Inattention in the Used Car Market*

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This version: October 2009

Abstract

Analyzing over 22 million wholesale used-car transactions, we document a puzzling pattern: sale prices drop discontinuously as the odometer mileage on a used car crosses 10,000-mile thresholds. A model of how inattentive consumers process information contained in large numbers can explain this pattern. We obtain estimates for the inattention parameter in the model and investigate whether the inattention can be attributed to the final used-car customers, or the used-car salesmen who buy cars in the wholesale market. The pattern appears to be driven, at least in part, by the final customers. We discuss the significance of these results to the literature on inattention and suggest other settings where this type of inattention might matter.

*PRELIMINARY AND INCOMPLETE. DO NOT CITE WITHOUT PERMISSION. We thank David Clingingsmith, Rachel Croson, Hal Logan, Glenn Mercer, Uri Simonsohn, and seminar participants at Case Western Reserve University, University of Texas Dallas, and The Wharton School for helpful comments and suggestions. Financial support was provided by The Fishman Davidson Center and The International Motor Vehicle Program. All errors are our own.

1. Introduction

Economic life involves many complicated decisions that demand attention, but attention is a limited resource. Understanding how limited attention affects economic outcomes, particularly in market settings, is a topic of increasing interest for economists (see DellaVigna, 2009, for a review). Research has documented market-level effects of inattention to shipping prices and alternative buy-it-now prices in eBay auctions (Hossain and Morgan, 2006; Lee and Malmendier, 2007), of non-transparent sales taxes (Chetty, Looney, and Kroft, forthcoming), and of slow or incomplete reaction to changing demographics and non-salient news about companies in financial markets (Cohen and Frazzini, 2008; DellaVigna and Pollet, 2007; DellaVigna and Pollet, forthcoming; Hirshleifer, Lim, and Teoh, forthcoming). This research shows that despite competitive market pressures, systematic and identifiable inattention can have significant effects. However, there is not yet a clear picture of the range of situations where inattention may be relevant. In particular, in these existing studies, the relevant information, although often freely available, is hidden or obscured in such a way that decision-makers must know to look for it. Whether individuals might fail to fully incorporate information when the information is relevant and clearly visible is an open question.

In this paper we examine whether inattention affects how continuous quality metrics are incorporated into decision-making by exploring how customers incorporate the odometer mileage when purchasing used cars. This may seem like an unlikely setting to observe the effects of inattention. After all, car mileage is clearly visible and is obviously an important quality signal that all used-car buyers incorporate to some degree into their purchasing decisions. Furthermore, used-car markets are competitive and one might think that the effects of biases in individual decision-making could be eliminated by competitive forces. On the other hand, casual introspection and evidence in cognitive psychology (Korvost and Damian, 2008; Poltrock and Schwartz, 1984) suggests that individuals do not fully process large numbers -- paying more attention to left digits. Consider, for example, the difference between 5,347 and 5,382 versus the difference between 5,988 and 6,021. The former pair has the larger difference, yet the change in the first digits of the latter pair is likely more

noticeable. We hypothesize that this "left-digit bias" in the processing of large numbers can be widespread enough to influence the used car market.

In Section 2, we develop a simple model of partial inattention to large numbers that is an extension of the framework developed by DellaVigna (2009). In DellaVigna's framework, people receive signals of value V that are the sum of "a visible component v and an opaque component o." The perceived value, however, is given by $\hat{V} = v + (1 - \theta)o$, where θ is the inattention parameter that is equal to 0 in the full-attention case. This framework can be used to model how a left-digit bias affects processing of continuous quality metrics. A number can be thought of as the sum of its digits, and our version of the model assumes that the left-most digit receives full attention, while people may pay only partial attention to the digits further to the right. We show that incorporating this framework into a model of a competitive used-car market results in discontinuous drops in market prices as cars pass over mileage thresholds (e.g., 20,000, 30,000, etc.).

Section 3 discusses the details of the data set and provides context to the model presented in Section 2. The data come from the largest wholesale-car auction company in the U.S. These wholesale auctions provide a marketplace where used-car dealers purchase cars for resale to final customers. There are a range of seller types at the auctions, from car dealers to rental-car companies to university fleets. We observe the auction outcome as well as details about each car auctioned between 2002 and 2008, a total of more than 22 million cars.

In Section 4 we use these data to obtain estimates of how prices vary with mileage. A graphical, non-parametric analysis of the raw data shows that there are clear threshold effects at the 10,000-mile marks. Obtaining an accurate estimate of the size of price discontinuities induced by these thresholds, however, requires a regression framework that accounts for the possibility of selection. This is because sellers who are aware of threshold effects have some incentive to bring cars to auction before they cross a threshold, a phenomenon we confirm when looking at volume patterns as a function of mileage. This incentive, in turn, may depend on the age and underlying value of the car. Therefore, uncontrolled raw estimates of price discontinuities may not be consistent. Following established regression-discontinuity methods (Lee and Lemieux, 2009), we

include a flexible polynomial in the forcing variable (mileage) and fixed effects for the discontinuity thresholds. We account for selection on observables by controlling for fixed effects for the combination of make, model, model year, body style, auction year and, in our most restrictive specification, seller identifier. We find significant price discontinuities at each 10,000-mile threshold from 10,000 to 100,000 miles. The size of the discontinuities is similar across each threshold, consistently on the order of $200.

Based on the size of the price discontinuities, we can obtain estimates for the inattention parameter, θ. Averaging across the discontinuities we estimate that θ is approximately 0.3. In our setting, there is a natural interpretation of θ as the fraction of mileage depreciation that occurs discontinuously at thresholds. Hence, for a given car, our estimates predict that as mileage is added to the car, 30% of the reduction in value will occur at these salient thresholds. Although it is likely that the degree of inattention by economic agents varies by setting, it is instructive to compare these estimates to calculations of θ reported by DellaVigna (2009) from existing works. DellaVigna reports estimates ranging from 0.18 to 0.45 for the work on inattention to shipping charges on Ebay, and 0.46 to 0.59 for his own study with Joshua Pollet on inattention to earnings announcements. This is much lower than the degree of inattention DellaVigna calculates (0.75) for the Chetty, Looney, and Kroft (forthcoming) field experiment on non-transparent sales taxes.

In addition to adding to the economics literature on inattention, our findings are related to the "99-cent phenomenon", where list prices often end with .99 (e.g., $3.99), which has been discussed extensively in the economics and marketing literatures (Basu, 1997; Basu, 2006; Ginzberg, 1936). Consistent with our approach in this paper, most models of the 99-cent phenomenon incorporate some version of limited attention to smaller digits on prices. The fact that the 99-cent literature is about inattention to prices, however, makes it different from the type of inattention to a quality metric that we explore here. In most models of 99-cent pricing, since in equilibrium all firms use 99-cent pricing, an individual could not benefit by paying attention to the full price. Thus, it is not possible to quantify how "costly" inattention is – even a very small cost to full attention in a rational-inattention framework can lead to this equilibrium. In contrast, inattention to a quality

metric that leads to non-smooth pricing will mean that there is a potential benefit to an individual from paying full attention to the metric and allows us to estimate the cost of being inattentive.

In addition to determining the size of the discontinuities and the implied degree of inattention, the particular setting of our study -- the wholesale used-car market – allows us to analyze how inattention varies across different types of economic agents. For example, the observed patterns that we find could arise because used-car dealers are inattentive when making auction bids, or because used-car dealers are simply aware of the inattention of final retail customers. It is not easy to disentangle the two cases, because there is little observational difference between a savvy used-car dealer purchasing cars with an awareness of this bias from an un-savvy used-car dealer who happens to share the same bias as his end customers. We can, however, address whether inattention seems to be driven *primarily* by used-car dealers or final customers. Since we could expect that a costly bias on the part of the dealers at auction would be more likely for less experienced buyers (List, 2003), we investigate this question by examining the behavior of buyers at the auction with varying levels of experience. We find evidence that suggests the bias is unlikely to be driven solely by inattention on the part of dealers at the auctions. We also gathered some additional information on volume patterns in the automobile-classified website, Cars.com. This data shows threshold patterns similar to those we observe in our data, supporting the idea that the attention effects we find here are not solely a wholesale-auction phenomenon.

In Section 5, we conclude the paper with a discussion of the implications of our results, including a discussion of the rationality of inattention in this market and potential directions for future research. We argue that the framework we present is applicable to how people use continuous quality metrics in a variety of domains, and we suggest a number of additional settings where inattention of this type may play an important role.

2. Model

In order to structure our thinking about inattention in the used-car market, we begin by laying out a simple model of consumer inattention to a continuous quality metric, and then incorporate it into a competitive market framework for used cars.

Consumer inattention to continuous metrics:

We propose an extension of the framework presented by DellaVigna (2009). In this framework, a person considers purchasing a product and receives signals about the value V of the product. DellaVigna assumes that the value of the product is the sum of "a visible component v and an opaque component o." The *perceived* value, however, is given by $\hat{V} = v + (1-\theta)o$. The parameter θ is the inattention parameter. When $\theta = 0$, a person is fully attentive to both quality signals and $V = \hat{V}$. When $\theta = 1$, in contrast, the person is completely inattentive to the opaque signal. Intermediate values of θ in the (0, 1) interval indicate partial inattention.

This framework can be extended to model how people with a left-digit bias process large numbers. Any number can be broken down as the sum of its assorted base-10 digits. Consistent with the left-digit bias, we assume that the left-most digit of a number that a person observes is fully processed, while the person may display (partial) inattention to digits further to the right.

Formally, let m be an observed continuous quality metric (in our case miles). Then let H be the base-10 power of the left-most non-zero digit of m, and let d_H be the value of that digit, such that $d_H \in \{1, 2, \ldots, 9\}$. The perceived metric $\hat{m}$ is then given by:

$$\hat{m} = d_H 10^H + \sum_{j=1}^{\infty}(1-\theta)d_{H-j}10^{H-j}, \qquad (1)$$

where θ is again the inattention parameter with the same interpretation as in the DellaVigna framework. As an example, consider the case where m takes on the value 49,000. From Equation 1, this would be processed as $\hat{m} = 40{,}000 + (1-\theta)9{,}000$.

The interesting dynamics of the model arise when we consider how different the perceived measure will be on either side of a left-digit change. Consider, for example, how $\hat{m}$ changes as m ranges from 40,000 to 50,000. As long as m is below 50,000, the decision-maker will perceive a

change of (1-θ) for every 1-unit increase in *m*. However, when crossing over the threshold from 49,999 to 50,000, the change in perceived value will be 1 + θ*9,999 or, in the limit, θ*10,000. The change in the left digit brings the perceived measure in line with its actual value and induces a discontinuous change in the perceived value.

Figure 1 demonstrates the effect this inattention would have in the basic case where the perceived value $\hat{V}$ of the product under consideration is a linear function of the perceived metric $\hat{m}$:

$$\hat{V} = V(\hat{m}) = K - \alpha\hat{m}. \tag{2}$$

We assume a negative slope (as expressed by $\propto$) to match the used-car setting. The figure shows an example of how this value function would look over a range of *m* from 60,000 to 100,000. The graph shows that the perceived-value will display discontinuities at each 10,000 threshold. The size of these discontinuities is constant and equal to (αθ)*10,000. Intuitively, at the threshold the perceived metric $\hat{m}$ changes discontinuously by θ*10,000, and the discontinuous effect this has on perceived value $\hat{V}$ depends on the relationship between value and the quality metric.

In the case of used cars, then, Figure 1 reveals a few basic predictions of the model. First, and most importantly, if customers are inattentive to digits in the mileage (i.e., θ is positive), there will be discontinuities in the perceived value of cars at 10,000 mile thresholds. In the limit as θ goes to 1 and consumers are attentive only to the left-most digit, the value function will be a step function. The second prediction is that, if the linear-value function holds, the size of these discontinuities will be constant across thresholds changes of the same size that induce a change in the left-most digit.

Of course, there is no reason to suspect *a priori* that the exact functional form in Equation 1 is appropriate. In particular, as stated, Equation 1 assumes that the individual is equally inattentive to all digits past the left-most digit. A reasonable alternative to consider would be the possibility that there is decreasing attention to digits further to the right. This could be captured by a reformulation of Equation 1 to:

$$\hat{m} = d_H 10^H + \sum_{j=1}^{\infty}(1-\theta)^j d_{H-j} 10^{H-j}. \tag{3}$$

As an example, consider the number 49,900; using Equation 3 this would be processed as $\widehat{m} = 40{,}000 + (1-\theta)9{,}000 + (1-\theta)^2 900$. With the specification in Equation 3, unlike Equation 1, we would expect to see discontinuities at each digit threshold, observing smaller discontinuities for smaller thresholds. While not a primary focus of this paper, our empirical analysis allows us to shed light on the extent of increasing inattention to smaller digits.

Application to the used-car market:

The model above shows that if consumers are inattentive, their perceived value for cars will be discontinuous at mileage thresholds. Here we incorporate this behavior by consumers into a basic model of a competitive retail used-car market and a competitive auction-based wholesale market for used cars. The goal is to demonstrate that in such an environment, we can expect the observed market prices of cars with different mileage to exhibit the same patterns as the individual-level value function.

Consider N consumers interested in purchasing at most one used car. Consumers are identical and all have the same value function for a car with perceived mileage $\widehat{m}$ given by Equation 2, which is their maximum willingness to pay for the car.[1] Consumers observe all available used cars in the market and purchase the car that gives them the highest surplus, measured as the difference between the perceived value and the purchase price of the car.

The other players in the market are used-car dealers. We assume that there is a competitive retail used-car market with an arbitrarily large number of car dealers, all attempting to serve the N consumers. These dealers purchase used cars at competitive, ascending-bid, first-price wholesale auctions and resell them to the consumers. There are M cars with varying mileage available at the wholesale auctions. For simplicity, we assume that each of these cars has a reserve price of zero.[2] As long as $M \leq N$, there will not be an oversupply of cars and the market will be well-behaved.

[1] We keep with the linear case here only for simplicity. The results do not depend on a linear value function.

[2] Note that we are putting aside the behavior of sellers at the auctions. This simplifies the exposition and matches roughly with the behavior of the fleet/lease category of sellers that we describe in the next section.

We claim that in this environment in equilibrium all cars will be sold and that both the auction price and final price to consumers of a car with arbitrary mileage *m* will be equal to the perceived consumer-value function $\widehat{V}$. More specifically, we argue that the equilibrium is for each used-car buyer to bid $V(\widehat{m})$ for a used car with *m* miles at the auction and then to resell the car for that same price.

This is an equilibrium, since no dealer has an incentive to deviate from this strategy. Bidding below $V(\widehat{m})$ will not win a car to sell. Bidding above $V(\widehat{m})$ at the auction will ensure the dealer obtains the car, but he will not be able to sell the car at a price above $V(\widehat{m})$, and would lose money. Holding fixed the wholesale prices, a dealer also cannot benefit by setting different retail prices. Setting a price above above $V(\widehat{m})$ will not produce a sale, and as long as our assumption that there is not an oversupply of cars holds, the dealer has no incentive to lower the price.

In fact, the equilibrium just described is unique. Note that any competitive equilibrium in which car dealers are driven to zero profit will require that the price of a car at auction equals the price to the final consumer. Therefore, in order to prove that our proposed equilibrium is unique, it suffices to show that the equilibrium price to the final consumers must be $V(\widehat{m})$. This is straightforward. If the equilibrium price were above $V(\widehat{m})$ for any arbitrary *m*, cars of that mileage would not sell and a dealer would have an incentive to lower the price. As long as $M \leq N$, if the equilibrium price were below $V(\widehat{m})$ for some *m*, a dealer could set a price above the going market price and make a profit.

Market prices of used cars will thus reflect the pattern of consumer value. In particular, if consumers are inattentive to mileage, this will be reflected in the market prices with discontinuities at threshold mileages. Note also that the arguments above do not depend on the distribution of mileage across the *M* cars in the market. The relative market prices depend only on the mileage of each individual car, and not on how many cars of that mileage are in the market. This result derives from the assumption that the customers do not have mileage-specific demand, but rather consider cars of all mileage, choosing the one that provides them with the highest surplus.

Note, finally, that while we used a representative-agent framework, the model can be generalized to the case of consumers with heterogeneous demands. As an example, the consumers could have variation in the level of their willingness to pay for all cars (i.e., variation in K). In this case, it can be shown that the market prices will reflect the perceived value function of the marginal (i.e., M^{th} highest K) consumer.[3] If there is also heterogeneity in the degree of attention, as long as the value functions of higher and lower-value buyers (i.e., high and low K) do not cross, then, again, the observed market prices will reflect the degree of inattention of the marginal buyer. With consumer heterogeneity, notice also that a change in the number of cars available in the market M will change the marginal buyers and thereby change the level of prices in the market for cars of any mileage. However, the *relative* prices for cars of different mileage will still be independent of the distribution of mileage over the M cars, and will simply reflect the value function of the marginal buyer.

3. Data

The data for this study come from the largest operator of wholesale used-car auctions in the United States. We first briefly describe the wholesale auction process. The process starts when a seller brings a used car to the one of the company's 89 auction facilities located throughout the U.S. Details of the car are registered into the company's system. The auction company also offers the seller, at a price, detailing or reconditioning services before a car is auctioned. Each auction site holds auctions once or twice a week. On these auction days, licensed used-car dealers come to the auction to purchase cars for resale. Depending on the particular auction site, more than 2,000 used cars may be auctioned in a day. Most auction sites have somewhere between 4 and 7 auction lanes operating simultaneously, through which cars are driven and put onto the auction block. Once on the auction block, the used-car dealers bid for them in a standard oral-ascending-price auction that lasts around 2 minutes per car. The highest bidder receives the car and can take it back to his used-car lot himself (by driving it or placing it on a truck), or can arrange delivery through independent delivery agencies that operate at the auctions.

[3] This requires the usual assumption used to guarantee that the law of one price holds, namely that the high-value customers get to purchase first in the market.

Our data set contains information about the auction outcome and other details for each car brought to auction from January, 2002 through September, 2008. Table 1 provides summary statistics for some of the key variables in the data. The full data set contains information on just over 27 million cars, around 4 million cars per year. We observe information about each car, including its make, model, body style, model year, and odometer mileage as well as an identifier for the seller who brought the car to the auction. The average used car at the auction is 4 years old and has approximately 57,000 miles on the odometer. We observe whether the car sold at auction, the selling price, as well as an identifier for the used-car dealer who made the purchase. Just over 82% of all cars brought to the auction sell, with an average selling price of $10,301.

While all of the buyers at the auctions are used-car dealers, there is more diversity in the type of sellers. There are two major classes of sellers: car dealers and fleet/lease. A typical dealer sale might involve a new-car dealer brining a car to auction that she received via trade-in and does not wish to (or cannot) sell on her own lot. The fleet/lease category includes cars from rental-car companies, university or corporate fleets, and cars returned to leasing companies at the end of the lease period. Table 1 breaks down the key variables by these two major seller categories. About 56% of cars brought to the auctions come from the dealer category. Dealer cars tend to be older than fleet/lease cars (average of about 5 years versus 3 years) and have higher mileage (66,197 versus 48,316). This is reflected in higher average sale prices for fleet/lease cars. Dealer cars are also less likely to sell at auction; 96% of fleet/lease cars sell, compared with 71% for dealer cars. Compared with fleet/lease companies, which typically sell more cars at one time with low reservation prices, car dealers generally have better outside options for selling used cars on their own lots and set reservation prices at the auctions that are sometimes binding. The greater discretion that dealers have in deciding which cars to bring to auction is also likely to increase concerns about adverse selection for these cars and may contribute to lower selling probabilities. We use this variation in seller type to conduct robustness checks and investigate questions about heterogeneity in attention in the next section.

It is also worth discussing here some of the details of the market that give us confidence that the empirical results reported below reflect responses to car mileage by market participants and are not driven by institutional features of the auctions. First, the auction company's business model is based on charging fees to both sellers and buyers at the auction, but these fees are not a direct function of the mileage of the car. Second, cars are not sorted into auction lanes or grouped together based on mileage. Finally, and importantly, the used-car dealers purchasing cars at the auction clearly observe the exact continuous mileage on a car. This information is reported in printouts available to the buyers with information about each car at the auction, as well as in a large screen at each auction block that lists information about the car currently on the block.[4] The dealers can also look into the car to see the odometer.

4. Results

Graphical analysis:

We begin the empirical analysis with a simple non-parametric plot of the raw price data. Figure 2 shows a graph of the price of sold cars against mileage using information on the over 22 million cars that were sold at auctions during our sample period. Each dot shows the average sale price for cars in a 500-mile mileage bin, starting at 1,000 miles, i.e. there is a dot for the average price of cars with 1,000 through 1,499 miles, then a dot for cars with 1,500 to 1,999 miles, and so on through 120,000 miles. We have inserted vertical lines in the graph at each 10,000-mile mark. As one would expect, average prices are decreasing in mileage. Within each 10,000-mile band average prices decline quite smoothly. However, there are clear discontinuities in average prices at each of these 10,000-mile marks. These discontinuities are sizeable in a range from $100 to even around $900.

This simple representation of the data demonstrates that mileage thresholds affect the market. With no other explanation for the importance of 10,000-mile thresholds, these results strongly suggest a role for inattention in this market. Yet although this analysis establishes that mileage thresholds matter, estimating how much they matter requires further analysis. Since our

[4] Our data includes all of the information presented on this screen including the vehicle identification number (VIN) of the car, information about the options on the car, and any text that the seller chooses to include about the car.

model predicts that inattention will generate price discontinuities, market participants who are aware of these effects may react to them. For example, sellers may decide to bring cars to the auction before they cross a mileage threshold. To the extent that this behavior could differ by seller types or by the type of car (e.g., luxury vs. economy vehicles), the estimated size of price discontinuities at thresholds will be biased. Accounting for these selection issues and obtaining a valid estimate of the size of the price discontinuities for a given car is the empirical challenge in this paper.

Figure 3 graphs the volume of cars brought to the auction using the full data set and the same 500-mile bins from Figure 2. The first aspect to notice is the presence of peculiar patterns in the 30,000 to 50,000 range; as we discuss in more detail below, this pattern is largely being driven by dynamics of lease cars. Setting those patterns aside for now, it is clear that there are spikes in volume right before the 10,000-mile thresholds at each threshold starting at 60,000 miles. These patterns lend further support for the importance of mileage thresholds in the market. Furthermore, they suggest that at least some sellers of used cars are aware of the inattention-induced price discontinuities. However, these results also make it clear that it is necessary to account for selection before obtaining estimates of the size of price discontinuities.

The primary concern we have with interpreting the magnitude of price discontinuities in the graphs in Figure 2, therefore, is that the cars on either side of the thresholds may differ in make, model, and age. Other than mileage, these characteristics of a car are the primary determinants of prices. In order to account for these differences, we regress the price of sold cars on fixed effects for the combination of make (e.g., Honda), model (e.g., Accord), body style (e.g., EX Sedan), model year, and auction year. Since the age of a car (determined by the combination of model year and auction year) is highly correlated with mileage, we include in these regressions a 7th order polynomial in mileage to ensure that the estimated fixed effects are not biased by their correlation with mileage. Visual inspection along with goodness-of-fit tests suggests that a 7th-order polynomial is necessary and sufficient. We then obtain a residual price for each car that partials out the influence of that car's fixed effect, but not the polynomial in miles. Figure 4 repeats the graphs in Figure 2, except now using these residuals. This figure clearly shows that price discontinuities remain after accounting for

specific car type. The size of the discontinuities is around $200 and much more similar across thresholds than in the raw data of Figure 2.

Another area of potentially relevant selection in our data is the seller type. As we mentioned in Section 3, there are two distinct categories of sellers in the data: car dealers and fleet/lease companies. Recall that fleet/lease companies tend to have somewhat newer cars than dealers, bring cars in larger lots, and set low reserve prices. The auctions are also typically organized so that the fleet/lease cars run in separate lanes from the dealer cars.[5] These differences suggest that we should conduct our analysis separately for the two seller types.

Because the low reserve prices used by fleet/lease sellers more closely mirror our theoretical discussion in Section 2, we begin with this category and then move to the dealer cars. Figure 5 repeats the same residual analysis from Figure 4, but now restricting to cars in the fleet/lease category. The results are very similar to those with the full sample of cars, again showing pronounced discontinuities at the 10,000-mile marks. These discontinuities are, again, generally in the order of $200.

Figure 6 shows the probability of a car selling and the volumes of cars sold by mileage for these cars in the fleet/lease category. Looking at Panels a and b, which show the probability of selling, reconfirms our discussion from Section 3 that the fleet/lease cars are sold with low reservation prices; the probability of selling is nearly 1 across most of the mileage range. Furthermore, this probability does not vary around the 10,000-mile thresholds. The fact that these selling probabilities are very high and smooth through the 10,000-mile marks gives us confidence that the inattention-effects we observe are not driven by variations in sale probabilities and that estimates of the price discontinuities can be obtained without the complication of considering a two-stage selling process.

Looking at the volume patterns for fleet/lease cars in Figure 6c/d we see that this category has a good deal of variation in volume for cars with less than 50,000 miles. This reflects institutional features of this segment of the car market. In particular, there is a large spike in sales volume around

[5] Car dealers bidding on cars at the auction can freely and easily move from lane to lane within the auction houses.

the 36,000-mile mark, which reflects the prevalence of 3-year leases with 12,000-mile per year limits.[6] However, the patterns smooth out for higher mileages, and in particular, there are no volume spikes at the 50,000, 70,000, 80,000 or 90,000 thresholds. The fact that we observe consistent price discontinuities at each of these mileage marks, strengthens our conviction that the size of the discontinuities in the residual graph, (Figure 5) are not biased by selection.

Turning to the dealer category, Figure 7 repeats this residual price analysis for dealer-sold cars. This graph is almost identical to Figure 5 for the fleet/lease category, showing consistent discontinuities of very similar magnitude to those in the fleet/lease category (e.g., $200-range for most thresholds). Given the differences between these two seller types, the similarity of the price discontinuities at 10,000-mile marks, once car-type fixed effects have been netted out, provides additional evidence for the importance of inattention in this market.

Figure 8 shows the probability-of-sale and volume-of-sales patterns for the dealer category. The probability of a sale for this category is significantly lower than it is for the fleet/lease cars, more in the 60% to 70% range. This reflects the higher reservation prices used by dealers. The modest upward slope of this probability fits with the fact that many of these cars are sold at auction by dealers who specialize in new and late-model used cars. This is because for cars with higher mileage, the outside option of these dealers likely falls relative to that of the used-car dealers who are buying cars at auction.

The volume patterns, in Panels c and d, for the dealers are particularly interesting, and show consistent peaks right before the 10,000-mile thresholds. This pattern clearly shows that these mileage thresholds are influencing market behavior. Importantly, though, we find in the residual graphs that once the characteristics of a car being sold are controlled for, the pricing patterns by mileage are consistent between the fleet/lease category (where these volume spikes do not occur) and the dealer category. This consistency fits with our theoretical discussion in Section 2. Recall from Section 2 that in our model, the distribution of mileage across cars in the used-car market place does not affect the relative prices of cars with different mileage. Hence, while it is important to

[6] The spike around 48,000 miles likely reflects 4-year leases with 12,000 miles per year.

account for selection on car-type that might be correlated with these volume spikes, spikes in volumes for a given car occurring before thresholds should not, and do not seem to, affect the estimated discontinuities.

Regression analysis:

Having established the existence of consistent price discontinuities at 10,000-mile thresholds using this largely non-parametric approach, we turn now to regression analysis to establish numerical estimates of the price discontinuities. Throughout we run our regressions separately for the fleet/lease and dealer categories. While the figures reflect results across all years and auctions, in order to save on the computing power needed to run regressions on this massive data set, we present these results for a single auction year, 2006. This year was chosen simply because it is the most recent year of data before the start of the financial crisis and recession in the U.S. None of the results that follow change if we use alternative auction years.

Motivated by the work on regression discontinuity design (see Lee and Lemiuex (2009) for a overview), we employ the following regression specification:

$$price_i = \alpha + f(miles_i) + \sum_{j=1}^{12} \beta_j D[miles_i \geq (10{,}000)^j] + \gamma X_i + \varepsilon_i.$$

The dependent variable in our primary regression is the sale price for cars that sold at the auction. The function $f(miles_i)$ is a flexible function of mileage intended to capture smooth patterns in how cars depreciate with mileage. The regression also includes a series of indicator variables (indicated with *Ds* in the equation above) for whether mileage has crossed a given threshold. The coefficients of interest are the β_j coefficients, which can be interpreted as the discontinuous changes in price (all else constant) that occur as cars cross a particular 10,000-mile threshold. In this way, the specification allows us to estimate the price discontinuities separately at each 10,000-mile threshold. Finally, X_i includes characteristics of the particular car being sold (make, model, etc).

Table 2 presents the regression results for the fleet/lease cars. The first column controls only for a 7th-order polynomial in mileage and the mileage-threshold indicators and provides estimates of the price discontinuities before any corrections for selection. Not surprisingly, given the size of our

data set, the coefficients are generally highly statistically significant. The majority of the coefficient estimates are negative, consistent with our theory of inattention. However, they vary substantially and a few (e.g., 30,000 miles) are even significantly positive. Columns 2 through 7 in the table add increasingly restrictive fixed effects to the model. Column 2 adds a control for the age of the car.[7] Once age is included in the regressions, all but one of the coefficient estimates become negative. Columns 3 through 5 report parameter estimates with the addition of the fixed effect for the make, model, and body of the car, respectively. Thus by Column 5, identification of the model is coming from observing different mileages of cars of the same make, model, body, and model year. Notice in Column 5 that the regression is essentially estimating the threshold discontinuities we observed in Figure 5. Once these controls are included in the model, all of the coefficient estimates are negative, and all but one highly statistically significant. The coefficients are similar across thresholds, with an un-weighted average across thresholds of -$170.

While the results in Column 5 control for both the type of car and the car's age, which likely captures most of the selection that would affect market prices, we can strengthen the controls further. Column 6 adds to the fixed effect a control for auction location, while Column 7 adds a control for seller identifier. Thus, the identification of the parameter estimate in Column 7 comes from the same seller selling identical cars at the same auction that differ in mileage. These controls do not meaningfully change the coefficient estimates, and in fact the estimates are quite stable from Column 4 through 7, suggesting that controlling for the model and age of the car accounts for most of the relevant selection.

Table 3 presents the same analysis for the dealer category. In Column 1, before any controls are included, the estimates of price discontinuities at the 10,000-mile thresholds are all negative and generally very large. In particular, the estimated drop at 50,000 miles is $1,107. Discontinuities so extreme suggest that selection may be playing a large role in these basic estimates for the dealer category. This would be consistent with the greater discretion this group of sellers displays in bringing cars to the market as illustrated by the large volume spikes before thresholds. Once

[7] Within a single year's data, because we observe age as the difference between auction year and model year, the controls for age are simply fixed effects for model year.

controls are included, however, the estimated discontinuities for the dealer cars are very close to those obtained for the fleet/lease cars. In fact, if we compare the un-weighted average of discontinuity estimates in Column 5 for these categories, we see that it is $180 for dealer cars and $170 for fleet/lease cars. As was the case for the fleet/lease cars, strengthening the controls to include auction location and seller fixed effects does not affect the results.

This regression analyses yields very stable estimates of significant price discontinuities at the mileage thresholds that, we believe, account for the impacts of selection on the size of discontinuities. Nonetheless, it is worth questioning whether there are sources of unobserved heterogeneity around the mileage thresholds that may bias the size of our discontinuity estimates. There are a number of reasons to feel confident that this is not the case. First, notice that selection on unobservables may be less of a concern in this setting than in most other contexts, for the market prices we observe can only be influenced by factors that are observable to participants at the auctions. Although we do not observe every detail that the market participants do, our data set captures most of the relevant information. Second, the similarity of the estimates obtained for the two different seller categories, gives us confidence in the estimates. Third, one of the reasons we are concerned about selection is that we observe volume spikes for the dealer cars around the thresholds. However, notice that while volume spikes and dives right before and after the thresholds, it is relatively stable elsewhere. This might make us worry that selection is heavily influencing average prices right around the thresholds. Yet if we look at the graphs in Figures 5, 6, and 7, we see that the discontinuities are not driven solely by the points right around the thresholds. There is a shifting down of the entire price schedule after each threshold, so even if one eliminated the dots around the thresholds, trend breaks would still be apparent. Finally, it is worth considering the nature of the selection effects that are revealed through our regression analysis. In the dealer category the effects of selection seem to bias the estimates in a uniform way – all of the coefficients in the first column are strongly negative and become smaller, in absolute value, once selection is accounted for. Despite the stability of the estimates across increasing controls, one might be concerned that some bias still exists. However, if we look at the fleet/lease category in the same way,

the changes in the coefficient estimates as we add controls do not change in a systematic direction. Some of the estimated discontinuities become less negative (as was the case for dealer cars), but others started out positive and became negative. These patterns, when coupled with the consistency of the estimates across the seller categories, make us confident that the estimated discontinuity sizes we find are valid.

Estimate of the inattention parameter:

The estimates of price discontinuities can be used to calculate the size of the inattention parameter θ from our model in Section 2. Recall from Section 2 (and Figure 1) that for the simple linear case, the size of the estimated price discontinuity at a 10,000-mile threshold should be approximately equal to 10,000 times the product of the inattention parameter θ and the slope of the value function with respect to actual miles, α. Notice also that the slope of the value function with respect to actual miles (the "full attention" case) can be observed by drawing a line through the value function at the thresholds. For instance, in the residual graphs in Figures 5 and 7, one can obtain an estimate of α by drawing lines between the dots centered on the threshold points. For the fleet/lease category the average slope across these points is -0.062 while for the dealer cars it is -.055. Using the average discontinuity estimates discussed above (i.e., $170 for fleet/lease and $180 for dealers), yields an estimate of θ equal to 0.28 for the fleet/lease estimation and 0.32 for the dealer estimation.

The inattention parameter has a natural interpretation in our setting. The value of θ gives the fraction of the reduction of value across mileage that occurs at 10,000-mile thresholds. As such, the results here suggest that approximately 30% of the depreciation that a car experiences due to mileage increases occurs discontinuously at 10,000-mile thresholds.

We can also start to investigate the appropriate functional form for inattention by examining whether there are price discontinuities at smaller thresholds, such as the 1,000-mile marks. Recall that the simple version of the inattention model in Equation 1 predicts the same level of inattention to all digits past the left-most digit and would not result in price discontinuities at 1,000-mile marks.

However, a form of inattention like that in Equation 3, where attention to digits is decreasing to the right, would predict additional but smaller discontinuities at these smaller thresholds. Figure 9 allows us to look at this question by plotting the average residual prices, using the same regression approach for the graphical analysis above, in 200-mile bins. For this figure, we have averaged 200-mile bins across the 10,000-mile thresholds, such that 10,200 miles is averaged with 20,200, 30,200, and so on; in turn 10,400 is averaged with 20,400, and so on. This allows us to graphically represent whether there are discontinuities on average within the 10,000-mile bands. There is a discontinuity of about $50 at the 9,000-mile marks, and some evidence of smaller discontinuities at the other 1,000-mile marks. Hence, there is some evidence that the correct functional form for inattention reflects at least some decreasing attention to digits further to the right.

Who is inattentive?

Because our data come from the wholesale market, a natural question is whether the observed patterns are arising because of inattention on the part of final customers or if it a result of inattention by the dealers themselves. When investigating this question, note first that if the end customers display inattention, it will be very difficult to distinguish between a savvy used-car dealer purchasing cars with an awareness of this bias and an un-savvy used-car dealer who happens to share the same bias as his end customers. What we can investigate, therefore, is whether inattention seems to be driven *primarily* by used-car dealers or final customers.

In order to address this question we exploit the variation in auction experience of the used-car dealers purchasing cars at the auction. On the one hand, consider first the possibility that it is the used-car dealers and not the final customers who are inattentive to mileage. This would mean that cars with mileage just below a threshold are overpriced relative to those just past the thresholds at the auction versus what they can be sold for in the retail market. In this case, we might expect that more experienced dealers would have learned to avoid the costly bias and would be more likely to purchase cars just after they have crossed the threshold. Hence, if we examine the fraction of cars purchased by experienced buyers we would see that fraction bump up at the 10,000-mile thresholds.

On the other hand, assume that the bias is driven by the final customers. If some of the inexperienced car dealers are unaware of inattention effects, they will wrongly believe that prices will be smooth across mileage thresholds. In this case, they will perceive cars before thresholds to be overpriced relative to those past the thresholds and could be expected to cluster more on the post-threshold cars. Hence, we would expect the share of cars purchased by experienced dealers to fall at the thresholds.

Table 4 investigates these experience patterns using the same regression framework as above, with the dependent variable being an indicator variable for whether or not the dealer who purchased the car at auction was experienced. We obtain our measure of experience by calculating the total number of cars each dealer in our data has purchased at the auctions in a given year. We label buyers who have purchased more cars than the median as "experienced" buyers and those below the median as "inexperienced". The estimated effects are significantly negative at each 10,000-mile threshold, and the estimated effect sizes are quite stable across specifications. The estimates can be interpreted as showing that crossing a threshold leads to a discontinuous drop in the probability that a car is purchased by an experienced buyer of around 1 to 2 percentage points. This evidence, then, supports the idea that the price discontinuities are primarily driven by inattention of final customers and that inexperienced used-car dealers may be somewhat less aware of this bias.

Another way of verifying that inattention is not solely an auction-participant phenomenon is to look for evidence of threshold effects in other parts of the used-car market. That type of data is generally difficult to obtain. However, we were able to collect some information about the number of used-cars listed online on *Cars.com*, a leading automotive-classifieds website. We graph these volumes in Figure 10, which clearly shows that there are spikes in the volume of used cars listed on Cars.com at mileages just before 10,000-mile thresholds. While these data do not provide information on the sale prices and the asking prices of these cars, these volume findings suggest that the inattention effects we observe are not a wholesale-auction phenomenon.

A final question is whether *sellers* at the auctions appear to be aware of these inattention effects. There is little evidence that the fleet/lease sellers adjust their behavior to these threshold

effects, as they uniformly set low reserve prices and do not show systematic volume spikes around the thresholds. The volume patterns for dealer cars, however, clearly suggest that some of these sellers are aware of the threshold effects. It is worth noting, however, that since many of the cars that dealers sell at auctions come from trade-ins on their lots, these volume patterns could be driven by individuals who decide to trade in their cars (perhaps quite rationally) before the thresholds.

The probability graphs for the different seller types, however, also provide some hints that some of the dealers who sell cars at the auctions may be unaware of the threshold effects. Recall that the probability graphs for the fleet/lease cars are uniformly high and smooth through the thresholds, revealing that there is no systematic drop in demand for cars at the thresholds in the auctions. Yet a close look at the probability graphs for the dealer category shows that there seem to be slight drops in the probability of dealer cars selling at the thresholds. This could be consistent with some dealer sellers being unaware of the inattention of final used-car customers. Since the dealers set reservation prices that are at times binding, if some fraction of these sellers are unaware of threshold effects, they may fail to adjust their reserve prices downward enough at thresholds. This in turn could lead to drops in the probability of sales for these dealers at the thresholds. We have run regression results on the probability of sale using the framework from above and find some weak evidence of drops in probability of sale at 10,000-mile marks for the dealer sellers.[8] However, the results are weak at many thresholds and are suggestive at best.

5. Discussion

We find strong evidence for the hypothesis that partial inattention to mileage has a significant impact on the used-car market. Inattention leads to market prices that show pronounced negative discontinuities of around $200 at 10,000-mile thresholds. We estimate that inattention accounts for around 30% of the decline in value a car experiences as it increases in mileage through the 100,000-mile mark. These effects are particularly striking if one considers how this market may have been thought to be a place where inattention was unlikely. Not only is this an efficient market

[8] The results of these regressions are available upon request.

with a large degree of competition, but the product in question is both highly valuable and a durable good, and the quality measure of interest is easily observable.

One of the questions commonly raised by studies of inattention is whether this inattention is "rational." Given that attention is a scarce resource, it seems sensible that individuals would choose to pay less attention to the finer digits of large numbers. In particular, since the degree of real depreciation that a car experiences is not large over small range of mileages, at first glance it does not seem unreasonable that customers would pay primary attention to the left-most digit of their mileage. Yet this type of potentially rational inattention on the part of individuals generates a market dynamic in which individuals have a significant incentive to pay more attention to precise mileage. We suspect that knowing the results of this study would cause most individuals to pay more attention to mileage. Anyone who purchases a 49,000-mile car will soon own the 50,000-mile version. Buyers can save $200 by purchasing cars after thresholds and as a seller one can benefit by the same amount from selling right before the threshold.

This paper contributes to the literature on inattention in a number of ways. By showing the importance of inattention in a market where the information is clearly observed, this paper suggests that economists would benefit by thinking seriously about the potential impacts of systematic inattention in a range of other settings, with particular reference to environments where inferences are made based on continuous quality metrics. Examples include hiring or admissions decisions based on GPAs and test scores of various types, how investors value companies based on financial reports (e.g. by looking at revenues or income), and how the public reacts to government spending programs.

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Figure 1. Example Value Function

This figure provides an example of how the consumer's value function from Eq 2 in Section 2 would look with a positive value of θ.

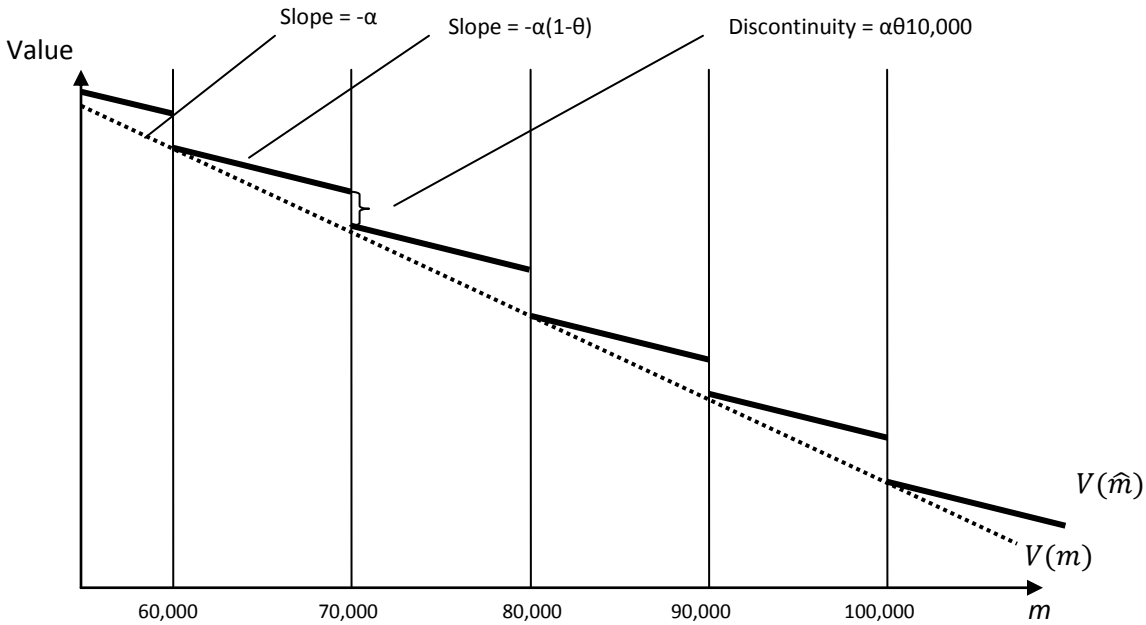
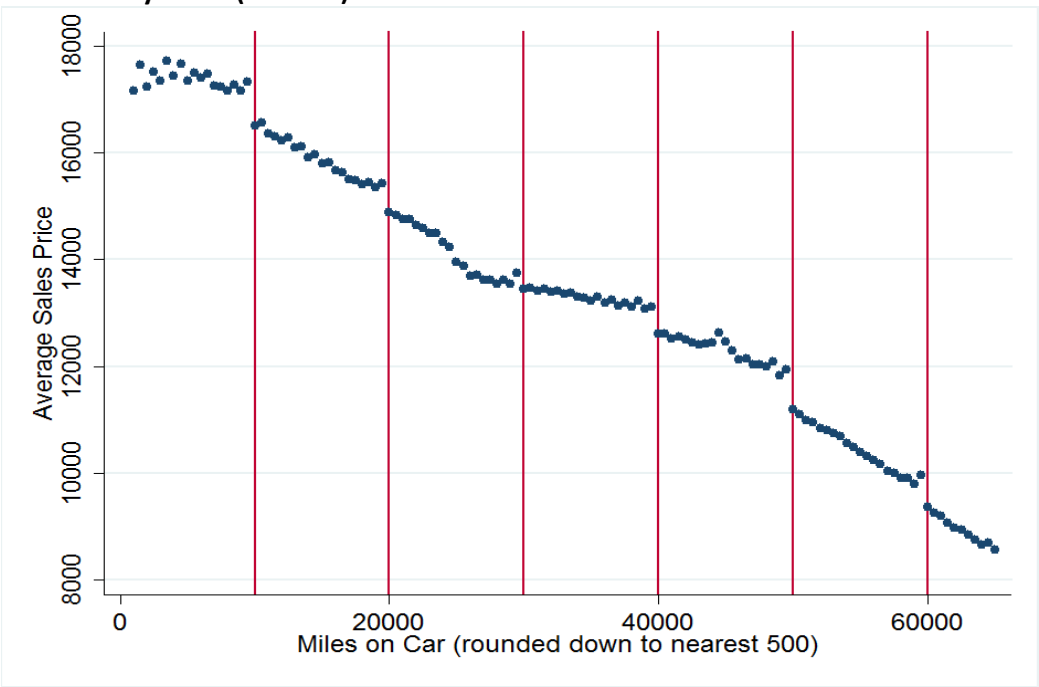


Figure 2. This figure plots the raw average sales price for the cars in our dataset within each 500-mile bin. Figure 2a plots points for 1k-65k mile cars and while 2b plots points for 65k-125k cars.

2a. Price by Miles (1k - 65k)



2b. Price by Miles (65k-125k)

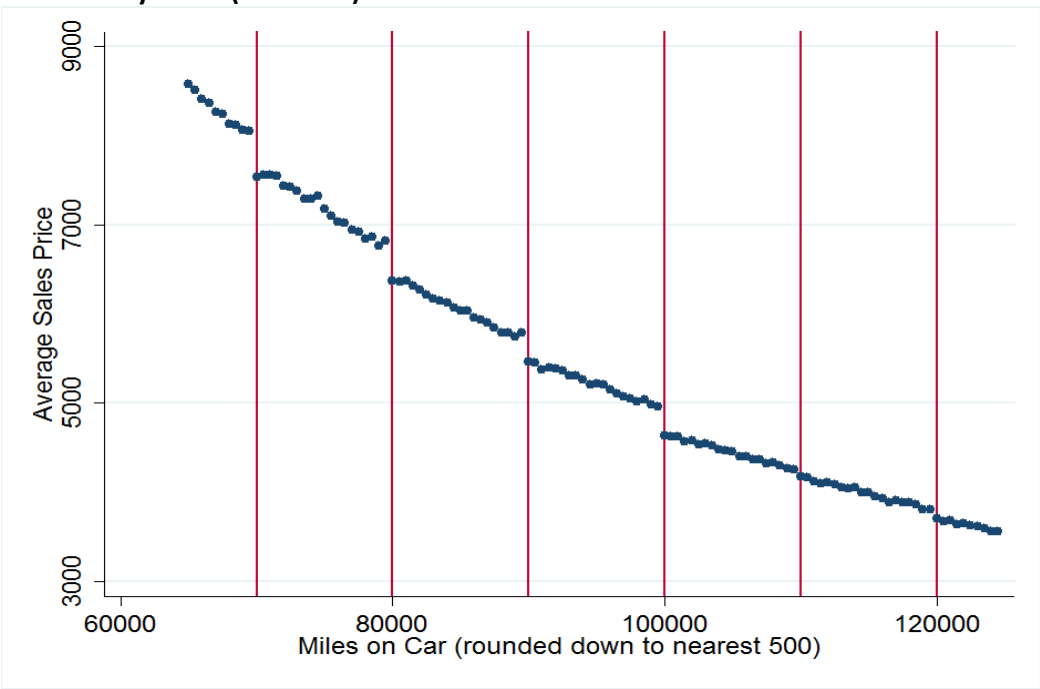
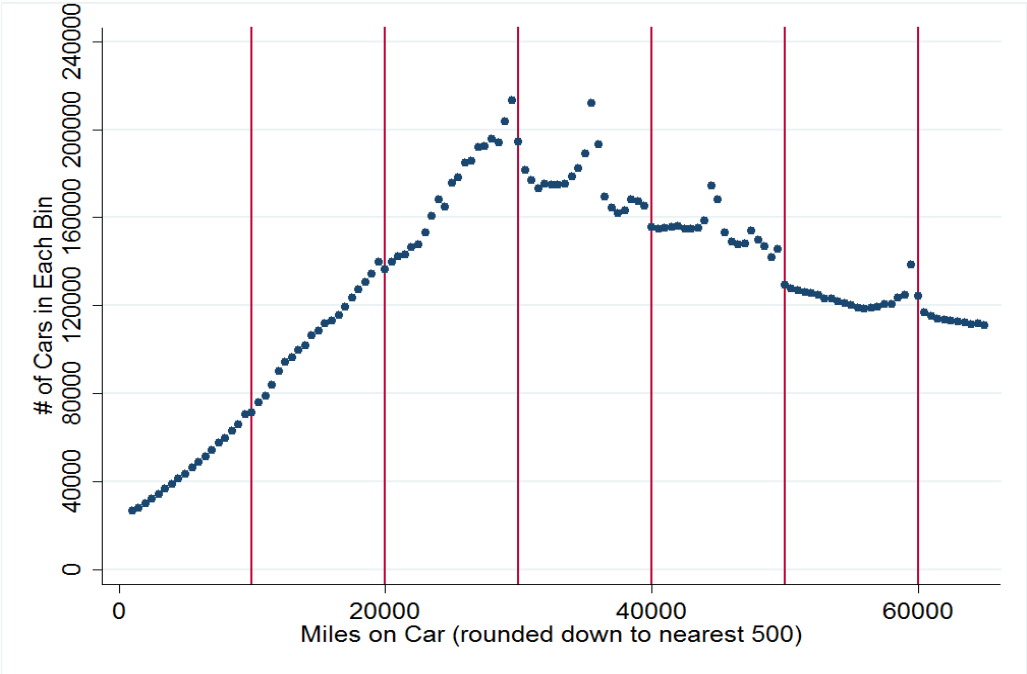


Figure 3. This figure plots the raw counts of all cars in our dataset within each 500-mile bin. Figure 3a plots points for 1k-65k mile cars and while 3b plots points for 65k-125k cars.

3a. Volume by Miles (1k - 65k)



3b. Volume by Miles (65k-125k)

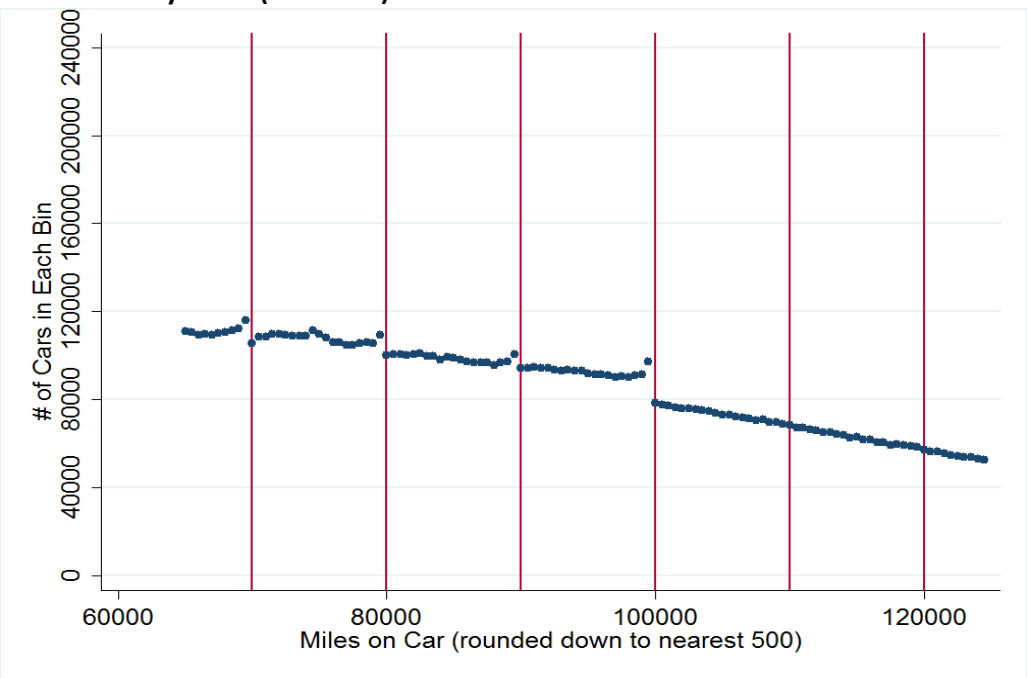
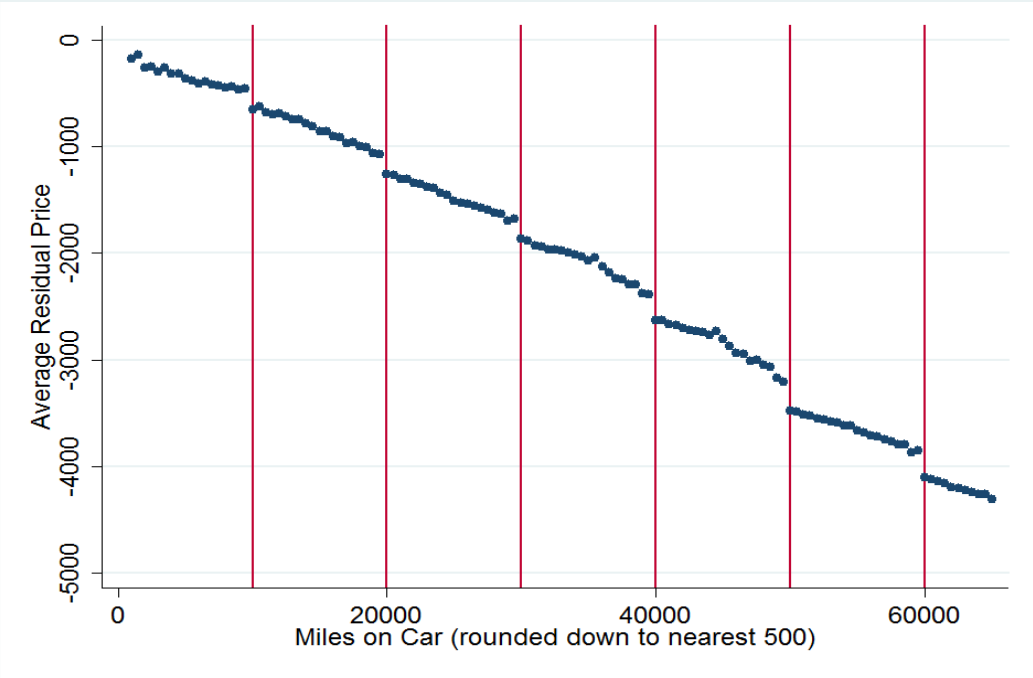


Figure 4. This figure plots the price residuals after netting out make*model*model_year*body fixed effects for each car. A 7th-order polynomial in miles was initially included in the regression but then not used to construct the residuals.

4a. Price Residual by Miles (1k - 65k)



4b. Price Residual by Miles (65k-125k)

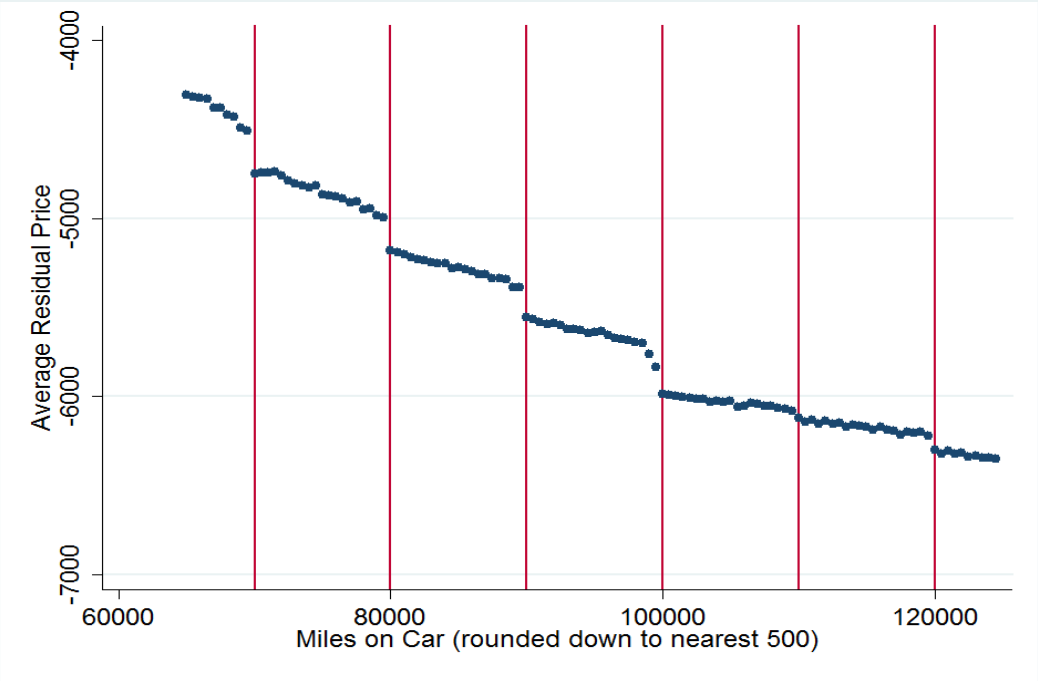
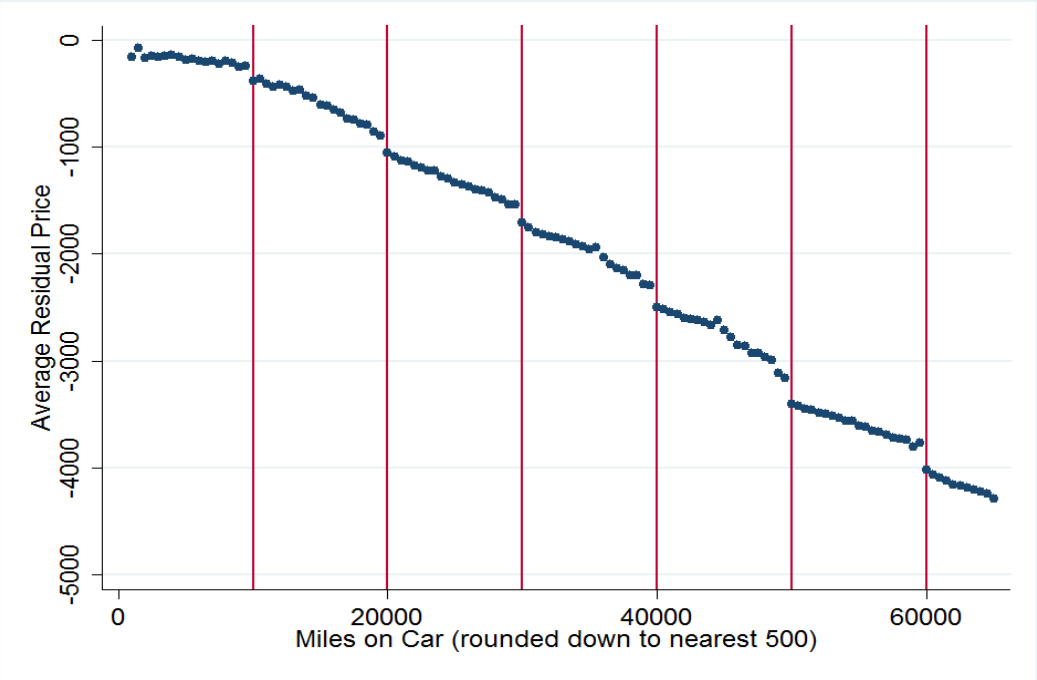
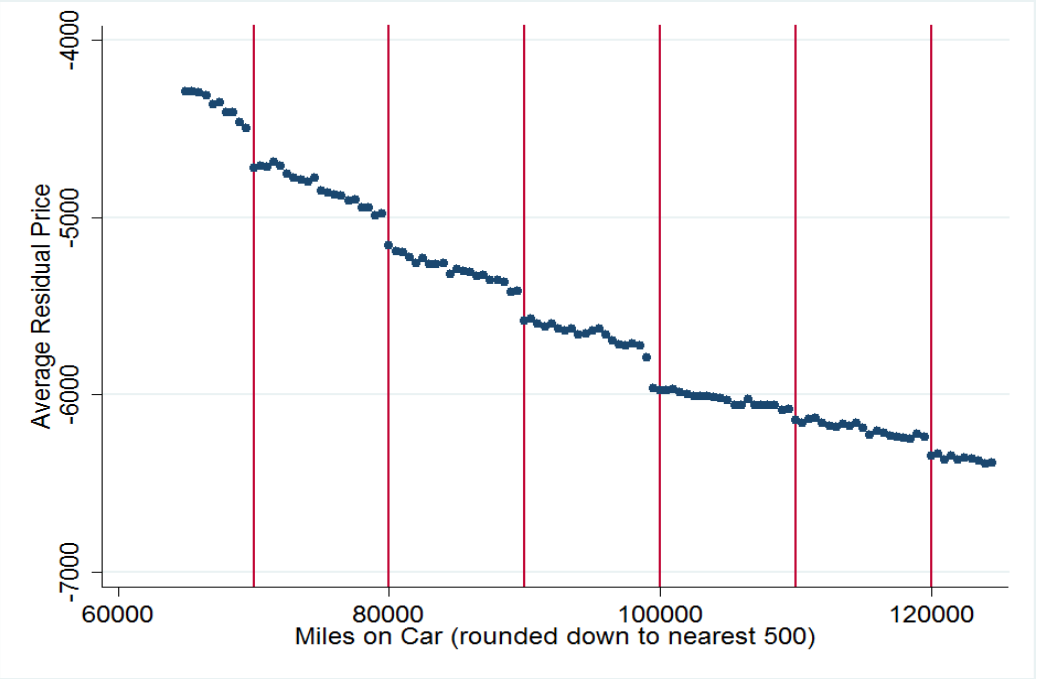


Figure 5. This figure plots the price residuals after netting out make*model*model_year*body fixed effects for all cars sold by Fleet/Lease companies. A 7th-order polynomial in miles was initially included in the regression but then not used to construct the residuals.

5a. Price Residual for Fleet/Lease Cars by Miles (1k - 65k)

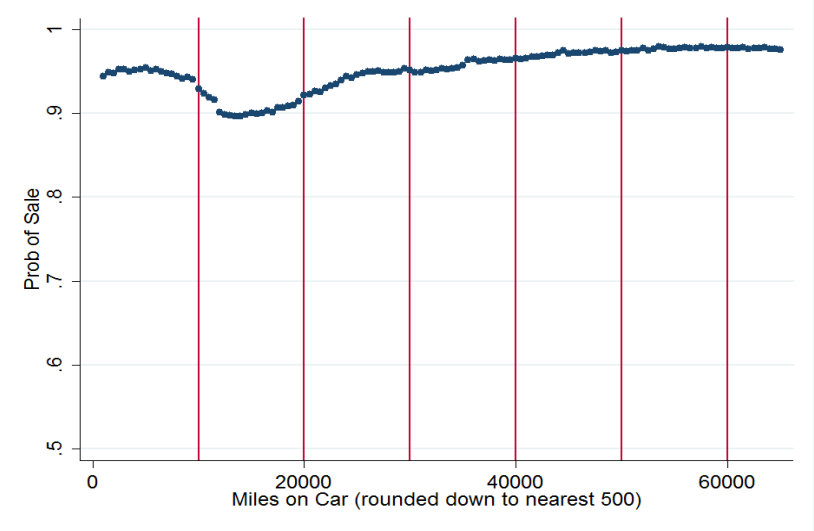


5b. Price Residual for Fleet/Lease Cars by Miles (65k - 125k)



Figures 6 a & b. These figures plot the raw average probability of cars selling for the Fleet/Lease cars in our dataset within each 500-mile bin. Figure 6a plots points for 1k-65k mile cars and 6b plots points for 65k-125k cars.

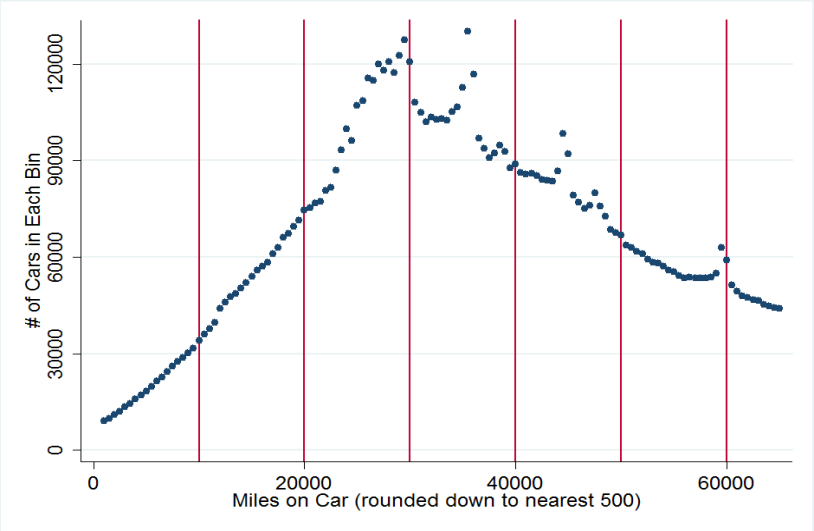
6a. Probabilty of Car Selling by Miles (1k - 65k) - Fleet/Lease



6b. Probabilty of Car Selling by Miles (65k - 125k) - Fleet/Lease

Figures 6 c & d. These figures plot the raw counts of all cars sold by fleet/lease companies in our dataset within each 500-mile bin. Figure 6c plots points for 1k-65k mile cars and 6d plots points for 65k-125k cars.

6c. Volume of Fleet/Lease-Sold Cars by Miles (1k - 65k)



6d. Volume of Fleet/Lease-Sold Cars by Miles (65k - 125k)

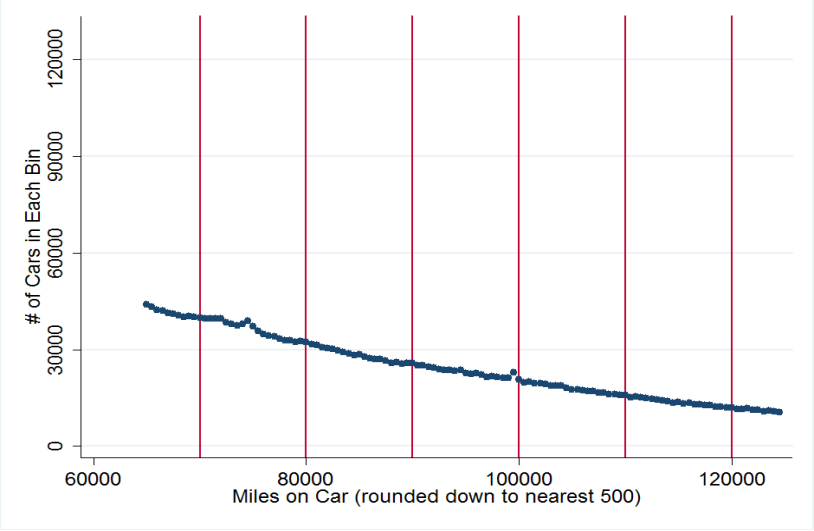
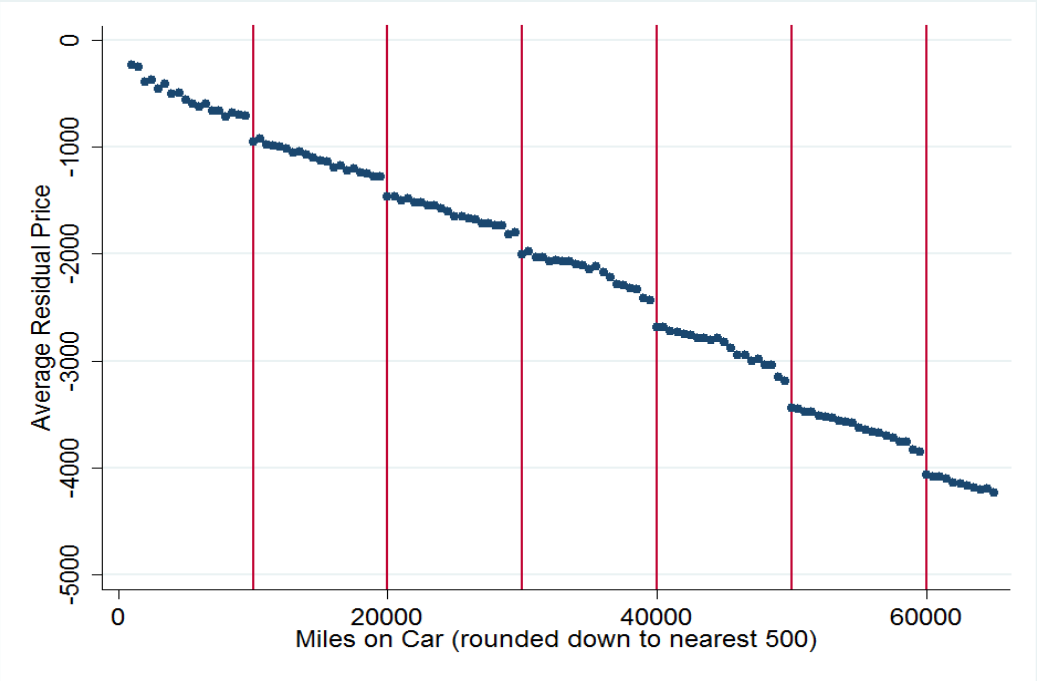
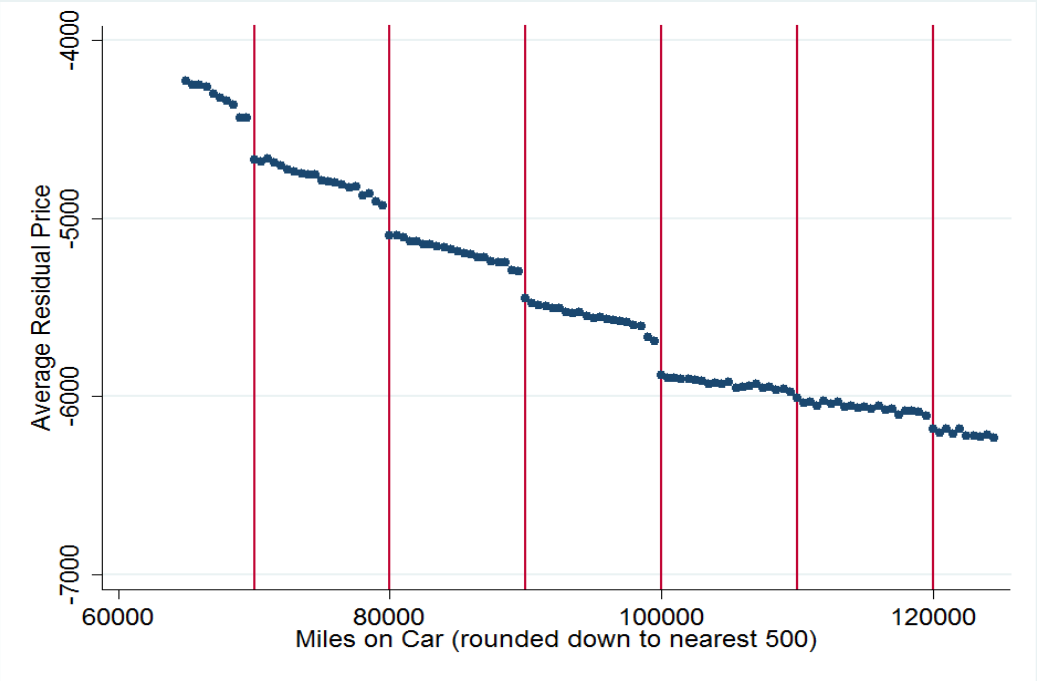


Figure 7. This figure plots the price residuals after netting out make*model*model_year*body fixed effects for all cars sold by Dealers. A 7th-order polynomial in miles was initially included in the regression but then not used to construct the residuals.

7a. Price Residual for Dealer by Miles (1k - 65k)

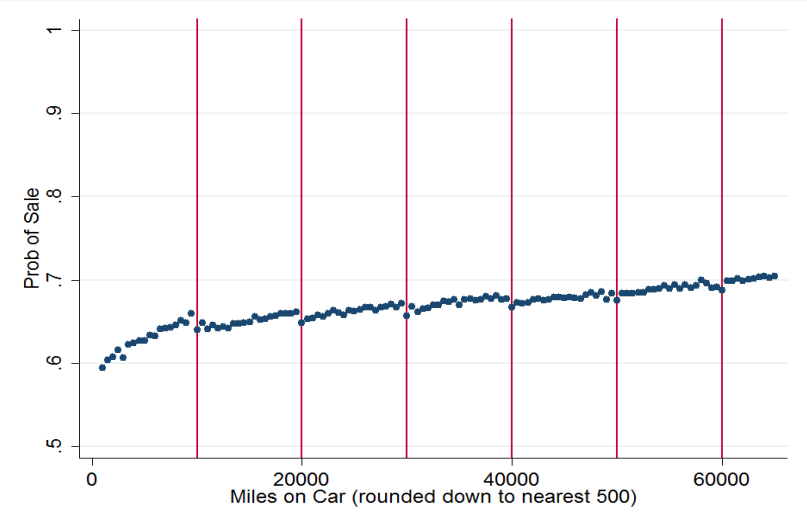


7b. Price Residual for Dealer Cars by Miles (65k - 125k)

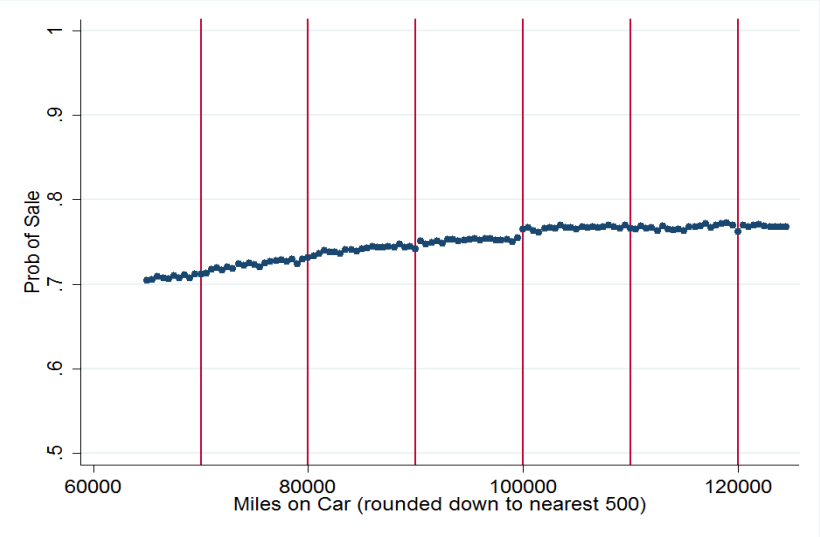


Figures 8 a & b. These figures plots the raw average probability of cars selling for the dealer-sold cars in our dataset within each 500-mile bin. Figure 8a plots points for 1k-65k mile cars and while 8b plots points for 65k-125k cars.

8a. Probabilty of Car Selling by Miles (1k - 65k) - Dealers

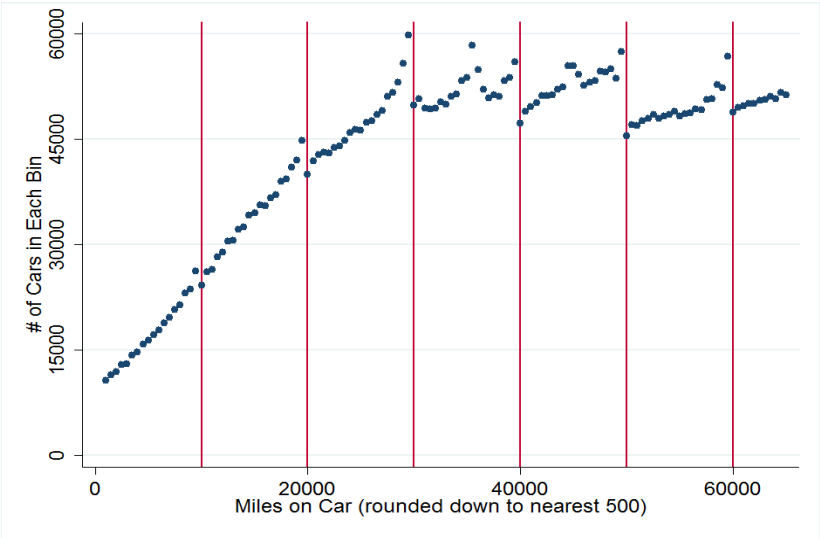


8b. Probabilty of Car Selling by Miles (65k - 125k) - Dealers



Figures 8 c & d. These figures plot the raw counts of all cars sold by dealers in our dataset within each 500-mile bin. Figure 8c plots points for 1k-65k mile cars and while 8d plots points for 65k-125k cars.

8c. Volume of Dealer-Sold Cars by Miles (1k - 65k)



8d. Volume of Dealer-Sold Cars by Miles (65k -125k)

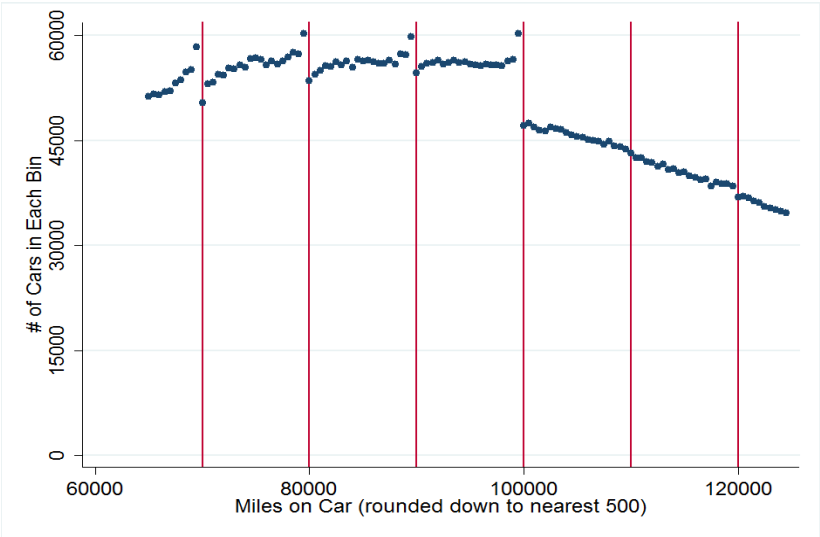


Figure 9. This figure plots the residuals prices for all cars in our data in 200-mile bins in order to test for discontinuities at every 1,000 mile mark. The 200 mile bins for every 1,000 mile mark across the different 10,000-mile thresholds were averaged together (10,200 + 20,200, + 30,200, + etc.).

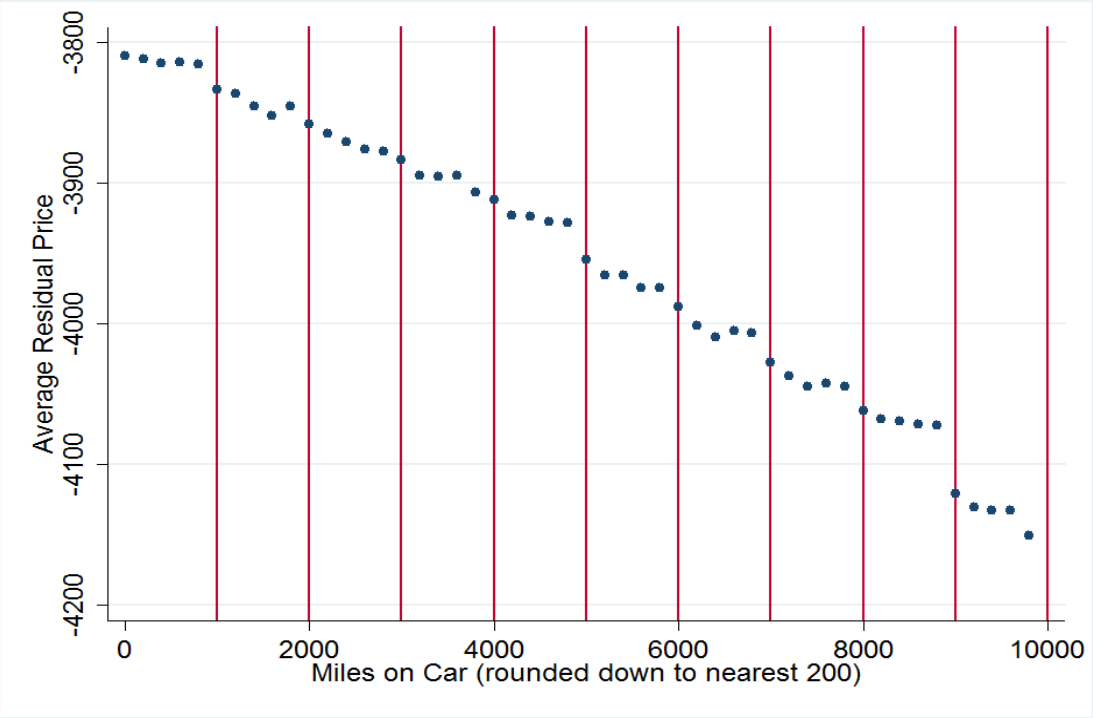
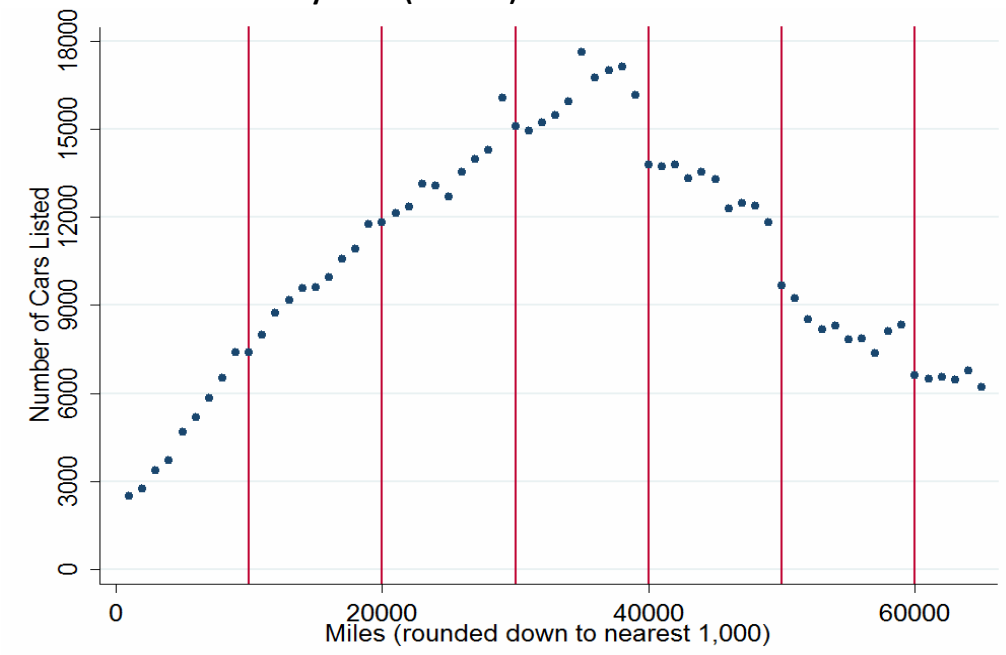


Figure 10. This figure plots the raw counts of all cars being sold on Cars.com in each 1000-mile bin. Figure 10a plots points for 1k-65k mile cars and while 10b plots points for 65k-125k cars.

10a. Cars.com Volume by Miles (1k - 65k)



10b. Cars.com Volume by Miles (65k-125k)

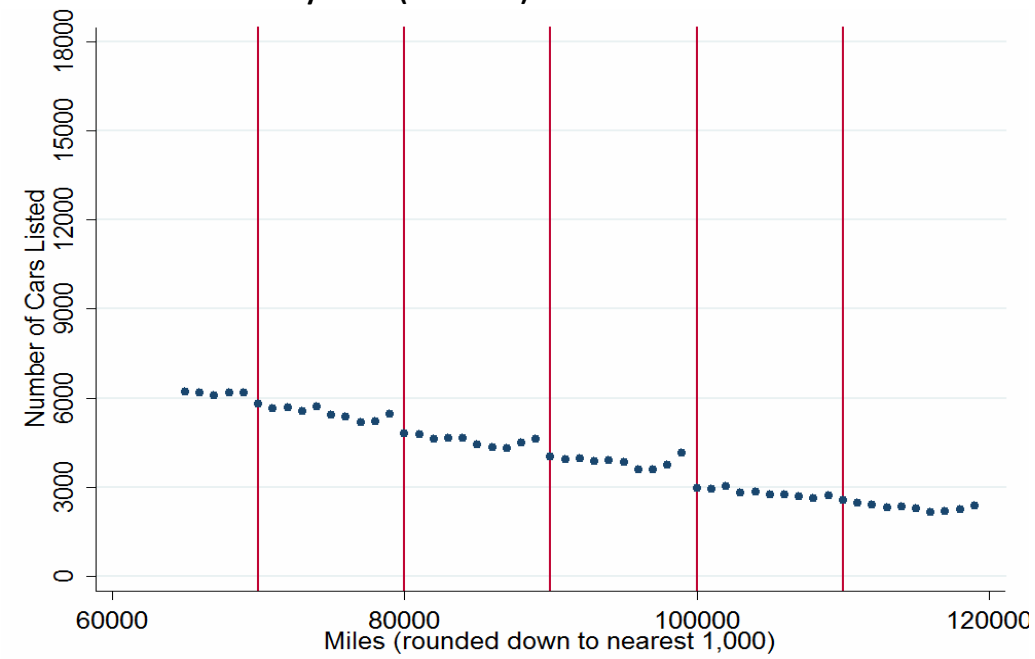


Table 1. Summary Statistics

	2002	2003	2004	2005	2006	2007	2008	All Years
All Cars								
Cars brought to auction	4,201,337	3,946,544	4,013,990	3,922,811	3,857,324	3,956,676	3,103,236	27,001,918
Cars sold at auction	3,465,958	3,324,874	3,276,768	3,226,587	3,132,033	3,238,287	2,531,154	22,195,661
Price Sold	$9,861	$9,396	$9,862	$10,421	$10,789	$11,141	$10,832	$10,301
Mileage	54,634	56,528	58,028	58,764	57,926	57,384	55,620	56,997
Model Year	1998.1	1999.0	1999.9	2000.8	2001.9	2002.9	2003.9	2000.8
Dealer Cars								
Cars brought to auction	2,010,481	2,060,560	2,318,420	2,406,979	2,384,672	2,313,739	1,604,615	15,099,466
Cars sold at auction	1,357,210	1,449,774	1,639,840	1,773,045	1,738,082	1,686,121	1,132,102	10,776,174
Price Sold	$8,493	$8,543	$9,144	$9,712	$9,867	$10,046	$9,270	$9,346
Mileage	65,269	65,473	65,327	65,710	66,242	67,582	68,128	66,197
Model Year	1996.8	1997.9	1999.0	2000.0	2000.9	2001.8	2002.6	1999.9
Fleet/Lease Cars								
Cars brought to auction	2,190,856	1,885,984	1,695,570	1,515,832	1,472,652	1,642,937	1,498,621	11,902,452
Cars sold at auction	2,108,748	1,875,100	1,636,928	1,453,542	1,393,951	1,552,166	1,399,052	11,419,487
Price Sold	$10,742	$10,055	$10,582	$11,287	$11,938	$12,329	$12,096	$11,203
Mileage	47,789	49,611	50,716	50,291	47,557	46,306	45,499	48,316
Model Year	1999.0	1999.9	2000.8	2001.9	2003.0	2004.2	2005.1	2001.7

Table 2. The Impact of 10,000-Miles-Driven Discontinuities on Price (Fleet/Lease, 2006)

	Dependent Variable: Auction Price for Car Sale						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
MT 10k miles	-200.2**	-292.9***	-247.8***	-65.2**	-84.4***	-69.9***	-104.0***
	[84.0]	[83.5]	[58.9]	[28.4]	[23.2]	[23.2]	[25.3]
MT 20k miles	-133.0***	-129.9***	-104.9***	-168.4***	-179.4***	-178.1***	-141.0***
	[46.7]	[45.9]	[32.1]	[14.9]	[11.9]	[12.2]	[13.4]
MT 30k miles	293.5***	-80.1**	-45.2*	-120.4***	-99.6***	-97.7***	-113.2***
	[35.6]	[34.4]	[23.4]	[11.0]	[9.0]	[9.5]	[11.1]
MT 40k miles	-259.8***	-193.5***	-100.0***	-187.9***	-189.4***	-173.3***	-185.1***
	[41.2]	[39.9]	[25.9]	[12.4]	[10.2]	[10.9]	[12.9]
MT 50k miles	-822.4***	-631.9***	-265.1***	-291.8***	-304.9***	-303.3***	-321.2***
	[40.8]	[39.4]	[25.4]	[12.6]	[10.6]	[11.6]	[14.5]
MT 60k miles	-490.7***	-493.0***	-276.4***	-181.5***	-172.0***	-169.7***	-165.7***
	[41.9]	[40.4]	[26.8]	[13.9]	[12.0]	[13.3]	[17.1]
MT 70k miles	91.2**	-48	-225.4***	-206.3***	-224.9***	-224.4***	-211.5***
	[40.5]	[39.2]	[26.8]	[14.3]	[12.5]	[14.0]	[19.0]
MT 80k miles	-20.2	-62.6*	-169.3***	-203.8***	-214.4***	-225.0***	-244.2***
	[39.0]	[37.5]	[27.0]	[15.1]	[13.5]	[15.6]	[22.5]
MT 90k miles	-316.0***	-219.2***	-161.4***	-213.4***	-215.9***	-246.4***	-293.7***
	[41.9]	[39.9]	[29.8]	[16.6]	[14.8]	[17.4]	[25.7]
MT 100k miles	-338.5***	-288.7***	-192.9***	-186.9***	-186.0***	-193.6***	-191.1***
	[39.9]	[37.7]	[29.9]	[17.4]	[15.7]	[19.1]	[29.8]
MT 110k miles	144.1***	85.2*	-13.5	-25.8	-16.9	-19.9	4.6
	[48.7]	[46.0]	[36.1]	[21.1]	[18.9]	[23.5]	[37.3]
MT 120k miles	-156.2***	-177.4***	-97.7**	-179.2***	-151.7***	-169.0***	-257.5***
	[60.0]	[56.1]	[46.6]	[28.8]	[26.0]	[32.3]	[52.6]
7th-Order Miles Poly	X	X	X	X	X	X	X
Fixed Effects	None	Age	Age*Make	Age*Make* Model	Age*Make* Model*Body	Age*Make* Model*Body*Auction	Age*Make*Model*Body*Auction*Seller_ID
R-Squared	0.25	0.293	0.673	0.923	0.948	0.964	0.975
Observations	1,429,164	1,429,164	1,429,164	1,429,164	1,429,164	1,429,164	1,429,164

** p < .05; *** p < .01

Table 3. The Impact of 10,000-Mile Thresholds on Prices (Dealers, 2006)

	Dependent Variable: Auction Price for Car Sale						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
MT 10k miles	-845.7***	-730.2***	-550.1***	-248.0***	-215.8***	-176.0***	-205.4***
	[114.5]	[109.1]	[73.2]	[30.0]	[20.3]	[23.1]	[64.4]
MT 20k miles	-235.2***	-185.5***	-124.9***	-136.1***	-135.9***	-134.5***	-126.3***
	[67.4]	[64.6]	[43.7]	[18.6]	[13.1]	[14.6]	[40.2]
MT 30k miles	-194.5***	-194.3***	-231.2***	-132.0***	-154.0***	-154.0***	-114.3***
	[49.9]	[47.5]	[32.8]	[14.3]	[10.7]	[12.0]	[36.0]
MT 40k miles	-682.1***	-572.3***	-315.5***	-228.6***	-210.5***	-201.0***	-194.9***
	[49.1]	[46.0]	[31.6]	[14.1]	[10.9]	[12.3]	[41.7]
MT 50k miles	-1,107.6***	-889.9***	-447.3***	-266.0***	-248.7***	-244.2***	-248.8***
	[42.5]	[38.7]	[27.0]	[12.3]	[9.9]	[11.2]	[42.2]
MT 60k miles	-613.9***	-553.5***	-374.8***	-235.0***	-218.3***	-208.3***	-209.3***
	[36.9]	[32.6]	[23.3]	[11.1]	[9.2]	[10.6]	[42.9]
MT 70k miles	-232.1***	-211.9***	-288.6***	-260.6***	-253.2***	-237.3***	-204.4***
	[33.2]	[29.2]	[21.3]	[10.2]	[8.6]	[9.8]	[40.0]
MT 80k miles	-241.1***	-179.4***	-220.5***	-184.2***	-177.7***	-159.9***	-159.2***
	[27.0]	[23.3]	[17.6]	[8.8]	[7.6]	[8.8]	[37.5]
MT 90k miles	-360.3***	-314.8***	-208.9***	-189.6***	-184.5***	-175.6***	-203.3***
	[26.6]	[22.8]	[17.5]	[8.9]	[7.8]	[9.1]	[38.9]
MT 100k miles	-459.2***	-410.1***	-301.9***	-221.1***	-202.0***	-176.5***	-178.4***
	[24.4]	[20.8]	[16.4]	[8.7]	[7.7]	[9.0]	[39.5]
MT 110k miles	-7.1	5.3	-57.4***	-59.0***	-56.7***	-61.2***	-52.2
	[27.0]	[23.0]	[18.3]	[9.9]	[8.9]	[10.5]	[48.6]
MT 120k miles	-69.5**	-96.9***	-87.7***	-102.0***	-106.3***	-92.7***	-103.1
	[31.8]	[26.9]	[21.9]	[12.3]	[11.3]	[13.8]	[66.9]
7th-Order Miles Poly	X	X	X	X	X	X	X
Fixed Effects	None	Age	Age*Make	Age*Make*Model	Age*Make*Model*Body	Age*Make*Model*Body*Auction	Age*Make*Model*Body*Auction*Seller_ID
R-Squared	0.361	0.46	0.733	0.945	0.966	0.979	0.996
Observations	1,851,407	1,851,407	1,851,407	1,851,407	1,851,407	1,851,407	1,851,407

** p < .05; *** p < .01

Table 4. The Impact of 10,000-Miles-Driven Discontinuities on Experienced Buyers (2006)

	Dependent Variable: Indicator equal to 1 if buyer of car is experienced					
	(1)	(2)	(3)	(4)	(5)	(6)
MT 10k miles	-0.0699***	-0.0686***	-0.0686***	-0.0663***	-0.0664***	-0.0679***
	[0.0034]	[0.0034]	[0.0034]	[0.0034]	[0.0034]	[0.0039]
MT 20k miles	-0.0171***	-0.0168***	-0.0166***	-0.0164***	-0.0164***	-0.0160***
	[0.0024]	[0.0024]	[0.0024]	[0.0024]	[0.0024]	[0.0027]
MT 30k miles	-0.0229***	-0.0217***	-0.0236***	-0.0264***	-0.0263***	-0.0266***
	[0.0021]	[0.0021]	[0.0021]	[0.0021]	[0.0021]	[0.0023]
MT 40k miles	-0.0113***	-0.0109***	-0.0110***	-0.0088***	-0.0084***	-0.0068***
	[0.0022]	[0.0022]	[0.0022]	[0.0022]	[0.0022]	[0.0024]
MT 50k miles	-0.0060***	-0.0038*	-0.0043**	-0.0029	-0.0023	-0.0019
	[0.0022]	[0.0022]	[0.0022]	[0.0022]	[0.0022]	[0.0024]
MT 60k miles	-0.0084***	-0.0081***	-0.0090***	-0.0085***	-0.0069***	-0.0080***
	[0.0024]	[0.0023]	[0.0023]	[0.0023]	[0.0024]	[0.0027]
MT 70k miles	-0.0068***	-0.0073***	-0.0075***	-0.0091***	-0.0083***	-0.0090***
	[0.0024]	[0.0024]	[0.0024]	[0.0024]	[0.0024]	[0.0027]
MT 80k miles	-0.0123***	-0.0118***	-0.0115***	-0.0116***	-0.0107***	-0.0126***
	[0.0025]	[0.0024]	[0.0024]	[0.0024]	[0.0024]	[0.0028]
MT 90k miles	-0.0133***	-0.0127***	-0.0124***	-0.0116***	-0.0113***	-0.0109***
	[0.0026]	[0.0026]	[0.0026]	[0.0026]	[0.0026]	[0.0030]
MT 100k miles	-0.0140***	-0.0151***	-0.0156***	-0.0154***	-0.0154***	-0.0151***
	[0.0027]	[0.0027]	[0.0027]	[0.0027]	[0.0027]	[0.0032]
MT 110k miles	-0.0042	-0.0038	-0.0042	-0.0053*	-0.0060*	-0.0049
	[0.0032]	[0.0032]	[0.0032]	[0.0032]	[0.0032]	[0.0039]
MT 120k miles	-0.006	-0.0076*	-0.0075*	-0.0062	-0.0063	-0.0036
	[0.0042]	[0.0042]	[0.0042]	[0.0042]	[0.0042]	[0.0052]
7th-Order Miles Poly	X	X	X	X	X	X
Fixed Effects	None	Age	Age*Make	Age*Make* Model	Age*Make* Model*Body	Age*Make* Model*Body*A uction
R-Squared	0.025	0.04	0.045	0.058	0.066	0.255
Observations	3,280,571	3,280,571	3,280,571	3,280,571	3,280,571	3,280,571

** p < .05; *** p < .01