of the number of sellers and the probability that their offered price is accepted: $Q(p^{D*}) = S(p^{D*}) \times P(\text{accept}|p^{D*})$. In equilibrium, all owners set the same price because the cost of entering the market is a sunk fixed cost in the second stage. We see the following impact of inattention on the equilibrium outcomes in equilibrium.

Lemma 2 *For sufficiently high potential gains of trade ($\bar{\theta} < V/(\Gamma_z - z)$):*

1. *Prices do not react to inattention ($\frac{\partial p^{D*}}{\partial \theta} = 0$)*
2. *The quantity of transactions is not affected by inattention.($\frac{\partial Q^*}{\partial \theta} = 0$)*

Proof. The proof follows directly from the comparing the first order condition of the profit maximization problem and the corner solution. Equilibrium price is given by $p^{D*} = 1 + V - z$, for $\bar{\theta} \leq V/z$ for $\Gamma_z < z$ and $p^{D*} = 1 - z + V/2$ for $\Gamma_z > z$. ■

If a seller could identify inattentive consumers, he would practice first-degree price discrimination and charge each consumer their willingness to pay, which is higher for more inattentive consumers who are inattentive to the negative attribute. However, because he cannot identify the consumer type, no surplus can be extracted from inattentive consumers without losing out on some attentive consumers. The presence of those attentive consumers protects inattentive consumers, particularly when the opportunity cost of not selling the product is high. When the potential gains of trade are sufficiently high, the seller sets a price that all consumers accept and the effect of inattention is fully muted[2].

A.4 Naive Owners

We now consider the case of naive owners. In the main analysis, we have assumed that owners are aware of the bias on the consumer side. To probe the importance of that assumption, we now consider the case in which owners are unaware of this inattention problem. We now solve the case with an intermediary and decentralized trade. We do so for the case of $\Gamma_z = 0$

Again, using backward induction, we start with the second period. Because sellers are unaware of the buyers inattention, they naively believe that they are facing a homogeneous group of consumers with reservation value $u_B = 1 - z + V$. As a result, individual sellers belief their profit

[2]Much of the literature has considered demand-side explanations for inattention observed in market transactions, and one often cited intuition is that consumers pay more attention when the stakes are higher. However, at least in this setting, higher stakes also reduce the incentive for sellers to distort their pricing to take advantage of consumer inattention

maximization problem is given by

$$\begin{aligned} p^{D*} &= \arg\max_{p^D} E[\pi_O(p^D)] = P(\text{accept}|p^D) \times p^D + (1 - P(\text{accept}|p^D)) \times (1 - z), \\ &\text{s.t. } 0 \leq P(\text{accept}|p^D) \leq 1, \end{aligned} \tag{17}$$

where $P(\text{accept}|p^D) = \begin{cases} 1, & \text{if } 1 - z + V > p^{D*} \\ 0, & \text{otherwise} \end{cases}$.

As before, consumers expect that the sellers extract all surplus and set $E[p^D|\theta] = 1 - z + V + z\theta$. The buyer indifferent between buying the product or entering the decentralized market is given by: $\hat{\theta} = \frac{p^I - V - 1 + z}{z}$ and demand for the intermediary is given by: $D(p^I) = \int_{\hat{\theta}}^{\bar{\theta}} f(\theta) d\theta$. The owner indifferent between selling to the intermediary or not is given by: $E[\pi_O] - p^{S*} = k$, and total supply for the platform is given by: $S(p^I) = \int_{E[\pi_O] - p^I}^{\bar{k}} f(k) dk$. The firm's profit-maximizing prices are the solutions to the following maximization problem:

$$\begin{aligned} p^{I*} &= \underset{p^I}{\text{argmax}} E[\pi] = D \times (p^I - p^S - c) \\ &\text{s.t. } 0 \leq (p^I) \leq S(p^I) \leq 1 \end{aligned}$$

We can now give the following result, stating that awareness of inattention is rendered irrelevant for individual owners because of the market segmentation.

Proposition 5 *For $V > 1$, the equilibrium with naive owners is identical to that of sophisticated product owners.*

Proof. In the second stage, owners set a price that maximizes equation 17. The profit-maximizing price is given by $p^{D*} = V + 1 - z$. Because p^{D*} and $E[\pi_O(p^D)]$ are identical to the case of sophisticated owners, the intermediary faces the same profit maximization problem as in the sophisticated case, and thus, the equilibrium outcomes are identical to the case with sophisticated owners. ■

The result seems perhaps counterintuitive because one would expect that owners who are aware of consumers' inattention should be able to use this information in a competitive market. In the previous equilibrium, sophisticated owners set a price of $p^{D*} = V + 1 - z$ because they are aware that the consumers in the private market are relatively attentive, and inattentive consumers have already purchased from the intermediary. In the case of naive owners, they are unaware of consumer inattention, but the information would not affect their behavior.

A.5 Heterogeneity in Preferences

This section aims to highlight the impact of consumer inattention and consider consumers that are heterogeneous w.r.t to their actual willingness to pay for an attribute, as opposed to heterogeneity stemming from inattention. An important difference is that consumers are fully rational in this setting and anticipate the firm's optimal pricing. Again, we consider the following utility functions: $u_S = 1 - z$ and $u_B(\psi) = u_S + V + z\psi$, where ψ captures the willingness to pay for attribute z

for buyers. To make the results comparable to the inattention results, we consider the case of a positive z, and Probnabsellers that are only heterogeneous regarding their cost of supplying the good, k. The solution concept is the Perfect Bayesian Equilibrium (PBE).

A.5.1 Consumer Trade Only

First, consider the case without an intermediary. Again, as in the case of inattention, owners with sufficiently low transaction cost sell to consumers with sufficiently high willingness to pay for quality. We again start by backward induction and solve the owners pricing problem first. The owners need to maximize their profit function, which is given by:

$$p^{D*} = \underset{p^D}{\text{argmax}} E[\pi_O] = P(\text{accept}|p^D) \times p +^P (1 - P(\text{accept}|p^D)) \times u_S,$$

where $P(\text{accept}|p) = min\left[1, \int_{\frac{p+V-z+\psi z}{z}}^{\bar{\psi}} f(\psi)d\psi\right]$.

The solution is then given by:

$$p^{D*} = \begin{cases} 1 + V - z, & \text{for } z \leq \frac{V}{\bar{\psi}} \\ \frac{2+V-(2-\bar{\psi})z}{2}, & \text{otherwise.} \end{cases}$$

Owners choose to enter the market in the first period if their transaction cost is sufficiently low. The solution is equivalent to the case with heterogeneity in inattention. The reason is that the consumers are not acting upon any expected prices, which are distorted by inattention.

A.5.2 Intermediary Trade Only

As before, the game consists only of the stage in which the intermediary buys and sells the product, and there is no decentralized trade. Without the option of trading directly with buyers, all owners are willing to sell the product as long as the intermediary offers a purchase price equal to the consumption utility. Thus, $p^{S*} = 1 - z$ The intermediary needs to maximize their profit function, which is given by:

$$p^{D*} = \underset{p}{\text{argmax}} E[\pi_O] = D(p) \times (p - c - p^{S*}),$$

where $D(p) = min\left[1, \int_{\frac{p+V-z+\psi z}{z}}^{\bar{\psi}} f(\psi)d\psi\right]$. The solution is then given by:

$$p = \begin{cases} 1 + V - z & \text{for } z \leq \frac{V-c}{2-\bar{\psi}} \\ \frac{2+c+V+\bar{\psi}z}{2}, & \text{otherwise.} \end{cases}$$

The solution is equivalent to the case with heterogeneity in inattention. Again, the reason is that the consumers are not acting upon any expected prices that are distorted by inattention.

A.5.3 Intermediary and Private Trade

Now we consider the full case with an intermediary and decentralized trade. To solve the model, we apply similar arguments as in the case of inattention. In the second period, owners need to set

a price. Then, taking this price as given, the intermediary maximizes profit in the first period. We again solve this by using backward induction[3]. In the second stage, the owners need to set a price that maximizes profit, taking $\hat{\psi}$ as given

$$p^{D*} = \underset{p^D}{\text{argmax}} E[\pi_O] = P(\text{accept}|p^D) \times p^D + (1 - P(\text{accept}|p^D)) \times u_S,$$

where $P(\text{accept}|p) = min\left[1, \int_{\frac{p^D+z-V-1}{z}}^{\hat{\psi}} f(\psi)d\psi\right]$. The solution is then given by: $p^{D*} = 1 + V - z$. To solve the firm problem, we first note that the intermediary price needs to be less or equal to the price in the decentralized market. Suppose the intermediary sets a price higher than the price in the decentralized market. All (potential) consumers will wait until the second period and purchase in the decentralized market, implying that the intermediary profit is zero. Secondly, owners can never set a price below $p^D = 1 + V - z$. Suppose owners set $p^D = 1 + V - z - \epsilon$. Then profit, is given by $\pi^P = 1 + V - z - \epsilon$. Alternatively, the profit at $p^D = 1 + V - z$ is given by $\pi^P = 1 + V - z$.

In equilibrium, the intermediary thus sets $p^{I*} = 1 + V - z$ and chooses the level of supply that maximizes profit. Owners supply to the intermediary if $k > V + 1 - z - t$. Thus, total supply is given by $S = \int_{V+1-z-t}^{\hat{k}} f(k)dk$. The firm chooses the purchase price that maximizes:

$$p^{S*} = \underset{p^S}{\text{argmax}} E[\pi^I] = S(p^S) \times (1 + V - z - p^S - c).$$

The solution is given by $p^{S*} = 1 + V - c - z - \frac{\bar{k}}{/}2$

Lemma 3 *Intermediary prices and prices in decentralized transactions are equal in equilibrium ($p^{D*} = p^{I*}$). As the average willingness to pay increases, owner surplus and profit stays constant. ($\frac{\partial OS}{\partial \bar{\psi}} = \frac{\partial \pi}{\partial \bar{\psi}} = 0$). Consumer surplus increases. ($\frac{\partial OS}{\partial \bar{\psi}} = \frac{z\bar{\psi}}{2} > 0$).*

The result is consistent with what one would expect in a market where two suppliers (i.e., intermediary and owners) compete for consumers. By simple arguments of contradiction, there is only one price in the market, and consumers gain all benefits from an increase in the willingness to pay.

B Testing of Γ_M

This section first outlines why Γ_M is not identified in any econometric specifications we are using in this paper. Secondly, we derive empirically testable predictions from the model that allow for sharp tests between the case of consumers "rounding up" or "rounding down."

B.1 Identification of Γ_M

In the paper, we propose (broadly) two types of econometric specifications. We provide a direct estimator for θ in equation 18. When allowing the perceived milage to also depend on the value of

[3]Again, we consider the case of $V > 1$ to facilitate the comparison of the two sets of results.

Γ_M, this equation is given by:

$$price_i = \beta_0 + \sum_{k=1}^{K} \alpha_k (\underbrace{M_i - \theta(M_i - \lfloor M_i \rfloor - \Gamma_M)}_{\text{Perceived Mileage}})^k + \psi X_i + u_i, \tag{18}$$

To see why this is not identified, consider the case with $k = 1$. In this case, we can rewrite the equations as $price_i = \beta_0 - \Gamma_M \alpha_1 \theta + \sum_{k=1}^{1} \alpha (M_i - \theta(M_i - \lfloor M_i \rfloor)^k + \psi X_i + u_i$. where the intercept absorbs the Γ-term. For any arbitrary k, we can take the partial derivatives with respect to α_k and Γ_M:

$$\frac{\partial \text{price}_i}{\partial \Gamma_M} = \theta \sum_{k=1}^{K} \alpha_k k \left(M_i - \theta(M_i - \lfloor M_i \rfloor - \Gamma_M)\right)^{k-1} \tag{19}$$

$$\frac{\partial \text{price}_i}{\partial \alpha_k} = \left(M_i - \theta \left(M_i - \lfloor M_i \rfloor - \Gamma_M\right)\right)^k \tag{20}$$

We can plug in and rearrange and write down the following expression for $K > 1$:

$$\frac{\partial \text{price}_i}{\partial \Gamma_M} = \theta \alpha_1 \sum_{k=2}^{K} \alpha_k k \frac{\partial \text{price}_i}{\partial \alpha_{k-1}} \tag{21}$$

Given that this does not depend on the data independently of any other parameters, we are unable to identify it and the intercept captures potential differences in Γ_M.

The second type of estimator (see equation 14 we used directly leveraged differences in outcomes around thresholds. The estimator assumes a homogeneous θ, which implies that any variation in Γ_M is a constant and does not affect the estimated coefficients.

B.2 Predictions for different values of Γ_M

The theoretical model we have presented is sufficientl rich to predict different outcomes for the case of different levels of Γ_M. Because we are unable to directly estimate this value from the data, we now present a rich set of predictions to test if the data is consistent with the data. Because we want to derrive directional tests, it is sufficient to consider the case of consumers always rounding up $\Gamma_M = 1$ or consumers always rounding down $\Gamma_M = 0$. We now present a number of predictions that follow from the model described in the body of the paper.

Proposition 6 *If consumers exhibit inattention (i.e., $\bar{\theta} > 0$):*

1. ***Inattention*** *Inattention in consumer transactions is lower than in intermediary transactions if $\Gamma_M = 0$, and higher if $\Gamma_M = 1$.*
2. ***Sales Price*** *The discontinuity in intermediary sales prices is negative (Δp^{I*}).*
3. ***Consumer Market Price*** *Whenever $\Gamma_M = 0$, there is no discontinuity in consumer market prices (Δp^{D*}). Whenever $\Gamma_M = 1$, there is a discontinuity and it is greater in absolute terms than the discontinuity in intermediary sales prices.*

4. ***Purchase Price*** *The discontinuity in purchase price is negative. For* $\Gamma_M = 0$*, it is smaller in absolute terms than the discontinuity in sales prices. For* $\Gamma_M = 1$*, it is greater than the discontinuity in sales prices*

5. ***Price Comparison*** *The discontinuity in the dealership purchase price is (weakly) larger in absolute terms than the discontinuity in consumer market prices (*$|\Delta p^{S*}| \geq |\Delta p^{I*}|$*).*

6. ***Absolute Quantity*** *The discontinuity in the quantity of intermediary transactions (*ΔQ^{I*}*) is (weakly) negative for* $\Gamma_M = 0$ *and (weakly) positive if* $\Gamma_M = 1$

7. ***Relative Quantity*** *The discontinuity in the number of intermediary transactions (*ΔQ^{I*}*)is (weakly) larger in absolute terms than the discontinuity in the number of consumer transactions (*ΔQ^{D*}*) for* $\Gamma_M = 0$ *and weakly smaller for* $\Gamma_M = 1$

Proof We have already derived the corresponding empirical results for all the predictions above in the main text. All results are consistent with $\Gamma_M = 0$. Note that this case is equivalent to the general case for each $\lfloor M \rfloor \leq M < \lfloor M \rfloor + 1$ because we can make the same substitutions. We first make the accurate substitutions. Utilities are given by: $u_S = v_s - \alpha M$ and $u_B = v_B - \alpha M + \alpha(M - \lfloor M \rfloor)$. Defining $z = \alpha M$ and $\Gamma_z = \alpha(\lfloor M \rfloor - \Gamma_M)$, we can use the previously derived results. The first statement comparing inattention between intermediary and consume transactions follows directly from Proposition 1.

Case where $\Gamma_M = 0$:

In this case, the inattention wedge is given by $\alpha(M - \lfloor M \rfloor)$. This is positive for $M \neq \lfloor M \rfloor$, and zero whenever $M = \lfloor M \rfloor$. Thus, we can rewrite $\Delta x = x(\theta = 0; z = 1, \Gamma_z = 0) - x(\theta = \theta'; z = 1, \Gamma_z = 0)$, and plug in from the general case. Further, note that $\frac{\partial x}{\partial \theta} > 0 \rightarrow \Delta x < 0$. Proposition 2 shows that $\frac{\partial p^{I*}}{\partial \theta} > 0$, which thus implies $\Delta p^{I*} < 0$. Similarly, straightforward algebra shows that $\frac{\partial p^{I*}}{\partial \bar{\theta}} > \frac{\partial p^{D*}}{\partial \bar{\theta}}$, $\frac{\partial p^{I*}}{\partial \bar{\theta}} > \frac{\partial p^{S*}}{\partial \bar{\theta}}$, $\frac{\partial p^{S*}}{\partial \bar{\theta}} \geq \frac{\partial p^{D*}}{\partial \bar{\theta}}$, $\frac{\partial Q^{I*}}{\partial \bar{\theta}} \geq 0$, and $\frac{\partial Q^{I*}}{\partial \bar{\theta}} \geq \frac{\partial Q^{I*}}{\partial \bar{\theta}}$,

Case where $\Gamma_M = 1$:

In this case, the inattention wedge is given by $\alpha(M - \lfloor M \rfloor - 1)$. This is negative for all M, and approaches zero whenever $\lim_{M \rightarrow \lfloor M+1 \rfloor} M$. We can rewrite $\Delta x = x(\theta = \theta'; z = 1, \Gamma_z = 1) - x(\theta = 0; z = 1, \Gamma_z = 1)$, and plug in from the general case. Similar to above, note that $\frac{\partial x}{\partial \theta} > 0 \rightarrow \Delta x > 0$. Proposition 2 shows that $\frac{\partial p^{I*}}{\partial \theta} < 0$, which thus implies $\Delta p^{I*} < 0$. Similarly, straightforward algebra shows that $\frac{\partial p^{I*}}{\partial \bar{\theta}} < \frac{\partial p^{D*}}{\partial \bar{\theta}}$, $\frac{\partial p^{I*}}{\partial \bar{\theta}} = \frac{\partial p^{S*}}{\partial \bar{\theta}}$, $\frac{\partial p^{S*}}{\partial \bar{\theta}} \leq \frac{\partial p^{D*}}{\partial \bar{\theta}}$, $\frac{\partial Q^{I*}}{\partial \bar{\theta}} \leq 0$, and $\frac{\partial Q^{I*}}{\partial \bar{\theta}} \leq \frac{\partial Q^{I*}}{\partial \bar{\theta}}$.

Inequalities

The above statements imply the following for the case of $\Gamma_M = 0$: $|\Delta p^{I*}| > |\Delta p^{D*}|$ and $|\Delta p^{I*}| \leq |\Delta p^{S*}|$ and $|\Delta p^{S*}| \geq |\Delta p^{D*}|$, $\Delta Q^{I*} \leq 0$, and $|\Delta Q^{I*}| \geq |\Delta Q^{D*}|$ and the following for the case of $\Gamma_M = 1 : |\Delta p^{I*}| > |\Delta p^{D*}|$ and $|\Delta p^{I*}| = |\Delta p^{S*}|$ and $|\Delta p^{S*}| \geq |\Delta p^{D*}|$, $\Delta Q^{I*} \leq 0$, and $|\Delta Q^{I*}| \geq |\Delta Q^{D*}|$

C Empirical Extensions

In this section, we present additional empirical analyses to test the robustness of our results. First, we present analyses that consider the impact of warranties. We then present placebo tests that allow us to rule out that the discontinuities in our anlysis are occuring by chance as well as a specification that identifies discontinuities without specifying the location of the discontinuities. Then, we present analysis that allows for different specifications of the functional form or differences in some of our choices regarding the selection of the sample. Finally, we carefully consider the prevalence of rounded responses in the two markets and find that rounding is common in consumer to consumer transactions only. Additionally, we find that the estimated level of inattention in non-rounded observations in consumer to consumer transactions is lower than previously estimated. Finally, we present results on the heterogeneity of the level of inattention across models and odometer readings.

C.1 Warranties

Our identification strategy assumes that discontinuities at multiples of 10,000 miles arise purely from inattention. A potential threat to this identification strategy is that vehicles have warranties, potentially expiring at multiples of 10,000 miles[4]. Warranties have a maximum time frame and odometer reading and are generally set at the brand level. For example, a vehicle with a 5-year/60,000-mile warranty is under warranty as long as the vehicle is less than 5 years old and has logged fewer than 60,000 miles. If there are discontinuities in price at the end of the warranty [5], we could mistakenly attribute the discontinuity due to the expiration of a warranty to inattention. We collect data on the length of standard warranties by each brand and present two robustness checks to alleviate this concern. Approximately 80% of basic warranties end at 36,000 miles, and approximately 80% of drivetrain warranties end at 60,000 miles[6]. This gives us confidence that only discontinuities at the 60,000-mile mark are potentially affected by the end of warranties. To formally test if warranties have an impact, we first leverage the fact that warranties have a time limit and reanalyze the data using observations of vehicles that are -due to their age- not under either drivetrain or basic warranty when they are being transacted. We present the results in the bottom panel of Figure A3. Obviously, this introduces some data limitations (e.g., all warranties are between 4 and 10 years and the set of vehicles that are transacted around low odometer readings and simultaneously sufficiently old is relatively small and not representative of the full sample. However, this empirical exercise shows patterns similar to the results presented in Table 4 also holds for vehicles for which warranties have expired already.

A second analysis uses the set of vehicles for which the warranty time limit has not yet lapsed and leverages the differences in mile thresholds for different makes. For example, Ford has a

[4]Most vehicles come with basic warranties that cover most defects and longer-lasting powertrain warranties that are more limited.

[5]A forward-looking consumer should anticipate that the warranty expires, and as a result, the expected value of the warranty decreases continuously over time. However, if consumers are inattentive to the warranty length, we might observe such a discrete drop.

[6]The distribution of the warranty terms is presented in Figure A13 in the Online Appendix.

36,000-mile basic warranty and a 60,000-mile drivetrain warranty, whereas Volkswagen has basic and powertrain warranties that both expire after 72,000 miles. We now estimate the following model, similar to equation 14:

$$y_i = \beta_0 + \psi_1 \mathbf{1}\left[miles_i \geq w_B\right] + \psi_2 \mathbf{1}\left[miles_i \geq w_{DT}\right] + \sum_{k=1}^{K} \alpha_k miles_i^k + \sum_{j=1}^{14} \beta_j \mathbf{1}\left[miles_i \geq j \times (10,000)\right] + \gamma X_i + u_i. \quad (22)$$

In the equation, $\mathbf{1}\left[miles_i \geq w_B\right]$ is an indicator that equals one for vehicles with odometer readings exceeding the basic warranty and $\mathbf{1}\left[miles_i \geq w_{DT}\right]$ is an indicator variable that equals one for vehicles with odometer readings exceeding the drivetrain warranty. Thus, the β coefficients now isolate the effect of the discontinuities while controlling for the (potential) discontinuities due to the expiration of warranties. For this analysis, we need to impose the assumption that the effect of the expiration of a warranty is homogeneous across different lengths of warranties. For example, the negative effect of a warranty ending at 50,000 miles should be equal to the effect of a warranty ending at 60,000 miles. Because many warranties end at 36,000 miles, 50,000 miles, and 60,000 miles, there is not much variation in the data to precisely identify the effect of warranties from the effect of inattention. However, the results (presented in the top panel of Figure A3 follow the same pattern as the main analysis (Table 4) and is consistent with the earlier results, with the exception of the discontinuity at 60,000 miles, which is now positive for purchase and sales prices. Given that 78% of drivetrain warranties end at 60,000 miles, this coefficient is identified from a small set of observations for which the warranty does not end at 60,000 miles. The positive coefficient could be the result of heterogeneous effects of the expiration of warranties[7].

C.2 Location of Discontinuities

So far, we have tested discontinuities in various outcomes at multiples of 10,000 miles, motivated by the theoretical model of left-digit bias. We present placebo tests in the Online Appendix C.4, and find our estimation strategy robust to the inclusion of placebo locations of discontinuities. We now aim to directly identify the location of the discontinuities without pre-specifying them occurring at multiples of 10,000 miles. To do so, we derive a flexible model that allows for a highly flexible relationship between the odometer and the outcome variables and test if discontinuities at 10,000 miles appear without pre-specifying them. We create a complete set of indicator variables that define each 1,000-mile bucket above which any vehicle falls. Then, using these buckets, we estimate the following "semi-lasso" model, in which we allow penalization of the indicator variables while maintaining the full structure of the fixed effects. To estimate the model and keep the computation feasible, we use a two-step approach. First, we run a regression with the full set of fixed effects

[7] If the average effect of warranties across all mileage policies is different from the effect of warranties ending at 60,000, the estimated coefficient on 60,000 miles might be capturing that heterogeneity and might not cleanly identify the effect of inattention.

but omit the odometer variables and store the residual. Then, using the residual as the outcome variable, we estimate the non-linear model and estimate the α_k and θ coefficients.

$$\hat{\beta} = \arg\min_{\beta} \sum_{n} \left(y_i - \sum_{j=6}^{149} \beta_j \mathbf{1}[miles \geq j \times (1,000)] - \gamma X_i \right)^2 + \lambda|\beta| \tag{23}$$

In the above model, y_i is the residual, X_i the full set of fixed effects, and each β_j term captures the relationship between a specific 1,000 mile bucket and price. One obvious downside to the lasso model is that the magnitude of the coefficients is difficult to interpret. Significant coefficients are not necessarily indicative of discontinuities, but our theoretical model would predict significantly negative coefficients at a multiple of 10,000 miles. Figure A15 presents the results for the 148 coefficients. Reassuringly, none of the coefficients at multiples of 10,000 miles are shrunk to zero and generally stand out as more negative.

C.3 Left-Digit Bias

The results we present in this paper could potentially be due to psychological processes different from left-digit bias. While we cannot fully rule out any of those alternative theories, we want to test one implication that follows from left-digit bias. If consumers are left-digit biased in the way we specified, we would expect the excess prices to increase continuously within each 10,000 mile bucket. To test the variation between 10,000-mile thresholds, we now estimate the following model.

$$y_i = \beta_0 + \sum_{k=1}^{K} \alpha_k miles_i^k + \sum_{j=1}^{9} \beta_j \mathbf{1}\left[j \times (1,000) \leq mod(miles_i) < j \cdot (1,000) + 1,000\right] + \gamma X_i + u_i. \tag{24}$$

In the equation, $mod(miles_j)$ is the modulus, which gives a number between 0 mi and 9,999 mi. Similarly to the model used to test for discontinuities, we include the polynomial to absorb the continuous portion of the depreciation and let the outcome variables be the purchase price, the sales price, and the per-unit profit. This allows us to interpret the results as the (weighted) average excess in purchase price, sales price, and profits for different mileages[8]. The results presented in Figure A16 show two patterns. First, the coefficients for all three outcome variables generally increase and are higher for vehicles with higher ending digits. Second, there is a drop at the 5,000-mi mark for most vehicles. This is consistent with consumers who are left-digit biased but also treat odometer readings differently, depending on being above or below multiples of 5,000.

C.4 Placebo Tests

This section considers the robustness of the analysis above by using a placebo tests. We re-estimate tables (4), (5). and (6), which estimate discrete drops at each multiple of 10,000 miles. Appropriately estimating both the continuous and discrete changes depends on fitting a sufficiently

[8]Note, again, that the intercept here is not identified, and the price differences are relative to the price for vehicles between vehicles with moduli between 0 mi and 1,000 mi.

high polynomial of the odometer reading. We now add discontinuities at every 10,000 kilometer cutoff to test if this is estimated accurately. Because the United States discloses odometer readings in miles, a consumer never observes the mileage in kilometers. As a result, we expect the coefficients on each 10,000-kilometer cutoff to be largely insignificant. We present the results in figures (A8), (A9), and (A10). The first figure presents the results for the various prices the dealership pays or receives. We have estimated 3×23 coefficients for kilometer cutoffs. Except for the sales price at 40,000km and the profit at 240,000km cutoff, no coefficient is significant at the $p = 0.05$ level. Purely by chance, we would expect 3.45 coefficients at the 5% level, In figure (A9), we observe five coefficients significant at the 5% level, which is slightly higher than what is expected purely by chance (2.3). Finally, in figure (A10) we observe two coefficients significant at the 5% level, compared to an expected number of 1.15. Given that some kilometer cutoffs are within a few 100 miles of a corresponding 10,000-mile cutoff, the results of the placebo test are generally reassuring.

C.5 Alternative Specifications

In the main analysis, we restricted our data set to a number of dimensions. In this section, we present some results to show the robustness of our results to specific assumptions or specifications.

C.5.1 Functional Form of Price Effects

To relax the assumption of linear effects, we re-estimate columns (1) and (2) of Table 5 using log of prices. Because profits can take negative values, we cannot use a log specification for column (3). We present the results in Table A2 and find that they are robust and qualitatively very similar to the results presented in the main paper.

C.5.2 Sample Selection

One of the key restrictions we applied to the data was to remove vehicles that were purchased and subsequently sold by different vehicles. These vehicles likely were transacted through an auction or directly sold to a different dealership. One concern is, of course, that restricting the sample on that dimension might lead to missing data problems if certain vehicles are more likely to be moved via auction.

We now present results that include vehicles that were purchased and subsequently sold by a different dealership. Because we do not observe the outcomes from potential wholesale auctions, we are unable to attribute profits to a specific dealership. However, we are able to test the overall implications from our paper. We reestimate the inattention coefficients presented in Table 3 and the coefficients in Table 4. The results are presented in Table A3 and Table A4, and the results are generally consistent with the results presented in the main text. The discontinuities are generally slighlty larger (in absolute terms). Additionally, the estimated level of inattention is slightly higher compared to the restricted sample.

C.5.3 Rounding

Possibly, consumers are rounding the odometer readings when filling out the tile form. This introduces measurement error that might be correlated with inattention. For example, a more attentive consumer may also be more likely to observe the odometer carefully and report the exact odometer reading on the title form. We plot the frequency of "round" numbers that are multiples of 100, 250, or 1,000 in Figure A14. Assuming that vehicles precise odometer is random, one could expect that about 1% of vehicles have odometer readings that are multiples of 100, about 0.25% have multiples of 250, and about 0.1% have odometer readings that are multiples of 1,000. For vehicles transacted in dealership transactions, the frequency of observing such round numbers is relatively close to what we would expect if the odometer is reported accurately. However, for vehicles transacted in the decentralized market, rounding is highly prevalent and increases drastically for vehicles with higher odometer readings. For example, in the "bucket" of vehicles between 100,000 miles and 110,000 miles, over 10% of vehicles have odometer readings that are multiples of 1,000 and over 20% of vehicles have odometer readings that are multiples of 100.

Clearly, rounding is prevalent in the decentralized market, and to deal with this issue, we remove numbers that are (presumably) rounded. We re-estimate the inattention parameters reported in Table 3 and remove all vehicles that end in a multiple of 1,000, a multiple of 250, or a multiple of 100. By removing these observations, we retain a sample that is presumably precisely reported. However, because more inattentive consumers are potentially more likely to round numbers, the remaining sample may also be comprised of more inattentive consumers. We present the results in Table A1 and they are virtually identical with the results from the full sample for vehicles sold at dealerships. Specifically, the estimated inattention coefficient is $\theta = 0.400$ or $\theta = 0.399$ in all specifications, including the full sample. The results for decentralized transactions show that removing rounded values drastically affects the reported coefficients. For the full sample, we estimate $\theta = 0.28$, while the estimates in the samples without rounded values are between $\theta = 0.201$ and $\theta = 0.213$. These results are consistent with the theory proposed in the paper and also with the fact that more attentive consumers are less likely to report rounded odometer readings.

C.6 Product Level Heterogeneity

I our empirical analysis, we have largely ignored heterogeneity of θ. As a robustness check, we now aim to describe product attributes that might affect the level of observed heterogeneity, both in the decentralized and centralized market.

For the analysis, we estimate a separate inattention parameter, price level, and depreciation for each model / 10,000 mile-bucket combination. We do this separately for dealership and decentralized transactions. For each value $j = \{10,000; 20,000; ...; 150,000\}$, we restrict the sample to observations in $(j - 5,000; j + 5,000)$. The estimated model, which we run separately for each car model and value of j is given by:

$$p_i = \gamma_0 + \gamma_1 \text{miles}_i + \gamma_2 \mathbf{1}\left[miles_i \geq j\right] + u_{\tilde{m}},$$

We estimate the inattention parameter $\theta_{Mod,j}$, where $j = \{10,000; 20,000; ...; 150,000\}$ and Mod denotes the model. Thus, we have an estimate for each model around each 10,000 mile cutoff, where $P^0_{Mod,j} = E[p|miles_i = j - 5,000] = \hat{\gamma_0} + (j - 5,000)\hat{\gamma_1}$. The average depreciation is given by $\alpha_{Mod,j} = \frac{\hat{\gamma_1} + \frac{\gamma_2}{10,000}}{E[p|miles_i = j-5,000]}$.

Using the estimated inattention parameter, we now run the following fixed effects regression to estimate partial correlations between inattention, depreciation, price level, and the specific thresholds[9]:

$$\theta_{Mod,j} = \beta_0 + \beta_1 P^0_{Mod,j} + \beta_2 \alpha_{Mod,j} + \gamma M_{Mod,j} + \psi X_{Mod} + \epsilon_{Mod,j},$$

where $P^0_{Mod,j}$ and $\alpha_{Mod,j}$ are price and depreciation as described above, $M_{Mod,j}$ is an indicator variable for each 10,000-mile threshold, and X_Mod is a fixed effect for each model.

The identification of coefficients, therefore, comes from the variation in odometer, price, and depreciation within car models. Table A5 presents the results. We first present the regression for vehicles in dealership transactions and then present the regression for decentralized transactions. W We find that the price coefficient and the depreciation coefficient are significant and positive. Similarly, the positive coefficients on higher odometer thresholds are positive and significant. This result implies that consumers pay less attention to vehicles with higher levels of depreciation and higher prices, which is seemingly inconsistent with models of rational inattention. Additionally, consumers treat specific ranges of odometer readings differently, with higher levels of inattention for vehicles with higher odometer readings, regardless of the depreciation or price of those vehicles. For transactions in the decentralized market, there is little observed heterogeneity.

D Ommited Details of Estimation

D.1 Inventory & Competition

To estimate the level of inventory, we consider the number of vehicles of a specific model on the lot for a specific dealership at the time of sale. Because we do not directly observe if a vehicle is on the lot, we need to back out which vehicles are on the lot at any time t. To do so, we consider all vehicles in our sample that were purchased and subsequently sold by a dealership. Then, we assume the vehicle is "on the lot" between those two dates. One obvious issue with this approach is that the measure of vehicles on the lot cannot account for vehicles the dealership purchased before our observation window or sold after the end of the observation window. To account for this, we exclude vehicles that were sold within 1 year of the start data and end date of our observational window. While this still leaves us with a sufficient number of observations, we are confident that it minimizes potential bias for the following two reasons. First, the median time of vehicles on the lot is 29 days, which is significantly less than one year. Secondly, when plotting the inventory (either for individual dealerships or at the aggregate level), the level of inventory apears to reach a "steady state" within a few months.

[9] We exclude observations with inattention parameter greater than 1 or less than 0.

Tables

Table A1: Estimate of the Inattention Parameters

	Removed multiples of:					
	1000 mi	250 mi	100 mi	1000 mi	250 mi	100 mi
	Dealership	Dealership	Dealership	Decentralized	Decentralized	Decentralized
	(1)	(2)	(3)	(4)	(5)	(6)
Inattention (θ)	0.40***	0.400***	0.399***	0.201***	0.201***	0.213***
	(0.015)	(0.015)	(0.015)	(0.045)	(0.048)	(0.048)
Observations	2,476,892	2,465,650	2,449,144	1,011,119	985,594	931,682
7th Polynomial	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

*p<0.1; **p<0.05; ***p<0.01

Note: We omitted polynomial coefficients in the table. The sample includes vehicles between 25,000 miles and 125,000 miles. The sample removes multiples of 100, 250, or 1000 mi from the dataset when estimating the inattention coefficient.

Table A2: Log prices in Estimation of Pricing Discontinuities

	log(purchase_price)	log(sales_price)
10K miles	-0.003	-0.005***
	(0.002)	(0.0008)
20K miles	-0.002	-0.003***
	(0.001)	(0.0006)
30K miles	-0.005***	-0.006***
	(0.001)	(0.0005)
40K miles	-0.007***	-0.007***
	(0.001)	(0.0006)
50K miles	-0.007***	-0.007***
	(0.001)	(0.0006)
60K miles	-0.010***	-0.010***
	(0.001)	(0.0006)
70K miles	-0.010***	-0.01***
	(0.001)	(0.0007)
80K miles	-0.01***	-0.01***
	(0.002)	(0.0009)
90K miles	-0.02***	-0.02***
	(0.002)	(0.001)
100K miles	-0.02***	-0.02***
	(0.002)	(0.001)
110K miles	-0.006*	-0.005**
	(0.003)	(0.002)
120K miles	-0.01***	-0.02***
	(0.004)	(0.003)
130K miles	-0.003	-0.009**
	(0.006)	(0.004)
140K miles	-0.02**	-0.01**
	(0.008)	(0.006)
Observations	3,219,973	3,219,973
R^2	0.83289	0.92959
Within R^2	0.12193	0.26375
Fixed Effects	x	x

This table re-estimates table X using log prices as dependent variable

Table A3: Estimate of the Inattention Parameters

	Sample	
	Dealership	Dealership
	(1)	(2)
Inattention (θ)	0.43***	0.44***
	(0.014)	(0.015)
Observations	3,420,993	3,420,993
7th order polynomial	Yes	Yes
Uniformly Weighted	No	Yes
Fixed Effects	Yes	Yes

*p<0.1; **p<0.05; ***p<0.01

Note: Columns (2) is estimated using weighted nonlinear least squares, giving each odometer reading equal weight. We omitted polynomial coefficients in the table. The sample includes vehicles between 25,000 miles and 125,000 miles. The sample contains all dealership transactions, including vehicles that were sold by a different dealership from the one that purchased it.

Table A4: Estimated discrete change in prices at 10,000 mile thresholds

Dependent Variables:	Purchase Price	Sales Price	Profit
Model:	(1)	(2)	(3)
Variables			
10K miles	-106.0*	-215.8***	-115.3**
	(60.35)	(27.98)	(58.59)
20K miles	-125.2***	-99.84***	31.12
	(35.55)	(35.27)	(46.56)
30K miles	-94.70***	-116.7***	-24.24
	(32.02)	(13.29)	(30.76)
40K miles	-140.4***	-168.6***	-32.49
	(30.10)	(12.84)	(27.88)
50K miles	-111.4***	-157.2***	-39.59
	(27.56)	(11.43)	(26.90)
60K miles	-150.3***	-208.2***	-55.09**
	(25.88)	(12.42)	(24.70)
70K miles	-138.0***	-247.4***	-117.1***
	(25.97)	(12.43)	(25.39)
80K miles	-99.42***	-191.1***	-95.00***
	(27.65)	(13.57)	(26.19)
90K miles	-159.5***	-286.4***	-117.4***
	(28.98)	(15.63)	(27.13)
100K miles	-10.46	-211.4***	-197.4***
	(33.06)	(18.24)	(31.82)
110K miles	8.193	-38.42*	-61.11*
	(36.84)	(22.79)	(34.04)
120K miles	-55.00	-191.8***	-138.8***
	(39.39)	(25.71)	(39.14)
130K miles	-44.77	-170.0***	-106.1**
	(48.60)	(31.73)	(44.85)
140K miles	-194.6***	-259.1***	-90.03
	(64.32)	(43.33)	(58.88)
Fixed Effects	Yes	Yes	Yes
Fit statistics			
Observations	4,458,189	4,458,189	4,458,189
R^2	0.76682	0.91307	0.16496
Within R^2	0.05242	0.17108	0.00076

Clustered (VIN_abr) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: We omitted polynomial parameters and intercepts in table. The outcome variables are (1) the purchase price, (2) the sales price, and (3) the difference between sales price and purchase price. A high order polynomial captures the continuous change in price as a function of the odometer reading. The estimated coefficients estimate the discrete change in the outcome variable at the respective 10,000 mile mark. The sample contains all dealership transactions, including vehicles that were sold by a different dealership from the one that purchased it.

Table A5: Heterogeneity of inattention in dealership and decentralized transactions

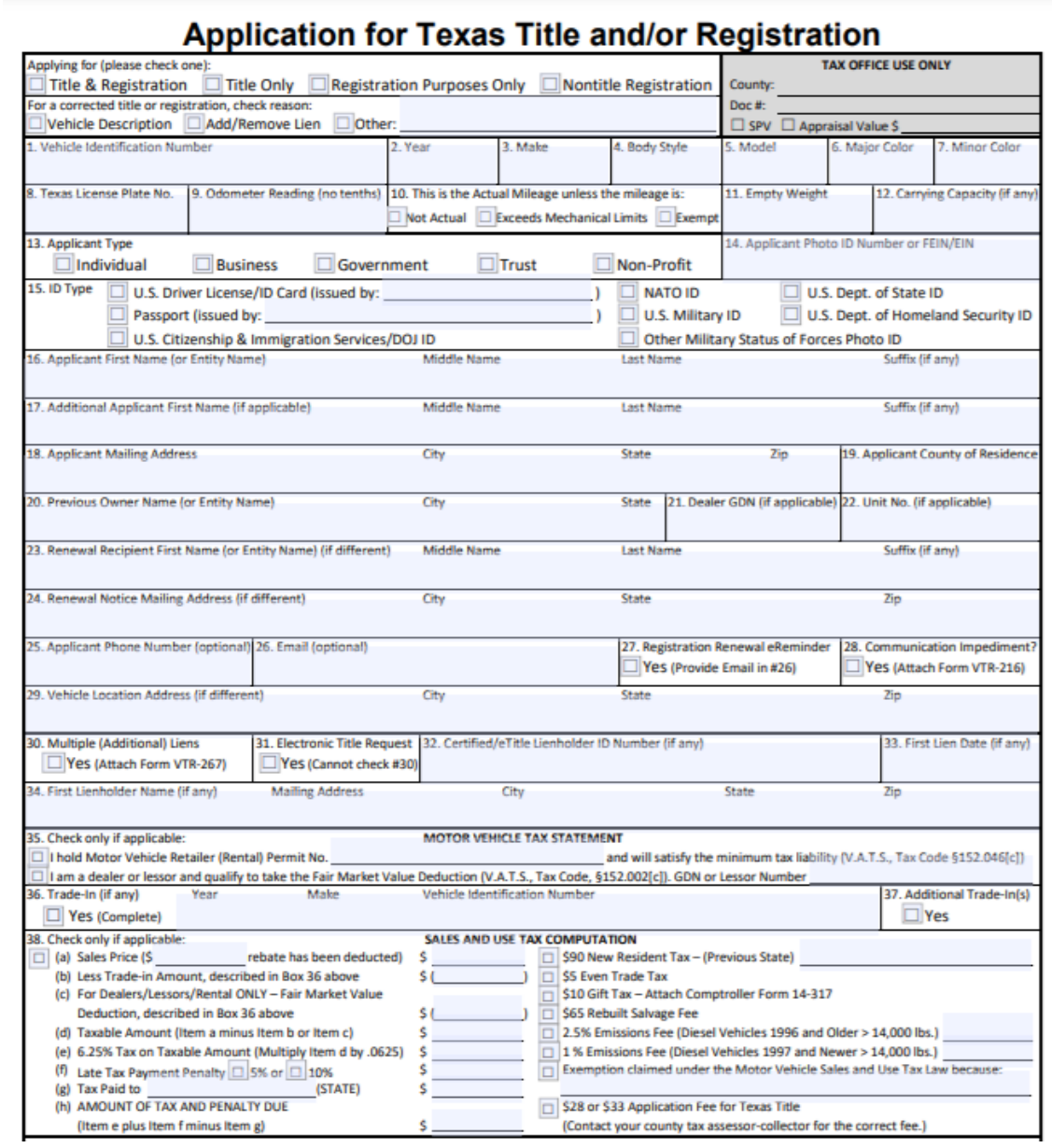
	Dependent Variable: Inattention Parameter (θ)	
	Dealership	Decentralized
Price	0.0305*	-0.0112
	(0.0177)	(0.0173)
Depreciation (α)	0.0915**	0.0180
	(0.0417)	(0.0164)
20K miles	0.0070	0.0389
	(0.0285)	(0.0333)
30K miles	0.0185	0.0030
	(0.0279)	(0.0372)
40K miles	0.0073	0.0163
	(0.0300)	(0.0410)
50K miles	0.0531*	-0.0107
	(0.0319)	(0.0451)
60K miles	0.0552*	-0.0003
	(0.0319)	(0.0446)
70K miles	0.0922***	-0.0184
	(0.0346)	(0.0481)
80K miles	0.0854**	0.0131
	(0.0399)	(0.0509)
90K miles	0.1404***	-0.0367
	(0.0419)	(0.0470)
100K miles	0.1467***	0.0328
	(0.0431)	(0.0529)
110K miles	0.0672	0.0662
	(0.0485)	(0.0522)
120K miles	0.1803***	-0.0078
	(0.0474)	(0.0551)
130K miles	0.2109***	0.0396
	(0.0537)	(0.0556)
140K miles	0.1488***	0.0597
	(0.0563)	(0.0554)
Fixed-effects		
Model	Yes	Yes
Fit statistics		
Observations	2,210	1,797
R^2	0.35842	0.43346
Within R^2	0.04225	0.01752

Clustered (Model) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: The columns estimate the partial relationship between price, depreciation, specific cutoffs, and inattention. Column 1 shows that in dealership transactions, inattention is largely higher for vehicles of higher mileage, independent of the specific price or depreciation rate of vehicles. Column 2 shows that there is limited observed heterogeneity of inattention in the decentralized market.

Figures

Figure A1: Texas Vehicle Title Form



Application for Texas Title and/or Registration

Applying for (please check one):
☐ Title & Registration ☐ Title Only ☐ Registration Purposes Only ☐ Nontitle Registration

For a corrected title or registration, check reason:
☐ Vehicle Description ☐ Add/Remove Lien ☐ Other: _____

TAX OFFICE USE ONLY
County: _____
Doc #: _____
☐ SPV ☐ Appraisal Value $ _____

1. Vehicle Identification Number	2. Year	3. Make	4. Body Style	5. Model	6. Major Color	7. Minor Color

8. Texas License Plate No.	9. Odometer Reading (no tenths)	10. This is the Actual Mileage unless the mileage is: ☐ Not Actual ☐ Exceeds Mechanical Limits ☐ Exempt	11. Empty Weight	12. Carrying Capacity (if any)

13. Applicant Type
☐ Individual ☐ Business ☐ Government ☐ Trust ☐ Non-Profit

14. Applicant Photo ID Number or FEIN/EIN

15. ID Type
☐ U.S. Driver License/ID Card (issued by: _____) ☐ NATO ID ☐ U.S. Dept. of State ID
☐ Passport (issued by: _____) ☐ U.S. Military ID ☐ U.S. Dept. of Homeland Security ID
☐ U.S. Citizenship & Immigration Services/DOJ ID ☐ Other Military Status of Forces Photo ID

16. Applicant First Name (or Entity Name)	Middle Name	Last Name	Suffix (if any)

17. Additional Applicant First Name (if applicable)	Middle Name	Last Name	Suffix (if any)

18. Applicant Mailing Address	City	State	Zip	19. Applicant County of Residence

20. Previous Owner Name (or Entity Name)	City	State	21. Dealer GDN (if applicable)	22. Unit No. (if applicable)

23. Renewal Recipient First Name (or Entity Name) (if different)	Middle Name	Last Name	Suffix (if any)

24. Renewal Notice Mailing Address (if different)	City	State	Zip

25. Applicant Phone Number (optional)	26. Email (optional)	27. Registration Renewal eReminder ☐ Yes (Provide Email in #26)	28. Communication Impediment? ☐ Yes (Attach Form VTR-216)

29. Vehicle Location Address (if different)	City	State	Zip

30. Multiple (Additional) Liens ☐ Yes (Attach Form VTR-267)	31. Electronic Title Request ☐ Yes (Cannot check #30)	32. Certified/eTitle Lienholder ID Number (if any)	33. First Lien Date (if any)

34. First Lienholder Name (if any)	Mailing Address	City	State	Zip

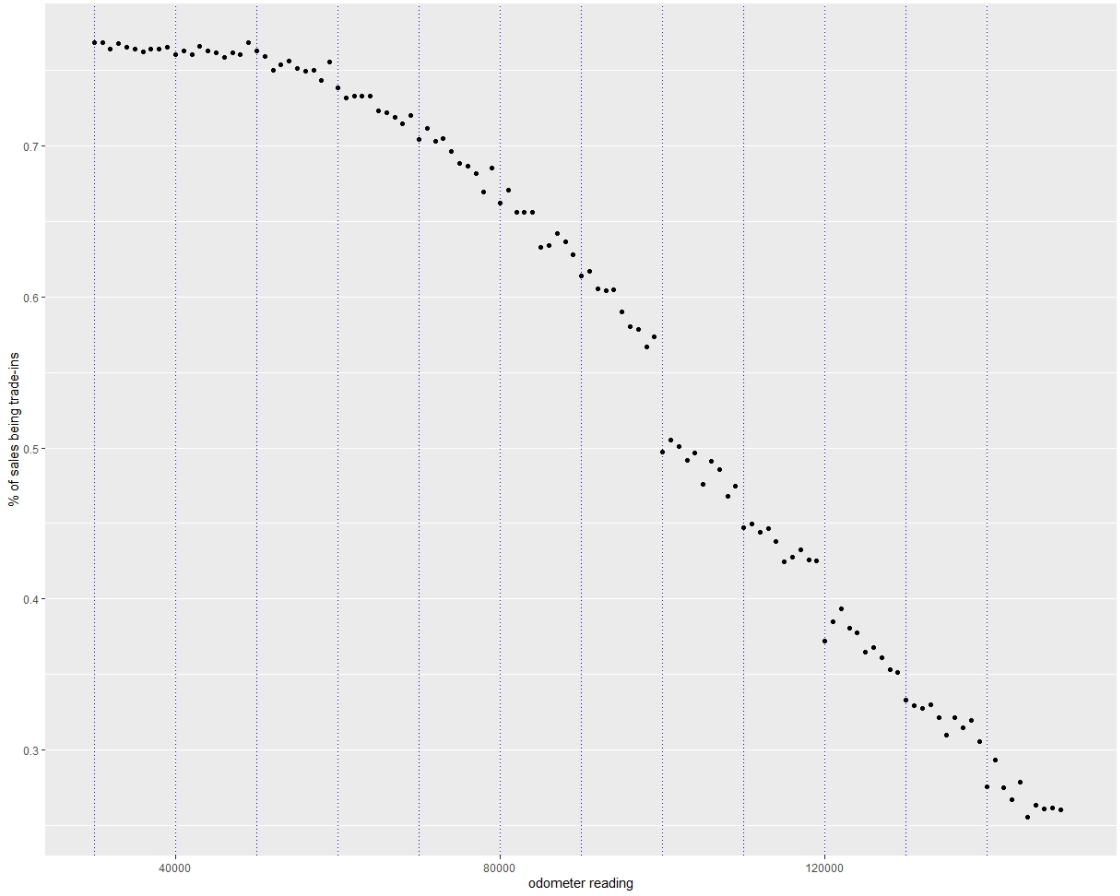
35. Check only if applicable:
MOTOR VEHICLE TAX STATEMENT
☐ I hold Motor Vehicle Retailer (Rental) Permit No. _____ and will satisfy the minimum tax liability (V.A.T.S., Tax Code §152.046[c])
☐ I am a dealer or lessor and qualify to take the Fair Market Value Deduction (V.A.T.S., Tax Code, §152.002[c]). GDN or Lessor Number _____

36. Trade-In (if any) ☐ Yes (Complete)	Year	Make	Vehicle Identification Number	37. Additional Trade-In(s) ☐ Yes

38. Check only if applicable:
SALES AND USE TAX COMPUTATION

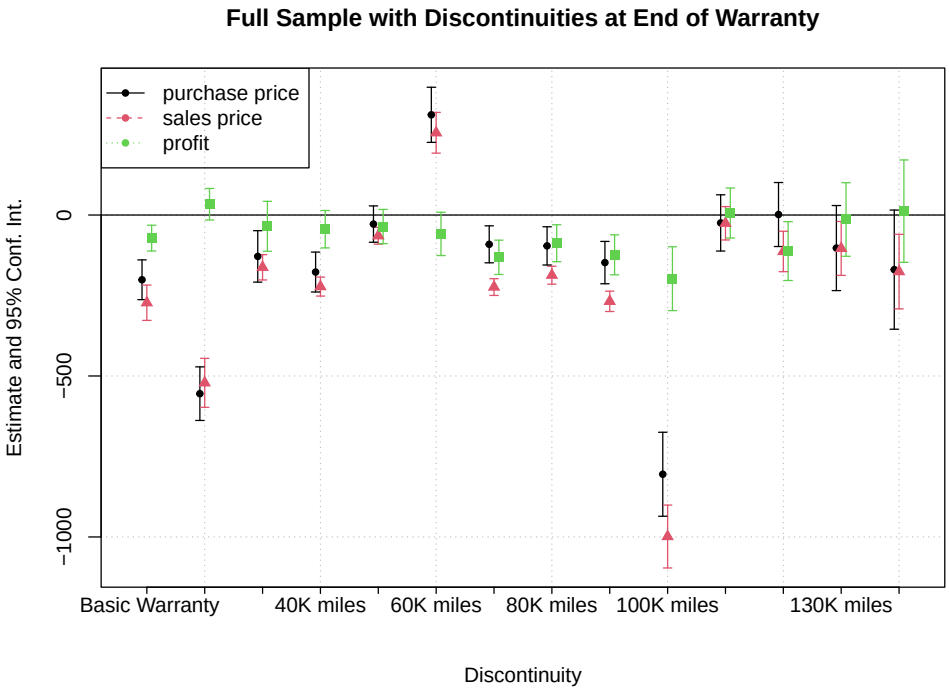
☐ (a) Sales Price ($ _____ rebate has been deducted)	$	☐ $90 New Resident Tax – (Previous State)	
(b) Less Trade-in Amount, described in Box 36 above	$ ( )	☐ $5 Even Trade Tax	
(c) For Dealers/Lessors/Rental ONLY – Fair Market Value Deduction, described in Box 36 above	$ ( )	☐ $10 Gift Tax – Attach Comptroller Form 14-317	
		☐ $65 Rebuilt Salvage Fee	
(d) Taxable Amount (Item a minus Item b or Item c)	$	☐ 2.5% Emissions Fee (Diesel Vehicles 1996 and Older > 14,000 lbs.)	
(e) 6.25% Tax on Taxable Amount (Multiply Item d by .0625)	$	☐ 1 % Emissions Fee (Diesel Vehicles 1997 and Newer > 14,000 lbs.)	
(f) Late Tax Payment Penalty ☐ 5% or ☐ 10%	$	☐ Exemption claimed under the Motor Vehicle Sales and Use Tax Law because:	
(g) Tax Paid to _____ (STATE)	$		
(h) AMOUNT OF TAX AND PENALTY DUE (Item e plus Item f minus Item g)	$	☐ $28 or $33 Application Fee for Texas Title (Contact your county tax assessor-collector for the correct fee.)	

Figure A2: Proportion of vehicles sold through intermediary

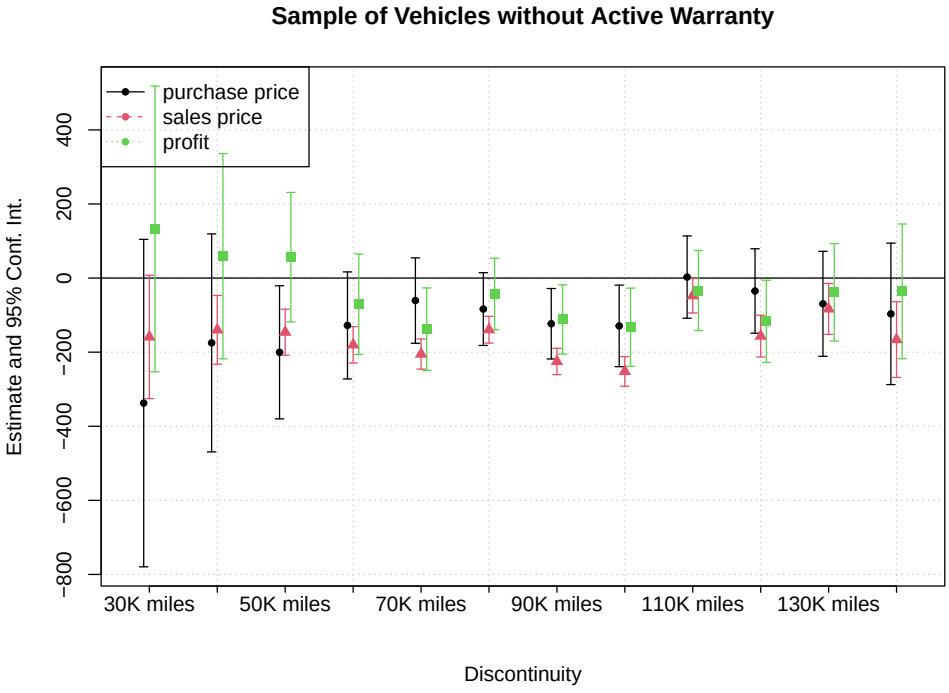


Note: Each dot represents the percentage of transactions via intermediary (compared to consumer transactions) for vehicles within a 1,000 mi band.

Figure A3: Warranties



(a)



(b)

Note: The top panel estimates the discontinuity at the end of warranty terms. The bottom panel estimates discontinuities while restricting the dataset to vehicles without active warranties, due to their age.

Figure A4: Histograms of Key Variables

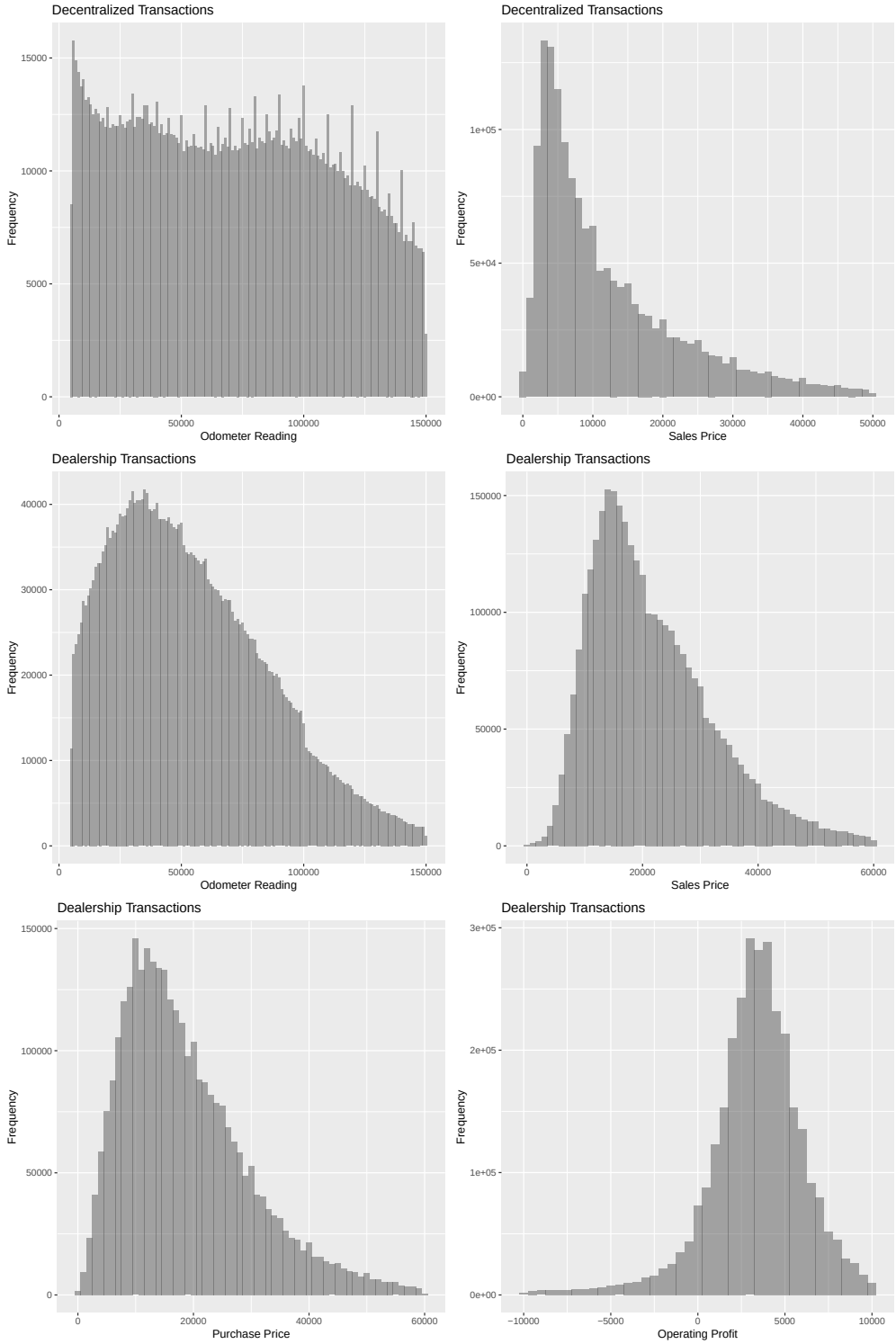


Figure A5: Robustness of Purchase Price Coefficients in Table 4

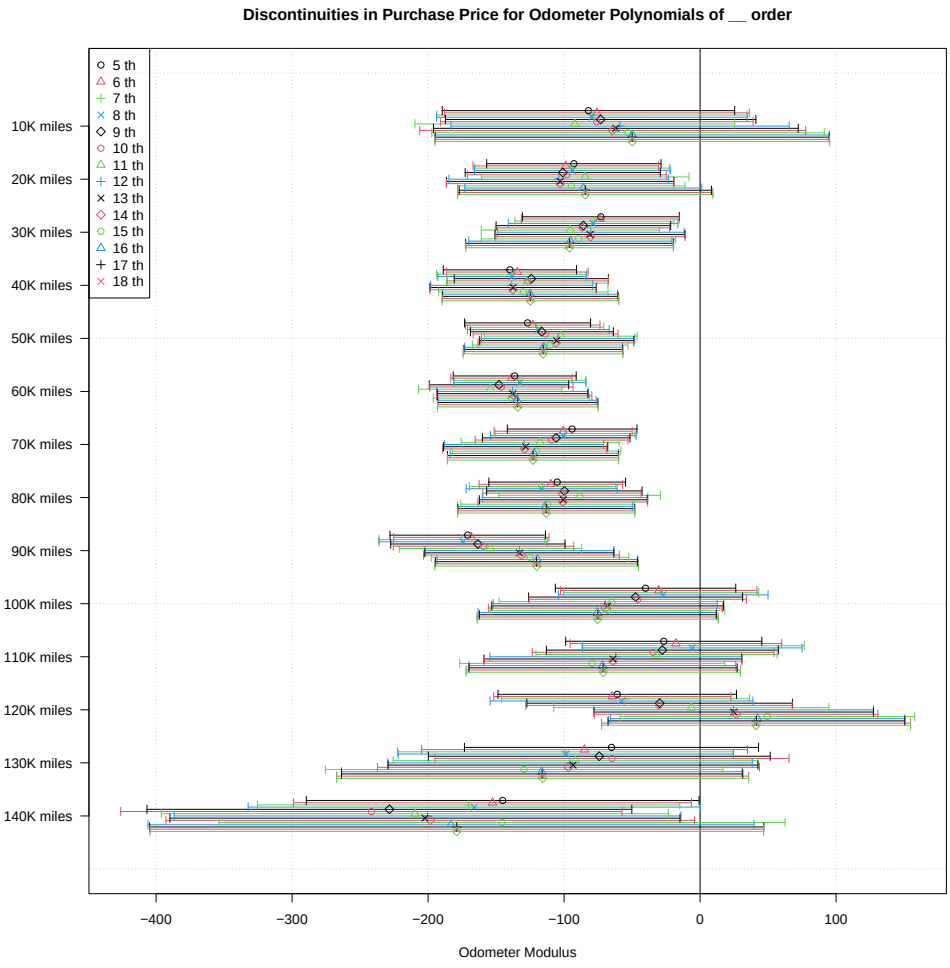


Figure A6: Robustness of Sales Price Coefficients in Table 4

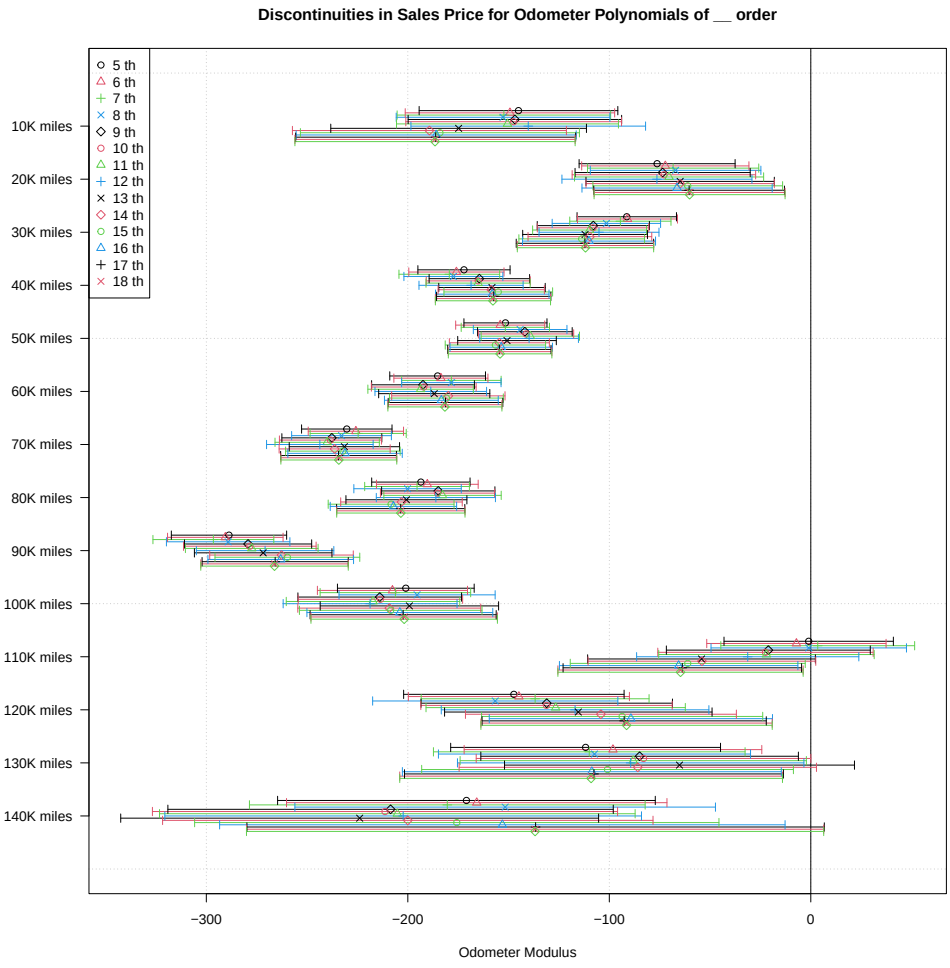


Figure A7: Robustness of Profit Coefficients in Table 4

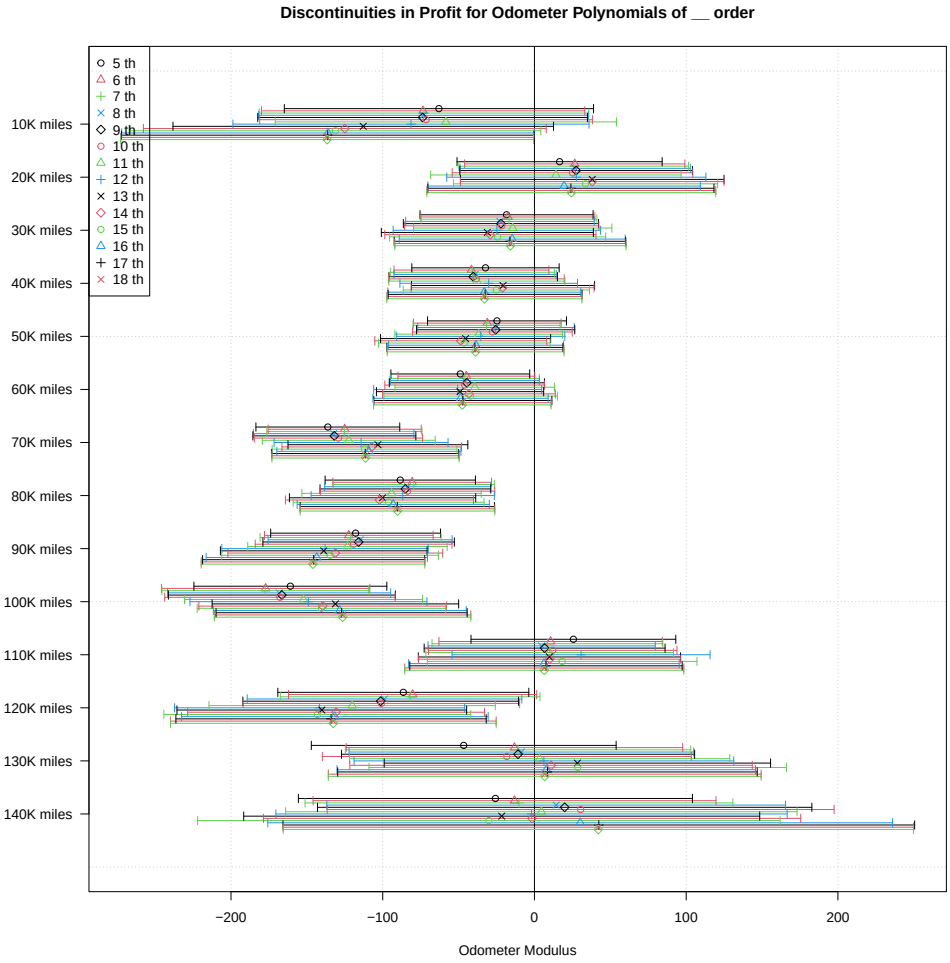


Figure A8: Placebo test reproducing Table 4 with 10,000km discontinuities

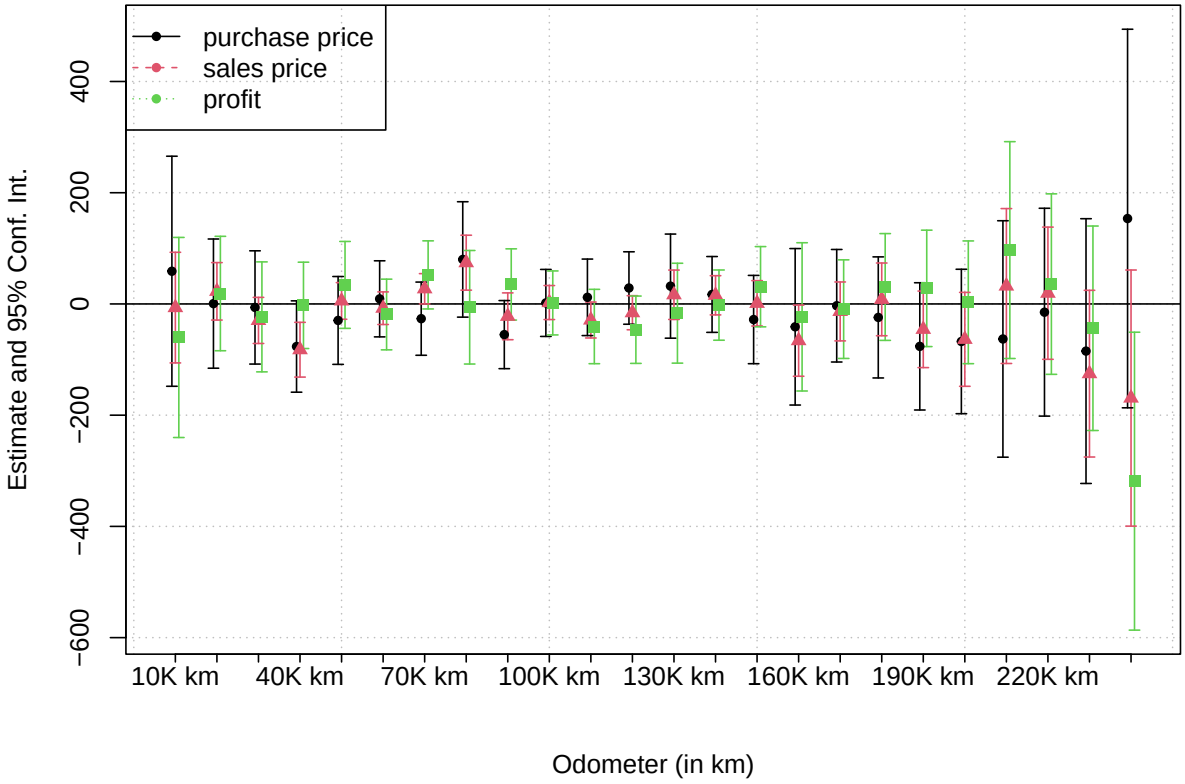


Figure A9: Placebo test reproducing Table 5 with 10,000km discontinuities

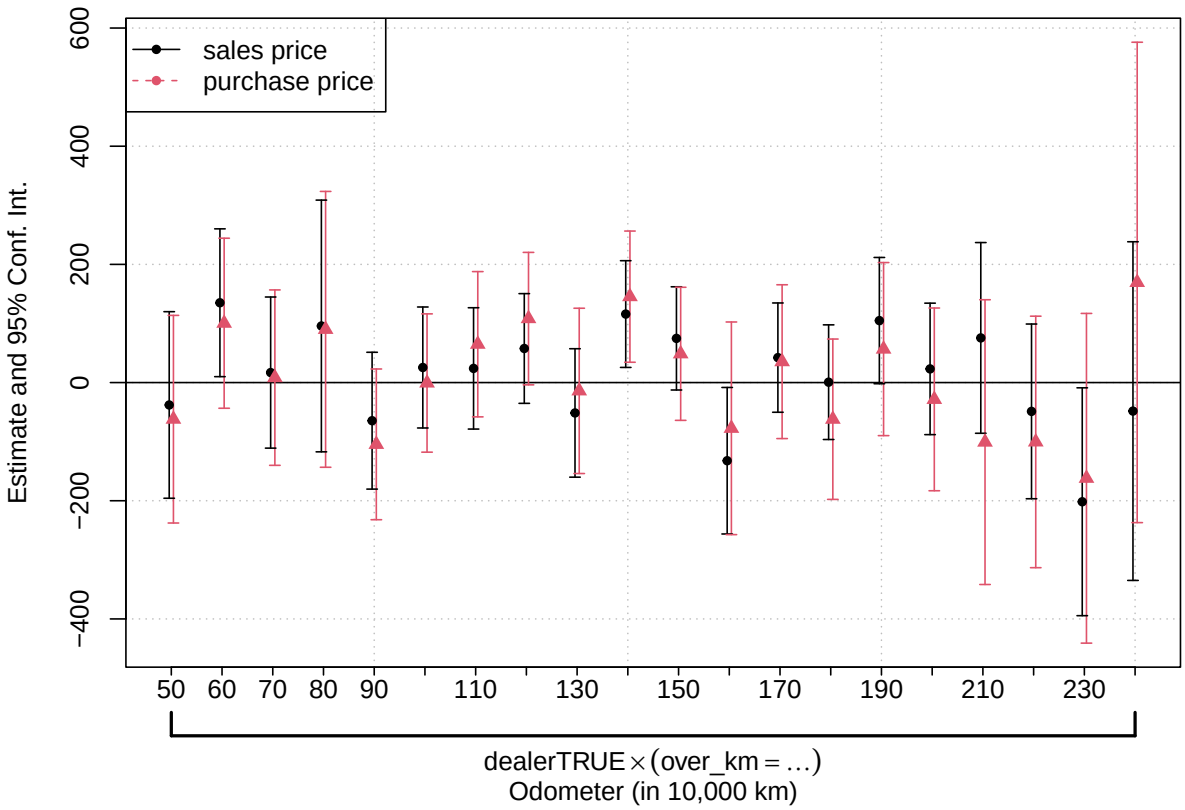


Figure A10: Placebo test reproducing Table 6 with 10,000km discontinuities

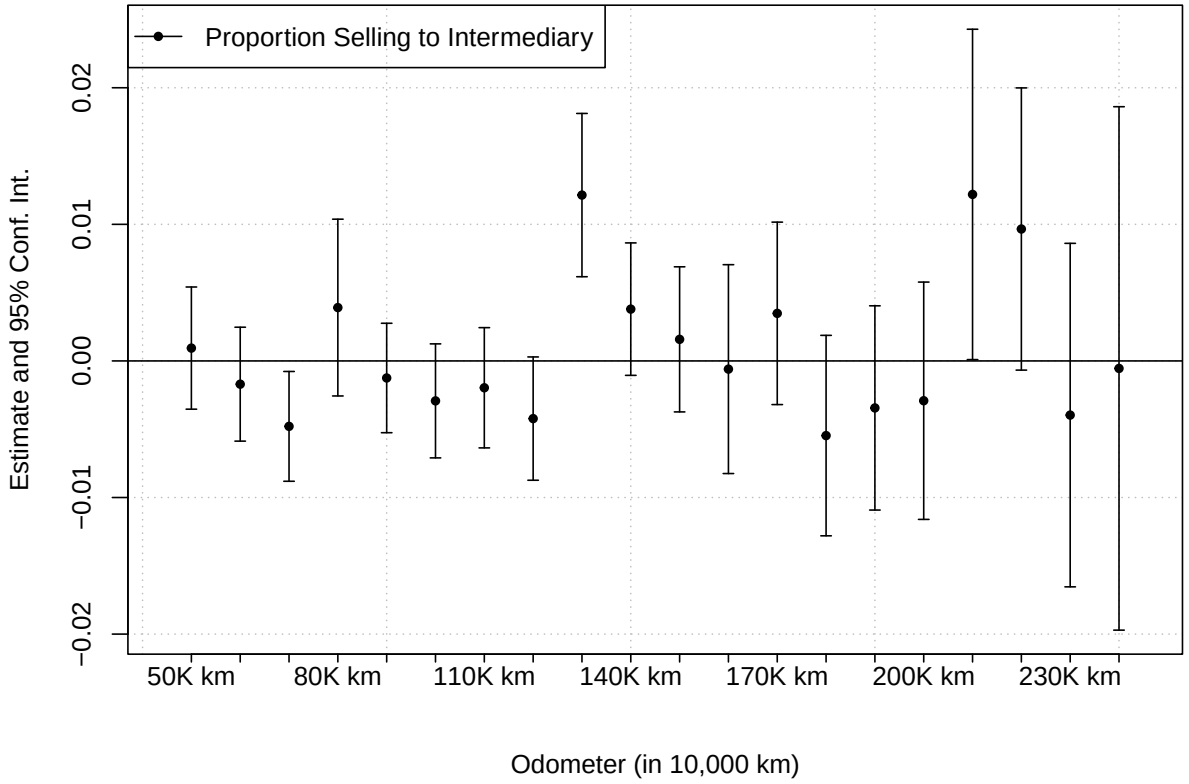
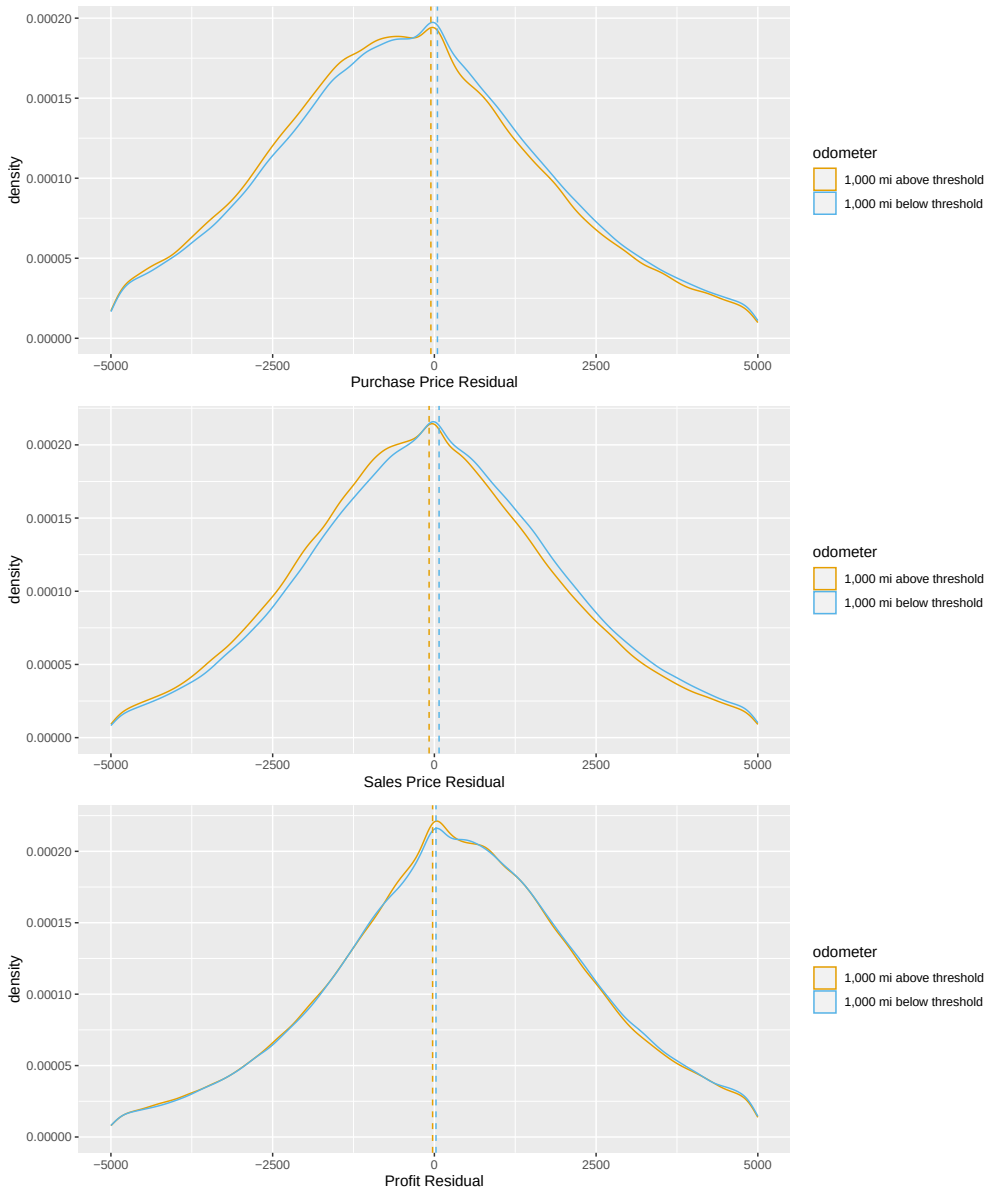
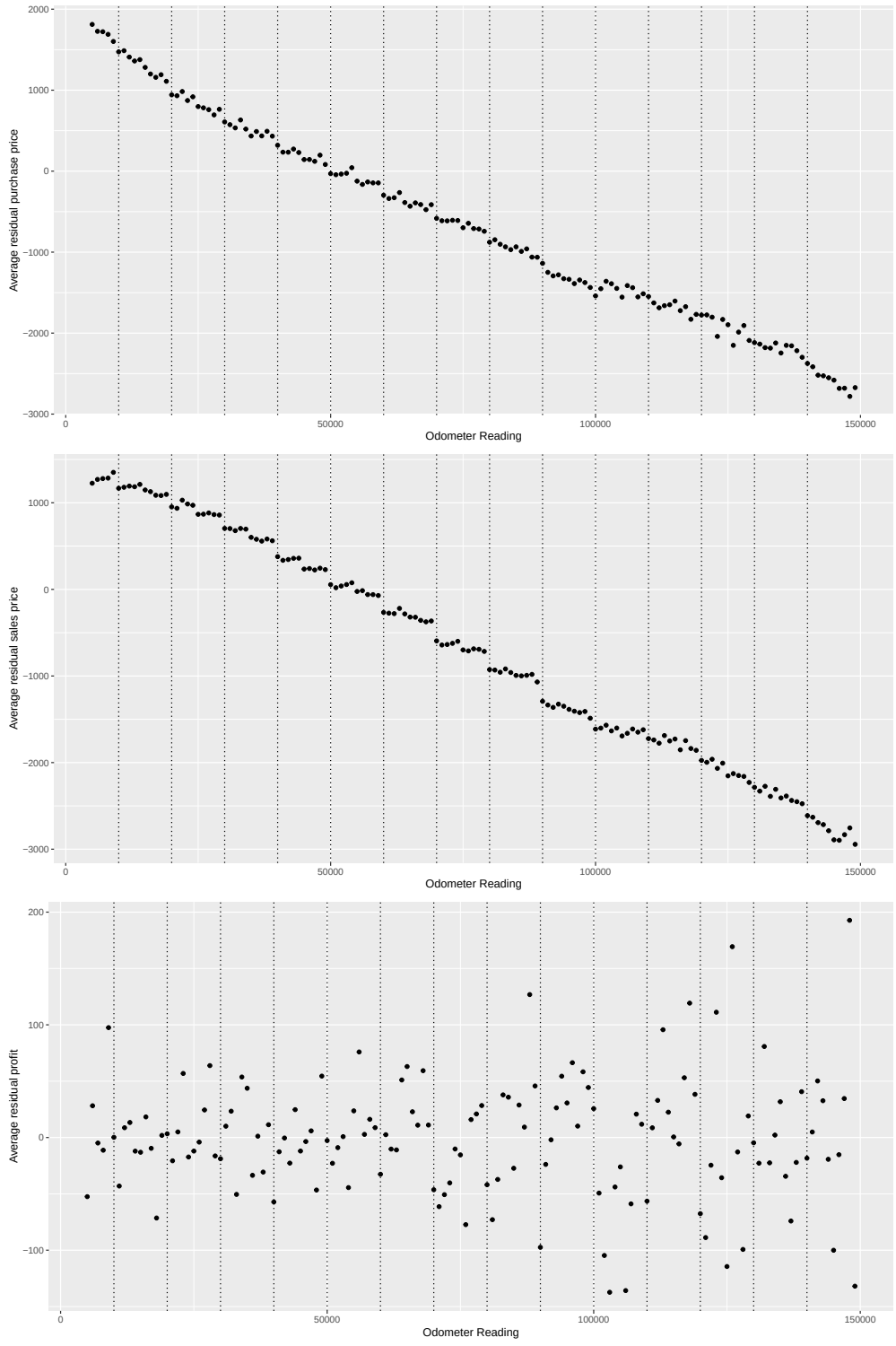


Figure A11: Density of Outcomes for observations immediately above and below 10,000 mile thresholds



Note: Estimated Density of the residual of regressing outcome variables on full set of fixed effects (dealership, customer zip code, vehicle make/model/trim/year, and week, odometer polynomial) .

Figure A12: Discontinuities of residual of outcome variables in Table 4



Note: Estimated residuals of regressing outcome variables on full set of fixed effects (dealership, customer zip code, vehicle make/model/trim/year, and week).

Figure A13: Distribution of Warranty Terms

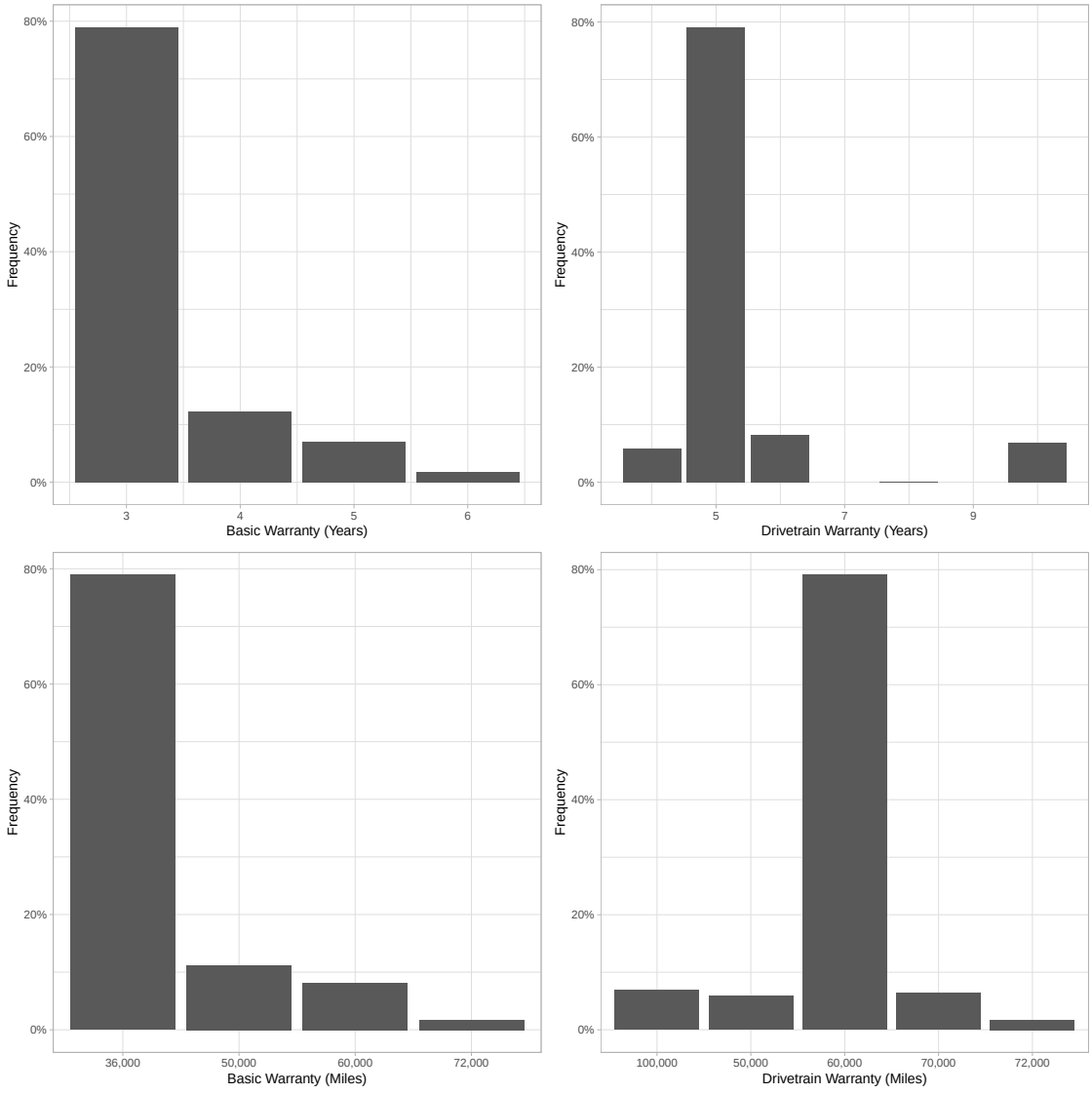
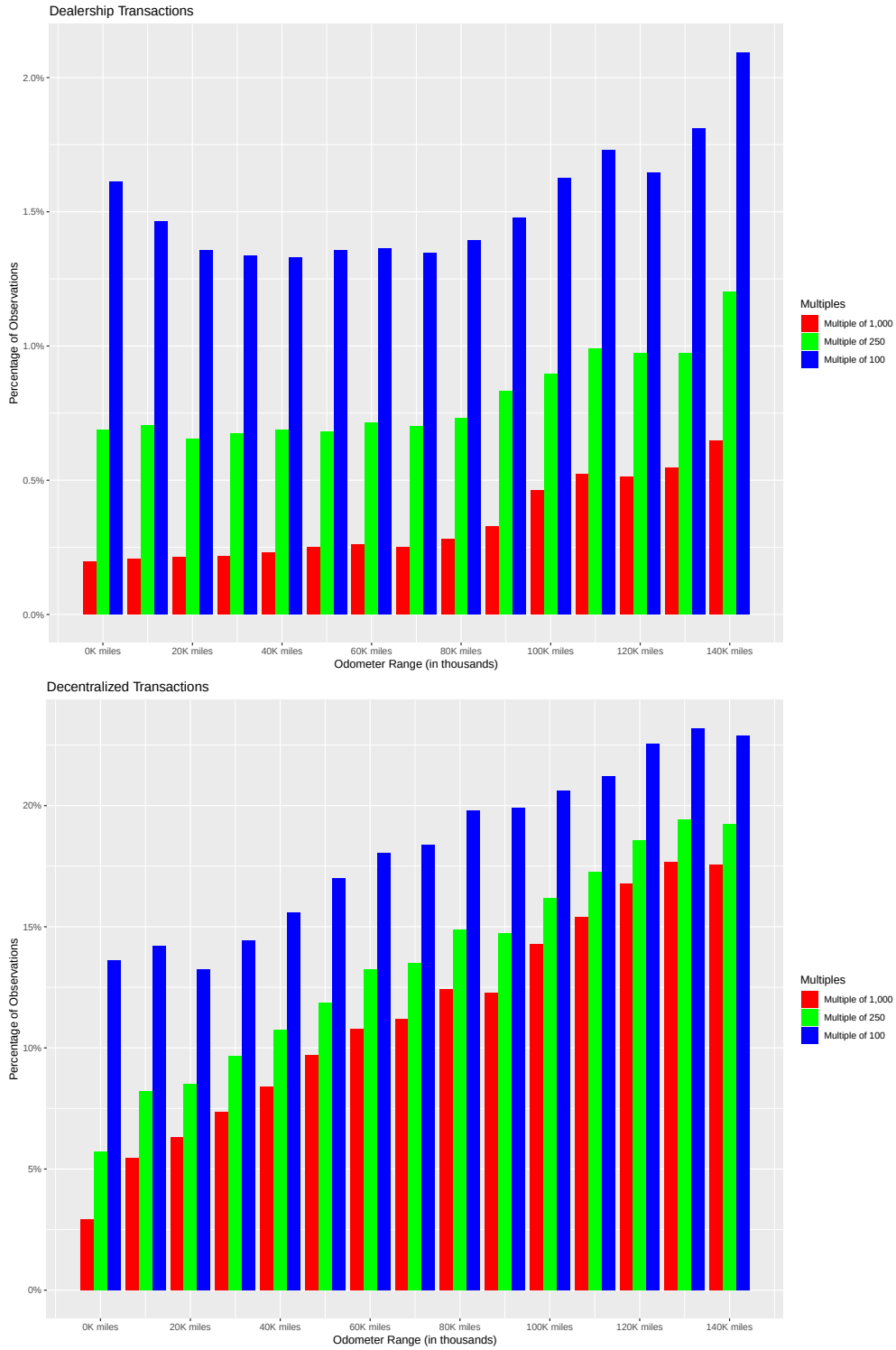
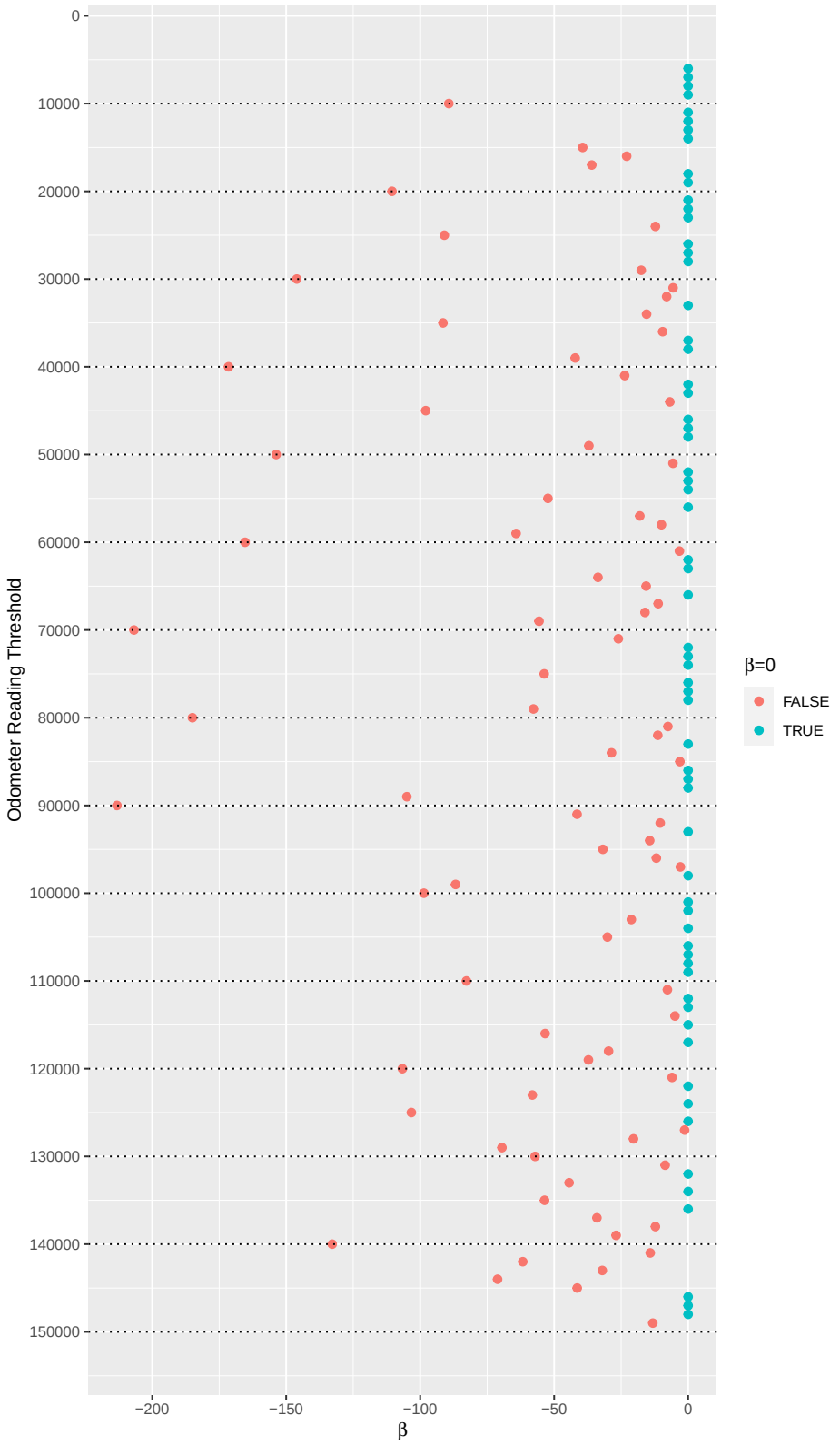


Figure A14: Proportion of vehicles with odometer readings as multiples of round numbers



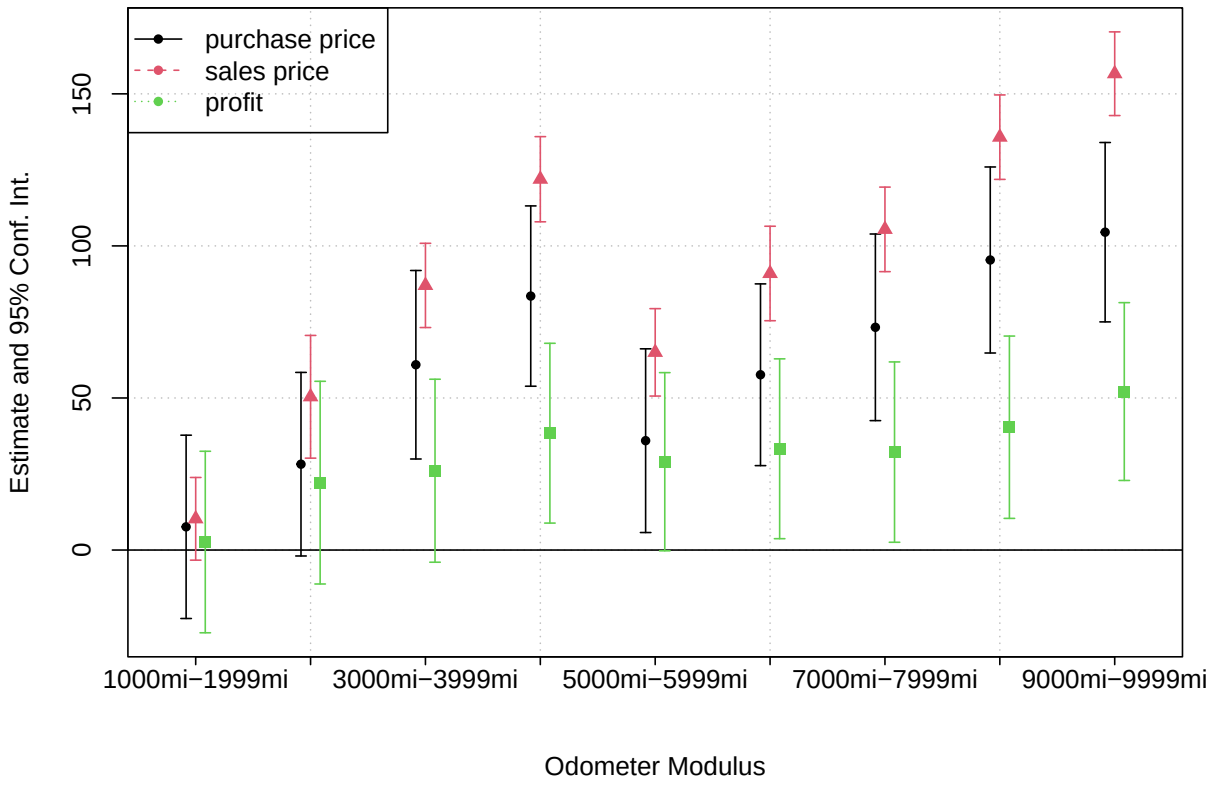
Note: Each bar represents the proportion of vehicles in a 10,000 mile "bucket" that has odometer readings that are multiples of 100, 250, or 1,000.

Figure A15: Estimation of discontinuities without exogenously defined breakpoints



Note: Above presents the estimated coefficients from a lasso regression. Each dot represents the average increase in price as mileage increases by 1,000 miles.

Figure A16: Excess purchase price, sales price, profits, by modulus of odometer



Note: Each coefficient represents the difference in outcome for vehicles within a specific modulus of mileage, relative to vehicles in the modulus of 0 mi to 999 mi.