Behavioral Skimming: Theory and Evidence from Resale Markets

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Abstract

Lack of information distorts markets, and communicating product value to potential consumers is a crucial ingredient of marketing strategy. However, a large body of behavioral research has suggested that even when information is easily accessible, consumers often fail to attend to it. Evidence of consumer inattention has been studied in various settings, both inside and outside the laboratory. How an intermediary should react when communication fails as a result of consumers' failure to use the provided information is unclear. Can or should firms profit from asymmetric information caused by consumer inattention? If so, by how much? Does competition alleviate the effect? We consider these questions in the context of resale markets, both theoretically and empirically. The theoretical model demonstrates that a centralized intermediary can extract surplus from serving consumers who are less attentive and, as a result, overestimate the product value. We test the theory using a detailed dataset of millions of automobile transactions from a seven-year period. First, we find clear evidence of a specific type of inattention: Buyers exhibit left-digit bias and systematically underestimate the depreciation of vehicles that have odometer readings immediately below round cutoffs. Second, the estimated level of inattention is twice as high in dealership transactions than in consumer transactions, so that dealers make a significantly higher margin on such vehicles. Third, we estimate the supply-side response to consumer inattention and find 2.53% additional transactions, compared to the *no-inattention* counterfactual. As a result, the average margin is 1.8% higher, leading to an aggregate increase in operating profits of 4.37%, or about $422 million, within the seven-year sample period. The surplus obtained by the product owners who sell in the market increases by about 2.77%. Back-of-the-envelope calculations imply that U.S. used vehicle dealers' annual profits attributable to consumer inattention are about $700 million.

Keywords: Behavioral Industrial Organization, Consumer Inattention, Game Theory

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1 Introduction

The purchase of a car or a home is among the more significant milestones in the economic life of a consumer. Due to the high prices of such durable goods, the majority of transactions occur in resale markets (Experian, 2021). Since Akerlof (1970), the presence of asymmetric information–that is, when sellers fail to disclose unfavorable information and buyers cannot easily observe quality–has been known to severely limit trade. The working assumption is that when sellers disclose all the relevant information, the frictions arising from the asymmetric information problem get resolved.

However, durable goods are often complex, and even if the quality of each attribute is disclosed, accurately evaluating a product can be challenging for consumers. Past research has shown that even in settings where information is provided transparently, consumers often fail to fully attend to it. Growing evidence indicates that consumers are inattentive to attribute information that is readily observable at the point of purchase, including information about prices (Clerides and Courty, 2017), product ingredients (Bronnenberg et al., 2015), and taxes (Chetty et al., 2009). In addition, consumers are often heterogeneous, with varying degrees of inattention (Taubinsky and Rees-Jones, 2018). Presumably, inattention is an even more significant problem in durable goods resale markets, where consumers are faced with a myriad of options (Iyengar and Lepper, 2000), consumers transact with relatively unknown consumers (Hendel and Lizzeri, 1999), and product evaluations are a complex task (Salant and Spenkuch, 2022).

Because of the complexity of durable goods markets, a number of third-party intermediaries, such as used car dealerships and real estate brokers, have taken a role. They provide numerous services, such as a one-stop shopping destination (e.g., car dealerships), offering warranties (Biglaiser, 1993) or facilitating trade-in transactions (Rao et al., 2009), and offering leasing (Gavazza, 2011). These intermediaries thus are able to profit when sellers fail to credibly supply information about quality.[1] However, when information is available but consumers fail to fully attend to it, what these strategic intermediaries can or should do in response and how they potentially can benefit from the situation is unclear.

In this paper, we aim to fill this gap and consider the role of intermediaries in markets where

[1] More broadly, firm strategies aimed at reducing informational asymmetries, such as cheap talk (Backus et al., 2019), advertising (Nelson, 1974), money-back guarantees (Moorthy and Srinivasan, 1995), and locking out demand (Kraft and Rao, 2022)) address the problem of insufficient supply of credible information.

of heterogeneously inattentive consumers leads to behavioral frictions. We present evidence, both theoretical and empirical, that (i) inattention affects resale markets in a meaningful way, and (ii) intermediaries react strategically to benefit from inattentive consumers. We also measure the magnitude of the aggregate impact and compare it to situations of no inattention and of extreme inattention to estimate the bounds of these effects.

For this work, we develop a model of a resale market where consumers can trade in a decentralized consumer-to-consumer market and via a centralized intermediary. Similar to the literature on traditional asymmetric information, we consider negative product attributes (e.g., depreciation, defects). However, we assume that the frictions arise not because of undisclosed attribute information, but because of consumers' heterogeneous inattention, whereby they (partially) ignore the attribute. Inattention to a negative attribute increases the willingness to pay because consumers fail to fully incorporate the negative attribute. In a monopoly setting, this potentially affects consumption because consumers overestimate the value of the product relative to the price. Using an analytical model, we show that inattention can also affect *where* consumers purchase the product. More specifically, we show that when a consumer visits a centralized intermediary first, the intermediary can use pricing to capture inattentive consumers and sell to them at a higher price. To understand the intuition of this skimming, consider the following highly stylized scenario of two consumers at a car dealership who are looking to see whether to buy a used car from the dealer or to rely on the consumer market and potentially buy it from an individual seller.

Suppose that a vehicle depreciates at a rate of \$200 per 1,000 miles and that similar vehicles cost (on average) \$500 more at a dealership, compared to the consumer market. Further, assume that consumers first visit the dealership because they can more easily search their website. Holding everything equal, an attentive consumer will forego buying at the dealership and instead purchase in the consumer market at a lower price. Now, to see how inattention can affect outcomes, consider a left-digit biased consumer who falsely perceives a vehicle with 45,000 miles as a vehicle with 40,000 miles. However, the vehicle is still priced according to the 45,000 miles. Thus, when the consumer visits the intermediary, the vehicle seems to be a good deal. In fact, it seems to be priced \$1,000 below what the consumer expected for a vehicle with 40,000 miles. Furthermore, the vehicle is priced below what the consumer expects to pay in the consumer market, and thus he purchases it at the dealership. In such a scenario, the inattentive consumer has a higher willingness to pay because he fails to anticipate the lower price in the decentralized market due to inattention. 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 the product somewhere else. 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, the degree of inattention- if it exist at all- is likely to vary among consumers, and so the effects are likely to be more nuanced than in this example. This is precisely the goal of our paper.

First, we show that in a market without an intermediary, the opportunity cost of missing out on transactions with *attentive* consumers can mute the ability of individual sellers to take advantage of inattention. Attentive consumers protect inattentive consumers because the seller cannot distinguish between the two. This protection disappears in markets that include both an intermediary and a decentralized consumer option. The intermediary avoids price competition and sets a high price that is attractive only to inattentive consumers, who self-select into buying from the intermediary. The intermediary thereby *skims* inattentive consumers from the market, leaving relatively attentive consumers in the 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) less attentive. 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, and interestingly, whether product owners are aware of consumer inattention at all is irrelevant because they do not face the inattentive consumers.

Our empirical analysis consider 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). Some potential examples are a house with a nine-year-old versus a ten-year-old roof, an airplane that has logged 9,900 versus 10,000 hours in the air, or a vehicle that has been driven for 9,900 miles versus 10,000 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 and vehicles that were purchased and subsequently sold again by an intermediary (i.e., used car dealership). 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 the skimming proposed in the theoretical model, 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. Meanwhile, in the consumer market, the same vehicle is perceived by consumers as if it has a reading, on average, of 55,752 miles.

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.

These findings are consistent with our proposed theory and present a first piece of evidence of how marketing intermediaries strategically react to consumer inattention. The overall effects are quite precisely estimated and are 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 [2].

To get an aggregate quantitative measure of the magnitude of the effect of inattention, we estimate a supply-side model that allows us to consider different levels of inattention and their

[2] 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.

effect on profits and owner surplus. We estimate a model that accounts for the change in the number of transactions resulting from the intermediary's taking advantage of the left-digit biased consumers, as well as for the change in the resulting prices. Our estimates show that inattention leads to a 4.37% increase in dealer profits relative to a counterfactual involving full attention. This amount is equivalent to about $422 million in profits for the car dealerships over our seven-year sample period. Carrying these estimates to the entire United States, our back-of-the-envelope calculations show that used vehicle dealerships' annual profits attributable to consumer inattention are about $700 million. The increase in profit is driven by higher profit margins (1.8%) and an increase in the number of transactions (2.53%). In addition, we find an increase in owner (seller) surplus of about 2.77%, or about $478 million, within our data during the sample period.

2 Literature Review

In this paper, we broadly contribute to two streams of literature. First, we provide marketplace evidence for the presence of inattention—a pervasive behavioral bias. Second, we investigate how marketplace entities react in the face of consumers' inattention and its effects on the outcomes. More specifically, we add to the literature on the role of intermediaries in relation to behavioral frictions. At a broader level, our study contributes to the literature in behavioral industrial organization that examines how firms react to boundedly rational consumers.

The first stream to which our work contributes is on the role of intermediaries in resale markets. Akerlof (1970) pointed 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 have considered 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. Other papers 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 specifically considers 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. In this paper, we aim to fill this gap.

The effects that asymmetric information stemming from inattention has are qualitatively different from the effects of asymmetric information stemming from sellers' failure to disclose information. Informational frictions generally reduce consumers' willingness to pay because they are unable to distinguish high-quality products from low-quality products. Intermediary strategies aim to reduce the asymmetry and increase willingness to pay. However, if consumers are not attentive to negative attributes, then their willingness to pay increases. In this case, the intermediaries' goal might be to establish a strategy to benefit from biased willingness to pay, rather than to reduce the informational asymmetry. The specific type of inattention in our empirical application is the left-digit bias. This consumer bias has been studied extensively in the laboratory, as well as in field settings (Poltrock and Schwartz, 1984; Thomas and Morwitz, 2005; Sokolova et al., 2020). For example, several papers have investigated the common practice of prices ending in 9 (Anderson and Simester, 2003). In a setting without posted prices, 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 have studied 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) have found evidence of incomplete attention to odometer readings in the wholesale vehicle market. Subsequent work has shown similar patterns in retail transactions (Busse et al., 2013) and in posted prices in online marketplaces (Englmaier et al., 2018).

Finally, our work is related to a broad stream of papers in the IO literature that studies firms' reactions to consumer biases (see Ellison (2006); Grubb (2015); Heidhues and Kőszegi (2018) for excellent surveys) and, more specifically, in the work that considers firms' reactions to inattentive consumers. This work is primarily theoretical (e.g., De Clippel et al. (2014)), and several firm strategies have been identified. Gabaix and Laibson (2006) shows that firms can "shroud" attributes and use hidden add-on prices to profit from inattentive consumers, 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 pricing, but they do not do so sufficiently to take full advantage of the bias.

The rest of the paper proceeds as follows. In Section 3, we present a theoretical model to motivate our empirical analysis, which is in Section 4. Section 5 presents a supply-side response model to quantify the aggregate outcomes arising from consumer inattention. We conclude with Section 6, a discussion of our main findings, limitations, and some avenues for future research.

3 Theoretical Model

This section describes 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, the model we present here is quite general and so can be applied to other types of inattention and markets. To isolate the effect of inattention, we abstract away other essential elements that occur in such markets, such as adverse selection from sellers not disclosing quality. We first describe the modeling of inattention in our model, then describe the game, and then present the analysis. Finally, we map our results to the specific context of left-digit bias and derive several empirically 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 DellaVigna (2009) and assume that consumers use a heuristic to imperfectly process information about an attribute. Our theoretical model is agnostic as to the source of inattention[3]. For simplicity, we assume that utility from each

[3] Behavioral economists and psychologists have identified a large number of biases and heuristics, and many of them can be represented as variants of inattention (Gabaix, 2019). For example, prospect theory can be thought of as

product can be separated into an additive combination of two attributes, where the first attribute (v) is easily observed and a second attribute (z) requires attention to be processed accurately[4]. In our empirical application, we consider that depreciation is measured by z and that it requires attention from consumers to be observed.

To model the level of inattention, we define $\theta \in [0, 1]$ as the exogenously 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 follows.

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

Consistent with the past evidence that ownership increases attention (Hartzmark et al., 2021), we assume that inattention primarily affects buyers during the purchase process, in which they potentially evaluate a large number of options and have limited time to fully process all the product-related information. As consumers consume the product, we assume that misperceptions resulting from inattention eventually get eliminated.[5]

3.2 Supply, Demand, and the Intermediary

Consider a game consisting of three types of players. A unit mass of risk-neutral owners is exogenously endowed with an (indivisible) homogenous product, and a unit mass of risk-neutral buyers do not own a product but could purchase it.[6] Finally, a risk-neutral intermediary firm can purchase

inattention to true probabilities. Projection bias can be cast as inattention to future circumstances and overconfidence as inattention to one's true ability. Many of these biases can distort a consumer's valuation of a durable good. For example, consumers' purchase intention for convertibles and houses with a pool are affected by the weather (Busse et al., 2015), consistent with projection bias. A consumer who is overly confident in doing vehicle or bike maintenance might underestimate the actual associated costs. A consumer might overestimate or underestimate the probability that external shocks (e.g., natural disasters) will affect the value of a particular house. Finally, a consumer might simply be inattentive to some attributes or the price of a product (Lacetera et al., 2012; Chetty et al., 2009)

[4]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.

[5]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.

[6]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

the product from the owners and sell it to the buyers.

Buyers' expected utility from consuming the product is given by $u_B(\theta) = v_B - \hat{z}(\theta)$, and 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 gives positive utility and that there are positive gains to trade, we assume a bound on attribute $z \in (0,1)$ and $V \in (0, \infty)$. The expected utilities for the buyers and the sellers can then be written as:

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

$$u_B(\theta) = u_S + \underbrace{V}_{\text{actual gains of trade}} + \underbrace{\theta z}_{\text{perceived gains of trade}} \tag{3}$$

Buyers with $\theta = 0$ accurately evaluate the product, and consumers with $\theta = 1$ completely ignore the value of attribute 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 pay (on average) less attention. On the supply side, current product owners are characterized by their transaction cost to supply in 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, such as the costs of traveling to where the potential buyers are and demonstrating and explaining the product, the opportunity cost of using the product in that time period, and potential legal liability after the sale. These costs might be higher for high-earning individuals who face a large opportunity cost and lower for owners geographically close to potential buyers. We assume that an owner trying to sell her asset directly to a buyer incurs this transaction cost (k), meets one buyer at random, and makes a take-it-or-leave-it offer.

The final type of player is the 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 c (e.g., cleaning and repackaging the product, salesperson effort) for each transaction. Several papers have considered similar settings in which intermediaries

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.

are more efficient at matching buyers to sellers. For example, Hendel et al. (2009) show that in the real estate market, the time required to sell is faster if an intermediary is used. We capture this improved efficiency by assuming that some owners have higher transaction costs than the intermediary. $c < \bar{k}$[7] The timing of the game is as follows:

t=1: The intermediary offers a purchase price p^S to all owners[8]. 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 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 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 this 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. Second, intermediaries proactively use marketing strategies, such as advertising, to find buyers.

3.3 Analysis

We now solve the game by backward induction[9]. 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, each player

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

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

[9]To facilitate tractability and exposition, we focus on the case of relatively significant gains of trade ($V \geq 1$). In addition, we assume that the intermediary's cost is sufficiently low, $c < V - z\bar{\theta}$, such that the intermediary never shuts down.

needs 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 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 that remain in the market because they did not purchase in the first period and. We show below that only consumers with a sufficiently high level of inattention (i.e., $\theta > \hat{\theta}$) purchase from the intermediary in the first period. Thus, for players with accurate beliefs about the distribution of inattention, this is given by $P(\text{accept}|p^D) = \int_{\frac{z-1-V+p^D}{z}}^{\hat{\theta}} f(\theta)d\theta$. Consumers misperceive the value of attribute z and thus expect that private sellers set the price conditional on this inaccurate value:

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

Solving the perceived profit maximization problem, buyers' expectation about the price in the decentralized market is $E[p^{D*}|\theta] = 1 + V - (1-\theta)z$. However, individual sellers set the price that maximizes profit, subject to the actual distribution of consumers.[10] Thus, the actual equilibrium price in the decentralized market is given by $p^{D*} = 1 + V - z$. In Figure 2, we show the resulting equilibrium prices and price expectations that define the segments of consumers purchasing in either the decentralized or intermediary market.

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: $\hat{\theta} = \frac{p^I - V}{z}$, and demand for the intermediary is given by: $D(p^I) = \int_{\hat{\theta}}^{\bar{\theta}} f(\theta)d\theta$. 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

[10] 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.

the following maximization problem:

$$(p^{I*}, p^{S*}) = \arg \max_{(p^I, p^S)} E[\pi] = D(p^I) \times (p^I - p^S - c) \\ \text{s.t. } 0 \leq D(p^I) \leq S(p^S) \leq 1 \tag{6}$$

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 the seller's transaction cost is sufficiently low, the intermediary's transaction quantity is zero. This treatment is consistent with other models in which the intermediaries' role primarily is to reduce transaction costs. However, when consumers are inattentive, the intermediary can capture inattentive consumers (with a higher willingness to pay), and the market gets segmented. This equilibrium outcome is formally presented as follows:

Proposition 1 *Consumers with high levels of inattention ($\theta > \hat{\theta}$) purchase from the intermediary, and the intermediary prices are higher than prices in the decentralized market ($p^{I*} > p^{D*}$).*

Consumers visit the intermediary first and decide between purchasing the product or waiting to potentially purchase in the decentralized market. 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, they also overestimate the price for such a product in the consumer market.[11] Because inattentive consumers overestimate the price in the consumer market, the intermediary's price simply 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

[11] Note that inattention, rather than heterogeneity in 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. The results are that competition between the centralized and decentralized market 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.

an offer's being declined. Because the consumer base in the decentralized market is relatively more attentive, the decentralized market price gets pushed down. This outcome is formally stated in the following result:

Proposition 2 *For sufficiently high gains of trade:*
As inattention increases, transaction prices in the decentralized market are constant ($\partial p^{D*}/\partial\bar{\theta} = 0$), intermediary prices are increasing ($\partial p^{I*}/\partial\bar{\theta} > 0$), and intermediary purchase prices are increasing ($\partial p^{S*}/\partial\bar{\theta} > 0$). Furthermore, the quantity of decentralized transactions decreases ($\partial Q^{D*}/\partial\bar{\theta} < 0$), and the quantity of intermediary transactions increases ($\partial Q^{I*}/\partial\bar{\theta} > 0$).

This equilibrium showcases the role of an intermediary in a market with inattentive consumers. To understand the intuition of the equilibrium, imagine prices are held constant. An increase in inattention leads to more demand for the intermediary and a drop in demand in the consumer market because inattentive consumers overestimate the value of the product, as well as the price they expect to pay in the decentralized market. However, prices are not fixed, and both the intermediary and individual sellers react strategically. As inattention increases, the intermediary reacts to the increased demand by raising sales prices and improves supply by setting a higher purchasing price. The remaining consumers that visit sellers in the decentralized market are relatively attentive. In equilibrium, the price charged in the consumer market does not react to the increase in inattention because inattentive consumers purchase from the intermediary. For the remaining attentive consumers, the potential gains from increasing the price to benefit from inattentive consumers are dominated by the opportunity cost of missing out on transactions with more attentive consumers. In equilibrium, we observe two prices for identical products. Inattentive consumers pay a higher price (to the intermediary) while attentive consumers pay a lower price (in decentralized transactions), and this difference between the two prices increases as the level of inattention increases.

3.4 Effect of Intermediary

We now analyze the effect of the intermediary more explicitly by comparing the market outcomes when only consumer-to-consumer trade occurs and when both intermediary and consumer trade are 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 relatively inattentive consumers will accept this price. Particularly when the gains of 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. Because sellers cannot identify inattentive consumers, the opportunity cost of missing out on transactions from relatively attentive consumers protects the most inattentive consumers 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 (i.e., $V > \bar{\theta}z$), the opportunity cost is sufficiently high and inattention has no effect on the market equilibrium. The situation changes when the intermediary is present. The intermediary sets a high price and sells to relatively inattentive consumers to avoid competing with individual sellers in the decentralized market for the relatively attentive consumers.

The effect of the intermediary's presence can be summarized in three succinct points. First, consumers can purchase either from the intermediary or directly from an owner, creating competition. Second, the intermediary purchases goods from owners who would not have entered the market in the absence of an intermediary because of high transaction costs, so that the intermediary's presence increases the quantity supplied. Third, the intermediary, with its lower transaction cost, is able to skim the inattentive consumers 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 consumer surplus and increases owner seller surplus.*

Other studies have shown that competition does not always eliminate excess surplus from behavioral biases (Gabaix and Laibson, 2006). Offering a different perspective, our result is noteworthy, in that it shows how adding an intermediary (which creates competition) decreases consumer surplus. In most economic scenarios, competition improves outcomes for consumers through an increase in welfare and makes firms worse off. For example, the Bertrand paradox implies that a single firm can set monopoly prices, but the entry of even one other firm could eliminate all potential profits in the market. This intuition does not hold in the present 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' inattention with the opportunity cost of attentive consumers' declining high-price offers. In the absence of an intermediary, attentive consumers "protect" inattentive consumers from being charged a higher price. However, in a market with an intermediary and decentralized trade, this opportunity cost is not an issue because the intermediary can "skim" the inattentive consumers while the more attentive consumers can purchase the good in the consumer market. Attentive consumers protect inattentive consumers from exploitation when there is only one seller. However, this outcome breaks down when two types of sellers are catering to consumers with different levels of attention, leading to market segmentation and the ensuing expropriation of the consumer surplus.

3.5 Left-Digit Bias and Testable Predictions

We have so far considered a general model in which z could capture any one of several attributes that consumers might not attend to. To empirically test predictions from this model, we require variations in the level of consumers' inattention while other variables are held 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 the well-documented finding that consumers in many marketplace interactions are left-digit biased. More specifically, in the resale markets for passenger vehicles, left-digit-biased consumers might pay full attention to the left-most digits of the odometer reading.[12] 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 results 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 left-most digit. In our model, utility decreases in magnitude of the continuous

[12]The identification strategy could easily be applied to other contexts where left-digit-biased consumers need to evaluate continuous attributes. Some potential examples are product attributes, such as fuel economy, the weight of a vehicle, expiration dates, the age of a product, or the size of a product.

attribute $M \in [0, 10)$.[13] For a consumer with an inattention parameter θ, the perceived value of attribute M is given by

$$\hat{M}(\theta) = \lfloor M \rfloor + (1 - \theta)(M - \lfloor M \rfloor), \tag{7}$$

where $\lfloor \cdot \rfloor$ is the floor operator.[14] For example, if $\theta = 1/3$ and $M = 4.92$, the perceived attribute value is given by $\hat{M} = 4 + (1 - 1/3)(0.92) = 4.61$.

Sellers' and buyers' product utility is given by the following:

$$u_S = v_S - \alpha M. \tag{8}$$

$$u_B = v_B - \alpha \hat{M}(\theta), \tag{9}$$

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.[15]

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. 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 can characterize predictions for equilibrium inattention, prices, and equilibrium quantities.

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

1. *Average inattention is lower in consumer-to-consumer transactions than in intermediary transactions.*

2. *There is a negative discontinuity in intermediary sales prices ($\Delta p^{I*} < 0$).*

3. *The discontinuity in intermediary sales prices is larger in absolute terms than the discontinuity*

[13] 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 fully pay 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.

[14] 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: $\lfloor M \rfloor = M - M \bmod 10,000$.

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

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

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 consumer transactions ($|\Delta Q^{I*}| \geq |\Delta Q^{D*}|$).*

The proposition derives six empirically testable predictions, regarding consumer inattention (θ), *prices*(p^I, p^D, and p^S), and the number of consumer market (Q^D) and intermediary (Q^I) transactions. In the proposed market equilibrium, the intermediary charges a higher price and serves relatively more inattentive consumers. This skimming of inattentive consumers leaves only relatively attentive consumers in the decentralized market. Because the intermediary can charge a higher price when consumers are inattentive, it also has an incentive to sell a higher quantity at the higher price. To obtain a higher quantity to sell, the intermediary increases the purchase price offered to owners. As noted, because the intermediary skims inattentive consumers from the market, owners are selling to relatively attentive consumers who do not accept higher prices. Thus, the 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: (i) that inattention increases intermediary prices relative to consumer market prices, and also (ii) that inattention increases the quantity of transactions for the intermediary, relative to the quantity in the consumer market. This seemingly counterintuitive increase in both the price and the quantity follows from the intermediary's selling to the relatively inattentive segment. Rationalizing this increase in quantity and price is difficult without this proposed behavioral segmentation.[16] The result provides a particularly strong test of our proposed theory.

[16]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 more detail and then proceed to test the main analysis.

4.1 Empirical Context

Our empirical context is the U.S. passenger vehicle resale market. The passenger vehicles are actively traded between consumers, as well as through intermediaries (i.e., used car dealerships). Despite the car 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 identify numerous reasons why consumers might first visit a dealership in search for a used car. First, vehicles traded through a dealer generally 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, potential consumers often can view and compare vehicles on the dealership website and inspect and test-drive multiple vehicles within a short time span when visiting a dealership. And third, dealerships offer additional services, such as accepting trade-ins or offering financing options that reduce the transaction costs further. To closely match the analytical model, we focus on transactions between consumers and transactions where the same dealership buys and sells a vehicle.

We observe detailed information on vehicle transactions, including the price a dealership paid to procure a vehicle (which we refer to as the dealer purchase price) and the price at which the dealer sold the vehicle[17]. We also observe the prices at which vehicles are sold in the consumer markets. The analytical model maps quite well to our empirical context. However, we also want to highlight a few important differences. First, in the analytical model, we consider one intermediary, 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 model. Third, for simplicity, we consider homogenous goods in our model, but the

[17]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.

vehicle market clearly is vertically and horizontally differentiated. Despite these differences, our data include enough useful ingredients of the resale market to allow our model to assess the role of inattention.

4.2 Data

The primary dataset of our study consists of all vehicle transactions (consumer-to-consumer and through a dealership) in the state of Texas between September 2015 and December 2021, which comprises approximately 10% of vehicle transactions in the United States (FHA, 2018). Our data come directly from 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 collection 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 at the transaction date[18]. 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 VIN in our sample. 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. In Table 2, we present summary statistics of the data.

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. Empirically, we consistently find discontinuities at 10,000-mile marks, while discontinuities at the smaller cutoffs are smaller

[18]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.

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

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

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 that follow from the model. The predictions concern three elements: (i) the level of inattention of consumers, (ii) the effect on prices, and (iii) the effect 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 at the intermediary. Third, we consider the effect of inattention on pricing and on quantity.

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 in the consumer transactions than in the dealership transactions.

To accurately estimate the inattention parameter, we need to jointly account for the continuous, potentially non-linear 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 estimate the inattention parameter.[19] We

[19]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.

estimate the model separately for dealership transactions and consumer-to-consumer 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 non-linear depreciation, and we rearrange the formula to get the following:

$$price_i = \beta_0 + \sum_{k=1}^{K} \alpha_k (\underbrace{M_i - \theta(M_i - \lfloor M_i \rfloor)}_{\text{Perceived Mileage}})^k + \psi X_i + u_i, \tag{11}$$

where X_i denotes a vector of the fixed effects we describe below. In this specification, 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 11 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. [20] 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. The 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 consumer 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 odometer readings and generally are less depreciated (see Figure A3 in the online Appendix). Thus, one potential issue might be that vehicles sold by intermediaries generally are newer, and consumers might 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

[20] 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 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 consumer 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 consumer 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 69,000mi is perceived as having 64,896mi by consumers at dealerships and 67,155mi 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 4 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 outcome.

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

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, and 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 implies 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 in and subsequently sold by the dealer. To show potential discontinuities in purchasing price and sales price, Figure 3 graphically shows the change in average purchasing price, average subsequent sales price, and average profit (i.e., the difference between purchase price and sales price). 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 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[21]. Even though the plot is based on millions of observations, the raw data remain noisy. To get more accurate estimates and to formally test our hypotheses, we next consider a regression, similar to Lacetera et al. (2012):

$$y_i = \beta_0 + \sum_{k=1}^{K} \alpha_k miles_i^k + \sum_{j=1}^{14} \beta_j \mathbf{1}\left[miles_i \geq j \times (10,000)\right] + \gamma X_i + u_i, \tag{12}$$

where y_i is our outcome variable of interest (sales price, purchase price, and profit). We fit a

[21]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.

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[22] . 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 cutoff. We present the results for the outcome variables of sales price, 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 are increasing 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.[23]

The interpretation of the coefficients is that dealerships charge a significantly higher price for 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, but the dealership also earns a higher margin on vehicles immediately under a 10,000-mile cutoff.

Predictions (4) and (5) focus on the differences 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

[22]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. 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.

[23]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.

sales price and purchase price, respectively. The model we estimate is given by:

$$y_i = (1 + \mathbf{1}[\mathrm{D}_i]) \left(\beta_0 + \sum_{k=1}^{K} \alpha_k miles_i^k + \sum_{j=3}^{14} \beta_j \mathbf{1}[miles \geq j \times (10,000)] \right) + \gamma X_i + u_i, \tag{13}$$

where $\mathbf{1}[\mathrm{D}_i]$ 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 13. We present the interacted coefficients in Table 5.[24] The differences between decentralized and dealership prices are significantly negative in the range between 60,000 miles and 100,000 miles, where most transactions occur. For example, the parameter at 60,000 miles is -\$115.17, which implies that, after controlling for all fixed effects and the continuous portion of depreciation, the difference between dealership prices and decentralized transaction prices decreases by -\$115.17. The difference between the dealerships' purchasing price and the decentralized prices is insignificant throughout. Thus, the discontinuity is not significantly different for intermediary transactions compared to decentralized transactions.

4.4.2 Number of Transactions

In this section, we test predictions about the quantity of transactions in intermediary and decentralized markets. We have shown that vehicles below round thresholds are relatively cheaper in the decentralized market. However, because of the proposed skimming strategy, we expect that the intermediary sells a larger quantity, despite the vehicles being more expensive. As a result, we test two predictions:

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

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

Figure 4 plots the number of dealership transactions, and decentralized transactions, using the same aggregation to 1,000-mile buckets as in figure 3. The plot 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 much less

[24] 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.

pronounced and are only significant for the cutoffs at 90,000 miles and 100,000 miles[25].

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, a clear discontinuity is visible at the 100,000-mile mark.

To precisely estimate the effects and test the predictions, we conduct a regression of the relative quantity of transactions through an intermediary vs. transactions in the decentralized market.[26] We re-estimate the model given in Equation 12, but the outcome variable of interest is an indicator for the transaction's 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 dealer, 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 highly 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.

4.5 Discussion of Results and Robustness Checks

We have derived numerous predictions emanating from the theoretical model that we identify by leveraging the discontinuity in *perceived* mileage around the 10,000-mile marks. Although different explanations could potentially rationalize each prediction in isolation, the combined validity of our predictions makes for a solid empirical test of our theory. In particular, our theory predicts that the intermediary is in a particularly good position to benefit from inattention and leverages this position by (i) charging higher prices and (ii) only partially passing this increased price through to sellers. Interestingly, the intermediary charges a higher price for vehicles valued by consumers and

[25]Due to the nature of the data, odometer readings for decentralized transactions may be more likely to be rounded. We deal with this likelihood in several robustness checks, such as removing presumably rounded observations (e.g., vehicles with precisely 51,000 miles), and conclude that rounding behavior cannot fully explain the observed pattern in the data.

[26]We consider the estimation of raw numbers (i.e., Prediction 6a in Table A1 in the online Appendix) because it largely mirrors the results for the relative change.

sells a higher quantity, both in absolute terms and relative 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 in the market by offering a higher purchase price for vehicles below the 10,000-mile cutoffs. Intermediaries significantly increase the price for vehicles below the 10,000-mile thresholds.

We provide additional robustness checks and analysis in online Appendix B, where we present a placebo test that includes 10,000-kilometer thresholds. The United States uses the imperial measurement system, and kilometers are never observed by consumers. We expect the kilometer variables to be insignificant and largely find insignificant coefficients. The placebo test provides additional confidence that the polynomials included to capture the non-linear effects of the odometer reading sufficiently capture the vehicle's depreciation.

5 Supply Response

In the theoretical model, we assumed that supply is a function of the (uniformly distributed) transaction cost. However, the exact level of pass-through is a function of the elasticity of supply. This section aims to estimate the supply-side response to inattention and how changes in inattention might affect consumer welfare, owner welfare, and firm profit. Similar to other papers that consider used car markets (Gavazza et al., 2014), we focus on the vertical differentiation associated with different odometer readings[27]. We estimate a supply-side model, as well as the depreciation and inattention on the demand side. After estimating the model, we then consider counterfactual scenarios of different levels of inattention. To focus on the supply-side response, we use a reduced-form approach to estimate the depreciation and inattention; we assume the market to be competitive enough that one price attaches to each odometer reading of vehicles and that sufficient market demand exists at that price. This clearly is a simplification of a complex market, but we believe the modeling approach is appropriate for our purposes because of our formulation of inattention to odometer readings.[28]

[27]Clearly, we are abstracting away from other features of the car market, such as horizontal differentiation (Berry et al., 1995).

[28]Furthermore, the gains from estimating a demand-side model with substitution between different vintages in our context are outweighed by the increased complexity and loss in interpretability.

5.1 Estimation

Estimation of the model broadly requires the following three steps:

1. Estimate the demand parameters (inattention and prices) and the counterfactual prices corresponding to different levels of inattention.
2. Estimate the elasticity of supply.
3. Using counterfactual prices, re-solve the firm's first-order condition, invert the quantity equation, and calculate counterfactual quantities and owner surplus.

We explain additional details about the estimation in online Appendix C. We begin by aggregating vehicles of the same mileage into 10-mile buckets, or bins. We then estimate the quantity of transactions, the mean sales price, and the mean purchase price for each bin of vehicles. We denote each bin as $\tilde{m}$ (e.g., $\tilde{m} = \{14,890mi, 14,891mi, ..., 14,899mi\}$ is one bin).

In Step 1, estimating the demand-side parameters, we use each 10,000-mile cutoff to identify the parameters locally and to allow for different depreciation and inattention for different odometer readings. Similar to Busse et al. (2013), we split the data into $j \in J$ buckets that contain vehicles within 5,000 miles above and below each cutoff of $10,000 \times j$ (e.g., vehicles between 15,000 and 24,499 miles). We let $J = \{2, 3, ...15\}$ and estimate the following:

$$ln(p_{\tilde{m}}) = \beta_0 + \beta_1 \text{miles}_{\tilde{m}} + \beta_2 \mathbf{1}\left[miles_{\tilde{m}} \geq j \times (10,000)\right] + u_{\tilde{m}}, \tag{14}$$

From this equation, we can estimate the average depreciation by "spreading" the discrete jump in price across the full 10,000 miles: $\alpha = \hat{\beta}_1 + \frac{\hat{\beta}_2}{10{,}000}$. We can estimate the inattention parameter as $\hat{\theta} = 1 - \frac{\hat{\beta}_1}{\alpha}$. Now, we can invert the price estimate and estimate a counterfactual price for any level of inattention $\theta = \theta'$:

$$ln\left(p(\theta')_{\tilde{m}}\right) = \beta_0 + \alpha \times \left(\underbrace{(1-\theta')\text{miles}_{\tilde{m}}}_{\text{continuous depreciation}} + \underbrace{\theta' \times 10,000 \times \mathbf{1}\left[miles_{\tilde{m}} \geq j \times (10,000)\right]}_{\text{discrete depreciation}} \right).$$

In Steps 2 and 3, we estimate the supply side and the supply side response to counterfactual prices. The opportunity cost for product owners (i.e., continuing to use the vehicle or selling it in the decentralized market) is given by some function $f(m)$, where m denotes the vehicle's odometer reading. We assume that $f(m)$ decreases smoothly as m increases. Each owner faces a binary choice of supplying the vehicle to the intermediary in exchange for a purchase price or keeping the vehicle; we assume that the aggregate supply function is given by the following iso-elastic function of the opportunity cost and the purchase price: $S(p^S) = Am^\beta p^{S^\epsilon}$. The intermediary needs to solve the following profit maximization problem:

$$p^{S*} = \underset{p^S}{argmax}\ \Pi(p^S) = Am^\beta p^{S^\epsilon} \times (p^I(\theta) - c - p^S).$$

Solving the first-order condition, the intermediaries' optimal purchase price is thus given by $p^{S*} = \frac{\epsilon(p^I(\theta)-c)}{1+\epsilon}$. To estimate the elasticity of supply, we estimate the following linear model:

$$ln(Q_i) = \alpha + \epsilon ln(p_i^S) + \beta ln(\text{mileage}_i) + u_i. \tag{15}$$

A common problem with the estimation of elasticity in such specifications is the endogeneity of price (or purchase price in our case) because dealers offer higher prices for vehicles of higher quality. To address the problem, we propose a novel identification strategy. Similar to the canonical econometric example of using a change in demand to identify supply curves, we propose using a *behavioral* demand shift to estimate the elasticity of supply. Thus, to estimate the elasticity, we instrument for the price by using the discontinuity in the purchase price that stems from the discontinuous change caused by inattention. The first stage estimator is given by $ln(p_i^S) = \gamma_0 + \gamma_1 \mathbf{1}\left[miles_i \geq j \times (10,000)\right] + \gamma_2 ln(\text{mileage}_i) + u_i$. We test for instrument relevance and find significant F-statistics for most 10,000-mile thresholds. The instrument also needs to satisfy the exclusion restriction, which implies that product owners' reservation value needs to be smooth around the 10,000-mile cutoffs.[29]

The assumption that the reservation price of owners is continuous can be justified both theoretically and empirically. First, in the theoretical model we proposed, the reservation price is constant around round cutoffs because of the inability to take advantage of the inattention in the

[29] In principle, we could identify elasticity even when owners are inattentive, as long as we observe the level of inattention. To do so, we would substitute the mileage in the supply function with the perceived mileage, conditional on the level of inattention.

decentralized market. Second, we find that the changes in decentralized transaction prices exhibit relatively small (largely insignificant) discontinuities at the 10,000-mile marks, which supports the assumption.[30] We describe the exact specification for estimating the elasticity of supply in online Appendix C.

We now invert the estimated supply function and use the estimated parameters to calculate the counterfactual quantity for each level of inattention. We also can estimate the change in owner surplus for each 10 mile odometer bin using the estimated parameters. Owners benefit in two potential ways when inattention increases. First, a higher purchase price benefits all owners who sold their vehicles at a lower price. Second, the number of transactions increases because some owners who were unwilling to sell at the lower price are now willing to supply the vehicle. The change in owner surplus is given by: $\Delta OS = \int_0^{Q^{CF}} (p^S - p^{S^{CF}})dQ + \int_{Q^{CF}}^{Q} (p^S - p^S(Q))dQ$. The first term is the gain in money for people who also would have sold the vehicle under the counterfactual (lower) price. The second term captures the surplus for owners who would not sell the vehicle at the lower purchasing price. From the econometric specification in Step 2, we can invert the elasticity formula, which gives $p^S(Q) = exp(\frac{ln(Q)-\gamma(m)}{\epsilon})$, where $\gamma(m)$ is the intercept, conditional on mileage. Now, taking the definite integral, we get the following closed-form solution for the change in owner surplus:

$$\Delta OS = Q^{CF} \underbrace{(p^S - p^{S^{CF}})}_{\Delta t} + \underbrace{p^S(Q - Q^{CF}) - \frac{e^{-\frac{\gamma(m)}{\epsilon}} \epsilon (Q^{1+\frac{1}{\epsilon}} - Q^{CF 1+\frac{1}{\epsilon}})}{1+\epsilon}}_{\text{Surplus for marginal owners}}. \tag{16}$$

We now estimate the counterfactual purchasing and sales prices, quantities, profits, and owner surplus for any level of inattention[31].

5.2 Results

The estimated elasticity of supply, inattention, and depreciation are presented in Table 7. Some observations are in order. First, inattention generally seems to increase for higher odometer readings. The estimated inattention parameter is close to 0.2 for most vehicles below 75,000 miles and significantly higher for older vehicles. Second, our estimates of the elasticity of supply seem

[30] Under the assumption that owners are unaware of consumer inattention, the change in purchase price is a random shock to owners.

[31] The results also allow us to approximate the payoff to increased attention. We do so in online Appendix B and find some limited evidence of increased attention when the payoff to attention is higher.

quite reasonable, with a mean value of 2.92. The elasticity generally decreases for older vehicles. Third, the depreciation (i.e., the approximate percentage change in the price of the vehicles across a 10,000-mile range) drops significantly for vehicles after 100,000 miles.

In addition, having estimated the model, we compute several counterfactual scenarios, presenting three broad sets of results. First, we consider the counterfactual of no inattention to measure the aggregate effect of inattention. Second, we estimate bounds to the aggregate effect and estimate the model under the two most extreme assumptions of fully attentive and fully inattentive consumers. Third, we consider an analysis at the dealership level and approximate the effect of inattention for each dealer in our data.

5.2.1 Aggregate Effect of Inattention

First, we consider the actual level of observed inattention and compare it to the counterfactual of full attention. We estimated the quantity, purchase price, and transaction price for each 10-mile bucket of vehicles. After aggregating vehicles of all mileages for each variable of interest, we estimated the following for these variables while letting $\hat{\theta}$ denote the actual estimated value of inattention:

$$\Delta x = \int_{\boldsymbol{M}} \Big(x(m, \theta = \hat{\theta}) f(m|\theta = \hat{\theta}) - x(m, \theta = 0) f(m|\theta = 0) \Big)\, dm.$$

We estimated the counterfactual outcomes for the full range of estimated odometer readings.

For the estimated aggregate effects, the observed total operating profits are 4.37% higher than in the full attention counterfactual. Average sales prices increased by 0.48%, and the average purchasing price increased by 0.31%. (Note that these average price changes represent the full range of odometer readings; the price increases are larger around the cut-offs.) In addition, the average profit per vehicle increased by 1.8%, and the number of transactions increased by 2.53%. Owner surplus increased by 2.77%.

An intermediary charges different selling prices and offers different purchasing prices, depending on the overall level of inattention. These decisions also affect which vehicles, with varying odometer readings, are bought and sold. More specifically, inattention increases the proportion of transactions involving vehicles that have relatively high odometer readings within each 10,000-mile range. We found that, on average, the odometer reading of transacted vehicles was 351 miles lower in the case of full attention. Thus, when inattention was present, consumers paid a higher price and -on average- received an older vehicle. Holding mileage constant,[32] we estimated that the average sales price increased by 0.75% and the average purchasing price increased by 0.64%.

Figure 5 shows a non-parametric regression and a plot of the estimated fit. We found a general pattern that vehicles around 100,000 miles are most affected by the inattention. In addition, we noted substantial heterogeneity in the effect of inattention on different odometer readings. For relatively new vehicles with low odometer readings and relatively old vehicles, inattention largely disappears.

Given the large number of transactions at high transaction prices, these numbers have non-trivial marketplace consequences. Total dealership operating profits were about \$10.068 billion during our sample period; in the counterfactual with full attention, they were about \$9.647 billion– a difference of about \$422 million during our sample period, or about \$58 million annually. Similarly, we estimated an increase in owner surplus of \$478 million during the sample period. Back-of-the-envelope calculations suggest that this increase in owner surplus comes close to about \$600 million annually when scaled to the full set of transactions in the United States.

5.2.2 Bounding the Effect of Inattention

In this section, we consider the two extreme cases– no inattention ($\theta = 0$) and complete inattention ($\theta = 1$)– to estimate bounds on how much inattention can affect market outcomes. A case in which all consumers ignore depreciation between 10,000-mile marks obviously is not realistic in the context of odometer readings, but this extreme case might emerge in different market contexts. This exercise allows us to be bound the magnitude of effects stemming from inattention. Again, We integrated the full mass of vehicles to estimate aggregate effects. To do so, we estimated the following for all variables of interest:

$$\Delta x = \int_{\boldsymbol{M}} \left(x(m, \theta = 1) f(m|\theta = 1) - x(m, \theta = 0) f(m|\theta = 0)\right) dm$$

Several observations are in order. First, the effects on average selling prices (4.03%) and purchasing prices (3.5%) are moderate. However, the intermediary's operating profit is significantly

[32]To do so, we estimated $\Delta x = \int_{\boldsymbol{M}} \left(x(m, \theta = \hat{\theta}) f(m|\theta = 0) - x(m, \theta = 0) f(m|\theta = 0)\right) dm$.

higher (19.7%). The gain in profits comes partially from higher margins and, almost as importantly, from a higher quantity of transactions.

Using the actual value of inattention, we can compare its outcome to these bounds. Figure 6 shows a plot of the estimated fit, based on non-parametric regressions for the estimated values of θ and the cases of both full and no inattention. The results reveal an interesting pattern: The *potential* change in profit from inattention was largest for lower values of odometer readings, but the observed values were relatively close to the bound of no inattention. For vehicles with higher odometer readings, an intermediary's profit was significantly closer to the bound of full inattention.

5.2.3 Intermediary Effects

We have shown that the effect of inattention varies greatly based on vehicles' different odometer readings. In this section, we briefly consider the effect of inattention, conditional on the product mix transactions at each dealership. We use the model estimated previously and integrate the distribution of vehicle transactions for each dealership d that has 100 transactions in our sample.

$$\Delta x_d = \int_{\boldsymbol{M}} \left(x(m, \theta = \hat{\theta}) g(m|\theta = \hat{\theta})_d - x(m, \theta = 0) g(m|\theta = 0)_d \right) dm$$

To illustrate the resulting heterogeneity, we estimated the empirical cumulative distribution of profit and compared it to the case with full inattention and the case without any inattention. Figure 7 provides the results. In the observed case, the median operating dealer profit was estimated to be \$2,460,687. In contrast, in the counterfactual case involving no inattention, the median dealer operating profit was \$2,354,437, and in the case with complete inattention, it was \$2,809,975.

6 Conclusion

For the past 50 years, the literature has considered solutions to the asymmetric information problem originally framed by Akerlof (1970). In this paper, we reframed the asymmetric information problem as a problem of consumers' failing to pay attention, instead of sellers' failing to disclose information. We explored the consequences of this inattention in durable goods resale markets, both 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 from the model and found evidence of intermediaries benefitting from being able to sell to (relatively) inattentive consumers via behavioral segmentation. Our supply-side estimates show that the effect of inattention is quite sizable, in that about 4.37% of total intermediary profits are attributable to consumer inattention. This effect is driven by a 2.53% increase in quantity and 1.8% improvement in margins.

Our paper has several limitations. The theoretical model is designed to be parsimonious to capture the proposed mechanism's key elements, but it abstracts away several important considerations. For example, both horizontal and vertical differentiation are omnipresent in durable goods markets, but we do not simultaneously model them in this study. Furthermore, we assume 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 traditional sources of asymmetric information, such as the lemons problem. The interplay of asymetric information and behavioral frictions might lead to additional insights, particularly because disclosing more information allows sellers to benefit from inattentive consumers. In the most extreme case, the benefit from selling to inattentive consumers might 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, research could look at how firm channel management decisions might differ when consumers are inattentive to certain attribute. 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 in evaluating a product and consumer inattention.

Our paper has several implications for policymakers, managers, and researchers. First, we document that inattention has a moderate yet significant effect on numerous outcomes in the market for durable goods. Disclosing information traditionally has 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 make systematically different choices about where to purchase the product. In our setting, the inattention of consumers who purchased from an intermediary was significantly higher than the inattention 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	Median	Pctl(75)	Pctl(25)	St. Dev.
Odometer Reading	4,820,961	59,979	54,450	85,023	30,591	35,894
Odometer Reading (D)	1,600,988	71,826	70,809	105,454	36,132	40,742
Odometer Reading (I)	3,219,973	54,089	49,223	74,963	28,930	31,610
Transaction Price	4,820,961	19,388	16,870	25,990	10,083	13,448
Transaction Price (D)	1,600,988	13,592	9,000	18,000	4,500	14,124
Transaction Price (I)	3,219,973	22,271	19,630	28,048	13,869	12,107
Purchase Price (I)	3,219,973	19,565	17,000	25,123	10,800	13,174
Profit (I)	3,219,973	2,706	3,464	4,991	1,887	6,655
10K miles	4,820,961	0.96	1	1	1	0.201
20K miles	4,820,961	0.86	1	1	1	0.344
30K miles	4,820,961	0.76	1	1	1	0.429
40K miles	4,820,961	0.65	1	1	0	0.478
50K miles	4,820,961	0.54	1	1	0	0.498
60K miles	4,820,961	0.45	0	1	0	0.497
70K miles	4,820,961	0.36	0	1	0	0.481
80K miles	4,820,961	0.29	0	1	0	0.452
90K miles	4,820,961	0.22	0	0	0	0.412
100K miles	4,820,961	0.16	0	0	0	0.365
110K miles	4,820,961	0.11	0	0	0	0.317
120K miles	4,820,961	0.08	0	0	0	0.265
130K miles	4,820,961	0.05	0	0	0	0.208
140K miles	4,820,961	0.02	0	0	0	0.140

Note: (D) denotes decentralized consumer-to-consumer trade. (I) denotes intermediary transactions through a used car dealership. x miles is the indicator variable that equals 1 for vehicles with odometer readings above x.

Table 3: Estimate of the Inattention Parameters

	Sample			
	Dealership	Dealership	Decentralized	Decentralized
	(1)	(2)	(3)	(4)
Inattention (θ)	0.400***	0.456***	0.281***	0.205***
	(0.015)	(0.016)	(0.042)	(0.044)
Observations	2,483,539	2,483,539	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

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

Note: 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.

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

	Dependent variable:		
	Purchase Price	Sales Price	Dealership Profit
	(1)	(2)	(3)
10k miles	-74.311^{*}	-146.470^{***}	-72.396^{*}
	(43.303)	(22.167)	(42.430)
20k miles	-99.497^{***}	-71.169^{***}	28.541
	(32.112)	(16.438)	(30.712)
30k miles	-86.629^{***}	-105.981^{***}	-20.499
	(28.805)	(14.745)	(28.424)
40k miles	-127.502^{***}	-166.062^{***}	-37.734
	(29.245)	(14.970)	(26.874)
50k miles	-113.434^{***}	-140.961^{***}	-26.211
	(29.182)	(14.938)	(28.174)
60k miles	-146.869^{***}	-192.465^{***}	-46.891^{*}
	(30.530)	(15.628)	(28.499)
70k miles	-108.450^{***}	-238.437^{***}	-131.878^{***}
	(32.816)	(16.798)	(31.307)
80k miles	-100.196^{***}	-185.423^{***}	-83.774^{**}
	(35.333)	(18.087)	(33.350)
90k miles	-162.354^{***}	-278.346^{***}	-113.127^{***}
	(40.102)	(20.528)	(37.829)
100k miles	-44.559	-212.804^{***}	-170.208^{***}
	(46.980)	(24.049)	(44.971)
110k miles	-35.891	-25.657	5.028
	(59.199)	(30.304)	(54.420)
120k miles	-31.413	-130.846^{***}	-96.122
	(70.165)	(35.917)	(67.901)
130k miles	-61.771	-80.636^{*}	-12.397
	(88.471)	(45.288)	(83.230)
140k miles	-233.719^{*}	-207.621^{***}	13.468
	(121.018)	(61.949)	(108.202)
Observations	3,219,973	3,219,973	3,219,973
R^2	0.782	0.932	0.142
Polynomial Order	11^{th}	11^{th}	9^{th}
Fixed Effects	Yes	Yes	Yes

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

Note: We omitted polynomial parameters and intercepts in 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.

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

	Dependent Variable: Price	
	(Decentralized vs Dealership Sales Price)	(Decentralized vs Purchase Price)
	(1)	(2)
$\mathbf{1}_{\text{Dealer}}\times$30k miles	−50.306	−27.078
	(44.451)	(67.676)
$\mathbf{1}_{\text{Dealer}}\times$40k miles	34.699	60.735
	(37.994)	(57.845)
$\mathbf{1}_{\text{Dealer}}\times$50k miles	48.716	84.831
	(36.112)	(54.979)
$\mathbf{1}_{\text{Dealer}}\times$60k miles	-115.165^{***}	−79.560
	(36.086)	(54.940)
$\mathbf{1}_{\text{Dealer}}\times$70k miles	-66.267^{*}	47.399
	(36.536)	(55.624)
$\mathbf{1}_{\text{Dealer}}\times$80k miles	-129.325^{***}	−38.784
	(36.146)	(55.031)
$\mathbf{1}_{\text{Dealer}}\times$90k miles	-143.767^{***}	−38.461
	(37.804)	(57.556)
$\mathbf{1}_{\text{Dealer}}\times$100k miles	-110.988^{***}	17.540
	(40.919)	(62.298)
$\mathbf{1}_{\text{Dealer}}\times$110k miles	61.413	50.540
	(45.997)	(70.029)
$\mathbf{1}_{\text{Dealer}}\times$120k miles	−13.913	92.650
	(52.903)	(80.542)
$\mathbf{1}_{\text{Dealer}}\times$130k miles	33.916	10.237
	(62.534)	(95.205)
$\mathbf{1}_{\text{Dealer}}\times$140k miles	−21.770	33.724
	(81.791)	(124.524)
Observations	3,909,925	3,909,925
R^2	0.907	0.791
Polynomial Order	11^{th}	11^{th}
Fixed Effects	Yes	Yes

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Note: We omitted polynomial, interacted polynomial, un-interacted 10k mile parameters and intercepts in table. (1) includes all decentralized transactions and dealership transactions. (2) includes all decentralized transactions and trade-in transactions. Both include vehicles between 25,000mi and 150,000mi.

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

	Dependent variable:
	$\mathbf{1}_{\text{Intermediary}}$
30K miles	-0.001
	(0.002)
40K miles	-0.003
	(0.002)
50K miles	-0.004^{*}
	(0.002)
60K miles	-0.007^{***}
	(0.002)
70K miles	-0.004^{***}
	(0.002)
80K miles	-0.006^{***}
	(0.002)
90K miles	-0.006^{***}
	(0.002)
100K miles	-0.038^{***}
	(0.002)
110K miles	-0.017^{***}
	(0.003)
120K miles	-0.020^{***}
	(0.003)
130K miles	-0.008^{**}
	(0.004)
140K miles	-0.022^{***}
	(0.004)
Observations	3,909,925
R^2	0.299
Fixed Effects	Yes
Polynomial Order	12^{th}
Note:	*p<0.1; **p<0.05; ***p<0.01

Note: We omitted polynomial and intercept in table. The table includes all decentralized transactions and intermediary transactions for vehicles between 25,000mi and 150,000mi.

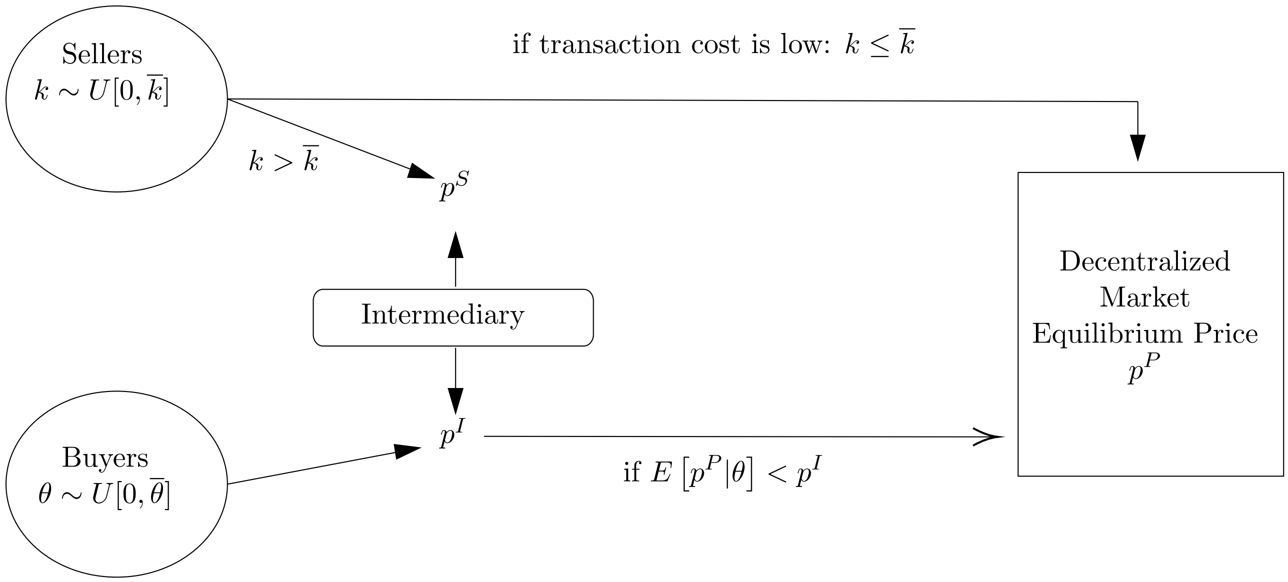
Table 7: Estimated elasticity, inattention, and depreciation

Odometer Range	Elasticity of Supply (ϵ)	Inattention (θ)	Depreciation (α)
15,000-24,999	2.94	0.08	-7.8%
25,000-34,999	3.32	0.11	-6.5%
35,000-44,999	3.13	0.09	-7.9%
45,000-54,999	3.75	0.22	-8.0%
55,000-64,999	3.63	0.19	-7.3%
65,000-74,999	3.44	0.23	-7.1%
75,000-84,999	3.50	0.32	-7.0%
85,000-94,999	2.60	0.43	-6.3%
95,000-104,999	3.67	0.62	-10.6%
105,000-114,999	2.70	0.47	-4.5%
115,000-124,999	1.66	0.69	-5.5%
125,000-134,999	1.92	0.17	-5.2%
135,000-144,999	1.60	0.43	-5.5%
145,000-154,999	3.03	0.62	-3.2%

Note: Elasticity of Supply is estimated locally for each 10,000 mile range using Instrumental Variables Estimator detailed in Section 5. Inattention and depreciation are estimated from observed intermediary prices. Depreciation is measured over 10,000 miles. For example, vehicles at 84,999 miles are (on average) worth 7.0% less than vehicles at 75,000 miles.

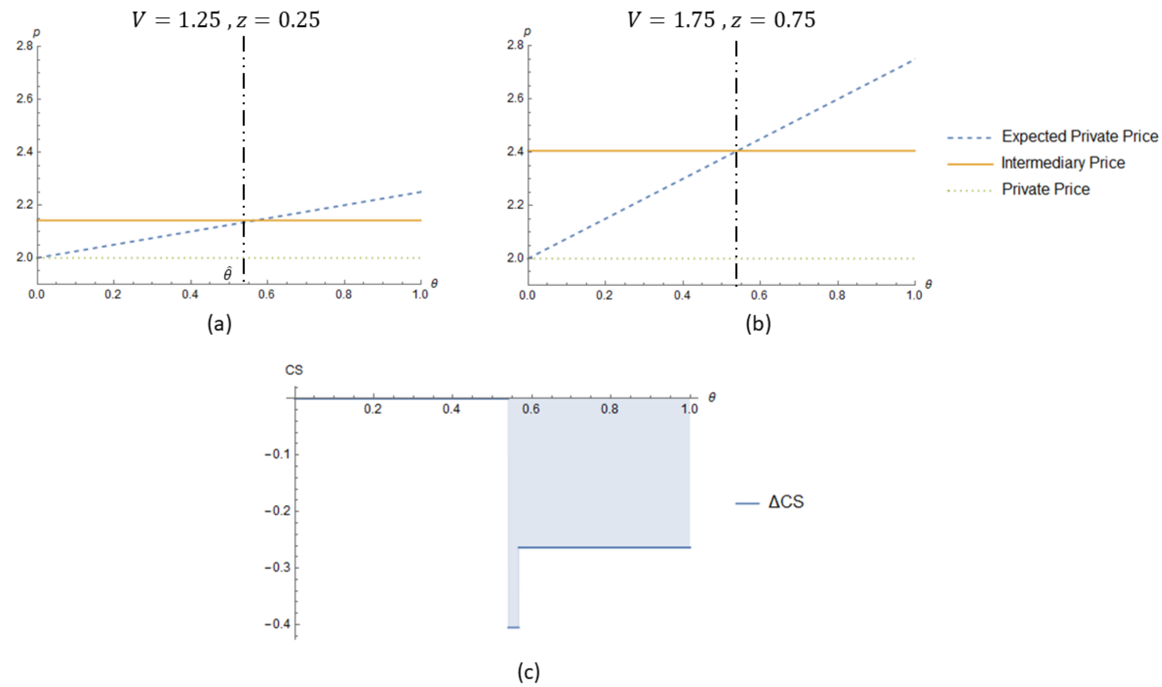
Figures

Figure 1: Market structure



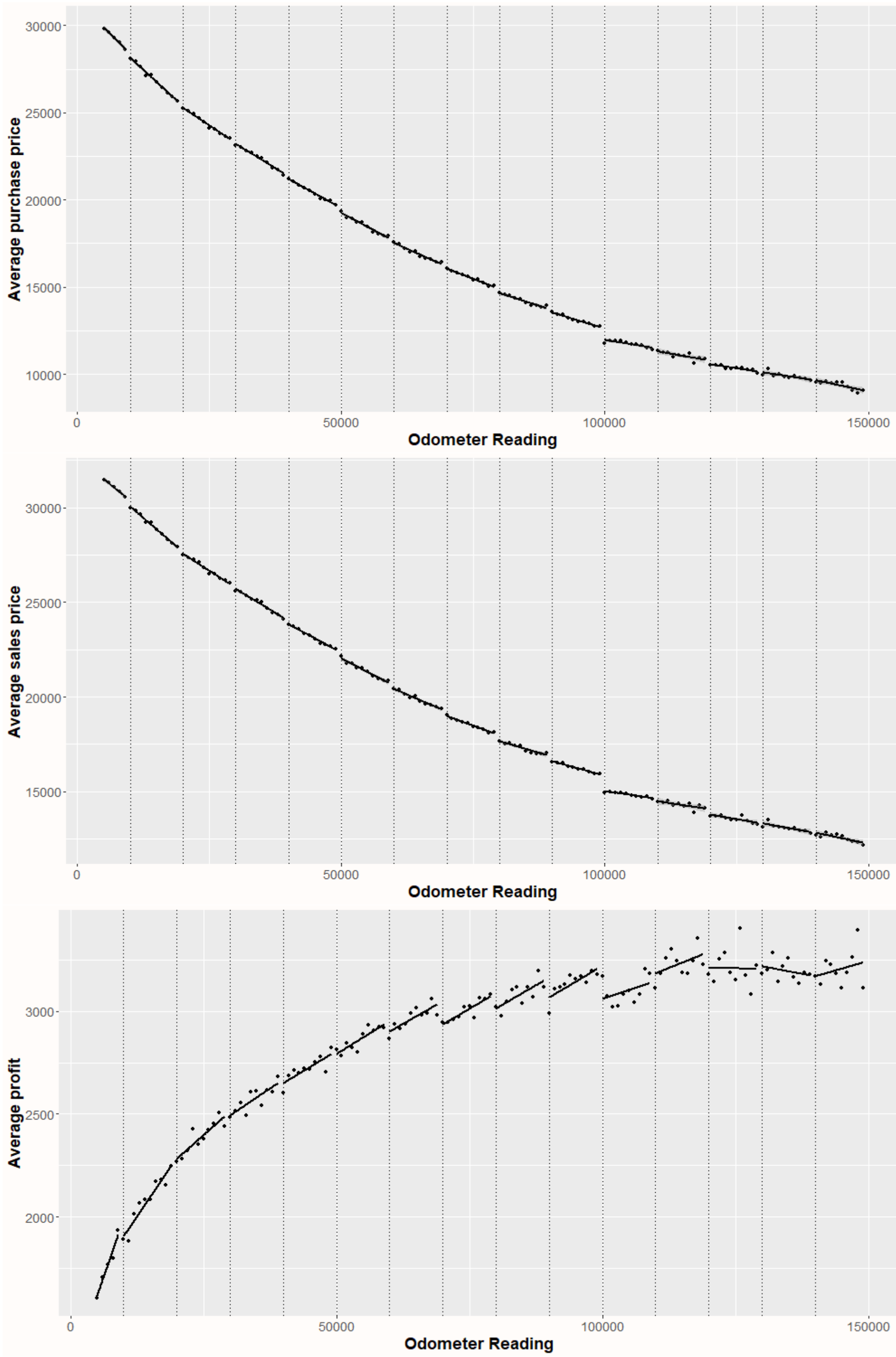
Note: Market structure with an intermediary and decentralized trade. Product owners with high transaction cost sell to the intermediary. Consumers with high levels of inattention buy from the intermediary because they have a higher $E\left[p^P|\theta\right]$. The remaining owners and consumers meet in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

Figure 2: Equilibrium price and consumer surplus comparison



Note: Comparison of equilibrium prices for intermediary and decentralized transactions and the ex-ante expected price in the decentralized market by consumers. The actual consumption utility is the same in both panels, but in the left panel, the attribute that is potentially underestimated by an inattentive consumer is smaller, in absolute value. Bottom panel plots the difference in consumer surplus between the two cases

Figure 3: Dealership purchase price, sales price, and profit.

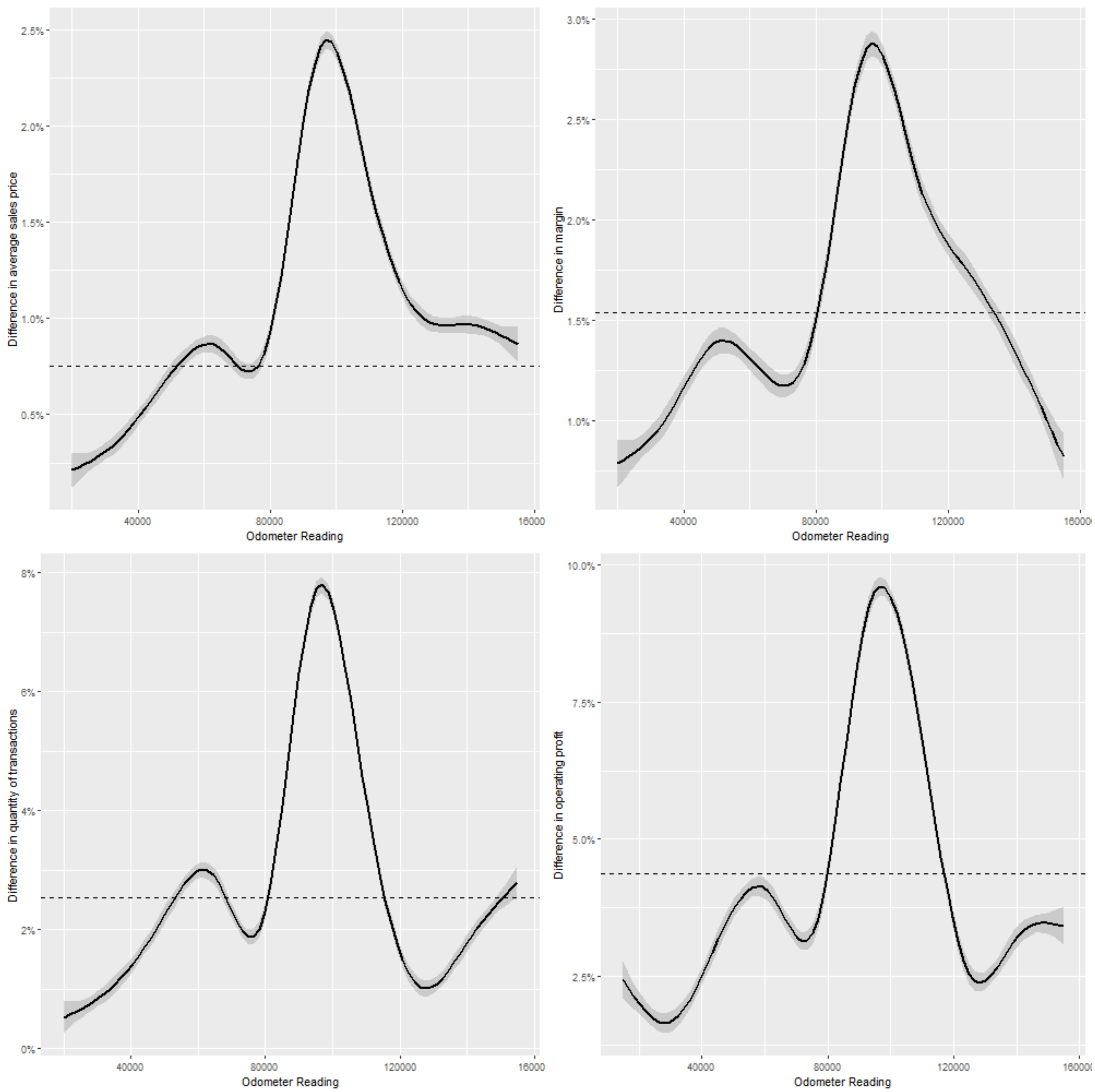


Note: Each dot represents the average purchase price/ sales price/ operating profit for vehicles within a 1,000mi band.

Figure 4: Quantity of intermediary and decentralized transactions

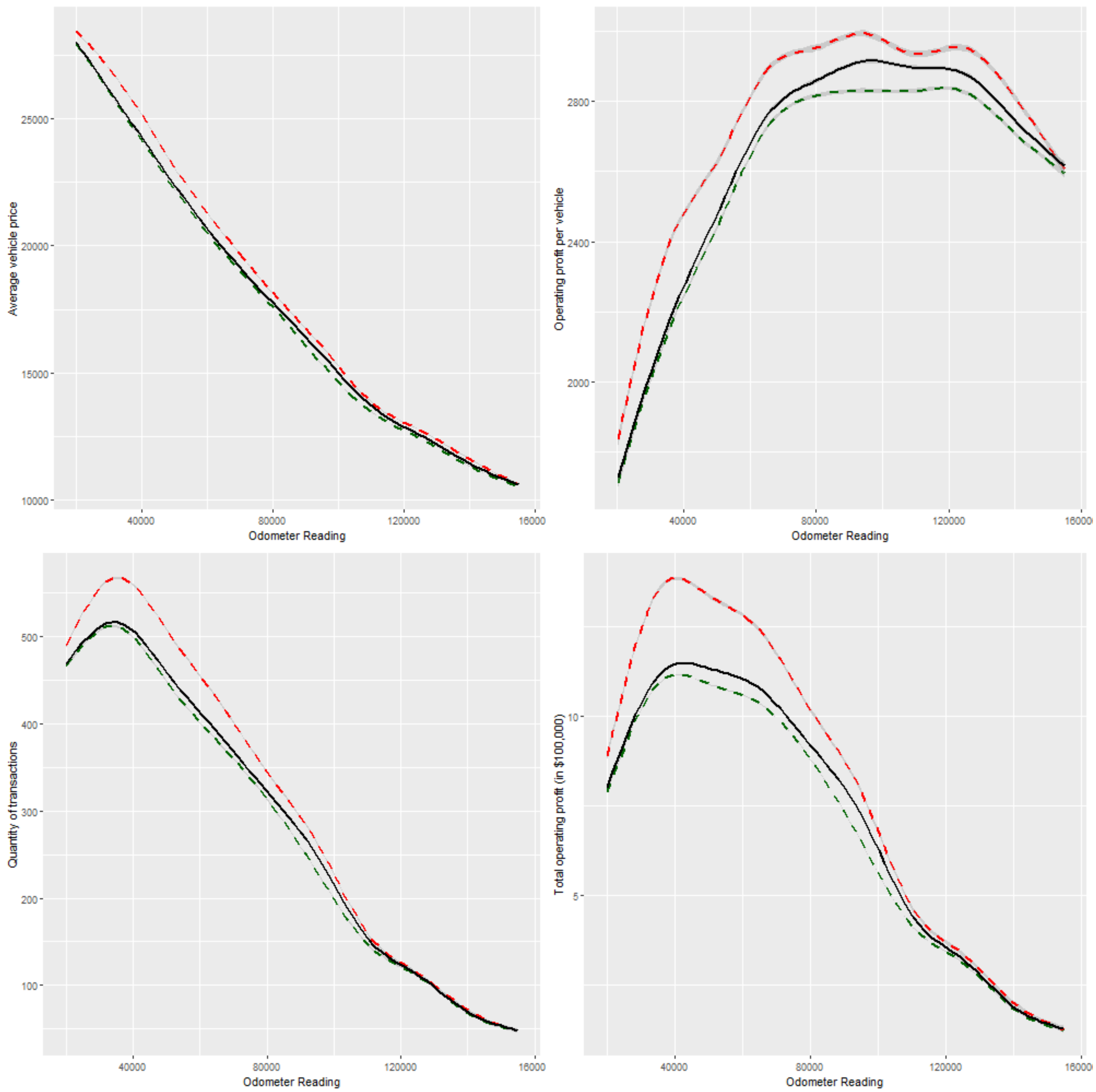
Note: Each dot represents the quantity of transactions for vehicles within a 1,000mi band.

Figure 5: Estimated difference between observed inattention and no inattention



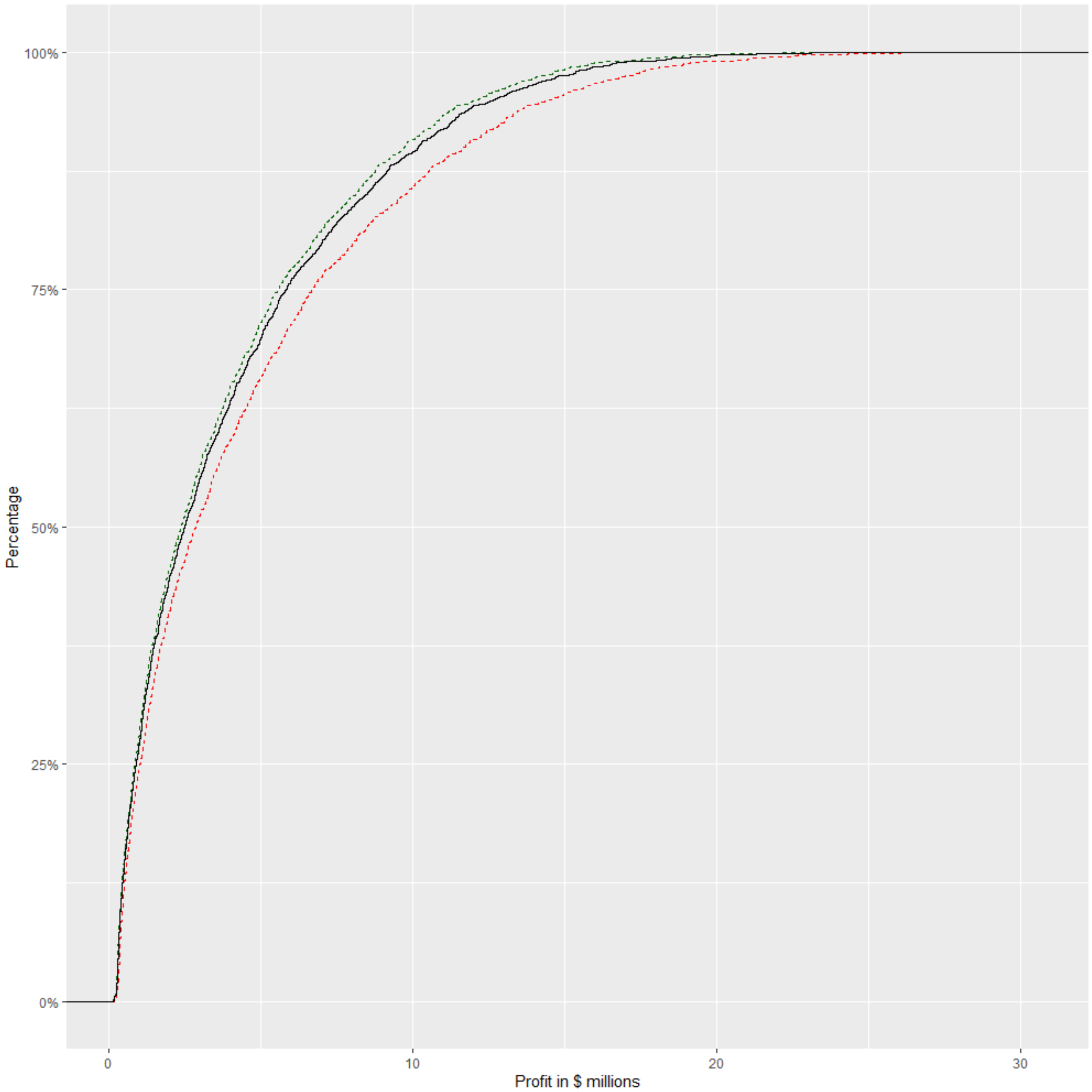
Note: Estimated difference between the case with estimated level of inattention and no inattention benchmark. Dashed line denotes the average value. Top left: average sales price, top right: average margin, bottom left: quantity of transactions. Bottom right: Total profit

Figure 6: Estimated values for full attention, inattention, and observed inattention



Note:Counterfactual bounds of outcome with full attention (green), and full inattention (red), and observed inattention (black). In the full inattention scenario, consumers ignore depreciation between 10,000 mile thresholds. The x-axis in all plots is the odometer reading of vehicles that were traded in and subsequently sold through an intermediary. Top left: average price per vehicle, top right: average profit (i.e., subsequent sales price minus trade-in allowance), bottom left: quantity of transactions within a 10 mile “bucket”. Bottom right: Total profit per 10 mile “bucket” of vehicles.

Figure 7: Estimated counterfactual dealership profit cumulative distribution



Note: Estimated empirical cumulative distribution function with full attention (green), and full inattention (red), and observed inattention (black)

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

By backwards 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 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: $D(p^I) = \frac{\bar{\theta}-\frac{p^I-V+z-1}{z}}{\bar{\theta}}$. The solution gives $p^{S*} = -\frac{\bar{k}(p^I-V+z-1)}{\bar{\theta}z} + V - z + 1$. Then, plugging the purchase price into the profit maximization problem given by equation 6, the optimal sales price is given by: $p^{I*} = \frac{1}{2}z\left(\frac{c\bar{\theta}}{\bar{k}+\bar{\theta}z} + \bar{\theta} - 2\right) + V - z + 1$. This solution is valid whenever the equilibrium purchase price is above the consumption utility of the seller. ($p^{S*} > u_S$), which implies $\bar{k} < 2V$. 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 $p^{I*} = \frac{\bar{\theta}Vz}{\bar{k}} + V - z + 1$. 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 and the corner solution is optimal else.

Proof for Proposition 2

The proof follows straightforward differentiation. Prices are derived in Proposition 1 and the derivatives are given by: $\frac{\partial p^{D*}}{\partial \bar{\theta}} = 0$, $\frac{\partial p^{I*}}{\partial \bar{\theta}} = \begin{cases} \frac{1}{2}z\left(\frac{c\bar{k}}{(\bar{k}+\bar{\theta}z)^2} + 1\right), & \text{if } \bar{k} \leq 2V \\ \frac{Vz}{\bar{k}}, & \text{otherwise} \end{cases}$,

$\frac{\partial p^{S*}}{\partial \theta} = \begin{cases} \frac{c\bar{k}z}{2(\bar{k}+\theta z)^2}, & \text{if } \bar{k} \leq 2V \\ 0, & \text{otherwise} \end{cases}$, $\frac{\partial Q^{I*}}{\partial \theta} = \begin{cases} \frac{cz}{2(\bar{k}+\theta z)^2}, & \text{if } \bar{k} \leq 2V \\ 0, & \text{otherwise} \end{cases}$, and $\frac{\partial Q^{D*}}{\partial \theta} = -\frac{\partial Q^{I*}}{\partial \theta}$.

Proof for Proposition 3

We derive the model without intermediary in online Appendix A in full detail. The price set by individual sellers is the solution to equation 4, and for $V > 1$, the solution is given by $p^{D*} = 1 + V - z$, which is the same price as in the case with an intermediary. Owner surplus is given by $OS^{\text{decentralized trade}} = \int_0^{\hat{k}} (p^{D*} - k) f(k) dk + \int_{\hat{k}}^{\bar{k}} u_B f(k) dk$, where $\hat{k}$ is the owner indifferent between selling or consuming. Consumer surplus is given by: $CS^{\text{decentralized trade}} = Q^{D*} * (1+V-z-p^{D*}) = 0$.

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 see why $OS > OS^{\text{private trade}}$, it is sufficient to observe that $p^{S*} \geq u_S$. Consumer surplus is given by: $CS = Q^{D*} * (1 + V - z - p^{D*}) + Q^{D*} * (1 + V - z - p^{I*}) < 0$. It is negative because $p^{D*} < p^{I*}$. As a result, $CS < CS^{\text{decentralized trade}}$.

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 $\Delta x < 0 \Leftrightarrow \frac{\partial x}{\partial \theta} > 0$. Proposition 2 shows that $\frac{\partial p^{I*}}{\partial \theta} > 0$, which thus implies $\Delta p^{I*} < 0$. Similarly, straightforward algebra shows that $\frac{\partial p^{I*}}{\partial \theta} > \frac{\partial p^{D*}}{\partial \theta}$, $\frac{\partial p^{I*}}{\partial \theta} > \frac{\partial p^{S*}}{\partial \theta}$, $\frac{\partial p^{S*}}{\partial \theta} \geq \frac{\partial p^{D*}}{\partial \theta}$, $\frac{\partial Q^{I*}}{\partial \theta} \geq 0$, and $\frac{\partial Q^{I*}}{\partial \theta} \geq \frac{\partial Q^{I*}}{\partial \theta}$, 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)[33] 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:

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

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

[33] 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:

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

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

$CS = 0$

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:

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

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

where $P(\text{accept}|p^D) = \int_{\frac{1+z-V+p^D}{z}}^{\bar{\theta}} f(\theta)d\theta$. 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 ($\bar{\theta} < V/z$):*

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

Proof. The proof follows directly from the first order condition of the profit maximization problem. Equilibrium price is given by $p^{D*} = 1 + V - z$, for $\bar{\theta} \leq V/z$. The equilibrium quantity is given by: $Q^{D*} = min[1, \frac{V-z+1}{\bar{k}}]$ ■

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[34].

A.3.2 Intermediary Trade Only

In this model, the timing is such that in t=1, the intermediary offers the owners a purchase price and offers a sales price to all potential buyers and in t=2 consumption occurs. In the first stage, each product owner decides to sell the product to the intermediary or keep the product. Owners are homogeneous in this setting because the decentralized market is closed. Thus, it is sufficient for the intermediary to offer a purchase price equal to the consumption value of the owners, which is given by $p^{S*} = u_S = 1 - z$. Consumers visit the intermediary and can purchase the product at price p^I. The game ends after the offer is accepted or declined. To solve the game, we need to solve the firm's first order condition to find p^{I*}. The sellers' equilibrium price is given by the following

[34] 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:

$$p^{I*} = \underset{p}{\text{argmax}} E[\pi_O] = D(p) \times (p - c - p^{S*}), \tag{17}$$

where $D(p) = min\left[1, \int_{\frac{p-V+z-1}{z}}^{\bar{\theta}} f(\theta)d\theta\right]$. The solution is given by $p^{I*} = \begin{cases} 1+c-z & \text{for } z+c \leq V \\ \frac{2+c+V+\bar{\theta}z}{2}, & \text{otherwise.} \end{cases}$

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.

Again, using backwards 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 maximization problem is given by

$$\begin{aligned} p^{D*} = \arg\max_{p^D} E[\pi_O(p^D)] &= P(\text{accept}|p^D) \times p^D + (1 - P(\text{accept}|p^D)) \times (1-z), \\ \text{s.t. } 0 \leq P(\text{accept}|p^D) &\leq 1, \end{aligned} \tag{18}$$

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 18. 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 again consider the case of sellers 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 backwards 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[35]. 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:

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

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

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 Empirical Extensions

In this section, we present three sets of additional empirical analyses. First, we present an analysis of the level of inattention at the dealership level. Secondly, we consider analysis at the level of the model and odometer to estimate conditional correlations between inattention and potential determinants of attention. Finally, we briefly consider the Ex-Ante payoffs to consumer attention and empirically measure the benefits of increased consumer attention.

B.1 Vehicle Model Level Analysis

We have assumed an exogenous level of inattention. While estimating a full rational attention model is beyond the scope of this paper, we consider a simple test intending to test if attention is correlated with factors affecting the payoff to increased attention.

If attention results from some rational process, we would expect consumers to increase attention for vehicles with a higher depreciation rate because that implies a higher potential payoff to being attentive. On the other hand, the absolute price level of a vehicle should not have a first-order effect on inattention because it does not directly affect the payoff from increased attention[36]. Finally, if some rational process determines inattention, the level of attention should depend on the financial payoffs and not on the specific 10,000-mile cutoff.

For the analysis, we estimate a separate inattention parameter, price level, and depreciation for each Model - 10,000 mile-bucket combination. 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 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 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 $\alpha_{Mod,j} = \hat{\gamma_1} + \frac{\gamma_2}{10,000}$. Using the estimated inattention parameter, we can now run the following fixed effects regression:

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

where $P^0_{Mod,j}$ denotes the price for model Mod at the lower bound of mileage in that bucket. (e.g., for the 25,000-34,999 bucket, $P^0_{Mod,j}$ denotes the estimated price at 25,000 miles), $M_{Mod,j}$ is an indicator variable for each 10,000 mile threshold, and .

We present the results in table A2. Inattention is lower for more expensive vehicles, vehicles

[36]Consider the case of a model that, at 25,000 miles costs \$22,000, and at 34,999 miles costs \$16,000 (on average). Comparing this model to a separate model that costs \$12,000 at 25,000 miles and \$6,000 at 34,999, it is clear that the payoff in dollar terms to increased attention does not change. However, unless utility is linear in money, there could be an income effect that affects the potential utility gain from increased attention.

that depreciate at a higher rate, and vehicles over 90,000 miles. We need to be careful to avoid over-interpreting these results but give some potential explanations for the observed pattern. These results are conditional correlations but not causal estimates. One explanation of the results is that consumers with higher income both purchase more expensive vehicles and have higher levels of attention Banerjee and Mullainathan (2008). Inattention appears to be significantly higher for vehicles with relatively high odometer readings. Several explanations could rationalize this. First, perhaps numbers over 100,000 are more difficult and costly to process because of the added digit. Secondly, lower-income consumers often purchase older vehicles, which is again consistent with the model in Banerjee and Mullainathan (2008).

The results are not conclusive, and we are unable to rule out that consumers are following a rational process to choose their level of attention. We find some evidence of higher levels of attention for vehicles presumably purchased by consumers with more resources.

B.2 Ex-Ante Payoff to Consumer Attention

In the paper, we have treated inattention as an exogenously given variable. We do not aim to answer if consumers are rationally choosing their level of attention because we cannot observe the cost of changing the level of attention. Rather, we approximate the *ex-ante* benefit of increasing attention to see if the value is consistent with potentially reasonable levels of attention costs. The literature testing inattention in the field has largely considered inattention's cost, conditional on some situation or choice. For example, Busse et al. (2015) show that consumers are affected by the projection bias and purchase more convertibles on sunny days. Lacetera et al. (2012), as well as our paper show that consumers could save $100 if they choose a vehicle that is at a mileage level right above a 10,000-mile threshold. Importantly, those mistakes are *conditional* on sunny weather or purchasing a vehicle around a round cutoff, respectively. An appropriate description of consumer behavior might be that they first choose the level of attention, observe the attribute, and make a consumption choice. A secondary benefit from estimating the counterfactual model is that we can use the change in prices to approximate the ex-ante payoff of attention. In particular, for an appropriately convex *cost of attention* function, a rational consumer increases attention up to the point where the marginal cost exceeds the marginal benefit. To estimate the marginal benefit, we estimate the change in price due to a 1 percentage point increase in attention, which leads to a $8.03 decrease in prices.

B.3 Placebo Tests

This section considers the robustness of the reduced form analysis above by using 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 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 tables (A3), (A4), and (A5. The first table presents the results for the various prices the dealership pays or receives. We have estimated 3×23 coefficients for kilometer cutoffs. Except for the 40,000km cutoff coefficient, no coefficient is significant at the $p = 0.01$ level. 40,000 kilometers corresponds to 24,855mi, and presumably, consumer inattention might lead to discrete jumps at multiples of 5,000 miles. Another potential explanation might be that some car warranties expire after 24,000 miles[37]. Purely by chance, we would expect 0.69 coefficients to be significant at the 1% level, 3.45 coefficients at the 5% level, and 6.9 coefficients at the 10% level. We find that one coefficient is significant at the 1% level, four coefficients are significant at the 5% level, and six coefficients are significant at the 10% level. These results are consistent with the expected null effect of the 10,000-kilometer indicator variables. In table (A4), we observe two coefficients significant at the 1% level, four coefficients significant at the 5% level, and eight coefficients significant at the 10% level. Finally, in table (A5) we observe one coefficient significant at 1%, two coefficient significant at the 5% level and 6 coefficients significant at the 10% level. coefficients at the 130k km and 210k km cutoffs have significant coefficients. Presumably, the coefficients at 210k km and 130k km are significant because they are close to the 130k mile and 80k mile cutoff and pick up some of the effects occurring at those cutoffs. Across the three tables, we have estimated 126 coefficients of 10,000km cutoffs and find that four coefficients are significant at the 1% level, 10 are significant at the 5% level, and 20 are significant at the 10% level. 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 overall reassuring.

C Omitted Details for Estimating the Supply Side Model

In this section, we expand the explanation of the estimation of the supply side model to include detailed information on the estimation of the elasticity.

C.1 Estimating Elasticity of Supply

On the supply side, we have assumed the supply function to be of the form $S(p^S) = Am^{\beta}p^{S^{\epsilon}}$. We can easily estimate this quantity with the following regression:

$$ln(Q_i) = \alpha + \epsilon ln(p_i^S) + \beta ln(\text{mileage}_i) + u_i. \tag{19}$$

where we use $\mathbf{1}\left[miles_i \geq j \times (10,000)\right]$ as an instrument for p^S. Because estimation is somewhat noisy for some cutoffs, we apply a regularization similar to bayesian shrinkage (see for example DellaVigna and Gentzkow (2019) for a similar application of this procedure. To do so, we take the elasticity ϵ^R observations with below-median values of estimated standard errors and calculate

[37] 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.

their variance and mean, which we denote as $\bar{\epsilon^R}$ and $Var(\epsilon^R)$. Using these values, we can now calculate a "shrunk" estimate of the elasticity as $\epsilon = \frac{Var(\epsilon^R)\epsilon_i^R + \sigma^2(\epsilon_i^R)\bar{\epsilon^R}}{Var(\epsilon^R)+\sigma^2(\epsilon_i^R)}$. An instrumental variable needs to satisfy the exclusion and the relevance assumption. The instrument is relevant for most of the cutoffs, as can be empirically verified (the majority of the F-stats are 10). For the instrument to satisfy the exclusion restriction, it is required that moving past a 10,000 mile threshold only affects the quantity demanded through the increase in purchase price. This is valid, given our assumed supply function $S(p^S) = Am^\beta p^{S\epsilon}$, because supply is smooth around the cutoff.

C.2 Solving the Firm Profit Maximization Problem

We have assumed that the firm needs to take prices as given, so the only choice variable for the firm is the purchase price. Given the supply function, the firms profit function for vehicles of a certain mileage is given by:

$$\Pi = S(p^S) \times (p^I - p^S - c). \tag{20}$$

Taking the first order condition with respect to to the purchase price gives $p^{S*} = \frac{\epsilon(p^I - c)}{\epsilon+1}$. We now first use the observed pricing, elasticity, and purchase price to estimate the cost $c = \frac{-\epsilon p^I - \epsilon p^S - p^S}{-\epsilon}$[38]. Now, we can estimate counterfactual purchase prices and quantities as:

$$p^I(\theta)_i = \frac{\epsilon(\hat{p_i^S} - \hat{c})}{\hat{\epsilon}+1},$$

$$Q(\theta)_i = \hat{\text{intercept}} + \hat{\epsilon} \times ln(p^S(\theta)_i) + \hat{\beta}_2 \times ln(\text{mileage}_i)$$

, where the intercept takes the shrinkage applied to the elasticity into account: $\hat{\text{intercept}} = \hat{\beta}_0 + ln(10,000 \times j)(\epsilon^R - \epsilon)$. This allows us to calculate the relevant counterfactual prices and quantities

[38]We treat this cost as nuisance parameter and do not include it in the welfare calculations for two reasons: (1) We have simplified the demand side somewhat, so it is possible that this cost is not precisely estimated, and (2) the cost is negative for the majority of observations. This negative cost makes sense in our context when dealerships use lower purchase prices to charge higher prices on new vehicle sales. For those two reasons, we do not include the cost in our profit estimation.

Tables

Table A1: Estimated discontinuity in quantity of transactions around cutoffs.

	Dependent variable:	
	log(Quantity)	
	(Dealer)	(Decentralized)
	(1)	(2)
20k miles	−0.016	−0.018
	(0.013)	(0.027)
30k miles	−0.006	−0.007
	(0.011)	(0.024)
40k miles	−0.034***	−0.037
	(0.011)	(0.023)
50k miles	−0.049***	−0.020
	(0.011)	(0.022)
60k miles	−0.053***	0.010
	(0.011)	(0.022)
70k miles	−0.045***	−0.029
	(0.010)	(0.021)
80k miles	−0.058***	−0.038*
	(0.010)	(0.022)
90k miles	−0.054***	−0.020
	(0.010)	(0.021)
100k miles	−0.272***	−0.028
	(0.011)	(0.022)
110k miles	−0.045***	0.026
	(0.011)	(0.022)
120k miles	−0.072***	0.064***
	(0.011)	(0.023)
130k miles	−0.023**	0.029
	(0.011)	(0.024)
140k miles	−0.089***	0.025
	(0.013)	(0.027)
Observations	1,400	1,400
Polynomial Order	9^{th}	9^{th}
R^2	0.998	0.855
Note:	*p<0.1; **p<0.05; ***p<0.01	

Note: Number of transactions is aggregated to 100 mile buckets.

Table A2: Heterogeneity of inattention for different models

	Dependent variable:
	theta
Price	0.028*
	(0.017)
α	0.089***
	(0.028)
20K miles	0.002
	(0.028)
30K miles	0.014
	(0.029)
40K miles	0.001
	(0.031)
50K miles	0.048
	(0.033)
60K miles	0.048
	(0.033)
70K miles	0.086**
	(0.037)
80K miles	0.079**
	(0.038)
90K miles	0.134***
	(0.040)
100K miles	0.140***
	(0.043)
110K miles	0.060
	(0.047)
120K miles	0.173***
	(0.048)
130K miles	0.203***
	(0.052)
140K miles	0.141***
	(0.053)
Observations	2,187
R^2	0.379
Model Fixed Effect	Yes
Note:	*p<0.1; **p<0.05; ***p<0.01

Table A3: Placebo Test for Intermediary Prices

	Dependent variable:		
	Purchase Price	Sales Price	Dealership Profit
	(1)	(2)	(3)
10k km	−61.187 (75.639)	−5.668 (42.642)	−65.088 (70.184)
20k km	5.660 (45.810)	22.112 (24.993)	13.895 (41.872)
30k km	−4.242 (39.320)	−26.604 (20.704)	−25.147 (39.280)
40k km	−75.035** (37.834)	−84.915*** (19.721)	−4.150 (33.236)
50k km	−30.112 (37.581)	4.981 (19.658)	36.155 (37.235)
60k km	11.775 (33.324)	−6.260 (17.456)	−20.523 (31.145)
70k km	−28.596 (32.550)	28.317 (17.725)	51.285* (30.869)
80k km	81.383 (61.501)	72.129** (31.661)	−11.607 (61.442)
90k km	−56.131 (34.220)	−23.425 (18.319)	35.986 (32.186)
100k km	3.411 (36.415)	4.033 (19.428)	4.730 (34.974)
110k km	11.058 (39.203)	−27.067 (20.626)	−35.258 (38.228)
120k km	30.766 (38.795)	−13.043 (20.823)	−44.322 (37.159)
130k km	35.579 (54.418)	15.122 (28.221)	−22.316 (53.717)
140k km	15.166 (43.292)	11.635 (23.276)	−6.533 (41.216)
150k km	−27.028 (47.895)	−0.245 (25.470)	23.027 (46.087)
160k km	−41.241 (72.640)	−62.146* (37.478)	−23.301 (72.167)
170k km	0.787 (60.659)	−6.366 (33.336)	−3.259 (57.012)
180k km	−18.974 (72.996)	7.116 (38.059)	38.641 (70.455)
190k km	−79.101 (79.175)	−50.571 (41.676)	42.097 (77.549)
200k km	−78.430 (88.350)	−62.657 (48.502)	6.078 (81.972)
210k km	−56.174 (146.138)	45.205 (75.528)	82.509 (145.638)
220k km	4.031 (121.840)	15.505 (65.570)	14.380 (118.292)
230k km	−83.389 (153.834)	−166.485** (84.656)	8.067 (130.442)
Observations	3,219,973	3,219,973	3,219,973
R^2	0.782	0.932	0.142
Fixed Effects	Yes	Yes	Yes
Polynomial Order	11^{th}	11^{th}	9^{th}
10k mile indicators	Yes	Yes	Yes

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

Note: We omitted polynomial parameters, 10k mile parameters and intercepts in 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.

Table A4

	Dependent variable: *Decentralized price vs*	
	(Sales Price)	(Purchase Price)
	(1)	(2)
$\mathbf{1}_{\text{Dealer}} \times$ 50k km	−45.922 (50.153)	−74.627 (76.357)
$\mathbf{1}_{\text{Dealer}} \times$ 60k km	129.884*** (43.312)	109.874* (65.942)
$\mathbf{1}_{\text{Dealer}} \times$ 70k km	20.390 (45.136)	−14.143 (68.718)
$\mathbf{1}_{\text{Dealer}} \times$ 80k km	98.936 (76.420)	98.267 (116.347)
$\mathbf{1}_{\text{Dealer}} \times$ 90k km	−58.385 (42.614)	−90.666 (64.879)
$\mathbf{1}_{\text{Dealer}} \times$ 100k km	22.195 (41.750)	16.478 (63.563)
$\mathbf{1}_{\text{Dealer}} \times$ 110k km	20.173 (43.994)	47.878 (66.980)
$\mathbf{1}_{\text{Dealer}} \times$ 120k km	52.419 (41.292)	107.159* (62.866)
$\mathbf{1}_{\text{Dealer}} \times$ 130k km	−52.014 (52.076)	−21.816 (79.284)
$\mathbf{1}_{\text{Dealer}} \times$ 140k km	117.218*** (42.947)	131.269** (65.385)
$\mathbf{1}_{\text{Dealer}} \times$ 150k km	80.792* (43.658)	43.133 (66.468)
$\mathbf{1}_{\text{Dealer}} \times$ 160k km	−130.923** (65.057)	−86.178 (99.048)
$\mathbf{1}_{\text{Dealer}} \times$ 170k km	49.434 (50.287)	44.917 (76.561)
$\mathbf{1}_{\text{Dealer}} \times$ 180k km	−2.829 (56.006)	−23.875 (85.267)
$\mathbf{1}_{\text{Dealer}} \times$ 190k km	101.979* (60.790)	84.519 (92.551)
$\mathbf{1}_{\text{Dealer}} \times$ 200k km	21.621 (64.538)	−33.226 (98.258)
$\mathbf{1}_{\text{Dealer}} \times$ 210k km	66.488 (96.622)	−100.171 (147.104)
$\mathbf{1}_{\text{Dealer}} \times$ 220k km	−56.233 (83.964)	−52.231 (127.833)
$\mathbf{1}_{\text{Dealer}} \times$ 230k km	−191.261* (107.577)	−120.975 (163.783)
Observations	3,909,925	3,909,925
R^2	0.907	0.791
Fixed Effects	Yes	Yes

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

Note: We omitted polynomial, interacted polynomial, un-interacted 10k kilometer parameters and mile parameters and intercepts in table. (1) includes all decentralized transactions and dealership transactions. (2) includes all decentralized transactions and trade-in transactions. Both include vehicles between 25,000mi and 150,000mi.

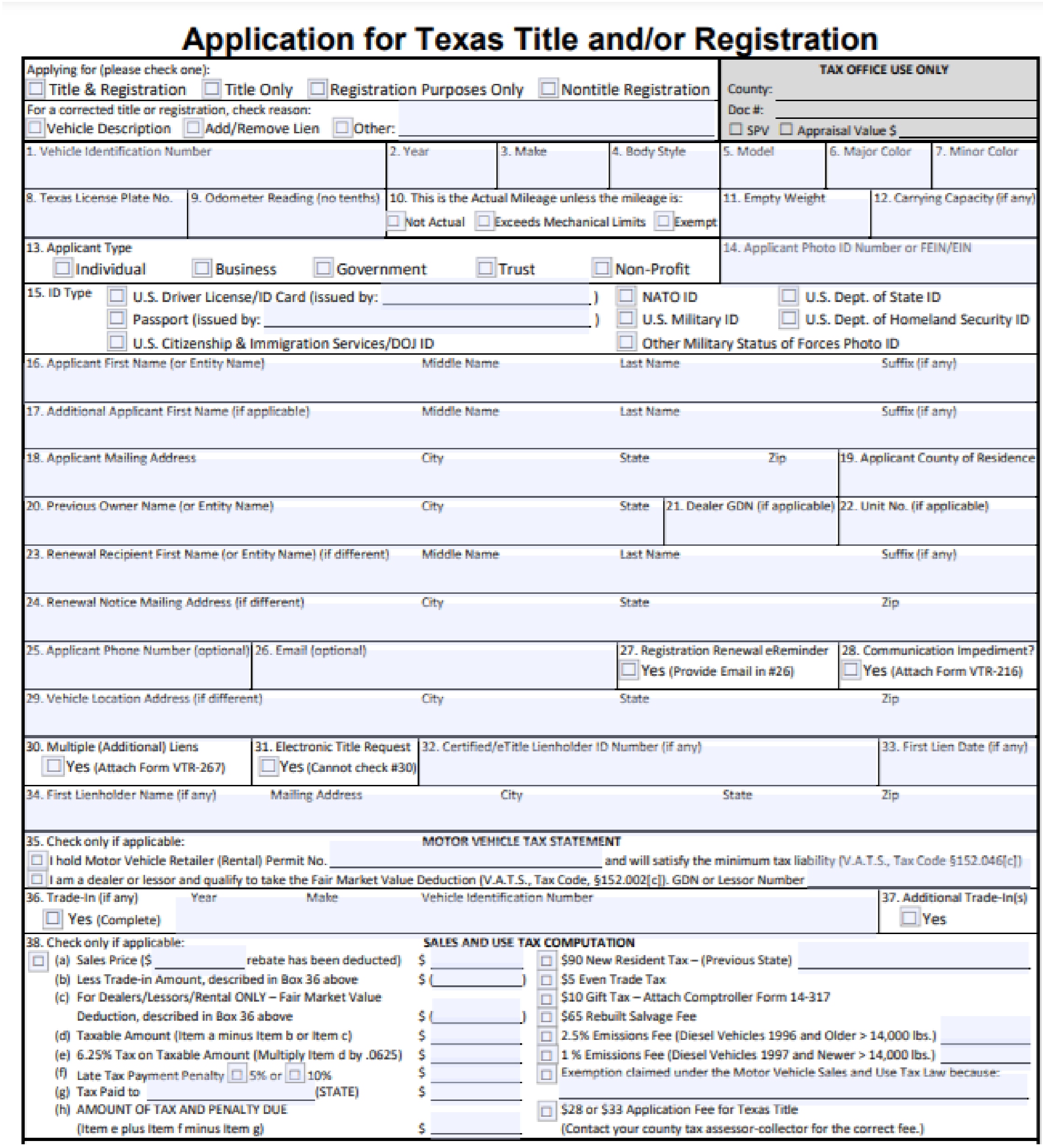
Table A5: Estimated discrete change in channel choice at 10,000 mile thresholds

	Dependent variable:
	$\mathbf{1}_{\text{Intermediary}}$
50k km	0.0003 (0.002)
60k km	−0.001 (0.002)
70k km	-0.005^{**} (0.002)
80k km	0.003 (0.004)
90k km	−0.0005 (0.002)
100k km	−0.003 (0.002)
110k km	−0.001 (0.002)
120k km	-0.004^{*} (0.002)
130k km	0.012^{***} (0.003)
140k km	0.003 (0.002)
150k km	0.001 (0.003)
160k km	−0.001 (0.004)
170k km	0.004 (0.003)
180k km	-0.006^{*} (0.003)
190k km	−0.002 (0.004)
200k km	−0.003 (0.004)
210k km	0.010^{*} (0.006)
220k km	0.009^{*} (0.005)
230k km	−0.004 (0.006)
240k km	−0.001 (0.009)
Observations	3,909,925
R^2	0.299
Fixed Effects	Yes
Polynomial Order	12^{th}
10k mile Indicators	Yes
Note:	*p<0.1; **p<0.05; ***p<0.01

Note: We omitted polynomial, intercept, and 10k mile cutoffs in table. The table includes all decentralized transactions and intermediary transactions for vehicles between 25,000mi and 150,000mi.

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

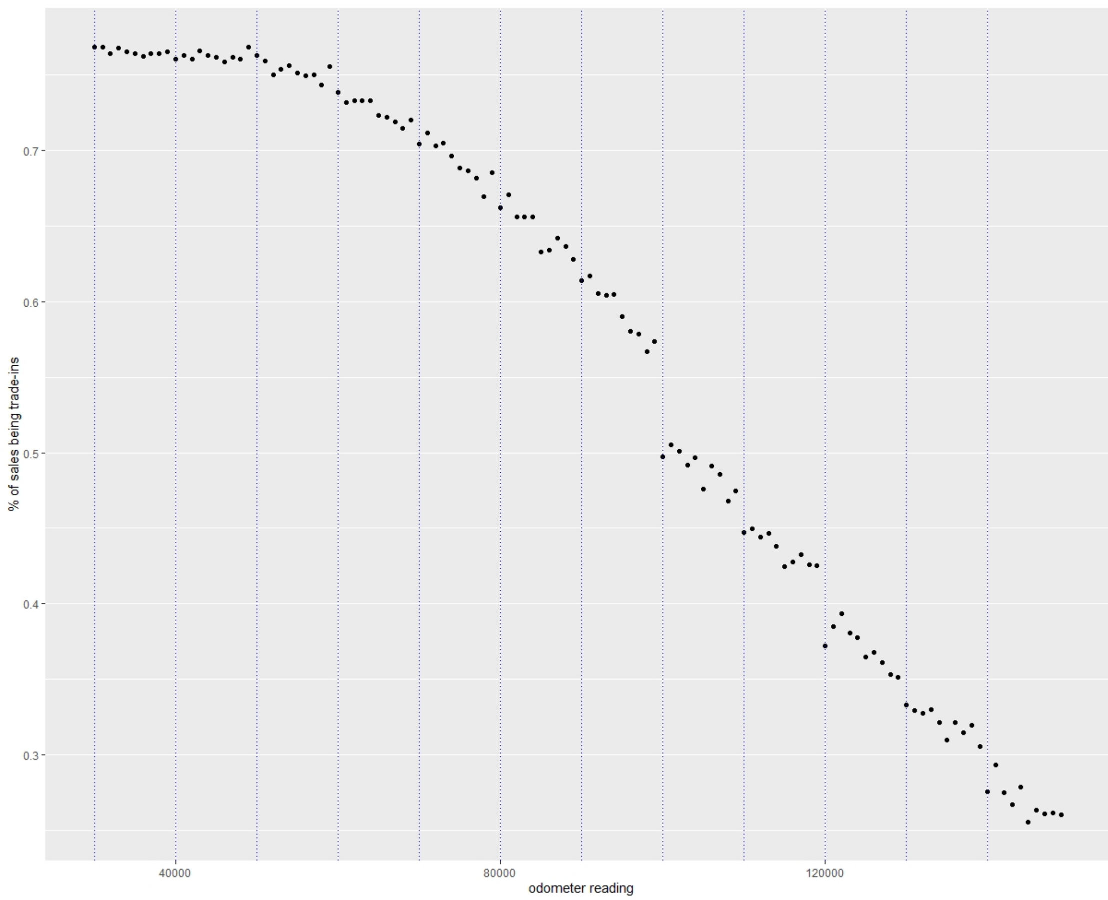
35. Check only if applicable: MOTOR VEHICLE TAX STATEMENT
☐ I hold Motor Vehicle Retailer (Rental) Permit No. ______ and will satisfy the minimum tax liability (V.A.T.S., Tax Code §152.046[c])
☐ I am a dealer or lessor and qualify to take the Fair Market Value Deduction (V.A.T.S., Tax Code, §152.002[c]). 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) $
(b) Less Trade-in Amount, described in Box 36 above $ ( )
(c) For Dealers/Lessors/Rental ONLY – Fair Market Value Deduction, described in Box 36 above $ ( )
(d) Taxable Amount (Item a minus Item b or Item c) $
(e) 6.25% Tax on Taxable Amount (Multiply Item d by .0625) $
(f) Late Tax Payment Penalty ☐ 5% or ☐ 10% $
(g) Tax Paid to ______ (STATE) $
(h) AMOUNT OF TAX AND PENALTY DUE (Item e plus Item f minus Item g) $

☐ $90 New Resident Tax – (Previous State)
☐ $5 Even Trade Tax
☐ $10 Gift Tax – Attach Comptroller Form 14-317
☐ $65 Rebuilt Salvage Fee
☐ 2.5% Emissions Fee (Diesel Vehicles 1996 and Older > 14,000 lbs.)
☐ 1 % Emissions Fee (Diesel Vehicles 1997 and Newer > 14,000 lbs.)
☐ Exemption claimed under the Motor Vehicle Sales and Use Tax Law because:
☐ $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 1,000mi band.

Figure A3: Density of odometer readings for intermediary and decentralized transactions