Online Appendix

A Proofs omitted in main text

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

Proof for Proposition 1

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

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

Interior solution

Suppose that supply equals demand at the interior solution. In that case, we can calculate the purchase price as a function of the sales price.

Supply is given by integrating over the transaction cost k:

$$S(p^S)=\frac{\bar{k}-1-V+p^S+z}{\bar{k}}.$$

Let the intermediary post a decreasing menu of B sales prices $\{p_1^I,\dots,p_B^I\}$ with $p_1^I>\cdots>p_B^I$. Demand is

$$Q(p)\;=\;\frac{\bar{\theta}-\frac{p-1-V+z}{z-\Gamma_z}}{\bar{\theta}}\;=\;1-\frac{p-(1+V-z)}{(z-\Gamma_z)\,\bar{\theta}},$$

and the quantity at the lowest price is $Q_B\equiv Q(p_B^I)$. The corresponding supply constraint implies the equilibrium purchase price

$$p^S(Q_B)\;=\;1+V-z\;+\;\frac{\bar{k}\,(1-p_B^I+V-z)}{\bar{\theta}\,(z-\Gamma_z)}.$$

By rearranging, we can express profits as follows, which allows for clean first order conditions:

$$\Pi=\left(p_B^I-p^S(Q_B)-c\right)Q(p_B^I)\;+\;\sum_{b=1}^{B-1}\left(p_b^I-p_{b+1}^I\right)Q(p_b^I).$$

Taking first-order conditions, we solve for the optimal prices:

$$(b=B): \qquad Q(p_B^I) + \big(p_B^I - p^S(Q_B) - c\big)\, Q'(p_B^I) - Q(p_{B-1}^I) - p^{S\prime}(Q_B)\, Q'(p_B^I)\, Q(p_B^I) \;=\; 0, \tag{16}$$

$$(b=2,\ldots,B-1): \quad Q(p_b^I) + (p_b^I - p_{b+1}^I)\, Q'(p_b^I) - Q(p_{b-1}^I) \;=\; 0 \iff p_b^I \;=\; \frac{p_{b-1}^I + p_{b+1}^I}{2}, \tag{17}$$

$$(b=1): \qquad Q(p_1^I) + (p_1^I - p_2^I)\, Q'(p_1^I) \;=\; 0 \iff 2p_1^I \;=\; 1 + V - z + \bar\theta(z - \Gamma_z) + p_2^I. \tag{18}$$

Define the step between adjacent tiers $s_b \equiv p_b^I - p_{b+1}^I$. From the interior FOC,

$$p_b^I \;=\; \frac{p_{b-1}^I + p_{b+1}^I}{2} \quad\iff\quad s_b \;=\; s_{b-1},$$

so all steps are equal: $s_b \equiv s$ for $b = 1, \ldots, B-1$. Parameterize

$$p_b^I = A - b\,s \quad (b = 1, \ldots, B), \qquad p_B^I = A - B\,s.$$

From the top FOC,

$$2p_1^I \;=\; \big(1 + V - z + \bar\theta(z - \Gamma_z)\big) + p_2^I \;\Longrightarrow\; A \;=\; 1 + V - z + \bar\theta(z - \Gamma_z).$$

From the bottom FOC, we obtain

$$s \;=\; \frac{\bar\theta\,(z - \Gamma_z)\,\big(\bar k + \bar\theta(z - \Gamma_z) - c\big)}{2B\,\bar k \;+\; (B+1)\,\bar\theta\,(z - \Gamma_z)}.$$

Therefore, all tier prices are

$$p_b^I \;=\; 1 + V - z + \bar\theta(z - \Gamma_z) \;-\; \frac{b\,\bar\theta\,(z - \Gamma_z)\,\big(\bar k + \bar\theta(z - \Gamma_z) - c\big)}{2B\,\bar k + (B+1)\,\bar\theta\,(z - \Gamma_z)}, \qquad b = 1, \ldots, B.$$

Corner solution

Now consider the corner in which the lowest inattention type is (weakly) served, $\hat\theta = 0$. The buyer with $\theta = 0$ is indifferent at price $p = 1 + V - z$, so to sell to this type we must have

$$p_B^I \;\le\; 1 + V - z.$$

On the supply side, an owner can transact directly at the decentralized price $p^{D*} = 1 + V - z$, so to procure any stock the intermediary must offer

$$p^S \;\ge\; p^{D*} \;=\; 1 + V - z.$$

Hence the per-unit margin at the corner satisfies

$$p_B^I - p^S - c \;\le\; (1+V-z) - (1+V-z) - c \;=\; -c \;<\; 0 \qquad \text{for } c>0,$$

so the corner is strictly dominated. Therefore, with any positive intermediation cost $c > 0$, the profit-maximizing menu sets $\hat{\theta} > 0$ (i.e., an interior solution).

Solution

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

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

The derivation follows the same exact steps as the case with a positive wedge. Decentralized prices are given by:

$$p^{D*} = 1 - \Gamma_z\bar{\theta} + V + (\bar{\theta} - 1)\, z.$$

We can again rule out the corner solution by the same arguments. Supply for the intermediary is given by:

$$Q^S(p^S) \;=\; \frac{-1 + \bar{k} + p^S + \Gamma_z\bar{\theta} - V + z - \bar{\theta}z}{\bar{k}}.$$

Demand is now given by:

$$Q(p) \;=\; \frac{1 - p + V - z}{\bar{\theta}(\Gamma_z - z)}.$$

The supply constraint implies:

$$p^S(Q_B) \;=\; 1 - \Gamma_z\bar{\theta} + V - z + \bar{\theta}z \;-\; \frac{\bar{k}\left(-1 + p_B^I + \Gamma_z\bar{\theta} - V + z - \bar{\theta}z\right)}{\bar{\theta}\,(\Gamma_z - z)}.$$

Profits and the first-order conditions are identical in form to the positive wedge case but with different equilibrium quantities. Solving for A and s, we obtain:

$$A \;=\; 1 + V - z,$$

$$s \;=\; \frac{\bar{\theta}\left(\bar{k} + \bar{\theta}(\Gamma_z - z) - c\right)(\Gamma_z - z)}{2B\bar{k} + \Gamma_z\bar{\theta} + B\Gamma_z\bar{\theta} - (1+B)\bar{\theta}z}.$$

The intermediary equilibrium prices are then:

$$p_b^{I*} \;=\; 1 + V - z \;-\; \frac{b\,\bar{\theta}\left(\bar{k} + \bar{\theta}(\Gamma_z - z) - c\right)(\Gamma_z - z)}{2B\bar{k} + \Gamma_z\bar{\theta} + B\Gamma_z\bar{\theta} - (1+B)\bar{\theta}z}, \qquad b = 1, \ldots, B.$$

Proof for Proposition 2

For the case with a positive wedge $z > \Gamma_z$, $\frac{\partial p_b^{I*}}{\partial \bar{\theta}} > 0$, $\frac{\partial p^{S*}}{\partial \bar{\theta}} > 0$, $\frac{\partial Q^{I*}}{\partial \bar{\theta}} > 0$, $\frac{\partial p^{D*}}{\partial \bar{\theta}} = 0$, and $\frac{\partial Q^{D*}}{\partial \bar{\theta}} = -\frac{\partial Q^{I*}}{\partial \bar{\theta}}$.

For the case with a negative wedge $z < \Gamma_z$, $\frac{\partial p_b^{I*}}{\partial \bar{\theta}} < 0$, $\frac{\partial p^{S*}}{\partial \bar{\theta}} < 0$, $\frac{\partial Q^{I*}}{\partial \bar{\theta}} > 0$, $\frac{\partial p^{D*}}{\partial \bar{\theta}} < 0$, and $\frac{\partial Q^{D*}}{\partial \bar{\theta}} = -\frac{\partial Q^{I*}}{\partial \bar{\theta}}$.

The proof follows straightforward differentiation. Prices are derived in Proposition 1. To avoid cumbersome expressions, we present the results with $B = 1$ here. For $\theta(z - \Gamma_z) > 0$: $\frac{\partial p^{D*}}{\partial \bar{\theta}} = 0$, $\frac{\partial p^{I*}}{\partial \bar{\theta}} = \frac{1}{2}\left(z - \Gamma_z + \frac{c\bar{k}(z-\Gamma_z)}{(\bar{k}+\bar{\theta}(z-\Gamma_z))^2}\right)$, $\frac{\partial p^{S*}}{\partial \bar{\theta}} = \frac{c\bar{k}(z-\Gamma_z)}{2(\bar{k}+\bar{\theta}(z-\Gamma_z))^2}$, $\frac{\partial Q^{I*}}{\partial \bar{\theta}} = \frac{c(z-\Gamma_z)}{2(\bar{k}+\bar{\theta}(z-\Gamma_z))^2}$, and $\frac{\partial Q^{D*}}{\partial \bar{\theta}} = -\frac{\partial Q^{I*}}{\partial \bar{\theta}}$. For the case of $\theta(z - \Gamma_z) < 0$, $\frac{\partial p^{D*}}{\partial \bar{\theta}} = z - \Gamma_z$, $\frac{\partial p^{I*}}{\partial \bar{\theta}} = \frac{1}{2}\left(\Gamma_z - \frac{c\bar{k}(\Gamma_z - z)}{(\bar{k}+\bar{\theta}(\Gamma_z - z))^2} + z\right)$, $\frac{\partial p^{S*}}{\partial \bar{\theta}} = \frac{c\bar{k}(\Gamma_z - z)}{2(\bar{k}+\bar{\theta}(\Gamma_z - z))^2} + z - \Gamma_z$, $\frac{\partial Q^{I*}}{\partial \bar{\theta}} = \frac{c(\Gamma_z - z)}{2(\bar{k}+\bar{\theta}(\Gamma_z - z))^2}$, and $\frac{\partial Q^{D*}}{\partial \bar{\theta}} = -\frac{\partial Q^{I*}}{\partial \bar{\theta}}$.

Proof for Proposition 3

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

Proof for Proposition 4

Note that this case is equivalent to the general case for each $\lfloor M \rfloor \leq M < \lfloor M \rfloor + 1$ because we can make the same substitutions. Thus, the first statement follows from the general case. For the remaining statements, observe that we can rewrite $\Delta x = x(\theta = 0'; z = 1) - x(\theta = \theta'; z = 1)$, and plug in from the general case. Further, note that $\Delta x < 0 \Leftrightarrow \frac{\partial x}{\partial \bar{\theta}} > 0$. Proposition 2 shows that $\frac{\partial p^{I*}}{\partial \bar{\theta}} > 0$, which thus implies $\Delta p^{I*} < 0$. Similarly, straightforward algebra shows that $\frac{\partial p^{I*}}{\partial \bar{\theta}} > \frac{\partial p^{D*}}{\partial \bar{\theta}}$, $\frac{\partial p^{I*}}{\partial \bar{\theta}} > \frac{\partial p^{S*}}{\partial \bar{\theta}}$, $\frac{\partial p^{S*}}{\partial \bar{\theta}} \geq \frac{\partial p^{D*}}{\partial \bar{\theta}}$, $\frac{\partial Q^{I*}}{\partial \bar{\theta}} \geq 0$, and $\frac{\partial Q^{I*}}{\partial \bar{\theta}} \geq \frac{\partial Q^{D*}}{\partial \bar{\theta}}$, which implies $|\Delta p^{I*}| > |\Delta p^{D*}|$ and $|\Delta p^{I*}| > |\Delta p^{S*}|$ and $|\Delta p^{S*}| \geq |\Delta p^{D*}|$, $\Delta Q^{I*} \leq 0$, and $|\Delta Q^{I*}| \geq |\Delta Q^{D*}|$, which completes the proof.

B 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. For all analyses presented in this section, we assume that the firm's bargaining power is set at $B = 1$ to simplify exposition.

B.1 Equilibrium Definition

To define the equilibrium, we need to consider who is aware of inattention. Under standard assumptions (i.e., rational beliefs), we cannot fully capture inattention because it would assume awareness about one's own inattention. To avoid the issue and capture the intuition of inattention, we relax the assumption of common knowledge about the distribution of inattention and let each player have a (potentially correct) belief about the distribution. We then use a solution concept based on (O'Donoghue and Rabin, 1999)[1] and require that all players' actions are perception-perfect strategies. Each player chooses the optimal action given their preferences, their perceptions of what the other players' current action will be, and their perceptions of all players' future actions. In a similar context, Haan and Hauck (2014) and consider higher-level beliefs in games of present biased consumers, which is also consistent with Fedyk (2021), who experimentally shows that individuals are naive about their own and (to a lesser extent) other people's level of present bias. Throughout the model, we focus on the inattention of consumers and assume that the supply is fully aware of the inattention of consumers, but we relax the assumption of full awareness of owners in appendix B.5.

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 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.

B.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 ($p^{I*} = p^{D*} = V$).*

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

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

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

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

and $CS = 0$

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

B.3 Omitted Cases of the Game

First, we consider the case with the intermediary being visited first, and then 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).

B.4 Case with Decentralized Trade First

First, we consider the case where consumers start their search in the decentralized market and only visit the intermediary as second stop.

Lemma 2 *Suppose that consumers exhibit inattention and visit the decentralized market before considering the intermediary. For a positive wedge ($z - \Gamma_z > 0$), private sellers set a price only accepted by consumers with $\theta \geq \theta^*$, where $\theta^* > 0$ for a sufficiently low V. For a negative wedge ($z - \Gamma_z < 0$), private sellers set a price only accepted by consumers with $\theta \leq \theta^*$, where $\theta^* < 1$ for a sufficiently low V.*

Proof. We can again solve this by backwards induction. In the final period, the firm is setting its price, conditional on the consumers it faces and the quantity of vehicles it purchased in the first period. In the previous period, individual sellers decide to enter or not enter the market and set a price. In the earliest period, the intermediary offers current vehicle owners a purchase price and individual owners decide to keep or sell the vehicle. By the same arguments as previously, consumers beliefs about inattention are inaccurate and they believe that the intermediary prices conditional on a homogenous θ, which implies a price that extracts all surplus $E[p_b^I|\theta] = u_B(\theta)$. Therefore, a consumer will purchase in the decentralized market whenever their utility, net of price, is positive. In the first stage, the intermediary sets a purchase price, so there are potentially more buyers than sellers in the first stage. We introduce a match parameter γ that denotes the probability of a buyer meeting a seller in the first period. We assume that buyers are randomly paired with sellers. There are therefore a proportion γ consumers who are matched and $1-\gamma$ consumers who are not matched in the decentralized market. Focusing on the stage in which individual sellers set prices, the prices are set to maximize

$$\begin{aligned} p^{D*} &= \arg\max_{p^D} E[\pi_O(p^D)] = P(\text{accept}|p^D) \times p^D + (1 - P(\text{accept}|p^D)) \times (1 - z), \\ &\text{s.t. } 0 \leq P(\text{accept}|p^D) \leq 1, \end{aligned} \tag{19}$$

where the solution is given by an interior solution

$$p^{D*} = \begin{cases} \frac{1}{2}\left(2 + V - 2z + \bar{\theta}(z - \Gamma_z)\right), & \text{if } z > \Gamma_z, \\ \frac{1}{2}\left(2 + V - 2z\right), & \text{if } z \leq \Gamma_z. \end{cases}$$

, or the corner solution

$$p^{D*} = \begin{cases} 1 + V - z, & \text{if } z > \Gamma_z, \\ 1 + V - z + \bar{\theta}(z - \Gamma_z), & \text{if } z \leq \Gamma_z. \end{cases}$$

. For $z > \Gamma_z$, matched consumers purchase from the private seller whenever

$$\theta > \theta^*,$$

where for $z > \Gamma_z$ we have $\theta^* = 0$ in the corner solution and $\theta^* > 0$ in the interior solution (the latter arising when V is sufficiently small). When $z < \Gamma_z$, the inequality reverses and consumers buy whenever $\theta < \theta^*$, with $\theta^* = 1$ in the corner solution and $\theta^* < 1$ in the interior solution (again requiring a sufficiently small V).

■

B.4.1 Case With Only Decentralized Trade

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

$$p^{D*} = \underset{p^D}{\text{argmax}}\ E[\pi_O(p^D)] = P(\text{accept}|p^D) \times p^D + (1 - P(\text{accept}|p^D)) \times (1 - z),$$
$$\text{s.t. } 0 \leq P(\text{accept}|p^D) \leq 1,$$

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

Lemma 3 *For sufficiently high potential gains of trade ($\bar{\theta} < V/(\Gamma_z - z)$):*

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

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

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

B.5 Naive Owners

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

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

$$\begin{aligned} p^{D*} &= \arg\max_{p^D} E[\pi_O(p^D)] = P(\text{accept}|p^D) \times p^D + (1 - P(\text{accept}|p^D)) \times (1 - z), \\ &\text{s.t. } 0 \leq P(\text{accept}|p^D) \leq 1, \end{aligned} \tag{20}$$

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:

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

$E[\pi_O] - p^{S*} = k$, 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:

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

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 20. 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.

B.6 Heterogeneity in Preferences

This section aims to highlight the impact of consumer inattention and consider consumers that are heterogeneous w.r.t to their actual willingness to pay for an attribute, as opposed to heterogeneity stemming from inattention. An important difference is that consumers are fully rational in this setting and anticipate the firm's optimal pricing. Again, we consider the following utility functions: $u_S = 1 - z$ and $u_B(\psi) = u_S + V + z\psi$, where ψ captures the willingness to pay for attribute z for buyers. To make the results comparable to the inattention results, we consider the case of a positive z, and Probnabsellers that are only heterogeneous regarding their cost of supplying the good, k. The solution concept is the Perfect Bayesian Equilibrium (PBE).

B.6.1 Consumer Trade Only

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

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

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

The solution is then given by:

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

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

B.6.2 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.

B.6.3 Intermediary and Private Trade

Now we consider the full case with an intermediary and decentralized trade. To solve the model, we apply similar arguments as in the case of inattention. In the second period, owners need to set a price. Then, taking this price as given, the intermediary maximizes profit in the first period. We again solve this by using backward induction[3]. In the second stage, the owners need to set a price that maximizes profit, taking $\hat{\psi}$ as given

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

where $P(\text{accept}|p) = min\left[1, \int_{\frac{p^D+z-V-1}{z}}^{\hat{\psi}} f(\psi)d\psi\right]$. The solution is then given by: $p^{D*} = 1 + V - z$. To solve the firm problem, we first note that the intermediary price needs to be less or equal to the price in the decentralized market. Suppose the intermediary sets a price higher than the price in the decentralized market. All (potential) consumers will wait until

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

the second period and purchase in the decentralized market, implying that the intermediary profit is zero. Secondly, owners can never set a price below $p^D = 1 + V - z$. Suppose owners set $p^D = 1 + V - z - \epsilon$. Then profit, is given by $\pi^P = 1 + V - z - \epsilon$. Alternatively, the profit at $p^D = 1 + V - z$ is given by $\pi^P = 1 + V - z$.

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

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

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

Lemma 4 *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.

C Testing of Γ_M

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

C.1 Identification of Γ_M

In the paper, we propose (broadly) two types of econometric specifications. We provide a direct estimator for θ in equation 12. When allowing the perceived milage to also depend on the value of Γ_M, this equation is given by:

$$price_i = \beta_0 + \sum_{k=1}^{K} \alpha_k (\underbrace{M_i - \theta(M_i - \lfloor M_i \rfloor - \Gamma_M)}_{\text{Perceived Mileage}})^k + \psi X_i + u_i, \tag{21}$$

To see why this is not identified, consider the case with $k = 1$. In this case, we can rewrite the equations as $price_i = \beta_0 - \Gamma_M \alpha_1 \theta + \sum_{k=1}^{1} \alpha(M_i - \theta(M_i - \lfloor M_i \rfloor)^k + \psi X_i + u_i$. where the intercept absorbs the Γ_M-term. The second type of estimator (see equation 13) we used directly leveraged differences in outcomes around thresholds. The estimator assumes a homogeneous θ, which implies that any variation in Γ_M is a constant and does not affect the estimated coefficients.

C.2 Predictions for different values of Γ_M

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

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

1. ***Inattention*** *Inattention in consumer transactions is lower than in intermediary transactions if $\Gamma_M = 0$, and higher if $\Gamma_M = 1$.*
2. ***Sales Price*** *The discontinuity in intermediary sales prices is negative (Δp^{I*}).*
3. ***Decentralized Market Price*** *Whenever $\Gamma_M = 0$, there is no discontinuity in decentralized market prices (Δp^{D*}). Whenever $\Gamma_M = 1$, there is a discontinuity and it is greater in absolute terms than the discontinuity in intermediary sales prices.*
4. ***Purchase Price*** *The discontinuity in purchase price is negative. For $\Gamma_M = 0$, it is smaller in absolute terms than the discontinuity in sales prices. For $\Gamma_M = 1$, it is greater than the discontinuity in sales prices*
5. ***Price Comparison*** *The discontinuity in the dealership purchase price is (weakly) larger in absolute terms than the discontinuity in decentralized market prices ($|\Delta p^{S*}| \geq |\Delta p^{I*}|$).*
6. ***Absolute Quantity*** *The discontinuity in the quantity of intermediary transactions (ΔQ^{I*}) is (weakly) negative for $\Gamma_M = 0$ and (weakly) positive if $\Gamma_M = 1$*
7. ***Relative Quantity*** *The discontinuity in the number of intermediary transactions (ΔQ^{I*})is (weakly) larger in absolute terms than the discontinuity in the number of consumer transactions (ΔQ^{D*}) for $\Gamma_M = 0$ and weakly smaller for $\Gamma_M = 1$*

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

Case where $\Gamma_M = 0$:

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

Case where $\Gamma_M = 1$:

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

Inequalities

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

D Empirical Extensions

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

D.1 Warranties

Our identification strategy assumes that discontinuities at multiples of 10,000 miles arise purely from inattention. A potential threat to this identification strategy is that vehicles have warranties, potentially expiring at multiples of 10,000 miles[4]. Warranties have a maximum time frame and odometer reading and are generally set at the brand level. For example, a vehicle with a 5-year/60,000-mile warranty is under warranty as long as the vehicle is less than 5 years old and has logged fewer than 60,000 miles. If there are discontinuities in price at the end of the warranty [5], we could mistakenly attribute the discontinuity due to the expiration of a warranty to inattention. We collect data on the length of standard warranties by each brand and present two robustness checks to alleviate this concern. Approximately 80% of basic warranties end at 36,000 miles, and approximately 80% of drivetrain warranties end at 60,000 miles[6]. This gives us confidence that only discontinuities at the 60,000-mile mark are potentially affected by the end of warranties. To formally test if warranties have an impact, we first leverage the fact that warranties have a time limit and reanalyze the data using observations of vehicles that are -due to their age- not under either drivetrain or basic warranty when they are being transacted. We present the results in the bottom panel of Figure A3. Obviously, this introduces some data limitations (e.g., all warranties are between 4 and 10 years and the set of vehicles that are transacted around low odometer readings and simultaneously sufficiently old is relatively small and not representative of the full sample. However, this empirical exercise shows patterns similar to the results presented in Table 3 also holds for vehicles for which warranties have expired already.

A second analysis uses the set of vehicles for which the warranty time limit has not yet lapsed and leverages the differences in mile thresholds for different makes. For example, Ford has a 36,000-mile basic warranty and a 60,000-mile drivetrain warranty, whereas Volkswagen

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

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

[6]The distribution of the warranty terms is presented in Figure A4 in the Online Appendix.

has basic and powertrain warranties that both expire after 72,000 miles. We now estimate the following model, similar to equation 13:

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

In the equation, $\mathbf{1}\left[miles_i \geq w_B\right]$ is an indicator that equals one for vehicles with odometer readings exceeding the basic warranty and $\mathbf{1}\left[miles_i \geq w_{DT}\right]$ is an indicator variable that equals one for vehicles with odometer readings exceeding the drivetrain warranty. Thus, the β coefficients now isolate the effect of the discontinuities while controlling for the (potential) discontinuities due to the expiration of warranties. For this analysis, we need to impose the assumption that the effect of the expiration of a warranty is homogeneous across different lengths of warranties. For example, the negative effect of a warranty ending at 50,000 miles should be equal to the effect of a warranty ending at 60,000 miles. Because many warranties end at 36,000 miles, 50,000 miles, and 60,000 miles, there is not much variation in the data to precisely identify the effect of warranties from the effect of inattention. However, the results (presented in the top panel of Figure A3 follow the same pattern as the main analysis (Table 3) and is consistent with the earlier results, with the exception of the discontinuity at 60,000 miles, which is now positive for purchase and sales prices. Given that 78% of drivetrain warranties end at 60,000 miles, this coefficient is identified from a small set of observations for which the warranty does not end at 60,000 miles. The positive coefficient could be the result of heterogeneous effects of the expiration of warranties[7].

D.2 Location of Discontinuities

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

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

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

In the above model, y_i is the residual, X_i the full set of fixed effects, and each β_j term captures the relationship between a specific 1,000 mile bucket and price. One obvious downside to the lasso model is that the magnitude of the coefficients is difficult to interpret. Significant coefficients are not necessarily indicative of discontinuities, but our theoretical model would predict significantly negative coefficients at a multiple of 10,000 miles. Figure A5 presents the results for the 148 coefficients. Reassuringly, none of the coefficients at multiples of 10,000 miles are shrunk to zero and generally stand out as more negative.

D.3 Left-Digit Bias

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

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

In the equation, $mod(miles_j)$ is the modulus, which gives a number between 0 mi and 9,999 mi. Similarly to the model used to test for discontinuities, we include the polynomial to absorb the continuous portion of the depreciation and let the outcome variables be the purchase price, the sales price, and the per-unit profit. This allows us to interpret the results as the (weighted) average excess in purchase price, sales price, and profits for different mileages[8]. The results presented in Figure A6 show two patterns. First, the coefficients for all three outcome variables generally increase and are higher for vehicles with higher ending digits. Second, there is a drop at the 5,000-mi mark for most vehicles. This is consistent with consumers who are left-digit biased but also treat odometer readings differently, depending on being above or below multiples of 5,000.

D.4 Placebo Tests

This section considers the robustness of the analysis above by using placebo tests. We re-estimate tables (3), (4). and (5), 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

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

discloses odometer readings in miles, a consumer never observes the mileage in kilometers. As a result, we expect the coefficients on each 10,000-kilometer cutoff to be largely insignificant. We present the results in figures (A7), (A8), and (A9). The first figure presents the results for the various prices the dealership pays or receives. We have estimated 3×23 coefficients for kilometer cutoffs. Except for the sales price at 40,000km and the profit at 240,000km cutoff, no coefficient is significant at the $p = 0.05$ level. Purely by chance, we would expect 3.45 coefficients at the 5% level, In figure (A8), we observe five coefficients significant at the 5% level, which is slightly higher than what is expected purely by chance (2.3). Finally, in figure (A9) we observe two coefficients significant at the 5% level, compared to an expected number of 1.15. Given that some kilometer cutoffs are within a few 100 miles of a corresponding 10,000-mile cutoff, the results of the placebo test are generally reassuring.

D.5 Accidents

Intermediaries play a role in reducing adverse selection and asymmetric information (Biglaiser et al., 2020). There are likely interesting interactions between this adverse information and inattention, but they are beyond the focus of this paper. However, we now present two sets of analyses. First, we collect data from the Texas DMV that records each accident with damages above \$1.000, for which a police report was filed. These accidents are categorized according to their damage of severity to each vehicle on a scale of 0 to 7. The vast majority of vehicles with damage ratings above 4 never get sold afterwards, so we focus on vehicles with damages between 0 and 4. First, we correlate the prices and profits to the vehicle damage for vehicles that have been in an accident before the first transaction, and present the results in table A1. First, we observe that the penalty in sales price due to a previous accident is significantly larger in decentralized transactions. Secondly, we find that dealerships earn higher levels of profit on vehicles with more severe accidental damage. The results are difficult to interpret, because the choice of channel is an endogenous outcome, chosen after a potential accident. Our preferred interpretation of the difference between the "accident penalty" in the two markets is selection. Consistent with previous work (Biglaiser et al., 2020), the intermediary might only accept vehicles of higher observed (and potentially unobserved by the consumer) quality, leaving worse vehicles to be transacted in the decentralized market. The results about intermediary profit could reflect two potential explanations, which we are unable to untangle. First, it could be that the intermediary invests more to "refurbish" vehicles with more severe accidental damage (e.g. changing tires , removing scratches, or cleaning the vehicle more thoroughly). Because we do not observe these investments, we might falsely attribute them to profit. Secondly, similar to the main result in our paper, some consumers might be inattentive to damages that are difficult to identify and the dealership might be extracting more surplus from these vehicles. However, if the intermediary would treat damages exactly like vehicles right below multiples of 10,000 miles, we would also expect them to sell a higher quantity of damaged vehicles, which we do not observe.

As a second analysis, we now split our sample into vehicles that previously had an accident or did not have an accident and re-estimate the inattention parameter. The results are presented in A2. The results show that in intermediary transactions, the estimated level of left-digit bias is similar between vehicles that were involved in no accidents ($\theta = 0.401$) and those that were previously in an accident ($\theta = 0.442$). Due to the relative scarcity of accidents, the estimate for vehicles that have been in an accident are quite noisy. For vehicles that transact in private transactions, there is a sizable difference between the two estimates. Vehicles that had no accident have an estimated parameter of ($\theta = 0.308$), while vehicles that were in an accident have a coefficient of ($\theta = 0.031$). There is no clear interpretation of these results, but it is reassuring that the result about inattention being higher in intermediary transactions holds across the sample of transactions with previous accidents as well.

D.6 Left-Digit Bias for Price

As a first step, we re-estimate the LDB coefficients from Table 6 while also permitting bias in the price dimension. This is implemented through a hedonic price regression framework. Because sellers may themselves act strategically when setting prices around salient thresholds, the resulting estimates should be viewed as a robustness exercise that coarsely aims to "control" for price-related LDB rather than as precise estimates of the underlying structural bias parameters with respect to the price. We illustrate the logic with a toy example. Suppose price is two digits, $p = \lfloor p \rfloor_{10} + r_{10}$ with remainder $r_{10} \in \{0, \ldots, 9\}$. If consumers are inattentive to the second digit, perceived price is $\hat{p} = \lfloor p \rfloor_{10} + (1 - \theta_P) r_{10}$. Equating this with the hedonic value $\alpha + g(M) + \varepsilon$ gives $\alpha + g(M) + \varepsilon = p - \theta_P r_{10}$, or

$$p \;=\; \alpha + g(M) + \theta_P r_{10} + \varepsilon,$$

so θ_P is directly estimated as the coefficient on the remainder.

In the empirical model, both price and mileage are subject to inattention. Define the mileage remainder $R_M = M - \lfloor M \rfloor_{10k}$ and the price remainders $P^{(1000)}, P^{(100)}, P^{(10)}, P^{(1)}$ at each place value. Then the estimating equation is

$$p_i \;=\; \alpha + \sum_{k=1}^{K} \beta_k \big(M_i - \theta_M R_{M,i} \big)^k + \theta_{P,1000} P_i^{(1000)} + \theta_{P,100} P_i^{(100)} + \theta_{P,10} P_i^{(10)} + \theta_{P,1} P_i^{(1)} + \mathrm{FE}_i + \varepsilon_i,$$

where θ_M captures inattention to mileage digits and $\theta_{P,\cdot}$ capture inattention to price digits. The results are presented in Table A3. Accounting for pricing, LDB does not affect the estimates of our LDB coefficients on mileage. Not surprisingly, consumers are highly attentive to the variation at the $1,000s level, but exhibit progressively higher levels of left-digit bias for digits to the right. While the hedonic regression in general comes with some strong assumptions about firms not being strategic, the regression would be particularly problematic if intermediaries set prices, knowing that some consumers are left-digit biased with respect to all attributes. As a thought exercise, we extend the baseline model to allow consumers to exhibit correlated LDB in both the *price* and the *mileage* of vehicless.

Again, let vehicle i have true price P_i, mileage M_i, and quality V_i. The consumer perceives both attributes with potential left-digit bias:

$$\tilde{P}_i = P_i - \theta^P \cdot (P_i - \lfloor P_i \rfloor), \tag{25}$$

$$\tilde{M}_i = M_i - \theta^M \cdot (M_i - \lfloor M_i \rfloor), \tag{26}$$

where $\lfloor P_i \rfloor$ and $\lfloor M_i \rfloor$ denote the nearest round-number thresholds (e.g., $20,000 for prices or 40,000 miles for mileage). The parameters $\theta^P, \theta^M \in [0, 1]$ capture the degree of left-digit bias for price and mileage respectively.

The consumer's utility from purchasing vehicle i is given by:

$$U_{ij} = V_i - \alpha \tilde{P}_i - \gamma \tilde{M}_i + \varepsilon_{ij}, \tag{27}$$

where $\alpha > 0$ measures the marginal disutility of perceived price, $\gamma > 0$ measures the marginal disutility of perceived mileage, and ε_{ij} is an idiosyncratic preference shock.

Finally, we allow for the possibility that left-digit bias in price and mileage are *correlated across consumers*, so that:

$$\begin{pmatrix} \theta^P \\ \theta^M \end{pmatrix} \sim F(\mu, \Sigma), \tag{28}$$

where μ is the mean vector and Σ is a covariance matrix. This formulation captures the idea that some consumers may be generally more susceptible to left-digit bias across multiple attributes. An implication of this sett is thatup is that, since vehicles right below round mileage thresholds are particularly attractive to consumers with high values of LDB across both dimensions, the firm might be more likely to price those vehicles at prices right below round thresholds. Moreover, if the firm increases their prices for those vehicles, this might exagerate the effect of left-digit bias we have estimated. While solving this firm problem is interesting, we do not aim to provide a solution here. However, in order to probe whether our results might be driven by LDB on the price coefficient, we test whether we see this specific firm behavior of bundling favorable mileages with favorable prices. To do so, we examine how consumer attention to left digits in price and odometer readings may interact and estimate correlations using a modulus-based specification.a The analysis proceeds in five steps:

1. **Variable construction.** For each transaction, we compute two modulus variables:

   $$\text{modulus\_price} = \text{sales\_price} \bmod M_p, \quad \text{odometer\_modulus} = \text{odometer\_reading} \bmod M_o,$$

   where the baseline choices are $M_p = 1000$ (price) and $M_o = 10{,}000$ (odometer). We further define a rounded odometer bin

   $$\text{odometer\_modulus\_round} = \left\lfloor \frac{\text{odometer\_modulus}}{1000} \right\rfloor \times 1000,$$

   which takes values in increments of 1,000 miles.

2. **Price bins.** We partition the price modulus into 10 bins of width 100 (e.g. $[900, 1000)$, $[800, 900)$, ..., $[0, 100)$).

3. **Model estimation.** For each price bin $b \in \{1, \ldots, 10\}$, we run a linear probability model:

   $$\mathbf{1}\{\text{modulus\_price} \in b\} = \sum_k \gamma_{b,k} \cdot \mathbf{1}\{\text{odometer\_modulus\_round} = k\} + \varepsilon,$$

where k indexes odometer modulus intervals of 1,000 miles. This gives us 10 regressions (one for each price bin).

4. **Coefficient extraction.** From each regression, we collect the coefficients $\gamma_{b,k}$ and their standard errors. These measure the relative association between being in price bin b and having an odometer modulus in interval k.

5. **Visualization.** We plot $\gamma_{b,k}$ with 95% confidence intervals for each bin b, with odometer bins k distinguished by color. The resulting figure shows the correlation structure between (i) being near a left-digit threshold in price and (ii) being near a left-digit threshold in mileage.

This procedure is applied separately for private transactions and dealer transactions, and for two different price modulus definitions ($M_p = 1{,}000$ and $M_p = 10{,}000$). The resulting four plots provide a robustness check for the presence of joint left-digit effects in both markets and across modulus scales. The results are presented in figures A10, A11, A12, and A13. Across all specifications, we find that prices below round thresholds are much more common than other prices in dealership transactions. However, this is largely orthogonal to favorable mileages. For example, from figure A10, we see that regardless of the odometer modulus, about 25% of all transactions have prices that end in values between $900 and $999. We see similar effects for private transactions, with the main difference being that prices are much more likely to end in round numbers, as opposed to below them.

D.7 Information Sources

Consumers often rely on third-party price recommendations to understand the value of a particular vehicle. We are not formally incorporating this external information into our model, but we now want to present some descriptive evidence about recommended prices for vehicles and how they might interact with left-digit bias. We collected data from a large price recommendation website that provides suggested used-vehicle values under various odometer readings, vehicle conditions, and geographic areas. Specifically, we systematically queried the recommended private-party and trade-in prices for a broad selection of makes, models, and model years across multiple ZIP codes in the United States at different points in time between 2018 and 2023. For each vehicle, we varied the odometer reading from 10,000 up to 150,000 or 200,000 miles in increments of 100 miles—and recorded the resulting recommended prices, along with the date, location, and condition indicators (e.g., 'Very Good,' 'Good').

Our final sample consists of 190 unique model/zipcode/query date combinations, and we collect the recommended price for each of the four conditions, ranging from "Fair" to "Excellent", separately for each odometer between 10,000 and 150,000, in increments of 100. A small number of odometer readings (1,192) return errors and therefore we have a final sample of 1,064,760 observations.

The collected data has some aspects that are consistent across different zip codes, vehicle models, times, and conditions. For older vehicles (where there presumably is little data available at low odometer readings), the recommended price is constant with respect to odometer until some point, after which the value begins decreasing weakly as a function of odometer. All vehicles in our sample show this decreasing function starting at some point before 40,000 miles. Newer models exhibit a weakly decreasing trend starting immediately at 10,000 miles on the odometer. Subsequently, up to exactly 70,000 miles, all vehicles decrease by a relatively constant, vehicle-specific amount every 500 miles. Between 70,000 and 100,000 miles, the decreases occur at multiples of 1,000. Beyond 100,000 (up to 150,000), the decreases happen at multiples of 2,000.

With respect to information affecting left-digit bias in our results, we do not observe larger decreases at multiples of 10,000 compared to the closest non-10,000 discontinuity. We first plot the recommended prices for one example vehicle (figure A14) to illustrate these patterns. Interestingly, the recommended price for most vehicles is nearly a linear function of odometer after the initial horizontal segment, with the granularity of odometer-based price updates varying by mileage range.

We then estimate discontinuities in this sample for private price recommendations. The results, shown in table A4, confirm that price discontinuities do occur at multiples of 10,000.

Next, we use the data for each odometer reading to estimate the inattention parameter. If consumers followed the recommended price exactly, the inattention parameter estimated here would perfectly match that from real-world market prices. While our sample of recommendations is smaller than actual transactions, we have the advantage of "holding constant" all other vehicle attributes when isolating variation in odometer. Accordingly, we re-estimate equation 12, include a fixed effect for each model, and obtain an inattention parameter in table A5 that is quite low (0.015). We also allow for inattention at 1,000-mile increments; unsurprisingly, that estimate is larger (0.66). Because there are ten times as many 1,000-mile thresholds than 10,000-mile thresholds, the coefficients are also more precisely estimated.

D.8 Alternative Specifications

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

D.8.1 Functional Form of Price Effects

To relax the assumption of linear effects, we re-estimate columns (1) and (2) of Table 4 using log of prices. Because profits can take negative values, we cannot use a log specification for column (3). We present the results in Table A6 and find that they are robust and qualitatively very similar to the results presented in the main paper.

D.8.2 Sample Selection

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

We now present results that include vehicles that were purchased and subsequently sold by a different dealership. Because we do not observe the outcomes from potential wholesale auctions, we are unable to attribute profits to a specific dealership. However, we are able to test the overall implications from our paper. We reestimate the inattention coefficients presented in Table 2 and the coefficients in Table 3. The results are presented in Table A7 and Table A8, and the results are generally consistent with the results presented in the main text. The discontinuities are generally slightly larger (in absolute terms). Additionally, the estimated level of inattention is slightly higher compared to the restricted sample. Additionally, we consider vehicles that were bundled with a trade-in and without in the main sample. Heterogeneity along this dimension could be driven by selection effects (e.g. consumers that have a trade-in might be older) or might be driven by the fact that the transaction becomes more complicated. Presumably, consumers that provide a trade-in might be more likely to transact at the dealership (e.g. due to significant tax savings), and might be quite different from consumers that do not trade-in a vehicle. As an additional analysis, we present table A11, in which we separately estimate inattention coefficients for consumers that bundle their transaction with a trade-in. The results show that vehicles without a trade-in are associated with higher levels of inattention.

D.8.3 Rounding

Possibly, consumers are rounding the odometer readings when filling out the title form. This introduces measurement error that might be correlated with inattention. For example, a more attentive consumer may also be more likely to observe the odometer carefully and report the exact odometer reading on the title form. We plot the frequency of "round" numbers that are multiples of 100, 250, or 1,000 in Figure A15. Assuming that vehicles precise odometer is random, one could expect that about 1% of vehicles have odometer readings that are multiples of 100, about 0.25% have multiples of 250, and about 0.1% have odometer readings that are multiples of 1,000. For vehicles transacted in dealership transactions, the frequency of observing such round numbers is relatively close to what we would expect if the odometer is reported accurately. However, for vehicles transacted in the decentralized market, rounding is highly prevalent and increases drastically for vehicles with higher odometer readings. For example, in the "bucket" of vehicles between 100,000 miles and 110,000 miles, over 10% of vehicles have odometer readings that are multiples of 1,000 and over 20% of vehicles have odometer readings that are multiples of 100.

Clearly, rounding is prevalent in the decentralized market, and to deal with this issue, we remove numbers that are (presumably) rounded. We re-estimate the inattention parameters reported in Table 2 and remove all vehicles that end in a multiple of 1,000, a multiple of 250, or a multiple of 100. By removing these observations, we retain a sample that is presumably precisely reported. However, because more inattentive consumers are potentially more likely to round numbers, the remaining sample may also be comprised of more inattentive consumers. We present the results in Table A9 and they are virtually identical with the results from the full sample for vehicles sold at dealerships. Specifically, the estimated inattention coefficient is $\theta = 0.400$ or $\theta = 0.399$ in all specifications, including the full sample. The results for decentralized transactions show that removing rounded values drastically affects the reported coefficients. For the full sample, we estimate $\theta = 0.28$, while the estimates in the samples without rounded values are between $\theta = 0.201$ and $\theta = 0.213$. These results are consistent with the theory proposed in the paper and also with the fact that more attentive consumers are less likely to report rounded odometer readings.

D.9 Product Level Heterogeneity

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

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

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

We estimate the inattention parameter $\theta_{Mod,j}$, where $j = \{10,000; 20,000; ...; 150,000\}$ and Mod denotes the model. Thus, we have an estimate for each model around each 10,000 mile cutoff, where $P^0_{Mod,j} = E[p|miles_i = j - 5,000] = \hat{\gamma_0} + (j - 5,000)\hat{\gamma_1}$. The average depreciation is given by $\alpha_{Mod,j} = \frac{\hat{\gamma_1} + \frac{\gamma 2}{10,000}}{E[p|miles_i = j - 5,000]}$.

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

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

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

The identification of coefficients, therefore, comes from the variation in odometer, price, and depreciation within car models. Table A10 presents the results. We first present the regression for vehicles in dealership transactions and then present the regression for decentralized transactions. W We find that the price coefficient and the depreciation coefficient are significant and positive. Similarly, the positive coefficients on higher odometer thresholds are positive and significant. This result implies that consumers pay less attention to vehicles with higher levels of depreciation and higher prices, which is seemingly inconsistent with models of rational inattention. Additionally, consumers treat specific ranges of odometer readings differently, with higher levels of inattention for vehicles with higher odometer readings, regardless of the depreciation or price of those vehicles. For transactions in the decentralized market, there is little observed heterogeneity.

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

E Omitted Details of Estimation

E.1 Inventory & Competition

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

F Survey Details

This appendix documents the Prolific survey conducted to measure consumers' vehicle search and consideration behavior. The survey was fielded in July 2025 on Prolific to a sample of 1,500 U.S. respondents aged 18–83 who had either purchased a vehicle or actively searched for one within the past five years. Respondents completed a short questionnaire and were paid standard Prolific rates.

The survey included screening questions about recent vehicle search or purchase activity, questions about whether respondents considered purchasing from a dealership or from another private individual, and questions about the channel in which respondents began their search. Respondents reported whether their most recent transaction occurred in the private market, at a dealership, or involved both channels.

Across respondents who reported purchasing in the private market, a larger share indicated that they also considered dealerships than the share of dealership buyers who indicated that they considered private-market options. In addition, the percentage of respondents who reported starting their search in a different channel than the one in which they ultimately purchased was higher among private-market buyers than among dealership buyers.

Table A13 presents results from a linear probability model regressing the indicator the opposite channel on an indicator in the private market. The results show that respondents who purchased in the private market were significantly more likely to have considered dealerships than dealership buyers were to have considered the private market.

Table A14 restricts the sample to respondents who reported considering the opposite channel and tests for differences in search origination. We regress an indicator for starting the search in the eventual purchase channel on the private purchase indicator. The results indicate that private market buyers are less likely to have started their search in the private channel compared to dealership buyers starting at a dealership. This suggests that private market transactions are more likely to be the result of consumers switching channels during the search process.

Tables

Table A1: Correlation between vehicle accident severity and intermediary sales price, purchase price, profit, and decentralized sales price.

Dependent Variables: Model:	Purchase Price (1)	Sales Price (2)	Profit (3)	Sales Price (Decentralized) (4)
Variables				
Vehicle Damage: 0	-132.2	-63.02	69.14	-691.5***
	(82.08)	(46.90)	(75.69)	(153.2)
Vehicle Damage: 1	-189.3***	-122.5***	66.83***	-452.1***
	(24.92)	(12.17)	(24.51)	(25.86)
Vehicle Damage: 2	-285.6***	-180.0***	105.7***	-939.6***
	(25.49)	(13.63)	(24.34)	(24.65)
Vehicle Damage: 3	-458.5***	-296.0***	162.5***	-1,497.7***
	(34.01)	(18.82)	(32.47)	(30.98)
Vehicle Damage: 4	-493.4***	-323.1***	170.3**	-1,926.2***
	(69.29)	(36.45)	(66.18)	(45.55)
Fixed Effects	Yes	Yes	Yes	Yes
Fit Statistics				
Observations	3,217,182	3,217,182	3,217,182	1,588,659
R^2	0.78260	0.93261	0.14473	0.87583
Within R^2	0.05979	0.19416	0.00056	0.07668

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

Table A2: Estimate of the Inattention Parameters by Dealer and Private Transactions, separately for vehicles with recorded accidents.

	Transaction Type and Accident Status			
	Dealer - No Accident	Dealer - Accident	Private - No Accident	Private - Accident
	(1)	(2)	(3)	(4)
Inattention (θ)	0.401***	0.442***	0.308***	0.031
	(0.015)	(0.071)	(0.045)	(0.189)
Observations	2,353,823	129,598	1,023,019	115,178
7th Polynomial	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes

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

Note: We omitted polynomial coefficients in the table. The sample includes vehicles between 25,000 miles and 125,000 miles. The inattention coefficient (θ) is estimated separately for dealership and private transactions, and further split by whether the vehicle has a recorded accident.

Table A3: Estimate of the Inattention Parameters

	Dealership	Decentralized
Inattention (θ)	0.401	0.271
	(0.015)	(0.043)
θ_{Price} (1000s)	0.0175	0.0496
	(0.0006)	(0.0016)
θ_{Price} (100)	0.245	0.380
	(0.0060)	(0.0143)
θ_{Price} (10s)	1.000	1.000
	(0.0575)	(0.1508)
θ_{Price} (1s)	1.000	1.000
	(0.5949)	(2.067)
Observations	2,483,421	1,138,197
7th order polynomial	Yes	Yes
Fixed Effects	Yes	Yes

Notes: We omitted polynomial coefficients from the table. The sample includes vehicles between 25,000 miles and 125,000 miles. Standard errors are in parentheses.

Table A4: Discontinuities in sample of vehicles price recommendations.

Dependent Variable: Model:	Value (1)
Variables	
20K miles	37.90***
	(5.428)
30K miles	-48.91***
	(6.607)
40K miles	-82.48***
	(5.708)
50K miles	-22.68***
	(3.477)
60K miles	-7.701***
	(1.670)
70K miles	16.29***
	(1.890)
80K miles	-6.962**
	(3.269)
90K miles	1.205
	(3.001)
100K miles	47.50***
	(3.193)
110K miles	6.865***
	(2.387)
120K miles	7.839***
	(2.367)
130K miles	-7.244***
	(2.136)
140K miles	-53.02***
	(3.332)
Fixed-effects	
Vehicle_id	Yes
ConditionType	Yes
Fit statistics	
Observations	1,063,568
R^2	0.95087
Within R^2	0.47617

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

Table A5: Estimate of the Inattention Parameters at Different Odometer Moduli, based on price Recommendations.

	$\theta_{1,000}$	$\theta_{10,000}$
Estimate	0.663***	0.015
Standard Error	(0.157)	(0.016)
Observations	1,063,568	
Number of Vehicles	190	

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

Table A6: Log prices in Estimation of Pricing Discontinuities.

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

This table re-estimates table 4 using log prices as dependent variable. Note that we do not include Dealership Profit because it includes negative numbers.

Table A7: Estimate of the Inattention Parameters.

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

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

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

Table A8: Estimated discrete change in prices at 10,000 mile thresholds.

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

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

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

Table A9: Estimate of the Inattention Parameters.

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

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

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

Table A10: Heterogeneity of inattention in dealership and decentralized transactions.

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

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

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

Table A11: Estimate of the Inattention Parameters

	with Trade-In	no Trade-In	with Trade-In	no Trade-In
Inattention (θ)	0.35***	0.43***	0.36***	0.45***
	(0.03)	(0.02)	(0.03)	(0.02)
Observations	844,560	1,638,861	844,560	1,638,861
7th order polynomial	Yes	Yes	Yes	Yes
Uniformly Weighted	No	No	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes

Notes: Columns (3) and (4) are estimated using weighted nonlinear least squares, giving each odometer reading equal weight. We omitted polynomial coefficients in the table. The sample includes vehicles between 25,000 miles and 125,000 miles. +p<0.1, *p<0.05, **p<0.01, *** p<0.001. The standard errors are estimated using a bootstrap with 2,000

Table A12: Replication of Table 4, restricted to vehicles without active warranty.

Dependent Variables:	Purchase_Price	Sales_Price	Profit
Model:	(1)	(2)	(3)
Variables			
10K miles	-95.11	-1,086.0***	-910.1
	(1,132.2)	(380.0)	(1,140.3)
20K miles	-161.4	-106.9	-17.55
	(395.3)	(149.7)	(334.0)
30K miles	-194.1	-109.7	209.8
	(205.6)	(75.22)	(227.2)
40K miles	-146.1	-132.1***	-7.456
	(146.3)	(44.04)	(159.3)
50K miles	-241.7**	-141.9***	39.69
	(95.45)	(31.83)	(92.17)
60K miles	-110.3	-176.8***	-44.89
	(71.53)	(24.32)	(78.61)
70K miles	-46.80	-210.0***	-124.6**
	(59.87)	(20.00)	(60.04)
80K miles	-100.4*	-139.1***	-56.52
	(51.48)	(18.65)	(54.28)
90K miles	-129.0***	-221.4***	-123.8**
	(48.26)	(17.54)	(52.24)
100K miles	-113.0*	-253.1***	-119.8**
	(58.01)	(20.22)	(57.77)
110K miles	1.445	-48.95**	-16.52
	(55.78)	(23.63)	(61.13)
120K miles	-45.22	-151.9***	-135.1**
	(60.22)	(28.24)	(62.40)
130K miles	-55.30	-84.78**	-53.91
	(74.18)	(34.89)	(71.39)
140K miles	-109.1	-161.1***	-1.246
	(98.79)	(52.04)	(107.2)
Fixed-effects			
Full Set	Yes	Yes	Yes
Fit statistics			
Observations	625,224	625,224	625,224
R^2	0.67096	0.93504	0.25679
Within R^2	0.07261	0.38289	0.00054

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

Table A13: Survey Results

Dependent Variable:	Considered Opposite Channel
Model:	(1)
Variables	
Constant	0.4868***
	(0.0170)
Purchased Privately	0.1958***
	(0.0334)
Fit statistics	
Observations	1,127
R^2	0.02967
Adjusted R^2	0.02881

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

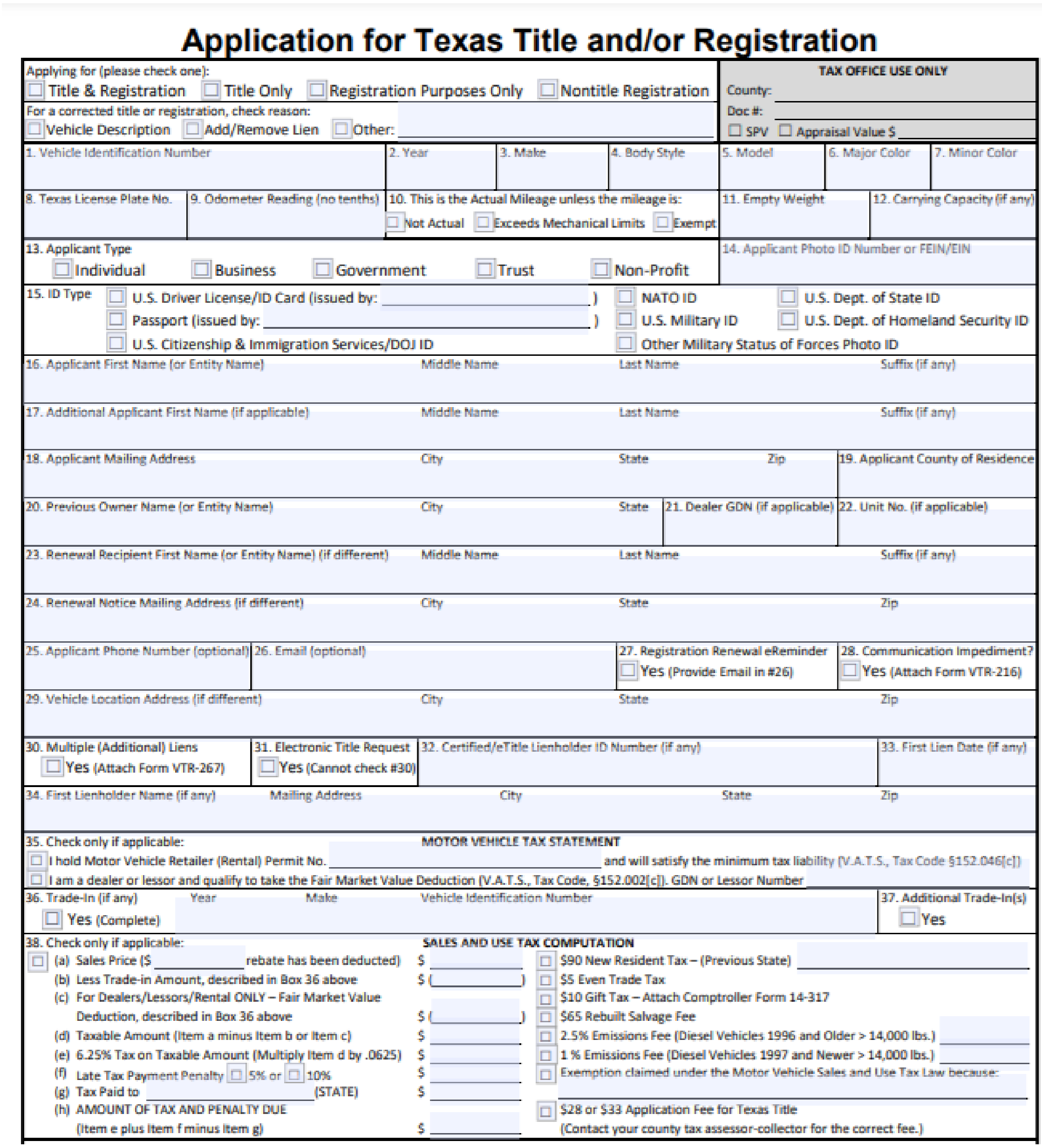
Table A14: Survey Results

Dependent Variable:	Started Search in Same Channel
Model:	(1)
Variables	
Constant	0.7463***
	(0.0209)
Purchased Privately	0.0637*
	(0.0365)
Fit statistics	
Observations	606
R^2	0.00502
Adjusted R^2	0.00338

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*
Includes sample of buyers that considered both channels

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

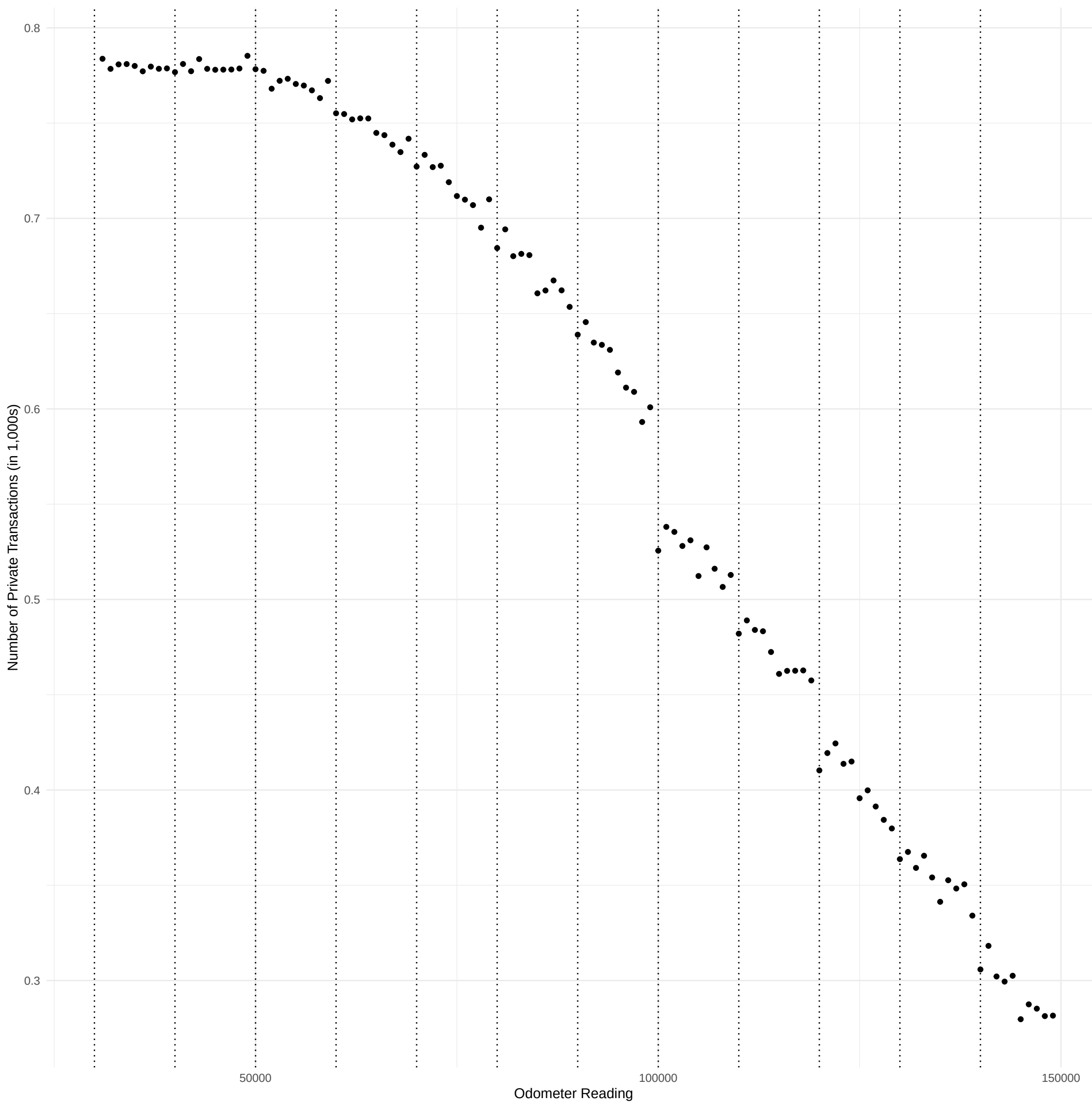
35. Check only if applicable: MOTOR VEHICLE TAX STATEMENT
☐ I hold Motor Vehicle Retailer (Rental) Permit No. ____ and will satisfy the minimum tax liability (V.A.T.S., Tax Code §152.046[c])
☐ I am a dealer or lessor and qualify to take the Fair Market Value Deduction (V.A.T.S., Tax Code, §152.002[c]).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

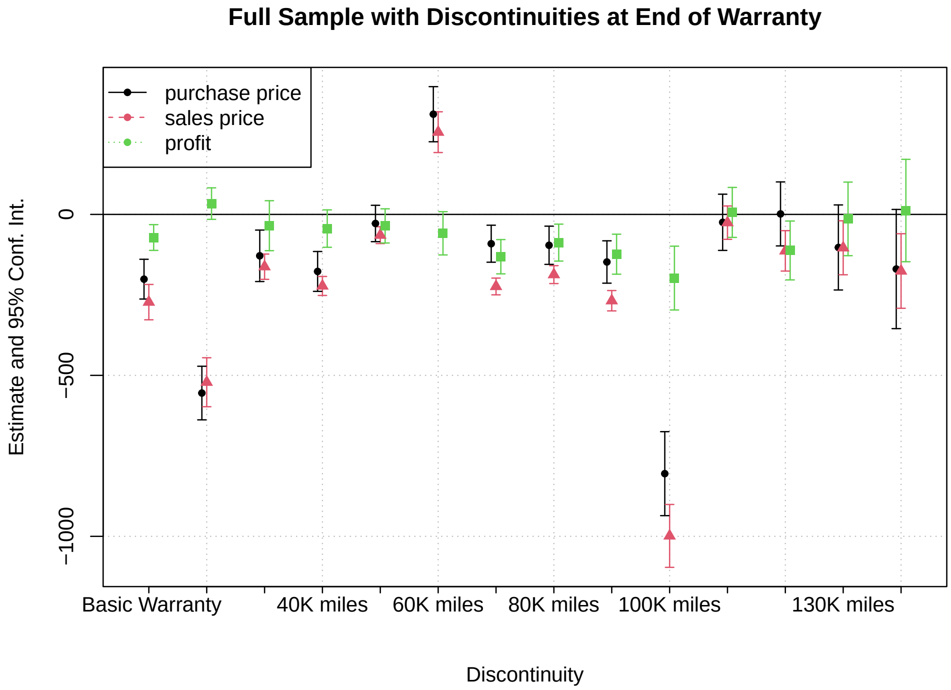
☐ $90 New Resident Tax – (Previous State)
☐ $5 Even Trade Tax
☐ $10 Gift Tax – Attach Comptroller Form 14-317
☐ $65 Rebuilt Salvage Fee
☐ 2.5% Emissions Fee (Diesel Vehicles 1996 and Older > 14,000 lbs.)
☐ 1 % Emissions Fee (Diesel Vehicles 1997 and Newer > 14,000 lbs.)
☐ Exemption claimed under the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

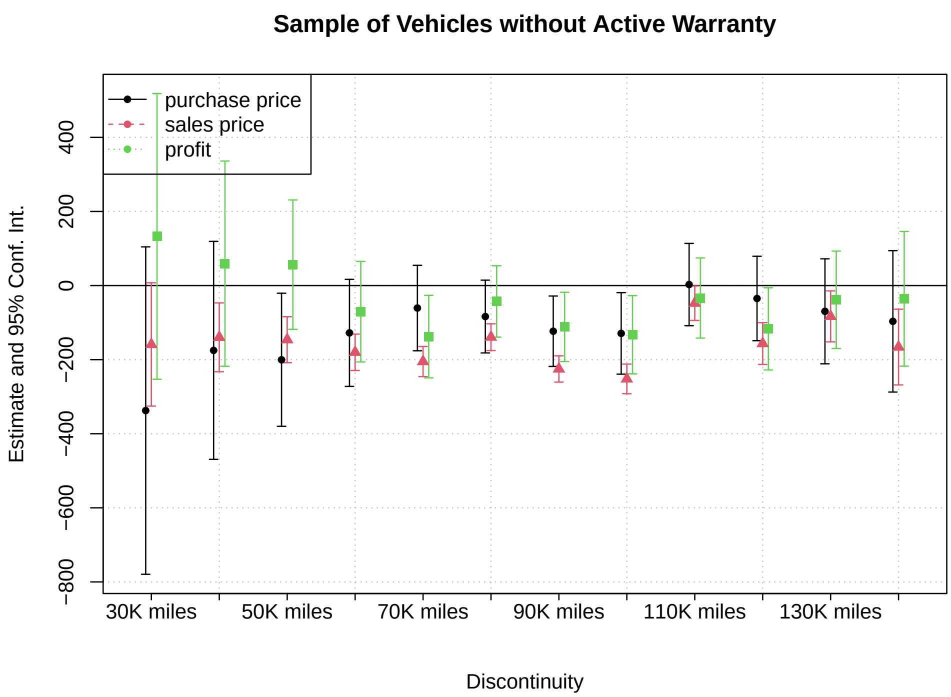


Note: Each dot represents the percentage of transactions via intermediary (compared to consumer transactions) for vehicles within a 1,000 mi band.

Figure A3: Warranties



(a)



(b)

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

Figure A4: Distribution of Warranty Terms

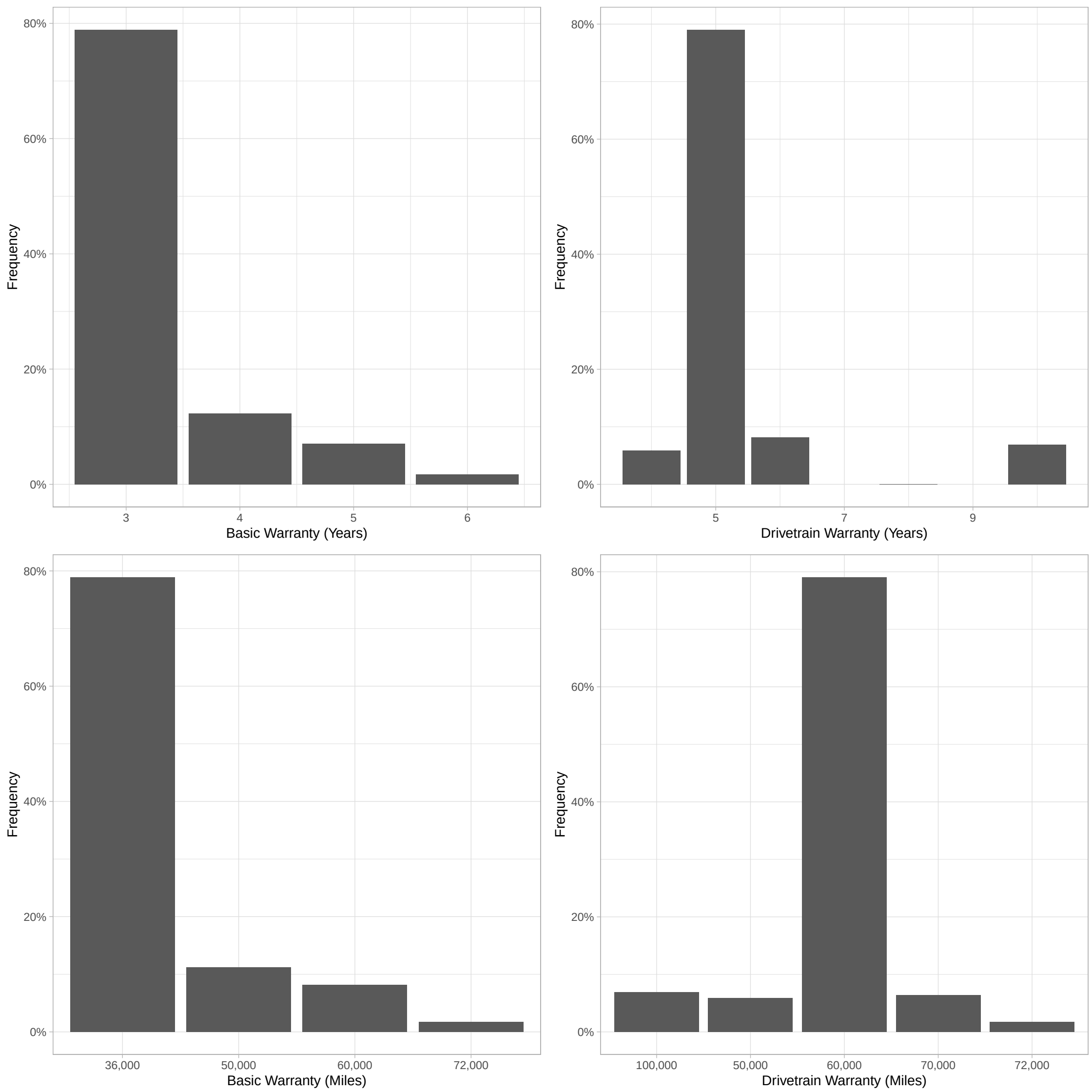
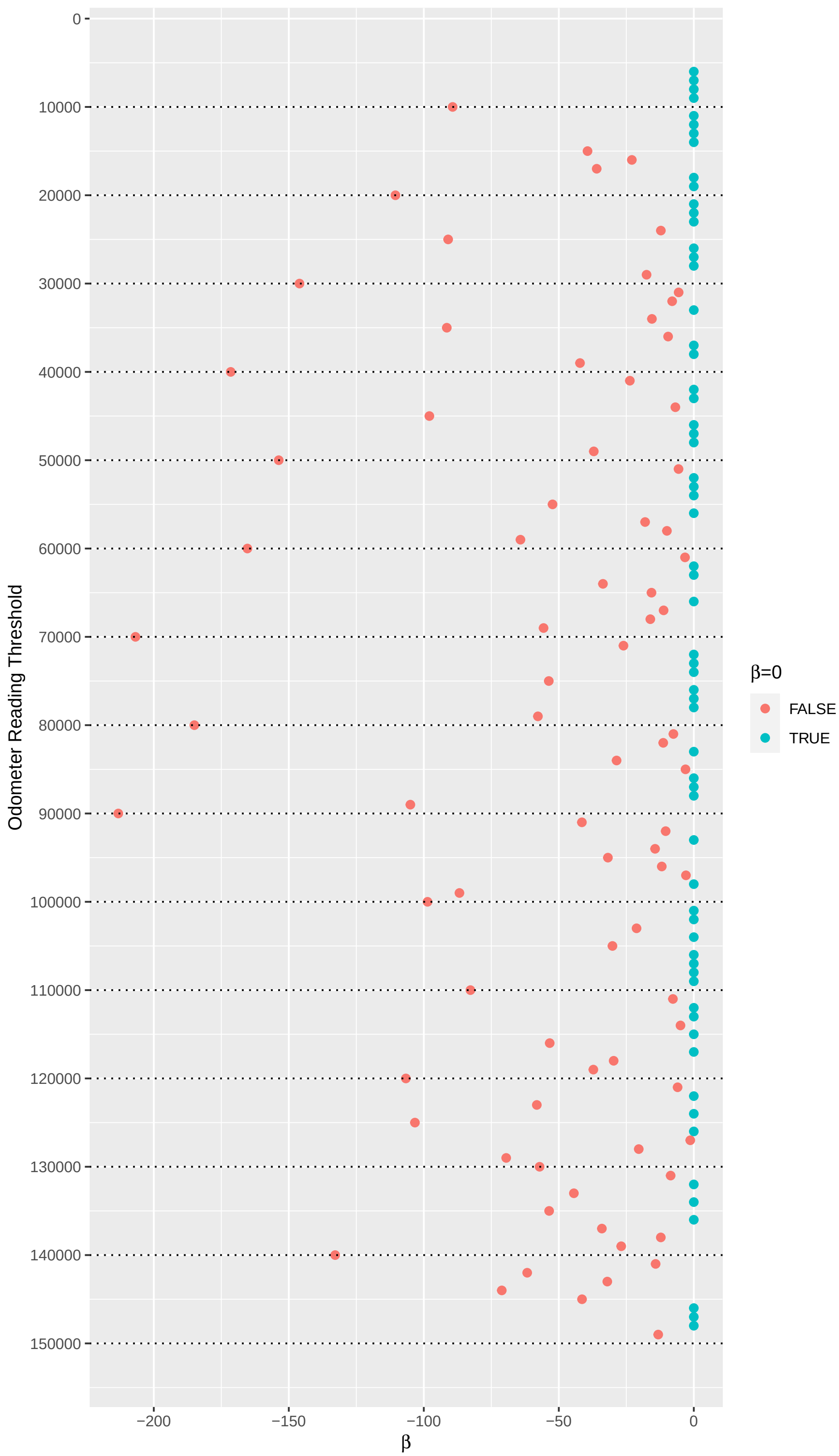
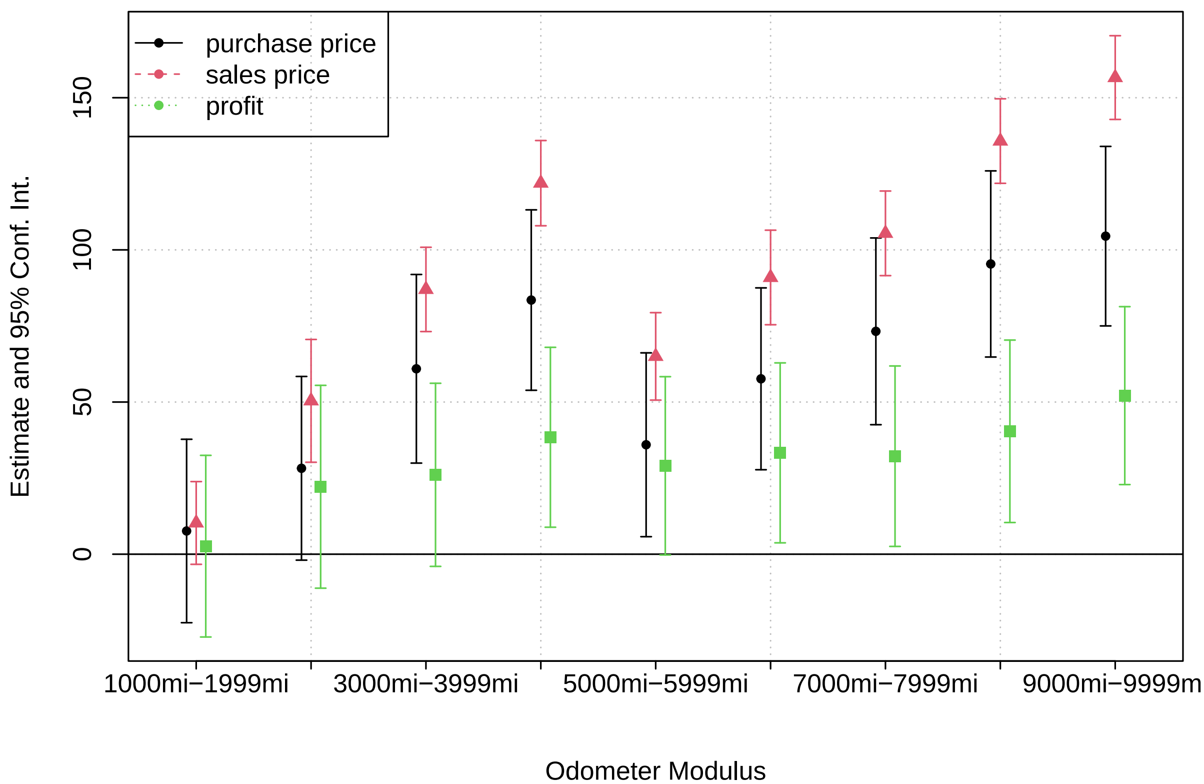


Figure A5: Estimation of discontinuities without exogenously defined breakpoints



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

Figure A6: Excess purchase price, sales price, profits, by modulus of odometer



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

Figure A7: Placebo test reproducing Table 3 with 10,000 km discontinuities

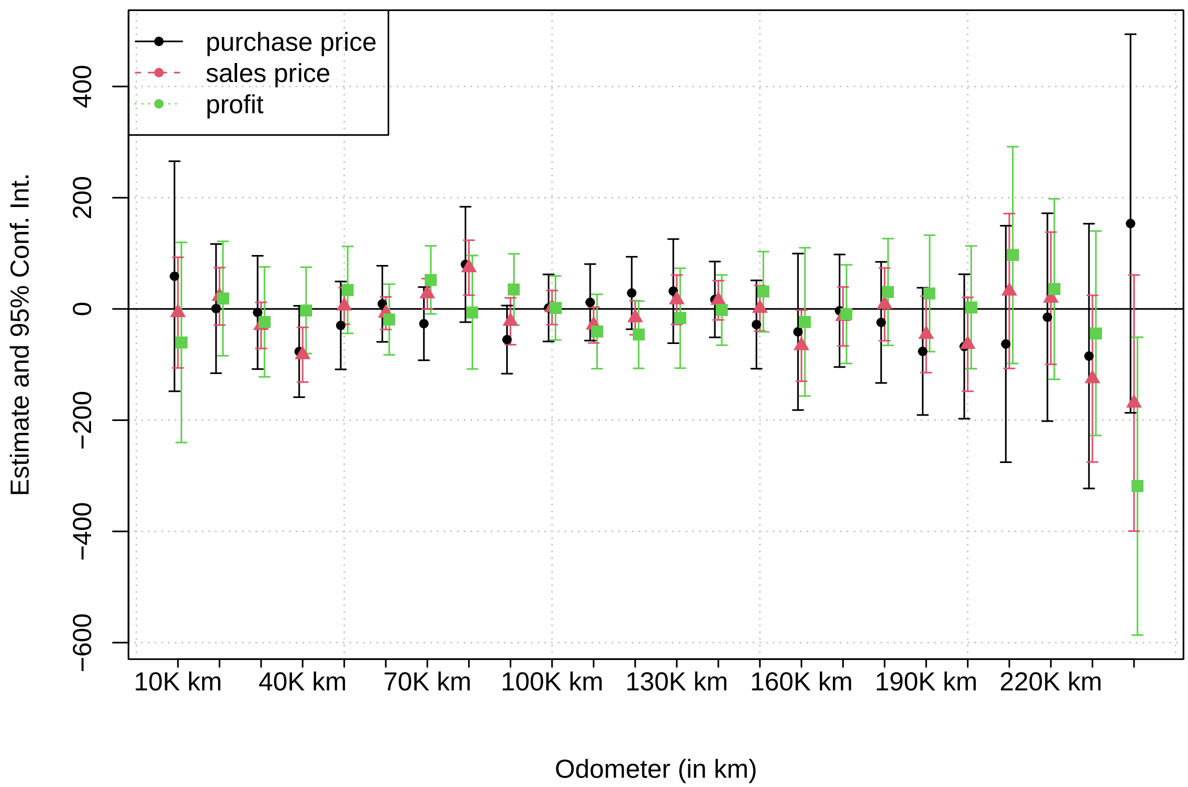


Figure A8: Placebo test reproducing Table 4 with 10,000 km discontinuities

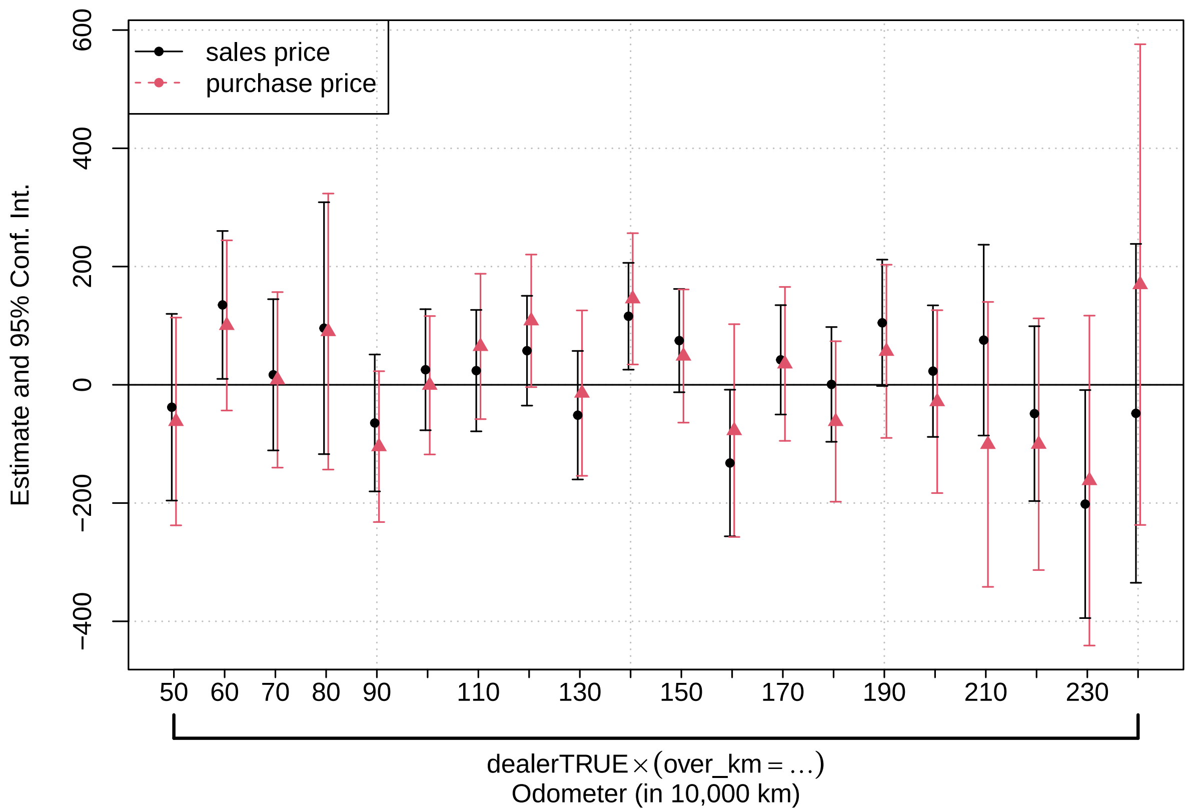


Figure A9: Placebo test reproducing Table 5 with 10,000 km discontinuities

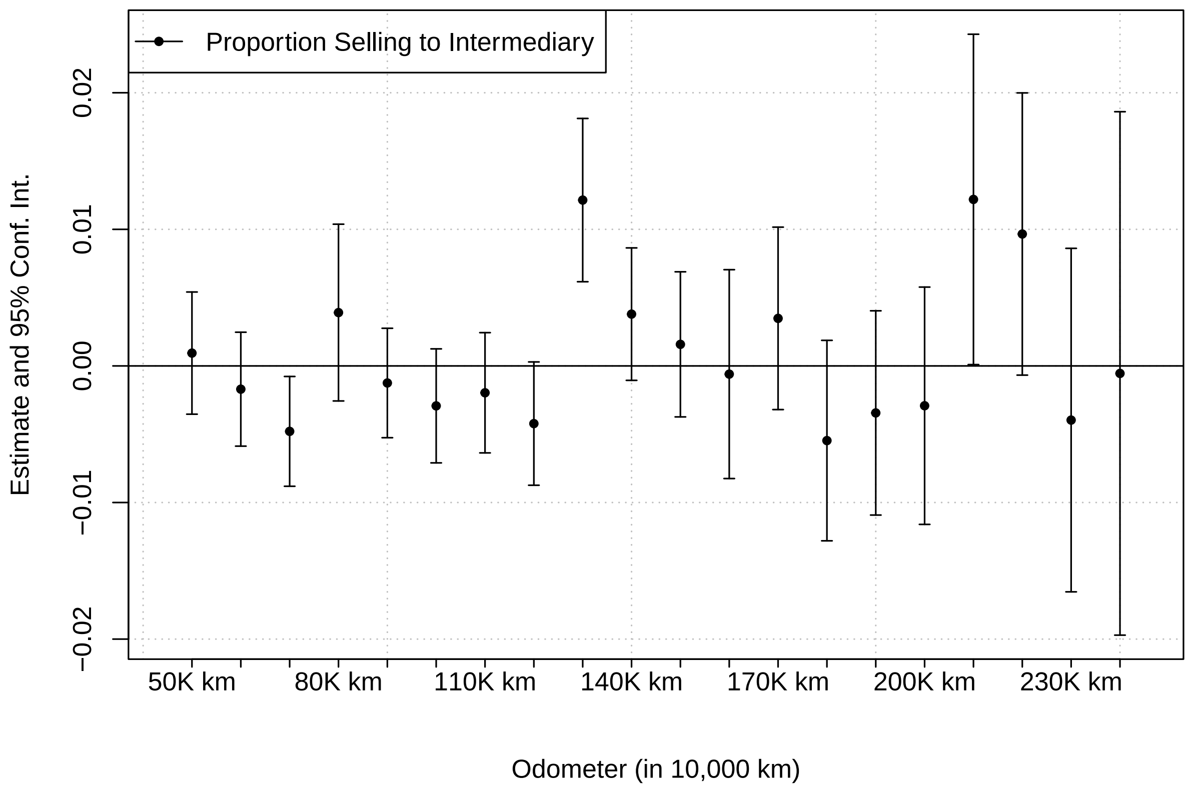
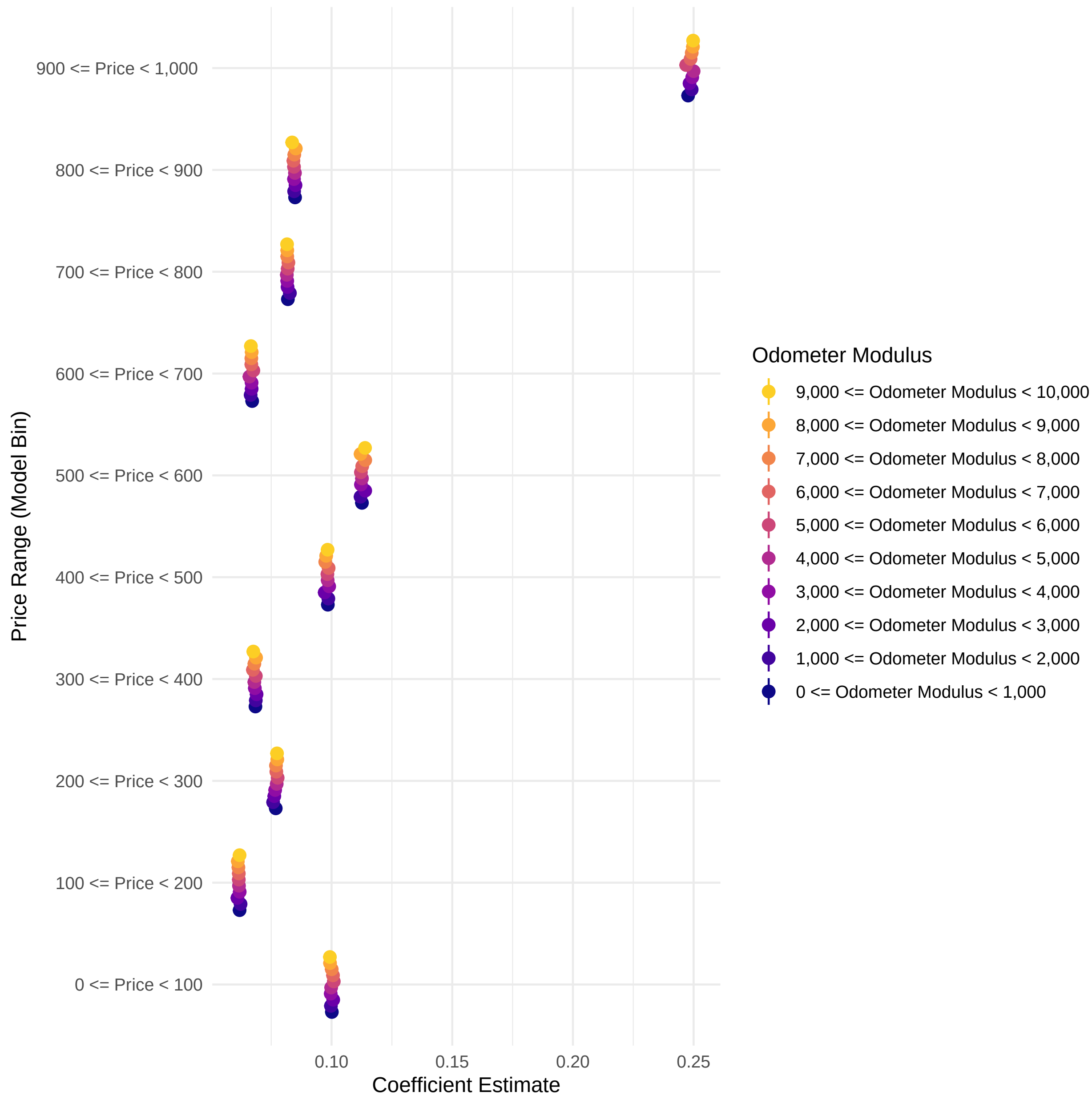
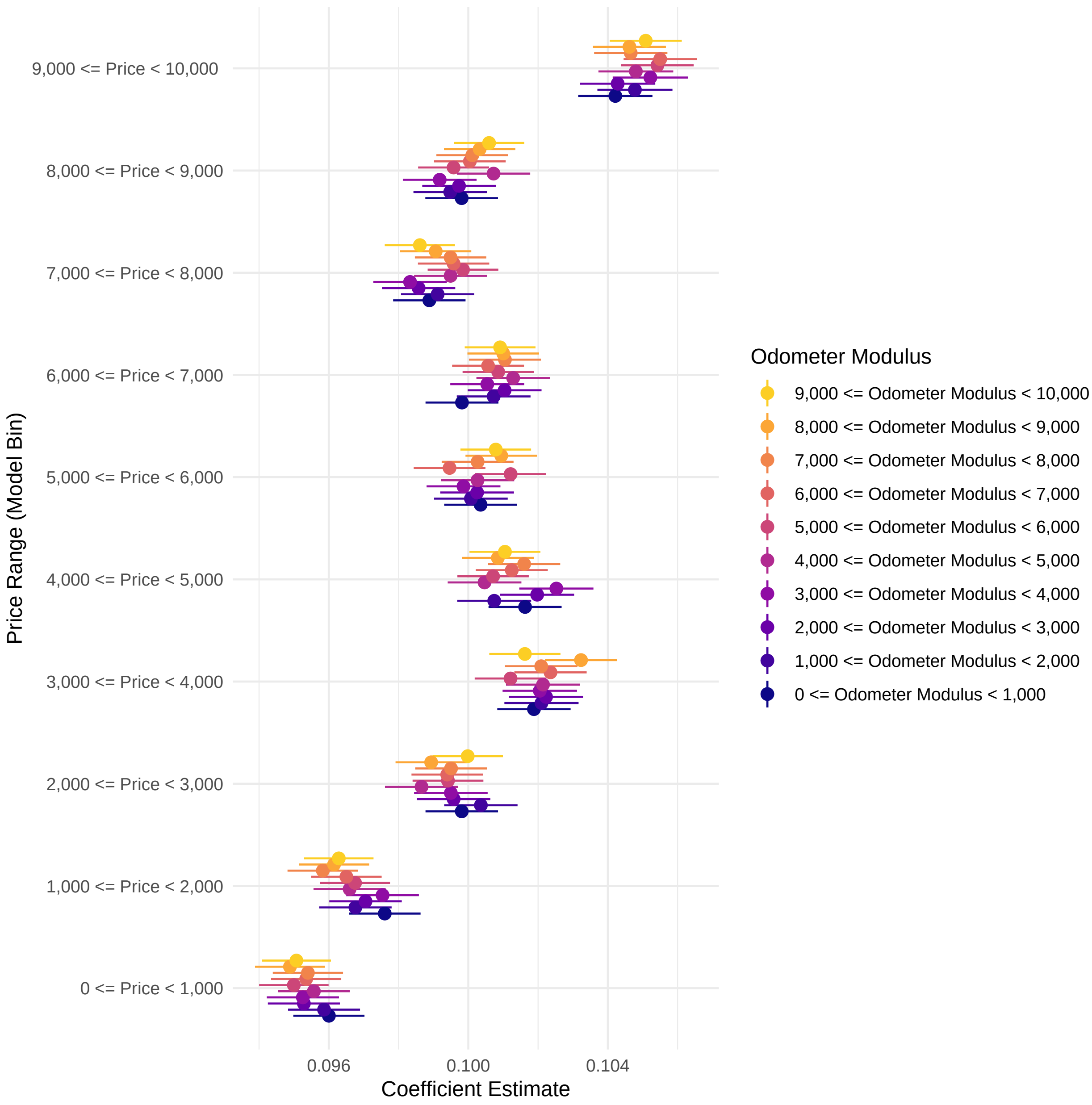


Figure A10: Correlation between Odometer Modulus and Price Modulus (0 to 999) for Dealership Transactions



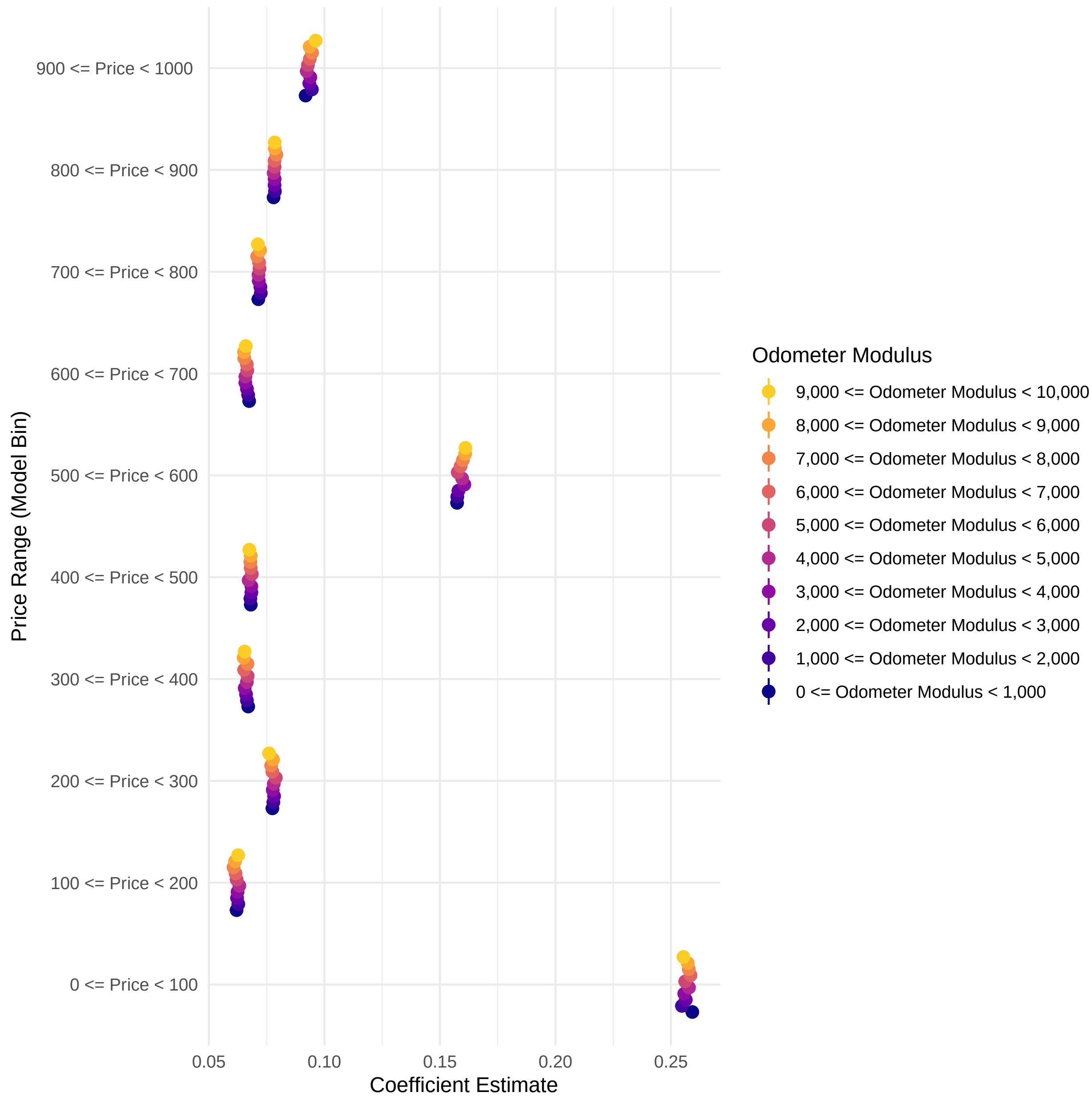
Note: Each "price bucket" is a separate regression and we present coefficients for each odometer modulus factor.

Figure A11: Correlation between Odometer Modulus and Price Modulus (0 to 9,999) for Dealership Transactions



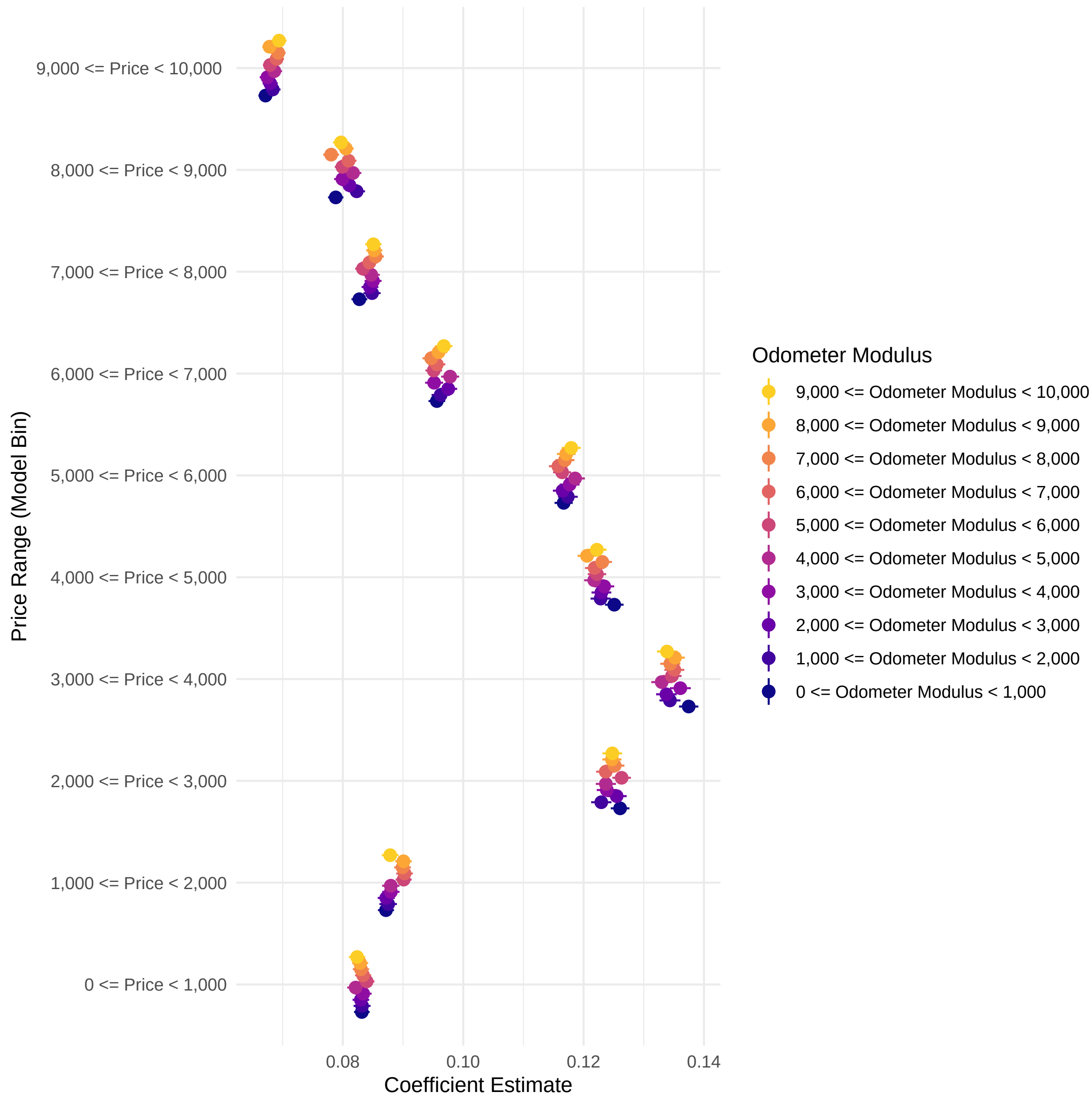
Note: Each "price bucket" is a separate regression and we present coefficients for each odometer modulus factor.

Figure A12: Correlation between Odometer Modulus and Price Modulus (0 to 999) for Private Transactions



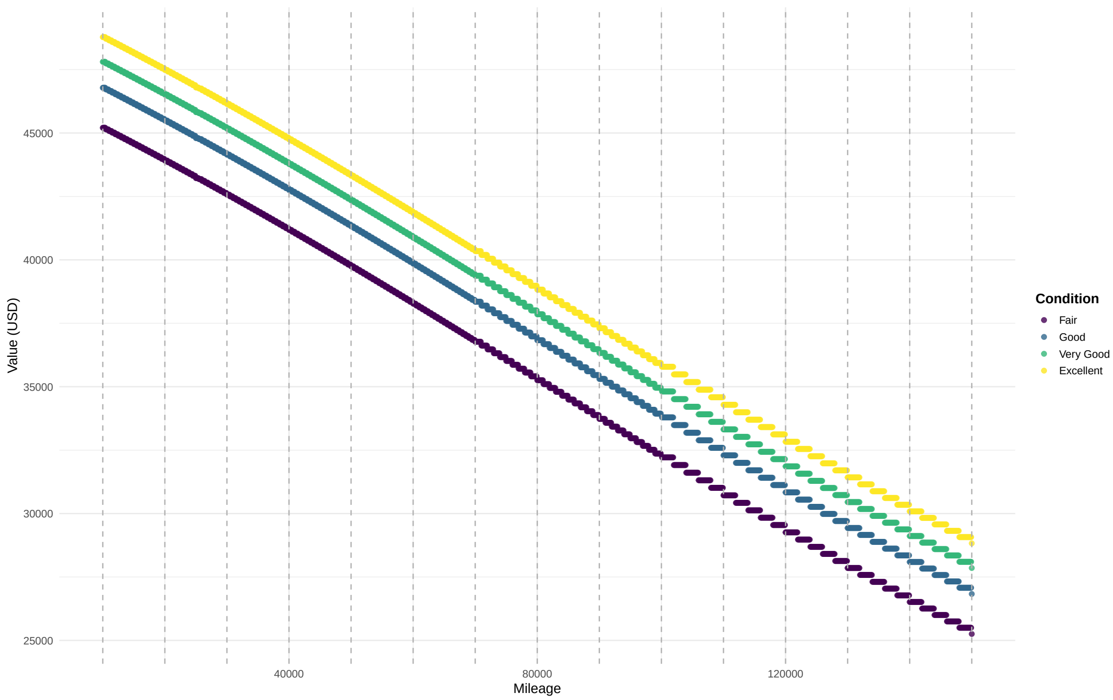
Note: Each "price bucket" is a separate regression and we present coefficients for each odometer modulus factor.

Figure A13: Correlation between Odometer Modulus and Price Modulus (0 to 9,999) for Private Transactions



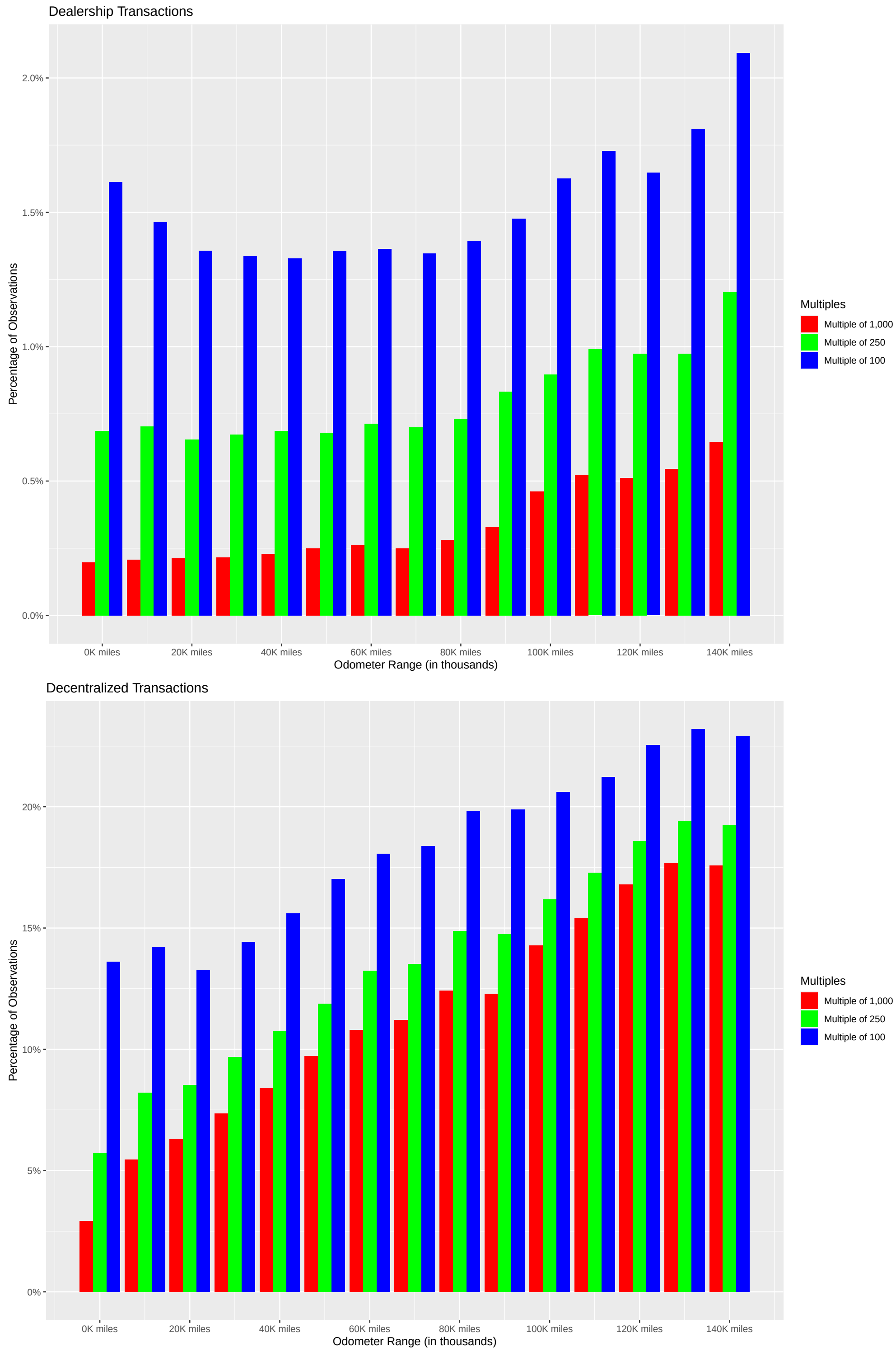
Note: Each "price bucket" is a separate regression and we present coefficients for each odometer modulus factor.

Figure A14



Value (USD)
45000
40000
35000
30000
25000
40000
80000
120000
Mileage
Condition
Fair
Good
Very Good
Excellent

Figure A15: Proportion of vehicles with odometer readings as multiples of round numbers



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

Figure A16: Histograms of Key Variables

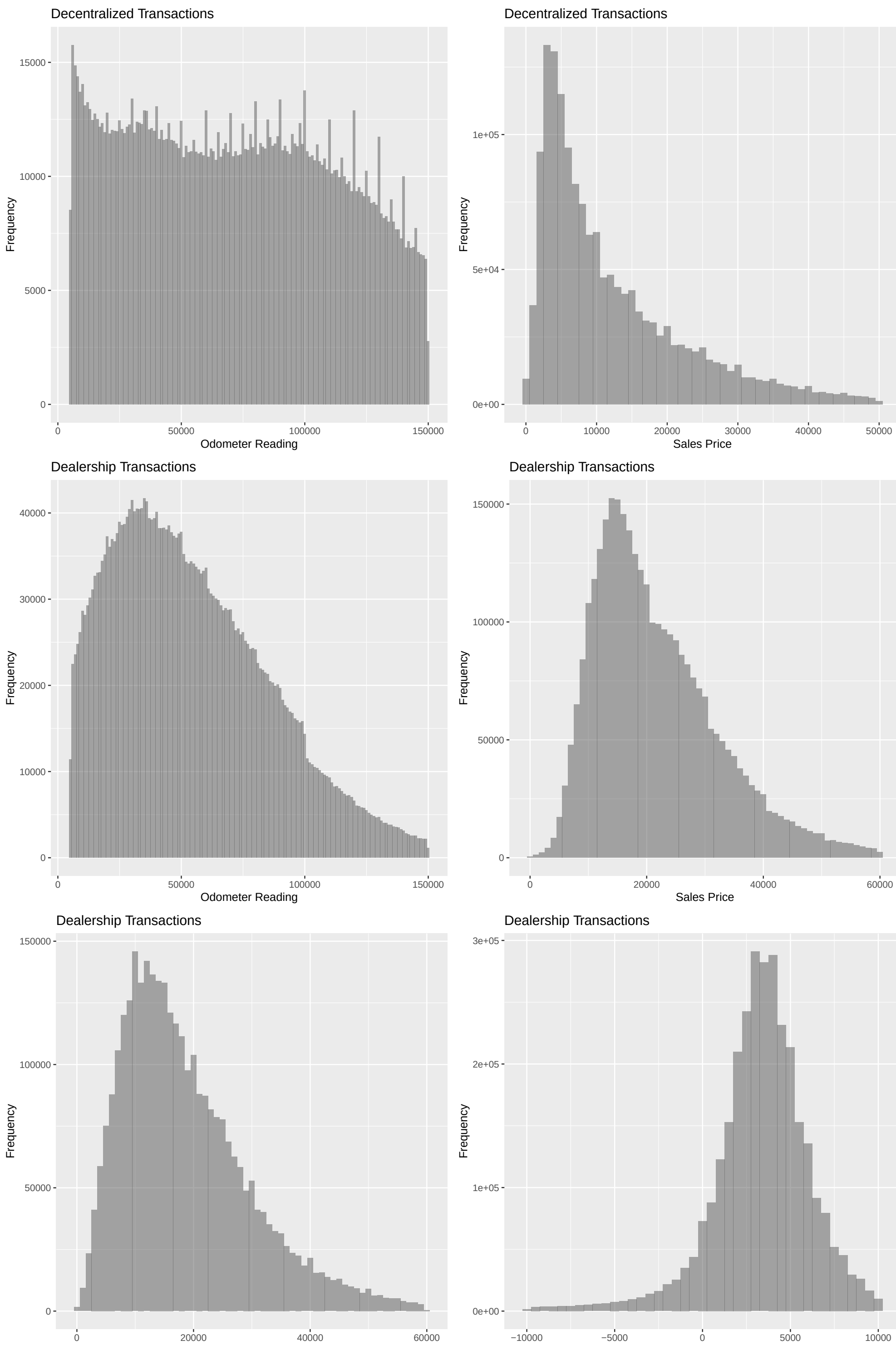


Figure A17: Robustness of Purchase Price Coefficients in Table 3

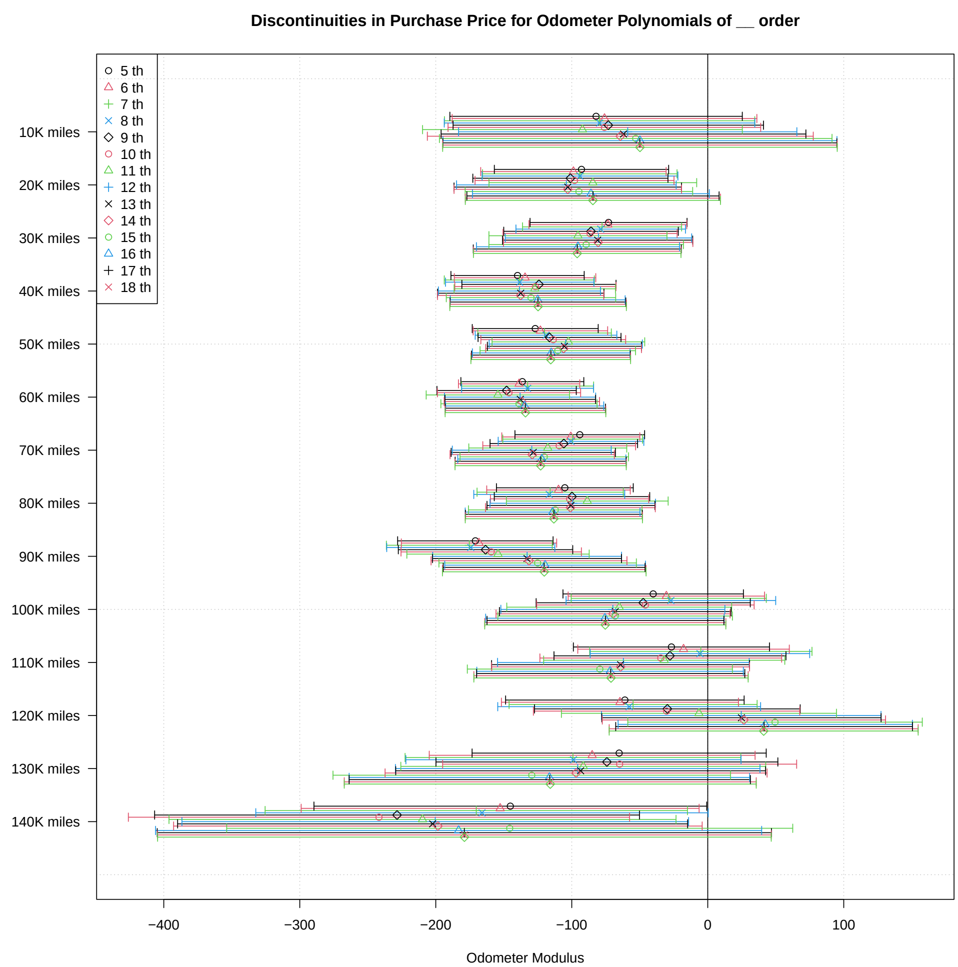


Figure A18: Robustness of Sales Price Coefficients in Table 3

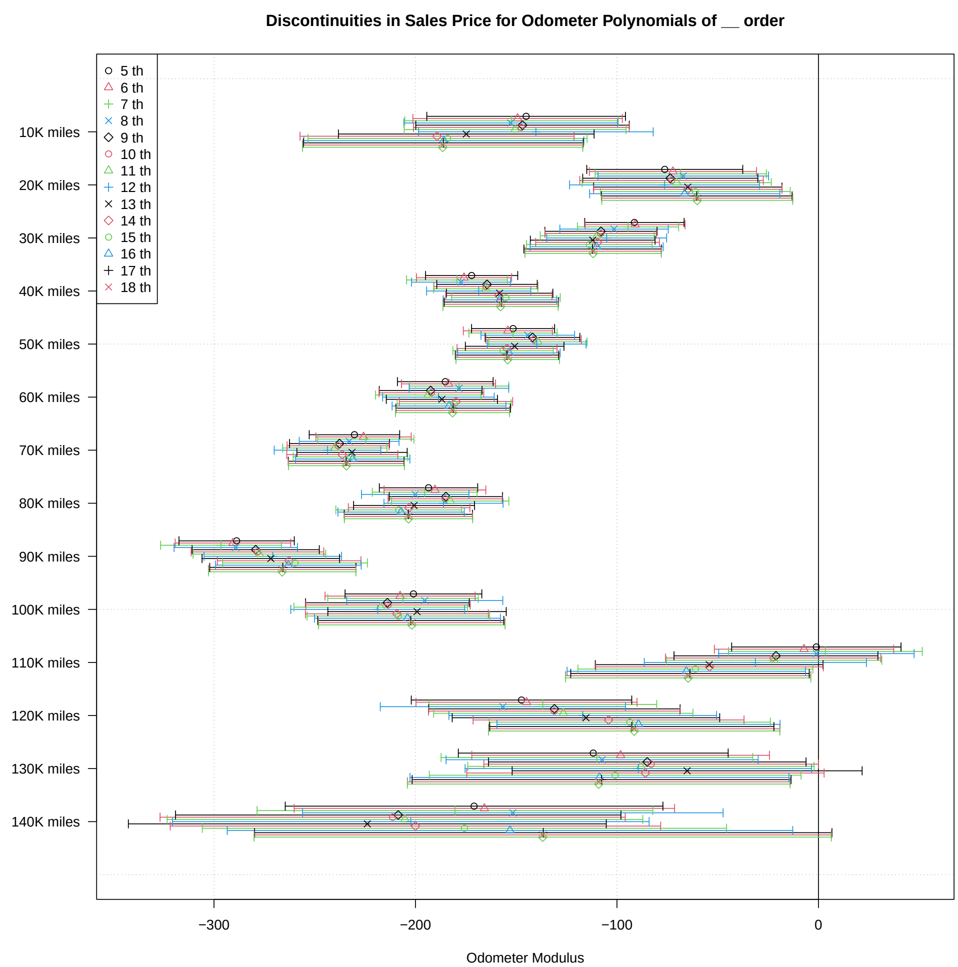


Figure A19: Robustness of Profit Coefficients in Table 3

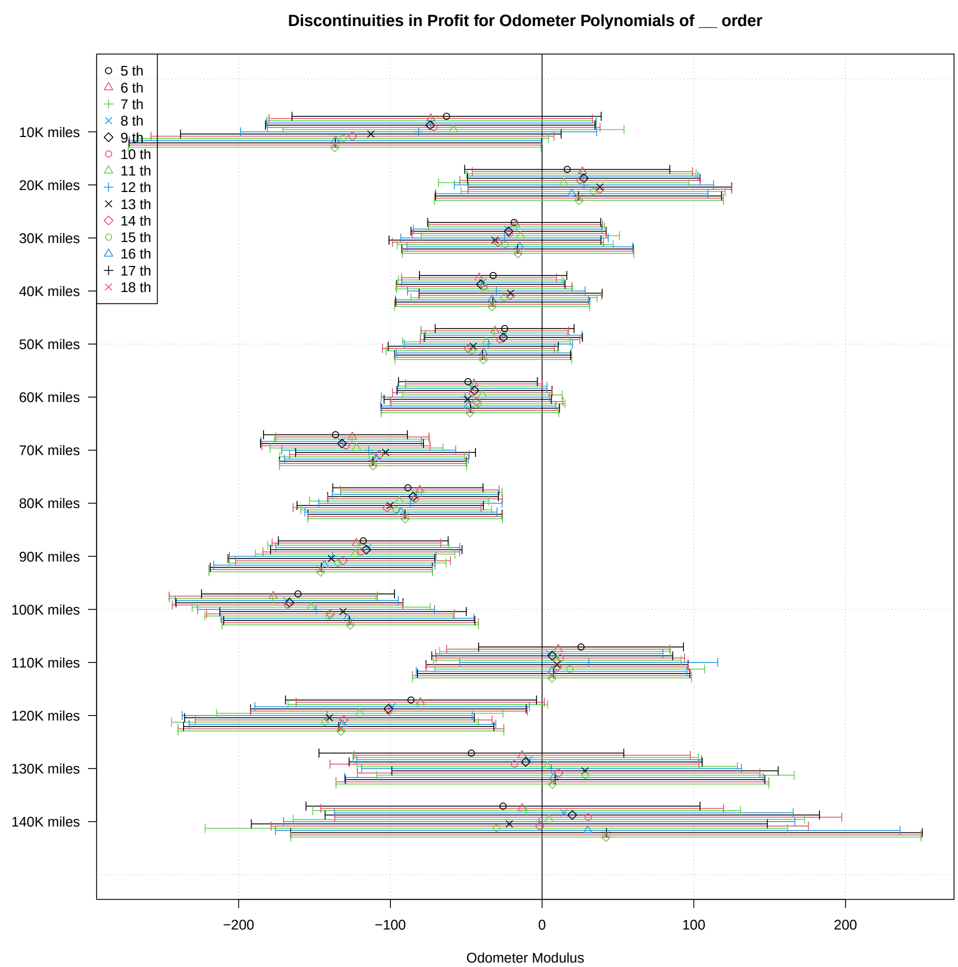
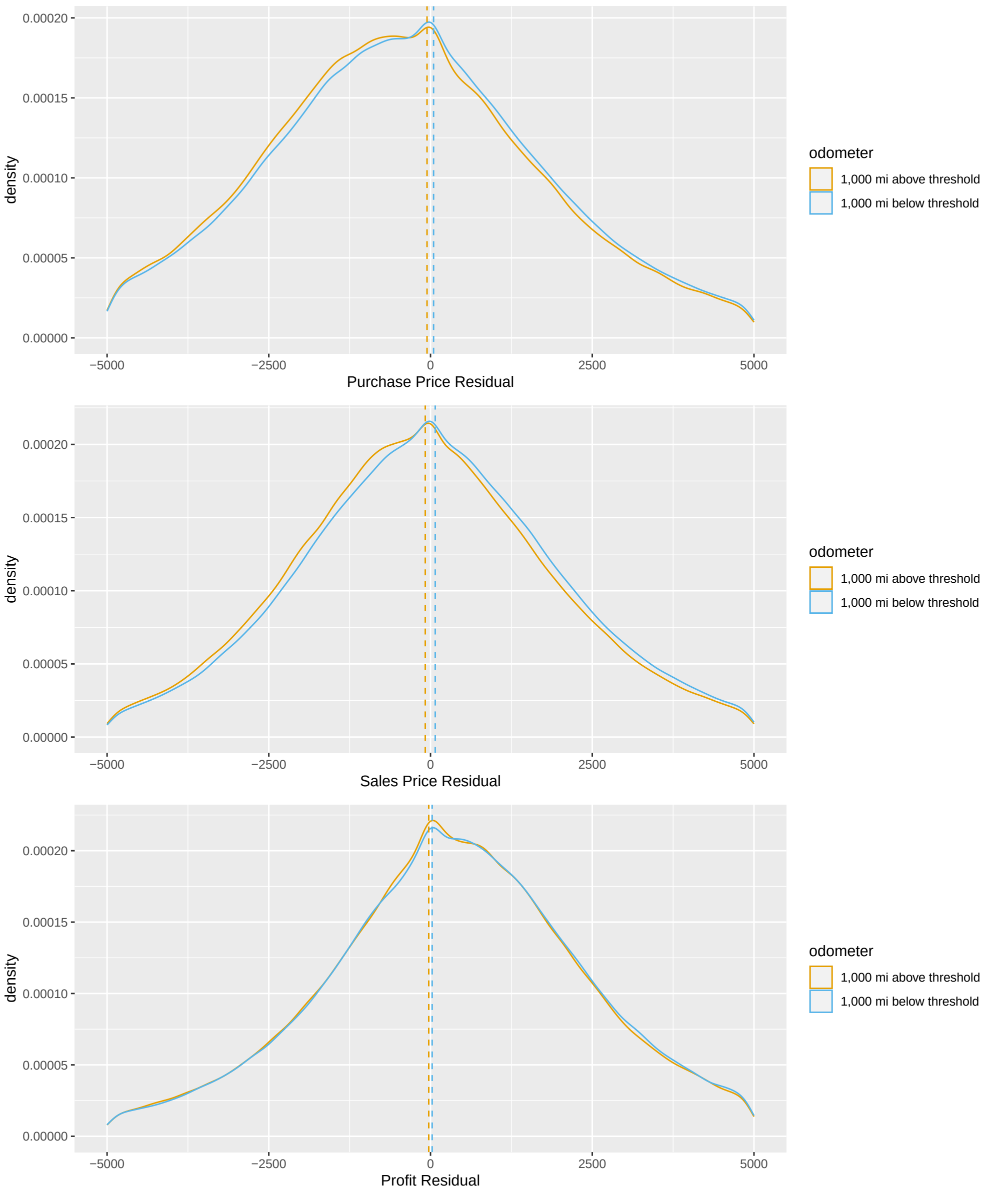
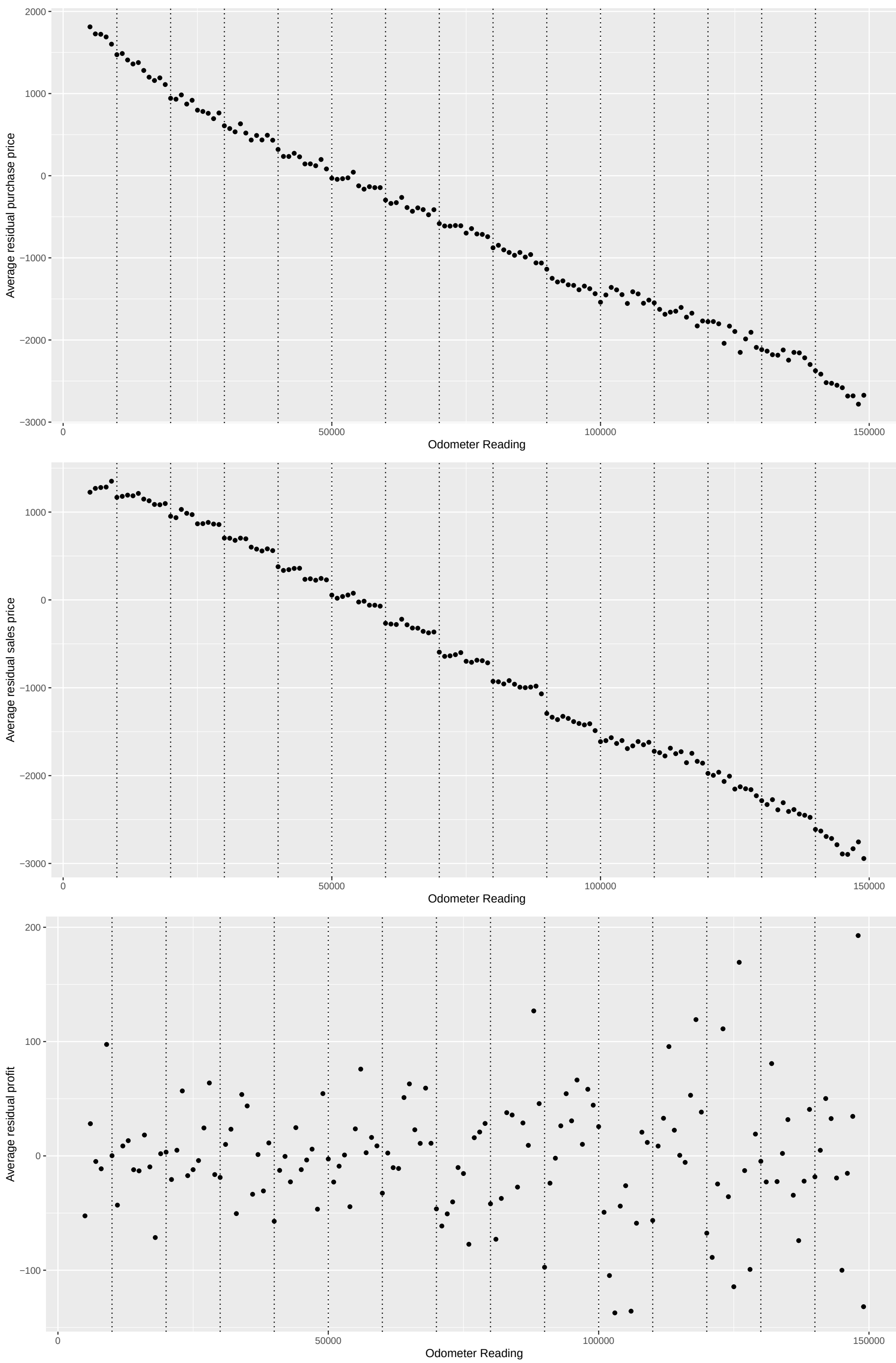


Figure A20: Density of Outcomes for observations immediately above and below 10,000 mile thresholds



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

Figure A21: Discontinuities of residual of outcome variables in Table 3



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