Heuristic Thinking and Limited Attention in the Car Market[1]

Nicola Lacetera
Case Western
Reserve University

Devin G. Pope
The Wharton School

Justin Sydnor
Case Western
Reserve University

May 2010

Abstract

Can heuristic information processing affect important product markets? We explore whether the tendency to focus on the left-most digit of a number affects how used car buyers incorporate odometer values in their purchase decisions. Analyzing over 22 million wholesale used-car transactions, we find substantial evidence of this left-digit bias; there are large and discontinuous drops in sale prices at 10,000-mile thresholds in odometer mileage, along with smaller drops at 1,000-mile thresholds. We obtain estimates for the inattention parameter in a simple model of this left-digit bias. We also investigate whether this heuristic behavior is primarily attributable to the final used-car customers or the used-car salesmen who buy cars in the wholesale market. The evidence is most consistent with partial inattention by final customers. We discuss the significance of these results for the literature on inattention and point to other market settings where this type of heuristic thinking may be important. Our results suggest that information-processing heuristics may be important even in market settings with large stakes and where information is easy to observe.

[1] We are grateful to seminar participants at the Second Annual Behavioral Economics Conference, Case Western Reserve, Drexel, Harvard, Melbourne, MIT, Sydney, Toronto, UC Berkeley, UT 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.

1. Introduction

Although economic models are based on the assumption that agents are unconstrained in their ability to process information, economists have long recognized that individuals have limited cognitive abilities (Simon, 1955). A large body of literature on heuristics and biases, originating primarily in psychology, has shown that people often use simple cognitive short cuts when processing information, leading to systematic biases in decision making.[2] There is a great deal of evidence on the nature of these heuristics from surveys and laboratory experiments, but there has been much less research exploring whether these cognitive limitations impact important market settings.

In this paper, we explore the effects of heuristic information processing in the used-car market. We investigate whether the market is affected by consumers exhibiting a heuristic known as left-digit bias when they incorporate odometer mileages into their decision process. Left-digit bias is the tendency to focus on the left-most digit of a number while partially ignoring other digits (Korvost and Damian, 2008; Poltrock and Schwartz, 1984). We develop a simple model of left-digit bias patterned after the model of inattention presented by DellaVigna (2009). The model predicts that, if consumers use this heuristic when processing odometer values, cars will exhibit discontinuous drops in value at mileage thresholds where left digits change (e.g., 10,000-mile marks).

Using a rich and novel dataset on more than 22 million used-car transactions from wholesale auctions, we show that there are clear threshold effects at 10,000-mile marks. These discontinuous drops in value are evident in simple graphs of the raw data. For example, cars with odometer values between 79,900 and 79,999 miles are sold on average for approximately $210 more than cars with odometer values between 80,000 and 80,100 miles, but for only $10 less than cars with odometer readings between 79,800 and 79,899. Using regression analyses, 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 $150 to $200. We also

[2] See Gilovich, Griffin, and Kahneman (2002) for a review.

find price discontinuities at 1,000-mile thresholds. As our model predicts, these discontinuities are smaller in size – approximately $20 on average.

The left-digit bias that we identify in this paper not only influences wholesale prices but also ripples through the market to affect supply decisions. If sellers are savvy and aware of threshold effects, they will recognize the incentive to bring cars to auction before the vehicle's mileage crosses a threshold. We confirm this intuition by looking at volume patterns at the auctions as a function of mileage. There are significant spikes in volume before each 10,000-mile threshold.

These volume spikes, however, also make the task of identifying unbiased estimates of the price drops at thresholds more difficult. Because of the seller response to threshold effects, it is necessary to account for potential selection in our analysis, and we do so in several different ways. First, we present our findings after controlling for selection on observables, including fixed effects for the combination of make, model, model year, body style of a car, and auction year. In our most restrictive specification, we are able to identify the impact of crossing a 10,000-mile threshold by comparing cars of the same make and model that are brought to auction by the same seller. We also run our analyses separately for different types of sellers at the auctions. All of the buyers at the wholesale auctions are licensed used-car dealers, but sellers can be both car dealers and companies with fleets of cars, such as leasing companies and rental-car companies. We show that the selection varies considerably across these seller types and yet we find similar price discontinuities for both types. We also provide a detailed discussion of selection issues, and present a range of evidence suggesting that unobserved heterogeneity is unlikely to affect our findings.

We present a series of robustness checks to our main results in order to allay concerns that the observed threshold effects might be a result of institutional features related to the used car market. For example, the results are robust to considering a number of alternative explanations, such as the potential for odometer tampering and the structure of car warranties. We also test a secondary prediction of our model; because inattention leads to discontinuous changes in perceived mileage around thresholds, the price discontinuities at these thresholds should be larger for cars that are depreciating at a faster rate (i.e., those more affected by mileage changes). Consistent with this prediction, we find larger price discontinuities for cars that depreciate quickly (e.g., Hummers) than for cars that depreciate slowly (e.g., Honda Accords). We also use a smaller sample from Canadian data to construct a type of placebo test. We find price discontinuities in the data from Canadian used-car auctions at the 10,000-*kilometer* marks, but not at the 10,000-*mile* marks, which is what we would expect from limited attention to the relevant units of the reported odometer reading. Finally, we present evidence of the mechanism from a controlled experiment using a simple memory-recall survey, which suggests that people pay more attention to left digits of car mileage in a hypothetical choice task.

The particular setting of our study – the wholesale used-car market – allows us to at least partially investigate the influence of heuristic information processing on different economic agents. The price discontinuities in the wholesale market may arise because used-car dealers who buy at the auctions recognize that their final customers will exhibit the left-digit bias and purchase cars at the auction accordingly. It is also possible, however, that it is the used car dealers themselves who are subject to the left-digit bias. It is not easy to disentangle the two cases because there is little observational difference between a savvy used-car dealer purchasing cars to sell to biased consumers and an un-savvy dealer who happens to share the same bias as his/her end customers. However, we can address whether inattention seems to be driven *primarily* by used-car dealers or final customers. A range of evidence – including volume patterns, purchase patterns for experienced versus inexperienced dealers at the auctions, pricing dynamics right before thresholds, and data from an online retail used car market – are all suggestive that the results are unlikely to be solely an auction phenomenon and are driven at least in part by limited attention of the final used-car customers.

Our research is related to a growing body of literature in economics that studies how inattention impacts market outcomes. Gabaix and Laibson's (2006) work on shrouded attributes and Mullainathan, Schwartzstein, and Shleifer's (2008) work on coarse thinking provide general frameworks for the type of inattention we consider here. Our paper is also related to recent empirical work by Chetty, Looney, and Kroft (2009), Finkelstein (2009), Hossain and Morgan (2006), Brown, Hossain, and Morgan (forthcoming), Lee and Malmendier (forthcoming), Englmaier and Schmoller (2009), and Pope (2009) that find evidence of consumer inattention in market settings.[3] Most of this existing evidence on the effects of limited attention comes from settings where certain product attributes are shrouded or hidden in some way. Our paper differs in that odometer mileage is not shrouded and is clearly being used to some extent by market participants. As such, our results expand the implications of the literature on limited attention in market settings by showing that systematic biases induced by heuristic information processing can impact markets even when information is fully visible. Furthermore, used cars are a valuable durable good, and buyers typically invest significant time and effort in the process of buying a used car.[4] Identifying the effects of left-digit bias in this setting, then, suggests that information-processing heuristics may be important beyond settings where consumers are making quick and unconsidered decisions.

Our paper is also linked to this existing literature because we use the same modeling framework for inattention. Because of this similarity, we can compare our estimate of the inattention parameter to estimates presented by DellaVigna (2009) for existing work. Using our discontinuity values, we estimate that the inattention parameter is approximately 0.30 in our setting. This estimate implies that 30% of the reduction in value caused by increased mileage on a car will occur at salient mileage thresholds. DellaVigna reports estimates for the inattention parameter ranging from 0.18 to 0.45 for the work on inattention to shipping charges on Ebay, from 0.46 to 0.59 for his own study with Joshua Pollet on inattention to earnings announcements, and 0.75 for the Chetty, Looney, and Kroft (2009) field experiment on non-transparent sales taxes.

Finally, our paper is clearly related to the marketing literature on 99-cent pricing (Basu, 1997, 2006; Ginzberg, 1936).[5] This literature typically assumes left-digit bias as the reason behind the prevalence of prices ending with 99 cents (e.g., $3.99). Our work provides a somewhat cleaner setting in which to test the impacts of this heuristic on market outcomes. In most models of 99-

[3] For evidence of the effects of limited attention in financial markets, see Cohen and Frazzini (2008), DellaVigna and Pollet (2007, 2009), and Hirshleifer, Lim, and Teoh (forthcoming).
[4] For example, JD Powers' Autoshopper.com Study for 2003 reports that the average amount of time automotive internet shoppers spent shopping for cars was over 5 hours, and that these customers visited, on average, over 10 different websites before making their purchase decision.
[5] There is also some existing evidence that the prices of initial public offerings tend to converge on integer values (Kandel et al., 2001; Bradley et al., 2004).

cent pricing, a rational-expectations equilibrium results when all firms use 99-cent pricing; therefore, all customers rationally expect such pricing and cannot benefit by paying attention to the full price. Thus, inattention can lead to 99-cent pricing, but ubiquitous 99-cent pricing can also cause rational inattention. In contrast, our paper analyzes left-digit bias in a market where buyers could benefit from timing their sale around thresholds. The durable goods nature of used cars also ensures that anyone who purchases a car with mileage just below a threshold will soon see that car cross the mileage threshold. In this paper, then, we are able to get a sense of the cost of the inattention generated by left-digit bias. Our paper also extends left-digit bias to consider continuous quality metrics (e.g., miles) other than prices. Given the importance of processing and using numbers in economic markets, this simple heuristic may have wide-ranging consequences. For example, heuristic processing of continuous quality metrics such as GPAs and test scores may have important implications for labor markets whereas heuristic processing of medical metrics (e.g., blood pressure, patient age, etc.) may result in discontinuous medical outcomes. Recognizing the importance of numeric-processing heuristics may provide economists with important instruments to study these markets, and, in many of these areas (e.g., hospitals), there may be useful policy changes that could eliminate the potentially costly effects of this bias.

The remainder of the paper proceeds as follows. Section 2 provides a simple model of left-digit bias and discusses its predictions for used-car values and wholesale-auction prices in a competitive environment. Section 3 describes the data used in our analyses and presents basic summary statistics. Section 4 presents our empirical results, including a variety of robustness checks and additional analyses. We conclude the paper in Section 5 with a brief discussion of the broader implications of this research and the question of whether we should think of this as a case of "rational inattention."

2. Model

In order to structure our thinking about the left-digit bias 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 setting for used cars.

2.1 Consumer inattention to continuous metrics

Our model follows the frameworks developed by Chetty et al. (2009), DellaVigna (2009) and Finkelstein (2009), where an individual pays full attention to the visible component of a relevant variable and only partial attention to the more opaque component of that value. We apply this approach to model how people with a left-digit bias process numbers. Any number can be broken down as the sum of its assorted base-10 digits. Consistent with the left-digit bias that has been reported in a number of studies (Korvost and Damian, 2008; Poltrock and Schwartz, 1984), we assume that the left-most digit of a number that a person observes is fully processed whereas 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 $\widehat{m}$ is then given by:

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

where $\theta \in [0,1]$ is the inattention parameter. As an example, consider the case where m takes on the value 49,000. From Equation 1, this would be processed as $\widehat{m} = 40{,}000 + (1-\theta)9{,}000.$

We can consider how different the perceived measure will be on either side of a left-digit change by focusing on how $\widehat{m}$ changes as the metric m ranges from (say) 40,000 to 50,000. As long as m is below 50,000, the decision-maker will perceive a change of $(1-\theta)$ 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 $1 + \theta*9{,}999$ or, in the limit, $\theta*10{,}000$. 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 that this inattention would have in the basic case in which 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 α) 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 displays discontinuities at each 10,000 threshold. Because of the linear value function, the size of these discontinuities is constant and equal to ($a\theta$)*10,000. Intuitively, at the threshold, the perceived metric $\hat{m}$ changes discontinuously by θ*10,000, and the discontinuous effect that this has on perceived value $\hat{V}$ depends on the relationship between value and the quality metric as expressed by α.

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. The final prediction is that cars with a steeper slope of depreciation (i.e., larger α) will have larger price discontinuities.

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 would be 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 $\hat{m} = 40{,}000 + (1-\theta)9{,}000 + (1-\theta)^2 900$. 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. Although not a primary focus of this paper, our empirical analysis allows us to shed light on the extent of increasing inattention to "smaller" digits.

The model as we have presented it also makes the assumption that limited attention results in the perceived mileage being lower than the actual mileage because we assume that, when inattentive to a digit, the individual perceives it to be zero. Although that assumption matches our intuition about the nature of limited attention to digits, a perfectly reasonable alternative would be to assume that individuals act as if the perceived mileage were equal to the midpoint of a range (e.g., 9,500). All of the results in this paper would hold in this alternative framework. The absolute values of the perceived worth of the car would be affected by the exact nature of inattention, but the relative values would not; that is what we test empirically.

2.2 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. 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 $\hat{m}$ given by Equation 2.[6] 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.

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. 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

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

that each of these cars has a reserve price of zero.[7] As long as $M \leq N$, there will not be an oversupply of cars and the market will be well-behaved.

In this environment, all cars will be sold in equilibrium, and 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 $\hat{V}$. Specifically, the equilibrium is for 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. In this simple model, any competitive equilibrium in which car dealers are driven to zero profit will require that the price of a car at the auction be equal to the price to the final consumer. In that case, no individual dealer has an incentive to deviate from the strategy of bidding the going retail price at the auction: bidding below the retail price will not win a car to sell, and bidding above will lead to a loss. Furthermore, the equilibrium retail price in the competitive market will equal $V(\widehat{m})$. If the equilibrium price were above $V(\widehat{m})$ for any arbitrary mileage *m*, cars of that mileage would not sell and a dealer would have an incentive to lower the price. Furthermore, as long as $M \leq N$, if the equilibrium retail price were below $V(\widehat{m})$ for some *m*, a dealer could set a price above the going market price and make a profit, which would violate the zero-profit assumption.

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 mileages, choosing the one that provides them with the highest surplus.

Note, finally, that although 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

[7] 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.

(i.e., M^{th} highest K) consumer.[8] 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. The auction 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, and the seller can choose to purchase detailing or reconditioning services from the auction company before the 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, over 2,000 used cars may be auctioned in a day. Most auction sites have somewhere between 4 and 7 auction lanes that operate simultaneously, through which cars are driven and put onto the auction block. Once on the auction block, the car dealers bid for cars 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.

Our dataset contains information about the auction outcome and other details for each car that was 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

[8] 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.

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, and an identifier for the used-car dealer who made the purchase. Just over 82% of all cars brought to auction sell, with an average selling price of $10,301.

Although 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 bringing 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 auction 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 sell large volumes of cars with low reservation prices, car dealers generally have better outside options for selling 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 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 auction participants, 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 who purchase 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 that is currently on the block. The dealers can also look into the car to see the odometer.

4. Results

4.1 Graphical analysis

Raw Prices. We begin the empirical analysis with a simple, non-parametric plot of the raw price data as a function of mileage. 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. 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 decrease with increasing mileage. Within each 10,000-mile band, average prices decline quite smoothly. However, there are clear and sizeable discontinuities in average prices at nearly all 10,000-mile marks.

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 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. As such, it is necessary to account for these selection issues in order to obtain a valid estimate of the size of the price discontinuities for a given car.

Volume. Figure 3 graphs the volume of cars brought to the auction using the full dataset 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 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 and 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.

Residual Prices. The primary concern we have with interpreting the magnitude of price discontinuities in the graph in Figure 2 is that the cars on either side of the thresholds may differ in observable characteristics such as 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. We also include a 7th-order polynomial in mileage to account for continuous patterns of mileage depreciation.[9] We then obtain a residual price for each car based on this regression prediction. Figure 4 repeats the graphs in Figure 2 except now uses these residuals.[10] This figure is much smoother than Figure 2 since car types have been accounted for and netted out. The figure also clearly shows that price discontinuities remain after accounting for specific car type. In fact, the price discontinuities become more uniform (~$150-$200 each) and are evident at every threshold (although very small at 110,000).

Fleet/Lease vs. Dealer. 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 do the dealers, bring cars in larger lots, and set low reserve prices. The auctions are also

[9] The 7th-order polynomial was chosen based on significance levels in regressions of price on mileage and visual checks of predicted values vs. raw data patterns. We have also run more "local" regressions by restricting the sample to various subsets (e.g., 25,000 to 35,000 mile cars), which does not require the parametric assumptions to be as strong and finds nearly identical results.

[10] Rather than plotting the exact residual prices, we add the estimated polynomial in miles and a constant back into the residual so that Figure 4 is visually similar to Figure 2. Note that the range of prices in Figure 4 ($7,000 to $14,000) is less than that of Figure 2. This is because we are plotting residual prices after removing fixed effects such as age. A car depreciates much less over a 120,000-mile span when keeping the age of the car fixed.

typically organized so that the fleet/lease cars run in separate lanes from those of the dealers.[11] 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 restricts cars to those 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.

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. Panel A, which shows the probability of selling, confirms 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 that 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 Panel B, 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 the 36,000-mile mark, which reflects the prevalence of 3-year leases with 12,000-mile-per-year limits.[12] 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) is 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

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

[12] The spike around 48,000 miles likely reflects 4-year/48,000-mile leases whereas the smaller spike around 60,000 could be driven in part by 5-year leases.

discontinuities of very similar magnitude to those in the fleet/lease category. Figure 8 shows the probability-of-sale and volume-of-sales patterns for the dealer category. The probability of a sale for this category, Panel A, is in the 60% to 70% range, significantly lower than it is for the fleet/lease cars. This difference 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. 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 pattern for the dealers, Panel B, is particularly interesting and shows consistent peaks right before the 10,000-mile thresholds. This pattern clearly suggests that these mileage thresholds influence market behavior. Importantly, though, we find in the residual graphs that, once the characteristics of the car being sold are controlled for, the pricing patterns by mileage are consistent with those of the fleet/lease category (where these volume spikes do not occur). 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, although it is important to account for selection on car-type that might be correlated with these volume spikes, spikes in volume for a given car that occur before thresholds should not, and do not seem to, affect the estimated discontinuities.

1,000-Mile Discontinuities. The pricing figures presented thus far allow us to investigate whether discontinuities also occur at 1,000-mile thresholds. When looking at the residual price figures, an interesting pattern emerges: dots in the figures tend to move in pairs. Each dot represents a 500-mile mileage bin, and, therefore, pairs of dots represent cars within 1,000 miles. The fact that dots move in pairs is evidence, then, of small price discontinuities at 1,000-mile thresholds.

To illustrate this in more detail, Figure 9 plots the average residual sale price of cars within 50-mile bins for all of the cars in our dataset. Since the data can become noisy when looking within 50-mile bins, we pool the data so that each dot represents the average residual for a bin that is a given distance from the nearest threshold. For example, the first dot in the figure represents the average residual value of all cars whose mileage falls between 10,000-10,050, 20,000-20,050, …, on through 110,000-110,050. Thus, all of the data can be condensed into a 10,000-mile range. The figure clearly demonstrates breaks that occur at several of the 1,000-mile thresholds. The two largest of these breaks occur at the 5,000- and 9,000-mile marks. Regression analysis indicates that the value of a car drops, on average, by approximately $20 as it passes over a 1,000-mile threshold.

4.2 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.[13]

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

$$price_i = \alpha + f(miles_i) + \sum_{j=1}^{12} \beta_j D[miles_i \geq j * (10{,}000)] + \gamma X_i + \varepsilon_i. \qquad (4)$$

The dependent variable in our primary regression is the sale price for cars that sold at an auction.[14] 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 on observables. Given the size of our dataset, the coefficients are generally highly statistically significant. The majority of the coefficient

[13] While the graphical analysis used all of the data in our sample, our regression analyses only use a 20% random sample of data from each year due to computing constraints.
[14] We have also run regressions with log(price) as the dependent variable. While the results are all qualitatively similar, the goodness of fit is significantly worse with logs than with levels.

estimates are negative, which is consistent with our theory of inattention. However, they vary substantially, and a few (e.g., at 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. Once age is included in the regressions, all but one of the coefficient estimates becomes negative. Columns 3, 4, and 5 report parameter estimates after adding make, model, and body of the car, respectively, to the fixed effects. Thus, by Column 5, identification of the model is coming from observing different mileages of cars of the same make, model, body style, and age. In fact, the regression in Column 5 estimates the threshold discontinuities that we observed in Figure 5. Once these controls are included in the model, all of the coefficient estimates are negative, and all but one is highly statistically significant. The coefficients are similar across thresholds with an un-weighted average across thresholds of -$157.

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 strengthen the controls further in Column 6 by adding a control for auction location to the fixed effect and in Column 7 by adding a control for seller identifier. Thus, the identification of the parameter estimates in Column 7 comes from the same seller selling identical types of cars that differ in mileage at the same auction.[15] These controls do not change the coefficient estimates meaningfully, and, in fact, the estimates are quite stable from Columns 4 through 7, which suggests 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 that this group of sellers displays in bringing cars to the market, as illustrated by the large volume spikes before thresholds. Once

[15] Of course, while the identification is driven by variation in mileage for a given car from a given seller, the size of the discontinuities at different mileage thresholds will be affected by a different mix of cars. That is, since the variation in mileage for a given car of a given age is sizeable but not huge, it is unlikely that any one car/seller combination could be used to tightly identify threshold discontinuities across the entire range that we analyze.

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 $173 for dealer cars and $157 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 meaningfully affect the results.

4.3 Robustness checks and alternative explanations

In this section, we address a number of alternative explanations and factors that might affect our findings and that the econometric specification developed above would not fully control for.

Differences across Time. The estimates that are presented in Tables 2 and 3 have been pooled across all of the years in our data. In Tables 4 and 5, we estimate price discontinuities for fleet/lease and dealer cars, respectively, when cutting the data by the different years in our dataset. Average discontinuities in each year range from $134 to $170 for fleet/lease cars and from $160 to $180 for dealer cars.

Heterogeneity across Car Models. In Table 6, we run regressions separately for the 8 most popular cars in our data in terms of volume sold. Although there is heterogeneity in the average discontinuity price across these car makes (which we explore further in Section 4.5), we find large and significant discontinuities for each of the car types. Hence, our overall results are not driven by any particular make or model of car.

Selection on Unobservables. The regression analyses in Section 4.2 yield 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, selection on unobservables may be less of a concern in this setting than in most other contexts because the market prices that 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 capture most of the relevant information. Second, the similarity of the estimates obtained for the two different seller categories (i.e., dealer and fleet/lease) gives us confidence in the estimates. This is especially convincing given that, for many of the 10,000-mile thresholds, there is no apparent selection (no volume spikes) for the fleet/lease vehicles. 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, although 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 in Figures 4, 5, and 7, we see that the discontinuities are not driven solely by points right around the thresholds. There is a shifting down of the entire price schedule after each threshold; therefore, even if one were to eliminate the observations right 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, for the fleet/lease category, 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 then became negative in other specifications. These patterns, when coupled with the consistency of the estimates across the seller categories, give us confidence in the discontinuity estimates.

Warranties. Another important concern regarding our findings is the possibility that expiring new-car warranties may produce price discontinuities at 10,000-mile thresholds. It is first worth noting that warranties would not necessarily cause a discontinuous drop in price. The value of a warranty likely diminishes at a smooth rate as a car approaches the warranty threshold. However, it is possible that, when adverse selection is a concern, having a warranty with even just a few hundred miles left could give a discontinuous increase to the value of a car because it could defray the possible cost of purchasing a car that is soon revealed to be a lemon. We gathered information about warranties during our sample period for the largest car makers (Chevrolet, Ford, Toyota, Nissan, and Honda). Across these makes, some type of warranty existed at the 36,000, 50,000, 60,000, and 100,000 mile marks. Importantly, there were no warranties at the 10k, 20k, 30k, 40k, 70k, 80k, 90k, and 120k mile marks, where we find significant discontinuities. This and the fact that we do not observe a significant discontinuity at 36,000 miles suggest that our results are not being driven by warranties. Further, warranties clearly cannot explain discontinuities at 1,000-mile marks.

Published Price Information. In the U.S., there are a number of sources of information that potential customers could investigate when shopping in order to form their expectations of the price of a used car. The leading providers of such information are Kelly Blue Book and Edmunds.com, which both offer information on average retail-level, used-car sale prices. If the data that these firms provide strongly influences purchasing behavior, then how they present information could conceivably influence market prices. In particular, if these companies published prices that were based on 10,000-mile averages, then the reported prices could show artificial discontinuities. We collected data on a number of cars from both the Kelly Blue Book and Edmunds websites for a range of mileage. There is no evidence that they use systematic 10,000-mile price averages, and, in fact, they appear (at least in the case of Edmunds.com) to use a smoothing algorithm that would lead consumers to expect price schedules that have no discontinuities by mileage at all.

Odometer Tampering. The actual mileage on a car may be different than the mileage indicated by the odometer if cheating is occurring in the market. For example, some sellers might anticipate 10,000-mile discontinuities and manipulate the odometer so as to report a mileage below a threshold. Though we find no evidence of odometer tampering in our data – for example, cars right before 10,000-mile thresholds are not older than expected – this phenomenon could potentially explain some of the volume patterns observed in the data. Notice, however, that odometer tampering would likely bias down the estimates that we find if buyers were aware that some cars before a threshold had more miles on them than the odometers indicated.

Canadian Data. The conceptual framework that we posit argues that the observed price discontinuities are a result of consumer inattention when processing numbers. None of the results should depend on the unit of measure in which the relevant numbers are reported. In addition to the main dataset from U.S. auctions, we have a smaller set of data for auctions that this company ran in Canadian cities between 2002 and 2005. In Canada, odometers report kilometers rather than miles, making it possible to test whether the same type of pricing dynamics emerge at the 10k kilometer marks as well. Although the sample size is much smaller (n = 289,055), we replicate our key findings using these data. The price residuals by kilometers (in 1,000-kilometer bins) are presented in Figure 10. The figure clearly demarks discontinuities at many of the 10,000-kilometer thresholds. A regression analysis confirms that 8 out of 12 of the 10,000-kilometer dummy variables are negative and statistically significant at the 5% confidence level (in addition to being jointly significant (p =.0000)). The average size of the discontinuities is -CAN$184, which is comparable to the results that we obtained with the U.S. data. As a placebo test, we also include dummy variables for 10,000-mile thresholds (by converting kilometer values to miles) in the regressions. None of the 10,000-mile threshold dummies are significant at conventional levels.

4.4 Estimate of the inattention parameter

The estimates of price discontinuities that were derived above 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 $\alpha\theta 10{,}000$, where α is the slope of the value function with respect to actual miles (true depreciation). This slope (α) can be observed by drawing a line through the value function at the 10,000-mile 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 -0.047 whereas for the dealer cars it is -0.060. Using the average discontinuity estimates discussed above (i.e., $157 for fleet/lease and \$173 for dealers) yields an estimate of θ equal to $\frac{157}{0.047*10,000} = 0.33$ for the fleet/lease estimation and $\frac{173}{0.060*10,000} = 0.29$ for the dealer estimation.[16]

The inattention parameter has a natural interpretation in our setting. From Equations (1) and (2), the overall decrease in a car's value between any two given 10,000-mile intervals is given by $\alpha 10,000$. The discontinuity at a 10,000-mile mark is $\alpha\theta 10,000$. Therefore, 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.

Note that the previous calculations are based on the assumption of a "linear" depreciation rate α, in which case the size of the discontinuity is independent of the specific mileage. Of course, the depreciation rate might differ at different mileage levels, which is why we use the flexible 7^{th}-order polynomial terms in miles in our regression analysis. From Equation (1) above, notice that, in the proximity of a 10K-mile mark, the perceived miles $\widehat{m}$ can be expressed as $\widehat{m} = m - \theta 10,000$ whereas the perceived and actual miles coincide at any exact 10K-mile mark. If we relax the assumptions implicit in Equation (2) about a linear depreciation and allow, as in the regression analysis, for a 7^{th}-order polynomial, the size of a given price discontinuity j can be expressed as $\left[K - \sum_{i=1}^{7} \alpha_i (m_j - \theta_j 10,000)^i\right] - \left[K - \sum_{i=1}^{7} \alpha_i {m_j}^i\right] = \sum_{i=1}^{7}\left[\alpha_i {m_j}^i - \alpha_i (m_j - \theta_j 10,000)^i\right]$. We can use the estimates of the size of the discontinuities from the regression analyses as well as the parameter estimated on the mile polynomial to derive the estimates of the inattention parameters θ_j at each different discontinuity j. Based on the discontinuity estimates from Column 5 in Table 2, we estimate an average θ across mileage thresholds of 0.34, quite similar to the estimate from the linear specification.[17]

---

[16] Based on the delta method, the standard error for these estimates is .013.

[17] We can also use the estimated discontinuities at the 10,000- and 1,000-mile marks to give an estimate of the level of inattention displayed to digits further to the right. Holding constant the inattention parameter, these estimates would imply that the third digit (D) from the left (in our case the hundreds digit) is perceived at $(1-\theta)^t D$. Here we estimate that this power (t) is approximately 2.8.

4.5 Heterogeneity in the size of the discontinuities

In Section 4.3, we mentioned that there is heterogeneity in the size of the price discontinuities across car types. Our model of inattention predicts this type of heterogeneity. As noted in Section 2, cars that depreciate at a faster rate (i.e., have a large α) should have larger discontinuities. To understand the intuition behind this prediction, imagine an extreme example in which a particular type of car depreciates by almost nothing between 20,000 and 30,000 miles. The perceived value that an inattentive buyer will place on this type of car when it has 29,999 miles will not be that different than the perceived value at 30,000 miles. However, on the flip side, a car that depreciates very steeply will result in an inattentive buyer placing very large differences in value around a 10,000-mile threshold.

To test this prediction, we estimate the average 10,000-mile price discontinuity for each of the 250 most popular (highest volume sold) car models in our dataset. We also estimate the linear α parameter of depreciation separately for each of these models. We find significant heterogeneity in depreciation rates across car types. For example, the cars that depreciated fastest included BMW series, Mercedes Benz classes, Chevy Corvette, Jaguar, and the Hummer H2. Cars with the slowest depreciators included the Honda Accord, Ford Escort, and Hyundai Accent. In Figure 11, we present a scatter plot of the depreciation rate (α) and the average 10,000-mile discontinuity for the 250 car types. As predicted by the model, we find a significant positive correlation between the depreciation rate and the threshold discontinuities (p <.001). This graph also provides a second way of estimating the size of the inattention parameter θ. The model predicts that the points in this scatter plot should lie along a ray from the origin with a slope equal to θ. The linear best fit through this scatter plot in actuality has an intercept term that is not statistically different from zero and gives an estimate of θ (the slope) of 0.3, which is nearly identical to the estimates obtained based on the average discontinuity size from our primary analysis in the previous subsection.

4.6 Who is inattentive?

Because our data come from the wholesale market, a natural question is whether the observed patterns arise because of inattention on the part of final customers or because of the inattention of the dealers themselves. When investigating this question, note that, if the end customers display inattention, it will be difficult to distinguish between a savvy used-car dealer who purchases 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 the price discontinuities seem 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 at the auction. Previous studies have shown that behavioral biases may be attenuated when agents accumulate market experience (List, 2003). Under this assumption, consider first the possibility that it is the used-car dealers and not the final customers who are inattentive to mileage. This would imply that cars with mileage just below a threshold are overpriced relative to those just past the thresholds at the auction relative to 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 were to 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.

We investigate these experience patterns in Figure 12. For each 500-mile bin, we report the average "experience level" of the buyers of cars in that bin. For each year of our data, we obtain an experience measure by calculating the total number of cars each dealer in our data purchased at the auctions. We then give each dealer an experience-percentile rating, which is 0 for the least experienced and 100 for the most experienced buyers, in the data. Figure 10 illustrates that crossing a 10,000-mile threshold leads to a discontinuous drop in the average experience level of car buyers. The experienced buyers at the auction are more likely to purchase the higher-priced cars with mileage just before a salient threshold. 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.

A further way to test who is inattentive is by looking at cars that are very close to passing over a threshold. Since the used-car dealer often drives the car back to his/her lot after the auction and since customers can test drive a vehicle, a car that is within a few miles of a 10,000-mile threshold may pass over the threshold prior to being sold to a final customer. Thus, if dealers are savvy, we would expect car values to drop several miles before a 10,000-mile threshold rather than dropping precipitously at the exact 10,000-mile marks. Figure 9 provides evidence that car values do drop significantly prior to reaching a 10,000-mile threshold. The last dot in Figure 9 is the value of cars that are within 50 miles of a 10,000-mile threshold. This dot illustrates that the average value of a car that is within 50 miles of a threshold drops by ~$60. Although not conclusive, this once again provides suggestive evidence that dealers are somewhat savvy and that it is the final customers who are inattentive to mileage. Note, however, that prices do not fully drop before the threshold, which leaves open the possibility of some degree of inattention by buyers at the auction.

Yet another approach to 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 do not include wholesale agents. 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 13, which clearly shows that there are spikes in the volume of used cars listed on Cars.com at mileages just before the 10,000-mile thresholds. Although these data do not provide information on sale prices, these volume patterns 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 because 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.[18] 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 above-mentioned framework and find some weak evidence of drops in probability of sale at 10,000-mile marks for the dealer sellers.[19] However, the results are weak at many thresholds and are suggestive at best.

4.7 Mileage-recall survey

To provide more direct support for the mechanism behind our conceptual approach to the left-digit bias, we conducted an online survey given to students at The Wharton School (University of Pennsylvania) and at Case Western Reserve University to test for systematic bias in the recollection of a car's mileage. Students were provided information about two different cars (e.g., price, picture, make, model, and mileage). In each treatment condition, the information about the two cars was the

[18] Some anecdotal discussions that we have had with used-car dealers reveal that they are, in fact, aware of these price discontinuities. Furthermore, one dealer explained that while he allows his salespeople to drive cars from the lot, everyone is instructed to avoid driving a car such that it crosses a 10,000-mile threshold. This type of behavior could influence the volume patterns that we observe.

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

same except that the mileage was randomized across 4 different mileage pairs.[20] The students were then asked to select the car that they would be most likely to purchase and explain why. The information about the cars then disappeared and the students were asked to attempt to recall the exact mileage of each car. If they did not know the exact mileage, they were asked to guess a number that was as close as possible to the actual mileage.

Figure 14 provides a summary of the results from the survey (n = 127). Panel A illustrates the percentage of students who correctly recalled the first through fifth digit of the mileage. Consistent with our framework, students exhibited a left-digit bias in that they were able to recall the first digit of the mileage over 90% of the time, the second digit just over 50% of the time, and the remaining digits less than 15% of the time.

Perhaps even more telling, however, is Panel B of Figure 14, which shows the difference between the average recalled mileage and true mileage for each of the 8 true numbers. Cars with true mileages that were approaching a 10,000-mile threshold (69,113, 69,847, 89,113, 89,847) were consistently recalled to have fewer miles than their actual mileage. Panel A suggests that this is driven by the fact that students could remember the first digit but oftentimes forgot digits further to the right. Conversely, cars with true mileages that had just surpassed a 10,000-mile threshold (62,113, 62,847, 82,113, 82,847) were remembered as having slightly more miles than their true mileage.

Although this recall task is not exactly identical to the mental process that a car buyer may follow when purchasing a used car, these results provide evidence in a controlled environment that individuals have a systematic bias in how they process/recall numbers around a 10,000-mile threshold. This evidence provides grounding for our conceptual framework and for tests of its predictions using field data.

[20] The 4 mileage pairs were: 62,113 and 89,847; 62,847 and 89,113; 69,113 and 82,847; and 69,847 and 82,113.

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 $150-$200 at 10,000-mile thresholds. Without a model of inattention, it would be difficult to even understand some of the basic descriptive statistics regarding the prices and quantities of cars sold. Furthermore, because of the size of the car market, this simple heuristic leads to a large amount of mispricing. In fact, our estimates of the difference between observed selling prices and the prices that we would expect under full attention suggest that there were approximately $2.4 billion worth of mispriced transactions in our full dataset. Additionally, the supply decisions of hundreds of thousands of cars were affected by this heuristic (e.g., sold right before a 10,000-mile threshold).

We anticipate that this simple heuristic could be widespread and that economists might benefit by thinking seriously about the potential impacts of heuristic numeric processing 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), how doctors treat test results, and how the public reacts to government spending programs.

The findings in this paper clearly show that market dynamics can be affected by systematic patterns of inattention, yet there remains a question of whether this inattention should be thought of as an irrational bias or a rational calculation in the face of mental processing constraints. Our intuition is that it is actually a little of both. It is clear that people have limited cognitive capacity, and, therefore, it is quite reasonable that people might employ a left-digit bias in their general cognitive processing. It is likely that mental processing costs can rationally explain a portion of our findings. However, some of the evidence that we present goes against a rational model of inattention. For example, we find that the price discontinuities at thresholds are significantly larger for cars that depreciate at a faster rate (e.g., BMWs) relative to cars that depreciate more slowly (e.g., Honda Accords). Assuming that purchasers of these two types of cars have similar mental processing costs, this finding goes against a model of rational inattention that would predict the same discontinuity size independent of car type (where the discontinuity size is equal to the average mental cost of processing additional digits). We also suspect that knowing the results of this study would cause most individuals to pay more attention to mileage. After all, anyone who purchases a 49,000-mile car will soon own the 50,000-mile version; buyers can save $150-$200 by waiting to purchase after the threshold, and sellers can reap the same benefit by selling before the threshold. Thinking of limited attention in this way – as a generally sensible human tendency that can be set aside when the situation warrants – points to a possible direction for future research in exploring what type of situations and cues cause people to devote more attention when making economic decisions.

References

Basu, K., 1997: "Why Are So Many Goods Priced to End in Nine? And Why This Practice Hurts Producers?," *Economics Letters*, 53, 41-4.

Basu, K., 2006: "Consumer Cognition and Pricing in the Nines in Oligopolistic Markets," *Journal of Economics and Management Strategy*, 15, 1, 125-41.

Bradley, D.J., Cooney, J.W., Jordan, B.D. and Singh, A.K., 2004: "Negotiation and the IPO Offer Price: A Comparison of Integer vs. Non-Integer IPOs," *Journal of Financial and Quantitative Analysis*, 39, 3, 517-40.

Chetty, R., Looney, A. and Kroft, K., 2009: "Salience and Taxation: Theory and Evidence," *American Economic Review*, 99, 4, 1145-77.

Cohen, L. and Frazzini, A., 2008: "Economic Links and Predictable Returns," *Journal of Finance*, 63, 4, 1977-2011.

DellaVigna, S., 2009: "Psychology and Economics: Evidence from the Field," *Journal of Economic Literature*, 47, 2, 315-72.

DellaVigna, S. and Pollet, J.M., 2007: "Demographics and Industry Returns," *American Economic Review*, 97, 1167-702.

DellaVigna, S. and Pollet., J.M., 2009: "Investor Inattention and Friday Earnings Announcements," *Journal of Finance*, 64, 2, 709-749.

Englmaier, F. and Schmoller, A., 2009: "The Evaluation of Complex Goods: Evidence from Online Car Sales," University of Munich, Working Paper.

Finkelstein, A., 2009: "EZ-Tax: Tax Salience and Tax Rates," *Quarterly Journal of Economics,* 124, 3, 969-1010.

Gabaix, X. and Laibson, D., 2006: "Shrouded Attributes, Consumer Myopia, and Information Suppression in Competitive Markets," *Quarterly Journal of Economics,* 121, 2, 505-40.

Gilovich, T., Griffin, D. and D. Kahneman, editors, 2002: *Heuristics and Biases: The Psychology of Intuitive Judgement,* New York: Cambridge University Press.

Ginzberg, E., 1936: "Customary Prices," *American Economic Review*, 26, 2, 296.

Hirshleifer, D., Lim, S.S. and Teoh, S.H., forthcoming: "Driven to Distraction: Extraneous Events and Underreaction to Earning News," *Journal of Finance*.

Hossain, T. and Morgan, J., 2006: "…Plus Shipping and Handling: Revenue (Non) Equivalence in Field Experiments on eBay," *B.E. Journals in Economic Analysis and Policy: Advances in Economic Analysis and Policy*, 6, 2, 1-27.

Kahn, C., Pennacchi, G. and Sopranzetti, B., 1999: "Bank Deposit Rate Clustering: Theory and Empirical Evidence," *Journal of Finance,* 54, 6, 2185-214.

Kandel, S., Sarig, O. and Wahl, A., 2001: "Do Investors Prefer Round Stock Prices? Evidence from Israeli IPO Auctions," *Journal of Banking and Finance*, 25, 1543-51.

Korvost, M. and Damian, M.F., 2008: "The Differential Influence of Decades and Units on Multidigit Number Comparison," *Quarterly Journal of Experimental Psychology*, 61, 8, 1250-64.

Lee, D. and Lemieux, T., 2009: "Regression Discontinuity Designs in Economics," NBER Working Paper 14723.

Lee, Y.H. and Malmendier, U., forthcoming: "The Bidder's Curse," *American Economic Review*.

List, J.A., 2003: "Does Market Experience Eliminate Market Anomalies?," *Quarterly Journal of Economics* , 118, 1, 41-71.

Mullainathan, S., Schwartzstein, J. and and Shleifer, A, 2008: "Coarse Thinking and Persuasion"', Quarterly Journal of Economics, 123, 2, 577-619.

Poltrock, S.E. and Schwartz, D.R., 1984: "Comparative Judgments of Multidigit Numbers," *Journal of Experimental Psychology*, 10, 1, 32-45.

Pope, D.G., 2009: "Reacting to Rankings: Evidence from 'America's Best Hospitals'," *Journal of Health Economics,* 28, 1154-65.

Simon, H.A., 1955: "A Behavioral Model of Rational Choice," *Quarterly Journal of Economics,* 69, 1, 99-118.

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.

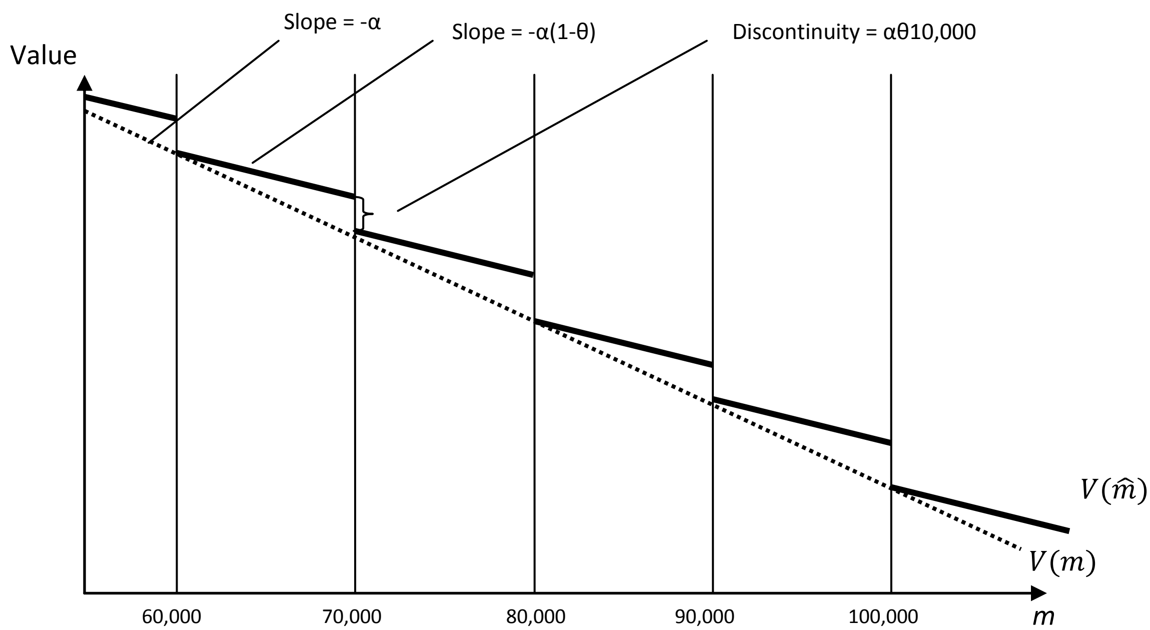


Figure 2 - Raw Price. This figure plots the raw average sales price within 500-mile bins for the more than 22 million auctioned cars in our dataset.

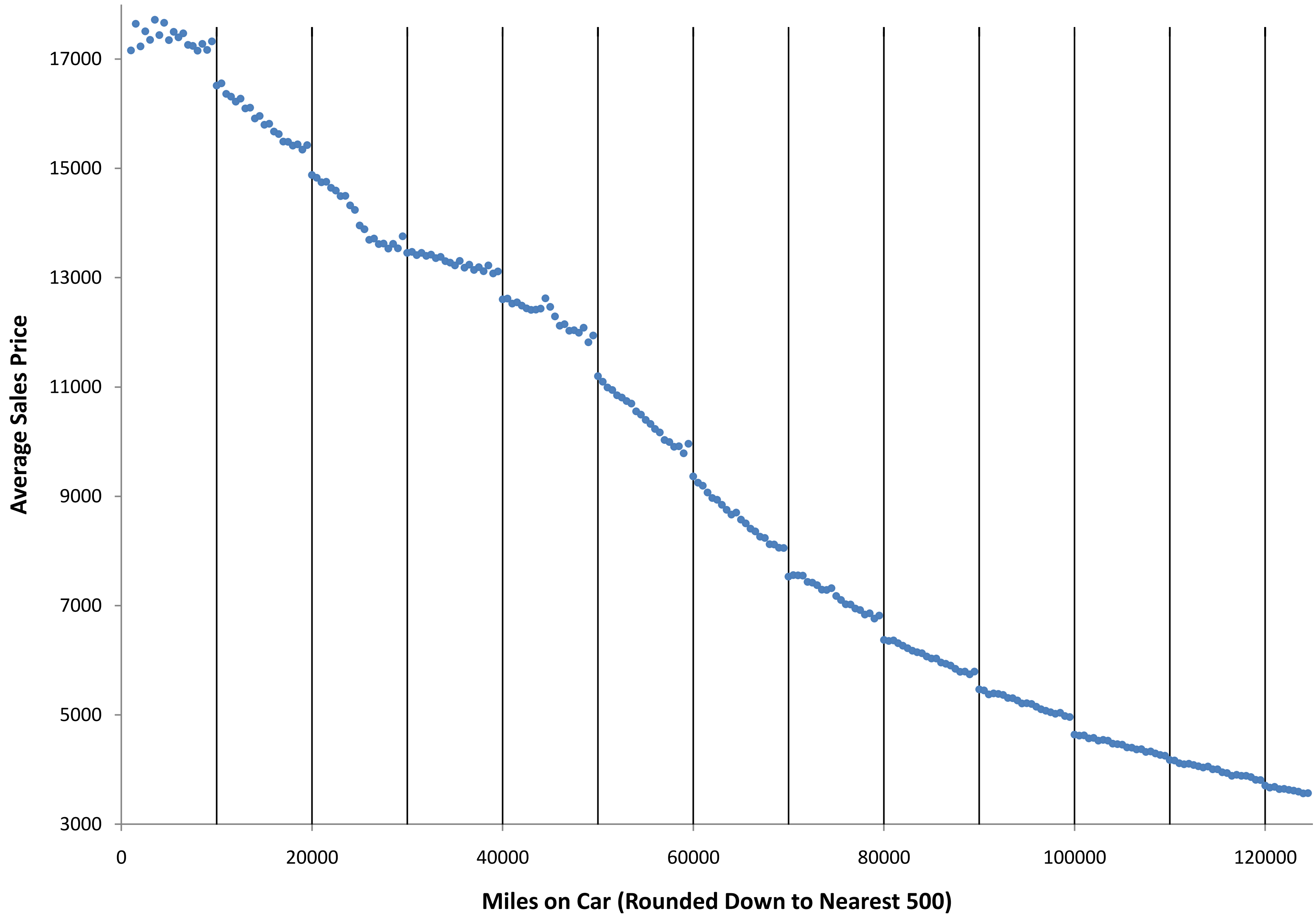


Figure 3 - Volume. This figure plots the raw counts within 500-mile bins for the more than 22 million auctioned cars in our dataset.

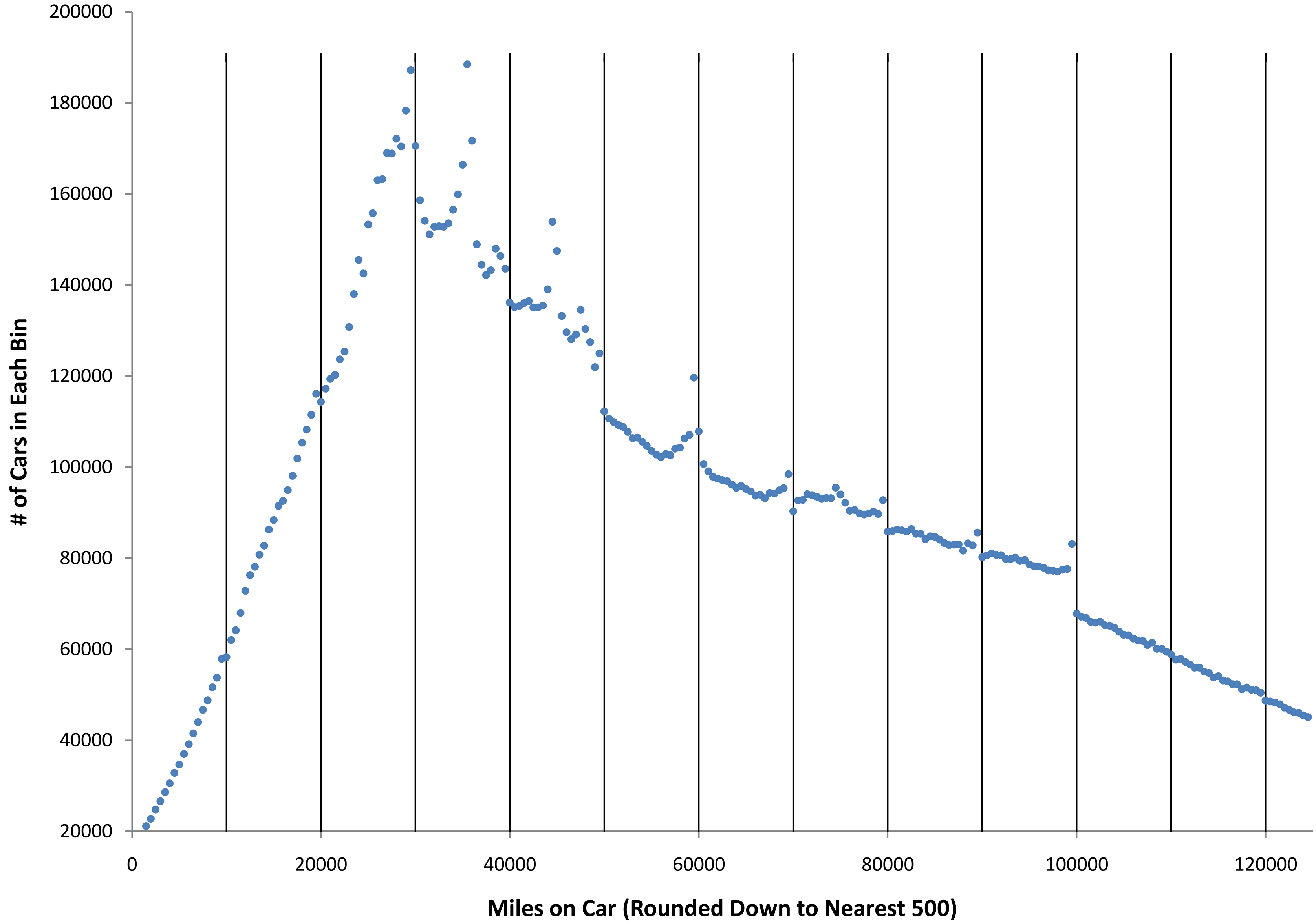


Figure 4 - Price Residuals. This figure plots the average residual sales price within 500-mile bins for the more than 22 million auctioned cars in our dataset. The residual is obtained by removing make-model-model year-body effects from the sales price.

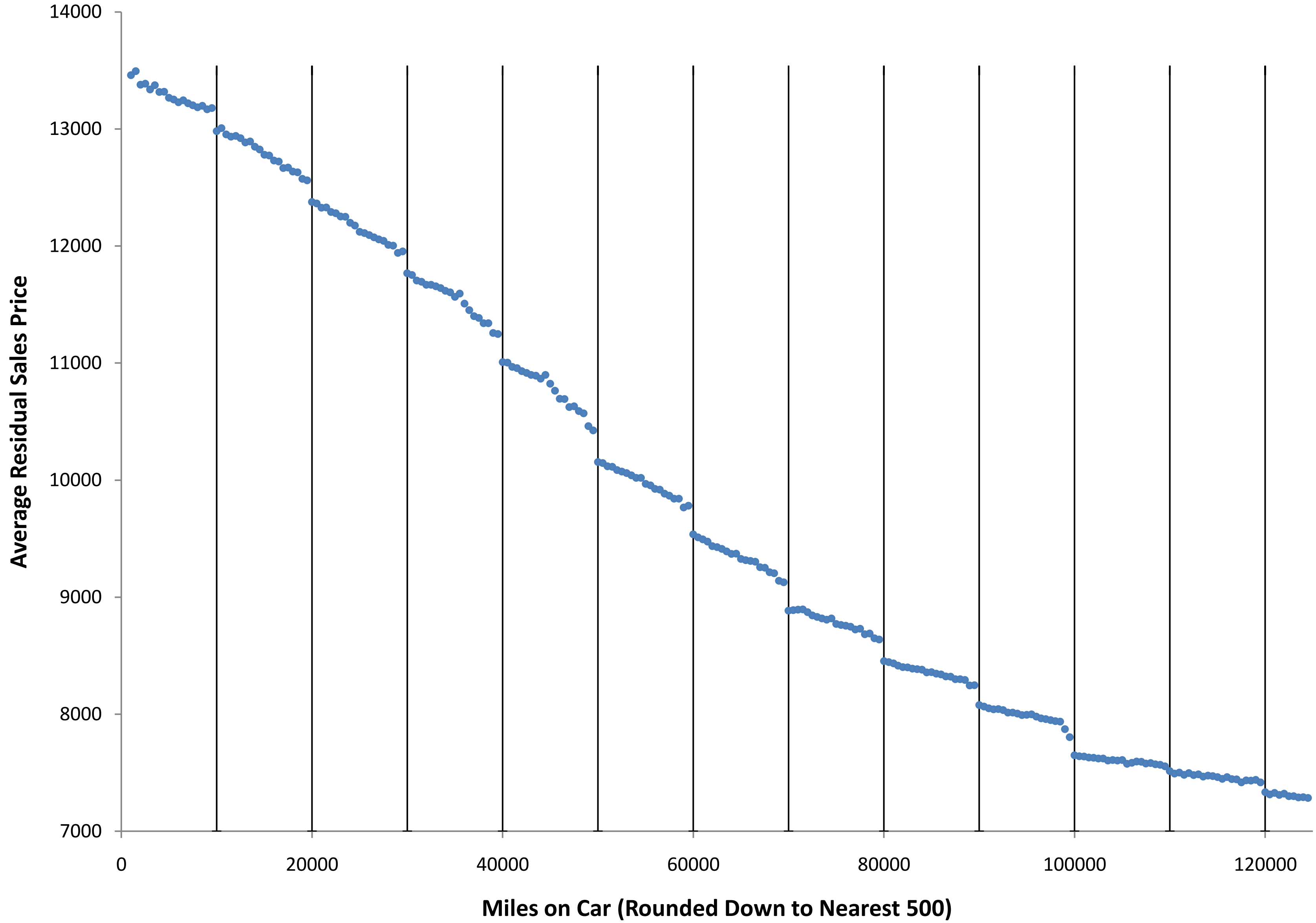


Figure 5 - Fleet/Lease Price Residuals. This figure plots the average residual sales price within 500-mile bins for the cars in our dataset sold by Fleet/Lease companies. The residual is obtained by removing make-model-model year-body effects from the sales price.

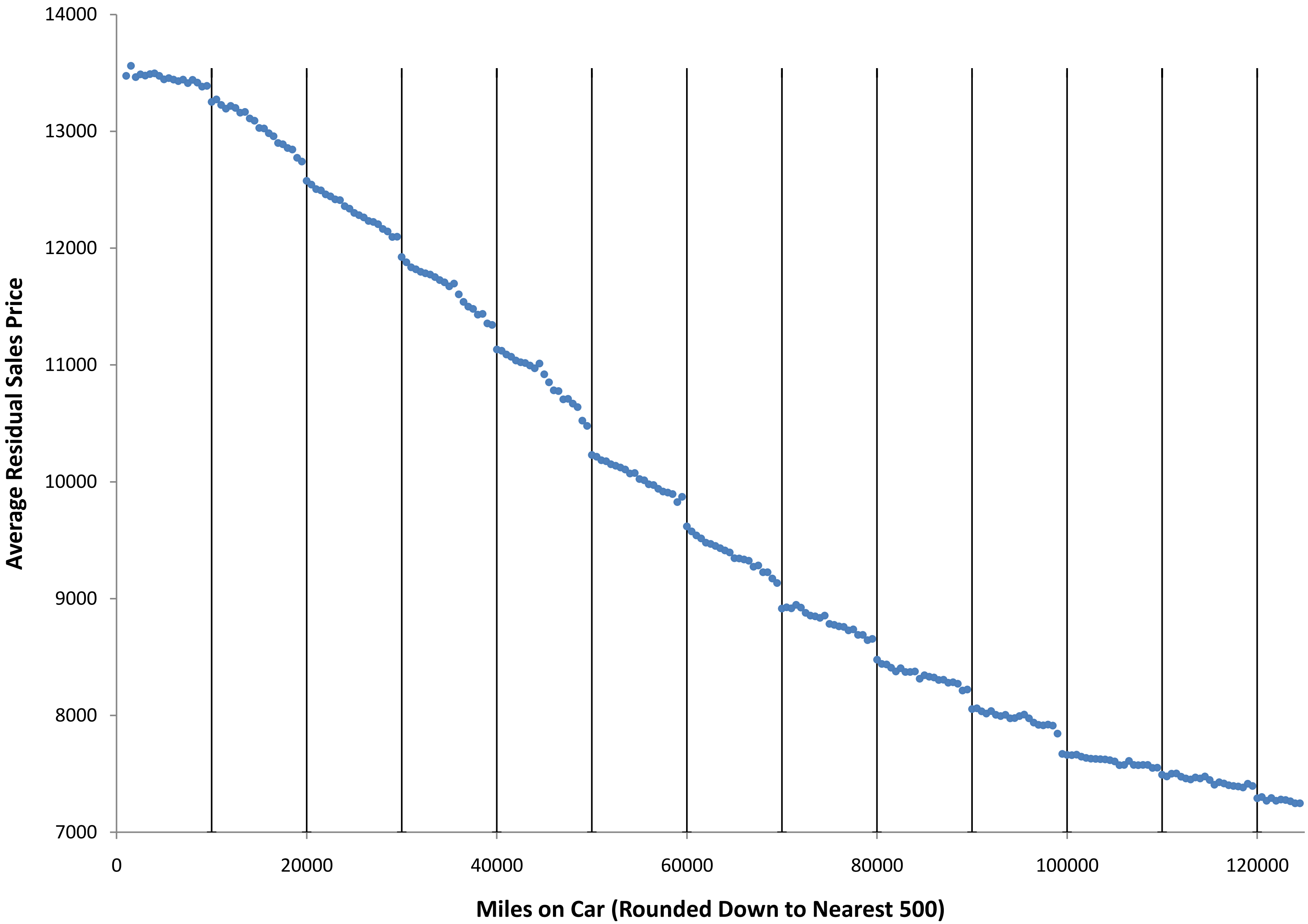
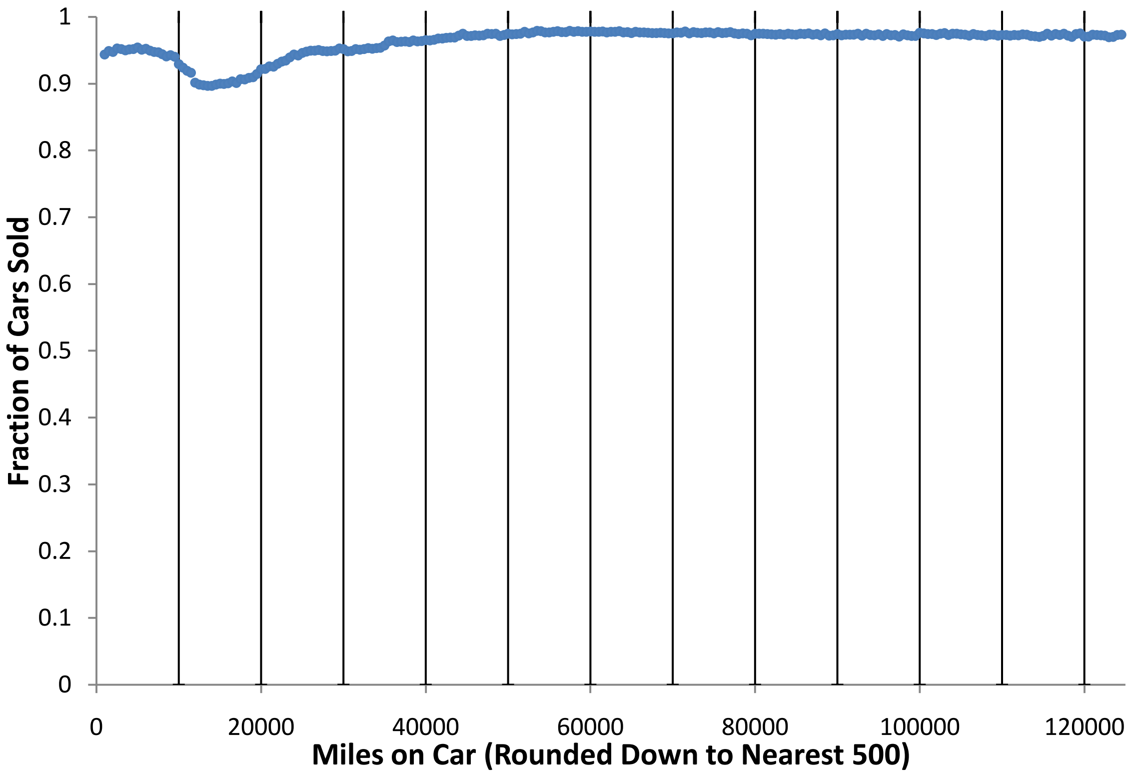


Figure 6 - Fleet/Lease Fraction Sold and Volume. Panel A plots the fraction of fleet/lease cars within 500-mile bins that sold. Panel B plots the raw counts within 500 mile bins for the fleet/lease cars in our dataset.

Panel A - Fraction Sold



Panel B - Volume

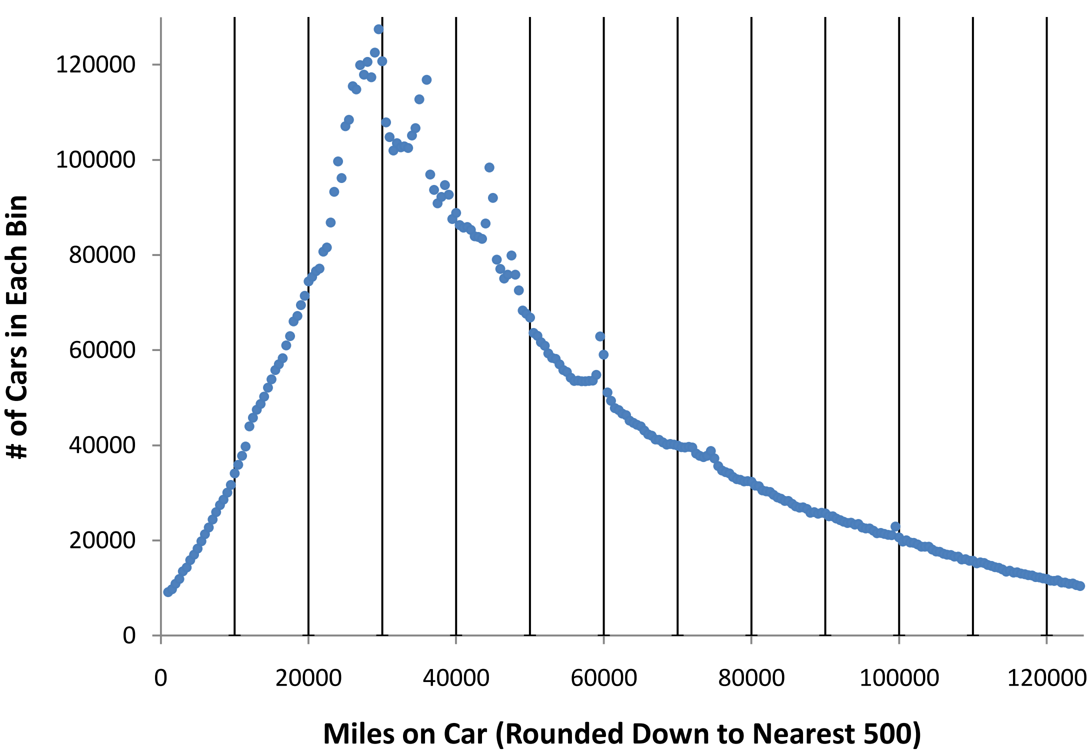


Figure 7 - Dealer Price Residuals. This figure plots the average residual sales price within 500-mile bins for the cars in our dataset sold by Dealers. The residual is obtained by removing make-model-model year-body effects from the sales price.

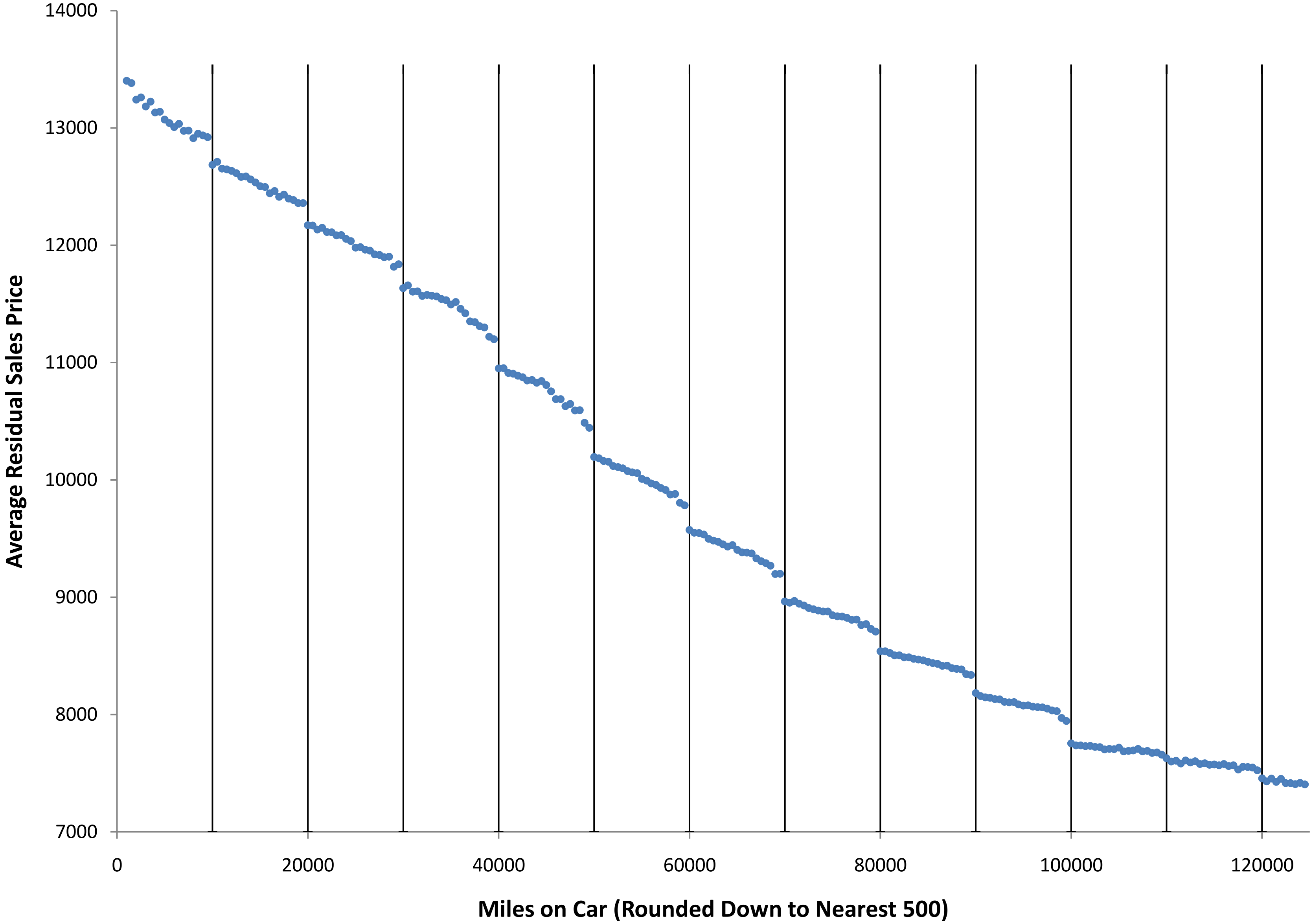
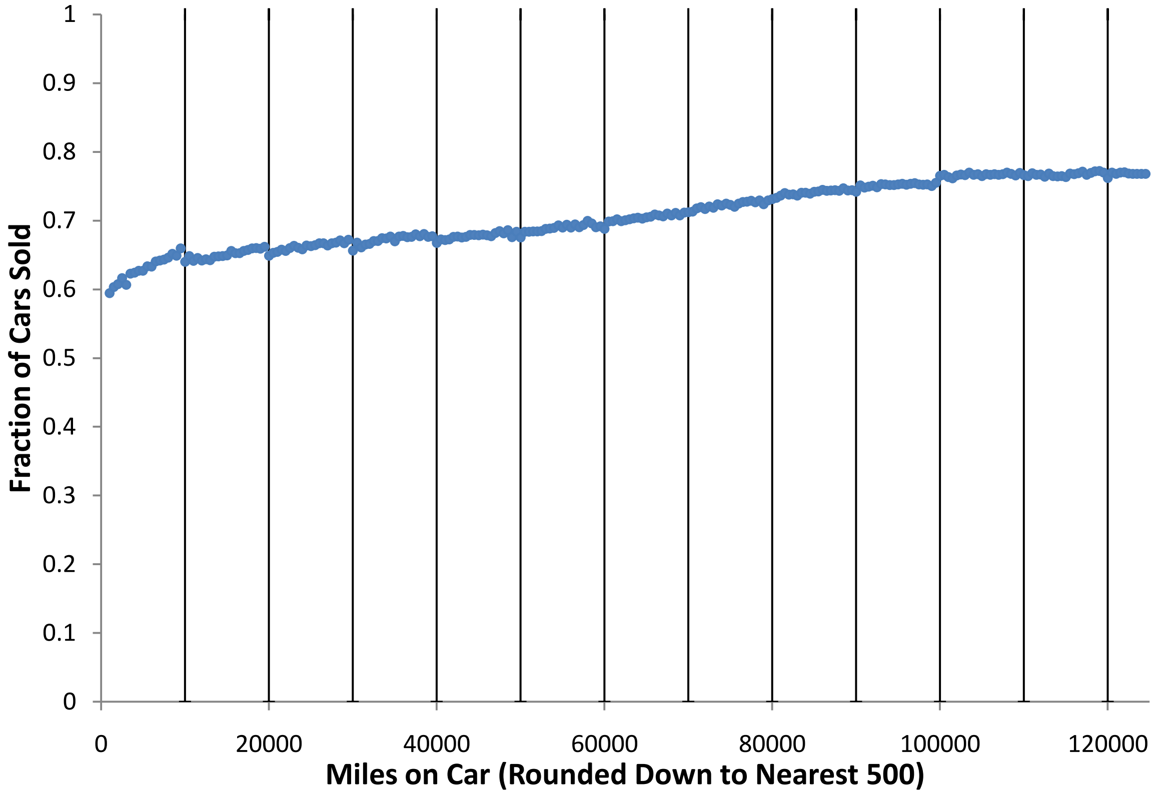


Figure 8 - Dealer Fraction Sold and Volume. Panel A plots the fraction of dealer cars within 500-mile bins that sold. Panel B plots the raw counts within 500 mile bins for the dealer cars in our dataset.

Panel A - Fraction Sold



Panel B - Volume

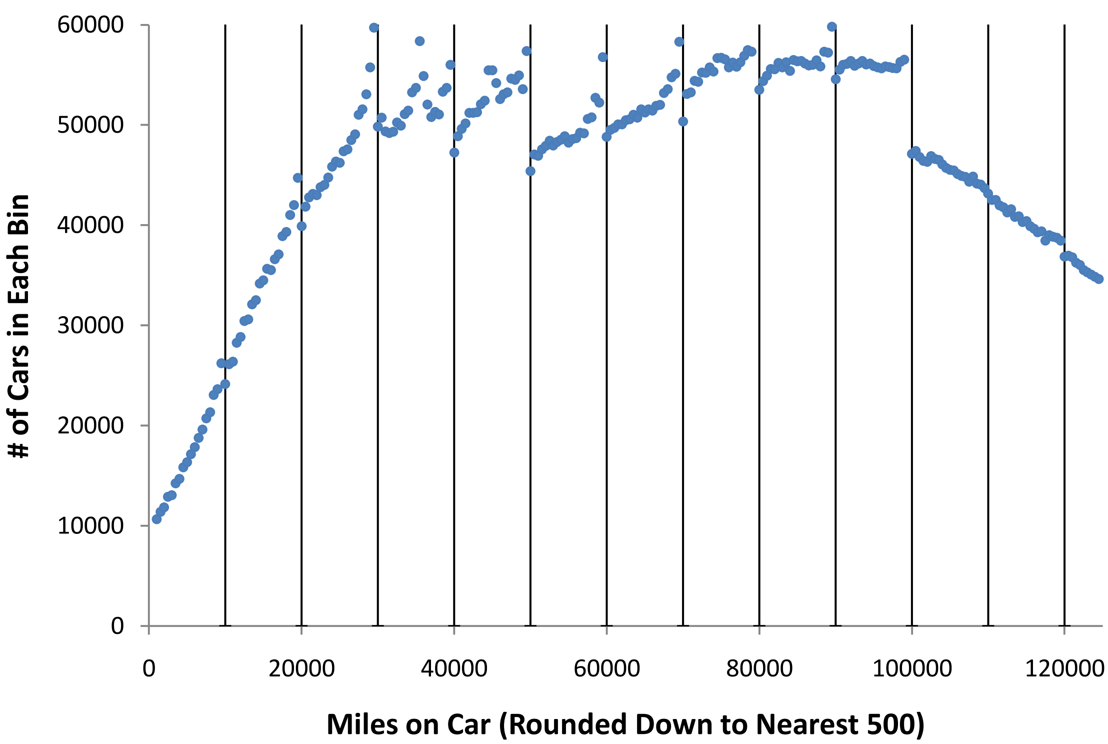


Figure 9 - 1,000-Mile Discontinuities. This figure plots the average residual sales price within 50-mile bins for all cars in our dataset. To decrease noise, the data were stacked so that each dot is the average residual for cars in the same bin relative to a 10,000-mile threshold. For example, the very first dot represents the average residual value of all cars whose mileage falls between 10,000-10,050, 20,000-20,050, 30,000-30,050, ..., or 110,000-110,050.

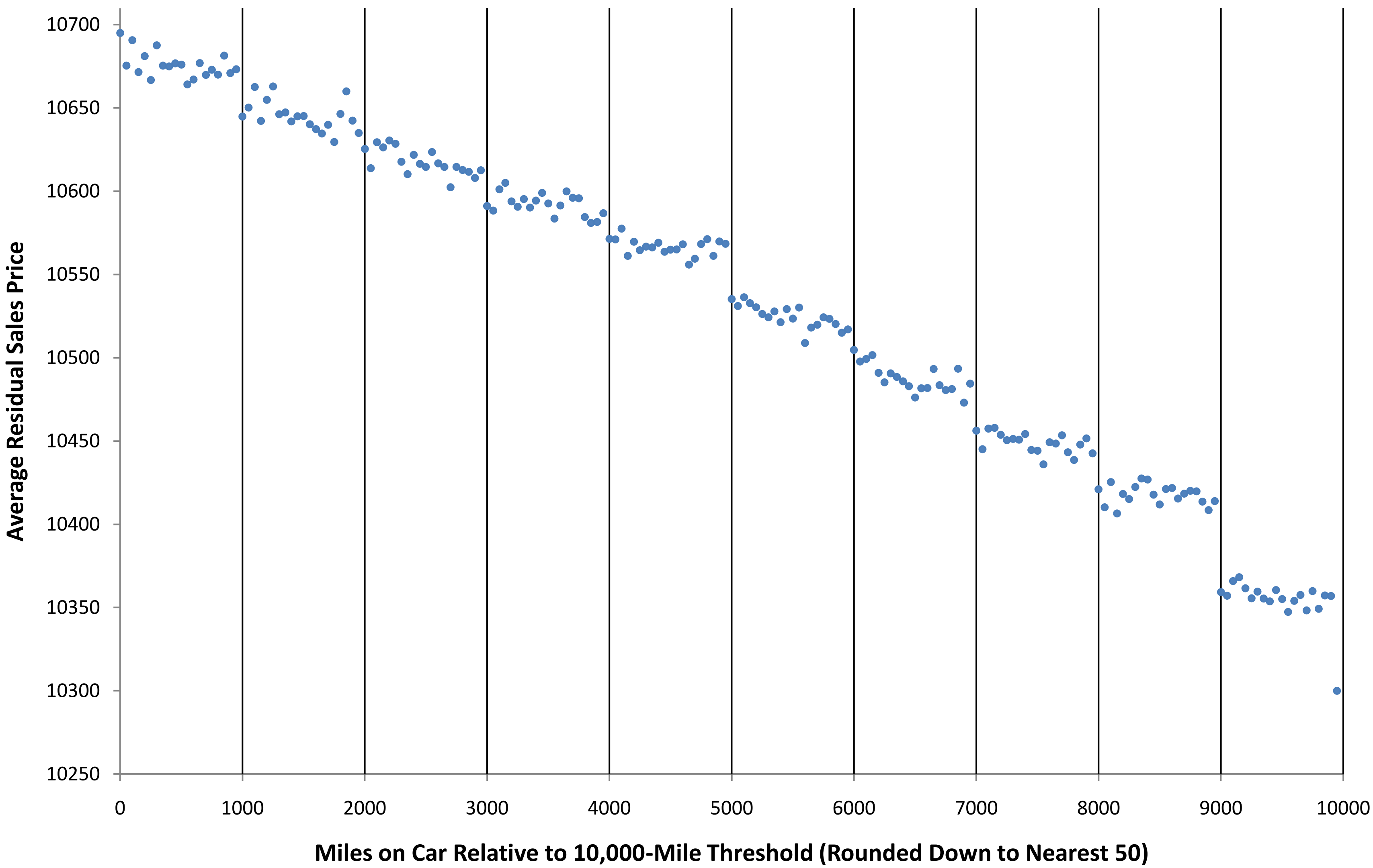


Figure 10 - Canadian Price Residuals. This figure plots the average residual sales price within 1,000-kilometer bins for cars sold by auction in Canada. The residual is obtained by removing make-model-model year-body effects from the sales price.

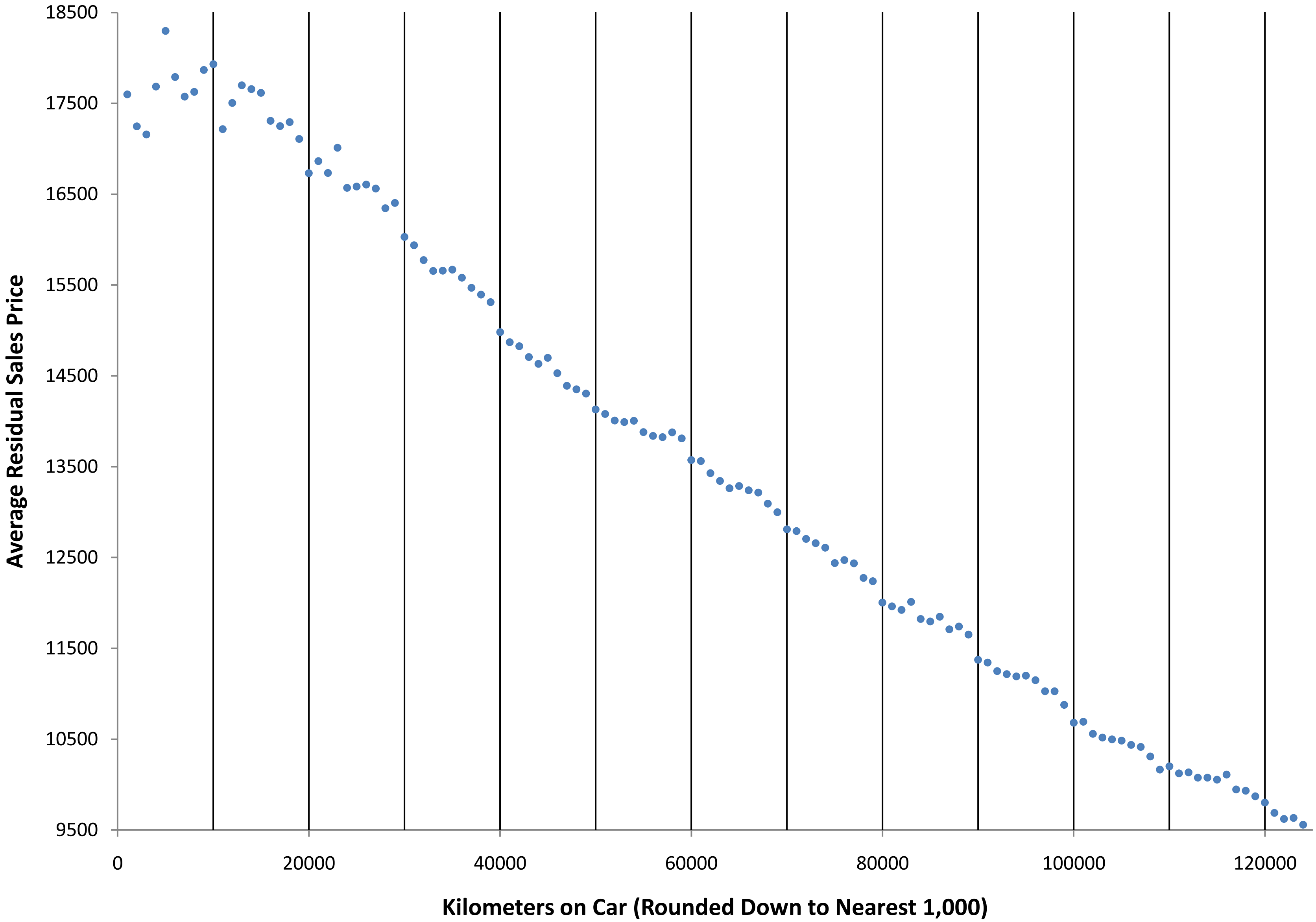


Figure 11 - Depreciation and Discontinuity Correlation. This figure plots the depreciation rate (alpha) and the average 10,000-mile price discontinuity for the 250 most popular cars in our data. A linear fitted line is included.

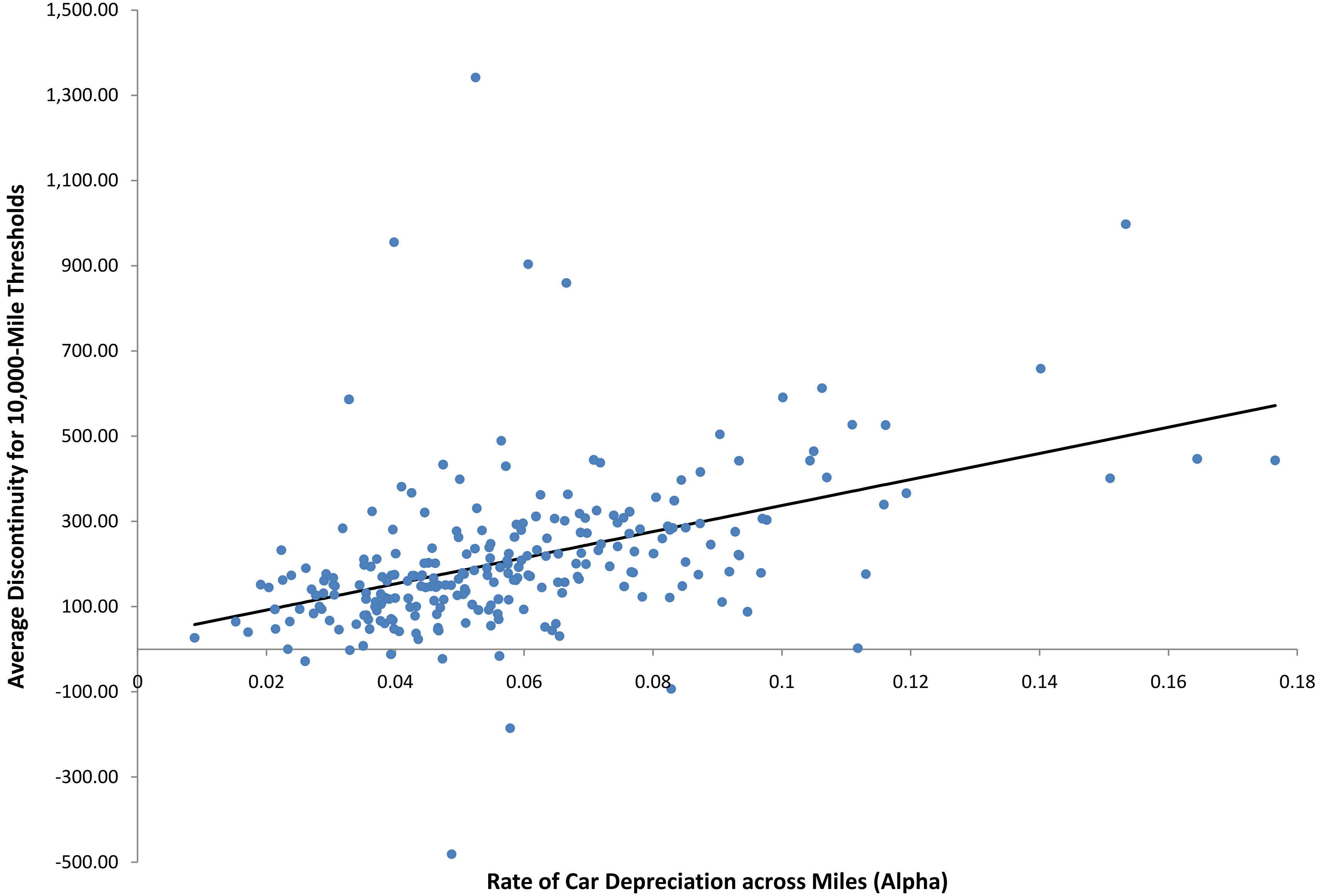


Figure 12 - Experience Percentile. Each buyer in the dataset is given a experience percentile rating based on total volume of purchases (the 1% of buyers with the highest volume receive a percentile score of 99%). This figure plots the average buyer experience percentile for each 500-mile bin.

Figure 13 - Cars.com Volume. This figure plots the raw counts within 1,000-mile bins for the number of cars being advertised on cars.com on 8/15/2009.

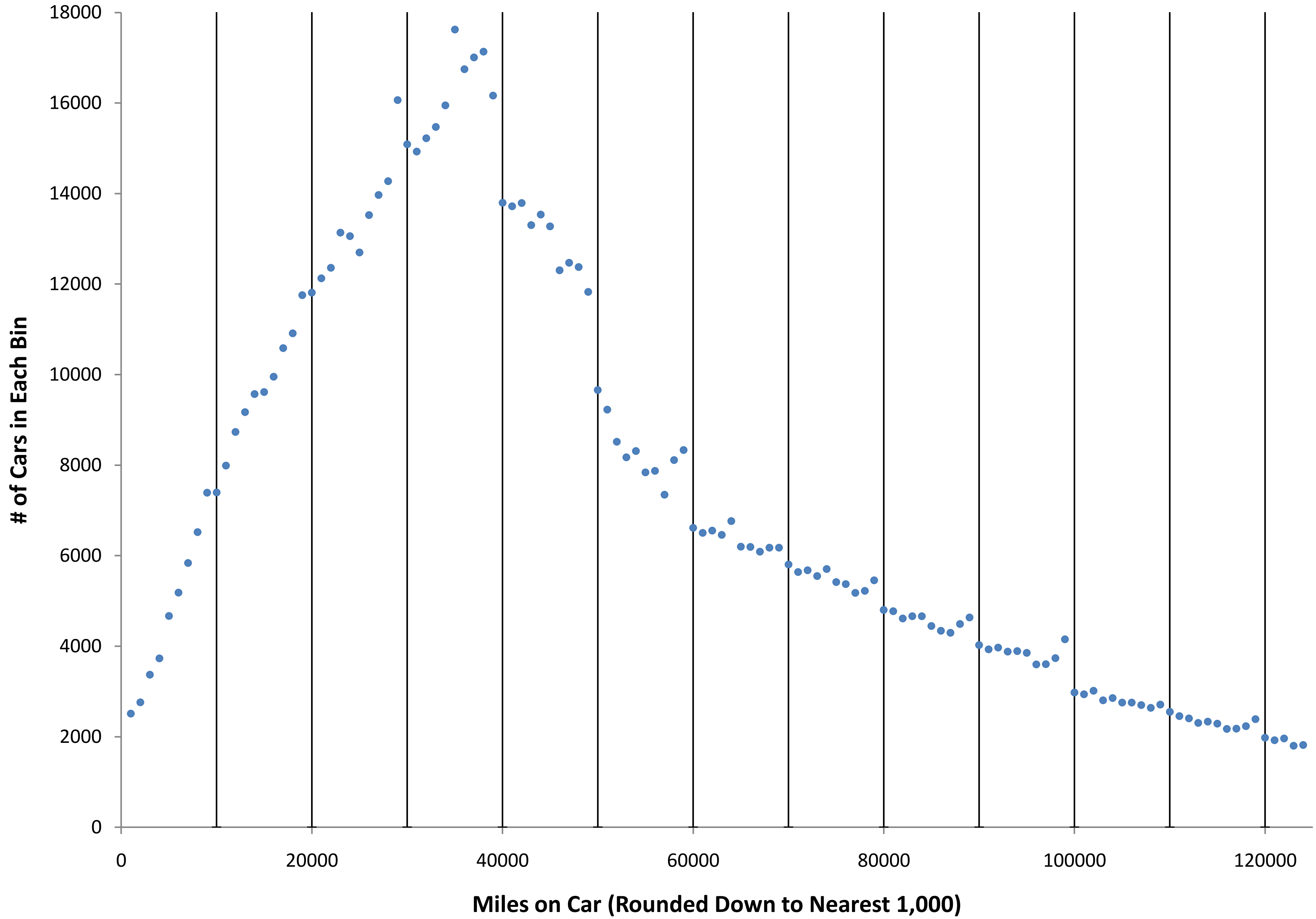
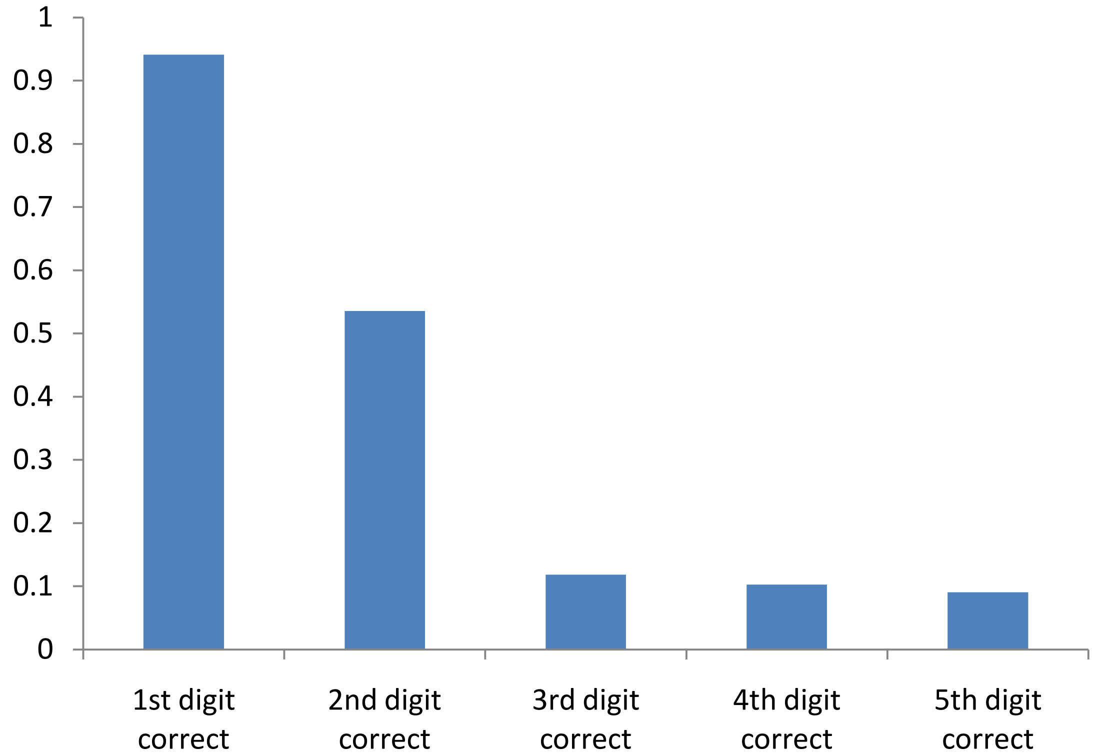


Figure 14 - Recall Results. Panel A shows the percent of people who correctly remembered the 1st-5th digits of a car's mileage. Panel B indicates the difference between the average recall value and the true mileage of a car by each of the 8 different true mileage amounts.

Panel A - Percent Correct by Digit



Panel B - Difference Between Recalled and True Mileage

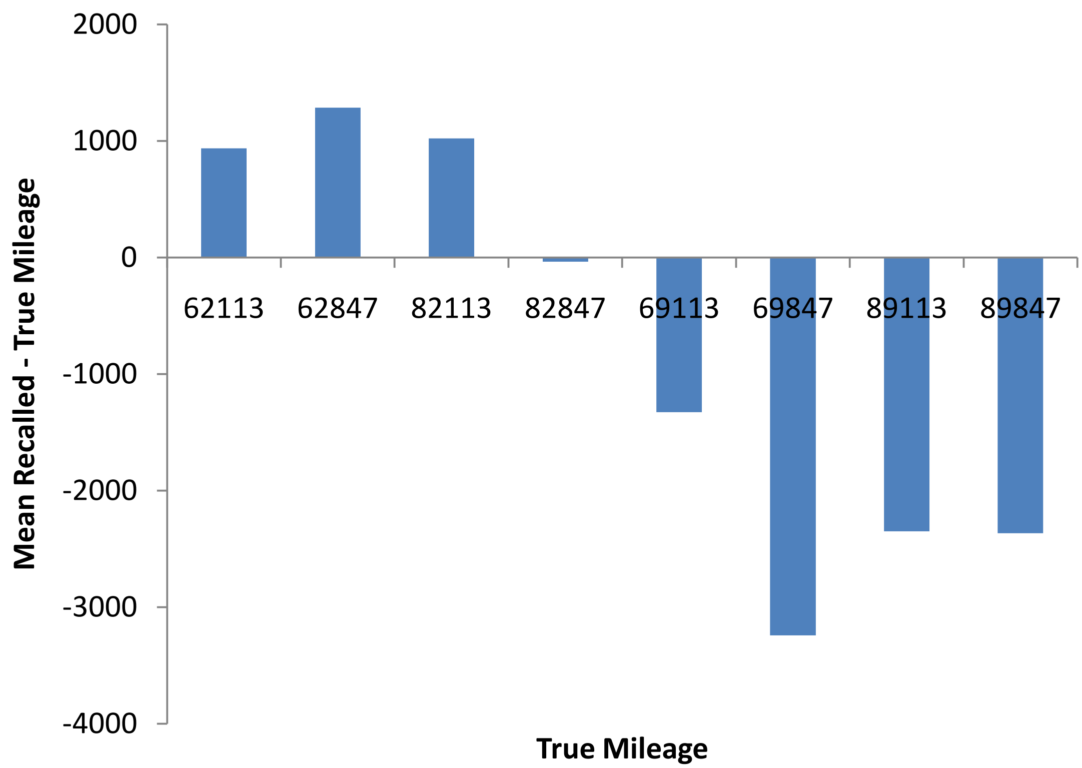


Table 1. Summary Statistics

	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 Only

	Dependent Variable: Auction Price for Car Sale						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Avg. Discontinuity Size	-131.8	-164.1	-141.9	-154.5	-156.8	-161.6	-168.8
MT 10k miles	-22.2	-81.6	-151.2***	-45.9*	-56.1**	-41.1*	-56.6**
	[73.8]	[73.1]	[52.6]	[27.3]	[22.4]	[23.1]	[26.9]
MT 20k miles	-191.2***	-190.2***	-113.4***	-149.6***	-157.8***	-158.5***	-135.8***
	[40.1]	[39.7]	[28.0]	[14.1]	[11.6]	[12.1]	[14.1]
MT 30k miles	218.2***	63.1**	45.5**	-94.5***	-84.7***	-101.7***	-101.0***
	[26.1]	[25.8]	[17.9]	[9.3]	[7.8]	[8.2]	[10.0]
MT 40k miles	-87.4***	-83.7***	-122.9***	-160.7***	-181.9***	-175.8***	-181.1***
	[29.3]	[28.9]	[19.6]	[10.2]	[8.7]	[9.1]	[11.2]
MT 50k miles	-653.2***	-574.8***	-312.5***	-268.9***	-289.3***	-305.6***	-317.9***
	[29.9]	[29.1]	[20.0]	[10.9]	[9.4]	[10.0]	[13.3]
MT 60k miles	-416.8***	-450.2***	-291.6***	-226.0***	-207.0***	-211.3***	-201.3***
	[31.6]	[30.6]	[21.8]	[12.4]	[11.0]	[11.5]	[16.1]
MT 70k miles	111.4***	27.4	-125.6***	-212.6***	-215.6***	-214.0***	-213.6***
	[31.5]	[30.2]	[22.3]	[13.2]	[11.8]	[12.4]	[18.6]
MT 80k miles	-4.3	-19.6	-133.6***	-213.7***	-216.6***	-216.0***	-210.8***
	[31.5]	[29.7]	[23.0]	[14.4]	[13.1]	[14.2]	[22.9]
MT 90k miles	-284.7***	-245.8***	-205.2***	-185.4***	-185.8***	-211.8***	-241.9***
	[34.7]	[32.4]	[25.5]	[16.2]	[14.8]	[16.3]	[27.0]
MT 100k miles	-305.9***	-347.8***	-266.7***	-167.2***	-154.0***	-160.5***	-174.2***
	[34.1]	[31.3]	[25.7]	[17.3]	[16.1]	[18.5]	[32.1]
MT 110k miles	153.5***	67.2*	6.8	-5.2	-3	11.1	15.2
	[40.9]	[37.8]	[30.9]	[20.2]	[18.6]	[22.8]	[40.6]
MT 120k miles	-98.4*	-133.7***	-32.3	-123.9***	-129.5***	-153.6***	-206.6***
	[54.3]	[48.9]	[40.9]	[28.1]	[26.3]	[34.3]	[63.5]
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	0.224	0.257	0.632	0.895	0.926	0.960	0.974
Observations	2,337,851	2,337,851	2,337,851	2,337,851	2,337,851	2,337,851	2,337,851

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

Table 3. The Impact of 10,000-Mile Thresholds on Prices - Dealer Only

	Dependent Variable: Auction Price for Car Sale						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Avg. Discontinuity Size	-446.0	-376.3	-264.0	-180.5	-173.2	-167.3	-146.4
MT 10k miles	-801.7***	-691.6***	-350.9***	-184.0***	-179.4***	-184.6***	-186.4
	[112.0]	[104.4]	[72.1]	[31.6]	[22.8]	[29.5]	[125.4]
MT 20k miles	-379.7***	-345.8***	-171.7***	-179.6***	-156.8***	-152.5***	-124.7*
	[65.1]	[61.7]	[43.1]	[19.0]	[14.2]	[17.5]	[70.7]
MT 30k miles	-339.9***	-209.2***	-204.1***	-122.3***	-127.8***	-126.0***	-64.7
	[45.2]	[42.9]	[30.5]	[13.9]	[10.9]	[13.3]	[58.3]
MT 40k miles	-564.7***	-509.9***	-341.0***	-231.1***	-226.1***	-201.4***	-156.0**
	[42.9]	[40.0]	[28.5]	[13.3]	[10.7]	[13.3]	[64.4]
MT 50k miles	-1,094.9***	-901.0***	-504.1***	-280.2***	-264.5***	-249.2***	-224.0***
	[37.2]	[33.8]	[24.4]	[11.8]	[9.7]	[12.2]	[68.2]
MT 60k miles	-610.4***	-499.1***	-346.8***	-212.0***	-199.3***	-187.7***	-163.4**
	[32.6]	[28.9]	[21.4]	[10.9]	[9.2]	[11.8]	[69.4]
MT 70k miles	-381.6***	-284.1***	-310.9***	-243.7***	-235.5***	-212.4***	-184.6***
	[29.7]	[26.2]	[19.7]	[10.1]	[8.6]	[11.0]	[67.3]
MT 80k miles	-315.5***	-220.0***	-224.2***	-182.6***	-171.6***	-163.7***	-103.8
	[24.0]	[20.8]	[16.1]	[8.7]	[7.7]	[9.9]	[63.4]
MT 90k miles	-337.2***	-311.1***	-239.5***	-189.5***	-186.5***	-183.7***	-176.7***
	[23.9]	[20.6]	[16.1]	[8.9]	[7.8]	[10.2]	[65.9]
MT 100k miles	-402.2***	-412.9***	-331.6***	-226.7***	-212.3***	-212.3***	-177.8***
	[21.8]	[18.6]	[15.0]	[8.6]	[7.8]	[10.3]	[67.6]
MT 110k miles	12.7	-4.7	-61.2***	-39.2***	-37.1***	-47.0***	-64.5
	[24.3]	[20.8]	[17.0]	[9.9]	[8.9]	[11.9]	[80.0]
MT 120k miles	-136.5***	-126.3***	-82.4***	-75.6***	-81.0***	-87.6***	-130.6
	[28.6]	[24.3]	[20.2]	[12.5]	[11.6]	[15.7]	[111.8]
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	0.335	0.443	0.708	0.933	0.957	0.980	0.998
Observations	2,299,007	2,299,007	2,299,007	2,299,007	2,299,007	2,299,007	2,299,007

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

Table 4. The Impact of 10,000-Miles-Driven Discontinuities on Price by Year - Fleet/Lease Only

	Dependent Variable: Auction Price for Car Sale						
	2002	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Avg. Discontinuity Size	-160.4	-146.4	-160.4	-152.7	-170.0	-155.1	-134.6
MT 10k miles	-91.5***	-100.9***	-109.8***	-91.7***	-84.4***	-102.9***	-83.6***
	[25.5]	[24.7]	[25.8]	[25.2]	[23.2]	[23.0]	[24.4]
MT 20k miles	-128.8***	-142.6***	-211.8***	-153.4***	-179.4***	-133.9***	-129.6***
	[13.0]	[11.8]	[13.6]	[14.2]	[11.9]	[10.6]	[12.5]
MT 30k miles	-102.3***	-90.5***	-101.0***	-87.9***	-99.6***	-93.4***	-23.2***
	[7.5]	[7.5]	[9.0]	[9.6]	[9.0]	[7.6]	[8.0]
MT 40k miles	-192.5***	-175.7***	-208.1***	-191.8***	-189.4***	-157.3***	-179.5***
	[7.9]	[7.6]	[9.2]	[10.3]	[10.2]	[9.9]	[10.6]
MT 50k miles	-283.0***	-276.6***	-279.0***	-300.8***	-304.9***	-280.8***	-235.4***
	[9.2]	[8.4]	[9.8]	[10.8]	[10.6]	[10.8]	[12.2]
MT 60k miles	-223.7***	-212.8***	-201.2***	-193.2***	-172.0***	-176.5***	-151.0***
	[11.6]	[10.2]	[11.2]	[12.4]	[12.0]	[12.3]	[13.9]
MT 70k miles	-206.4***	-218.5***	-237.8***	-191.2***	-224.9***	-216.2***	-179.1***
	[13.4]	[11.7]	[12.3]	[13.3]	[12.5]	[12.7]	[13.9]
MT 80k miles	-211.7***	-148.8***	-178.5***	-184.3***	-214.4***	-196.2***	-176.0***
	[15.6]	[13.5]	[13.6]	[14.5]	[13.5]	[13.5]	[14.6]
MT 90k miles	-161.0***	-130.0***	-140.3***	-167.7***	-215.9***	-222.0***	-195.9***
	[17.9]	[15.6]	[15.3]	[16.1]	[14.8]	[14.9]	[16.1]
MT 100k miles	-219.5***	-164.1***	-118.8***	-144.2***	-186.0***	-150.7***	-154.4***
	[20.6]	[17.4]	[16.9]	[17.6]	[15.7]	[15.9]	[16.4]
MT 110k miles	-42.3*	-20.7	-10.1	18.5	-16.9	-17.3	-24.2
	[24.0]	[20.3]	[19.5]	[20.4]	[18.9]	[18.8]	[20.0]
MT 120k miles	-61.7*	-75.4***	-128.8***	-144.7***	-151.7***	-114.0***	-82.9***
	[34.3]	[28.9]	[26.8]	[28.4]	[26.0]	[25.6]	[26.6]
7th-Order Miles Poly	X	X	X	X	X	X	X
Fixed Effects	Age*Make* Model*Body	Age*Make* Model*Body	Age*Make* Model*Body	Age*Make* Model*Body	Age*Make* Model*Body	Age*Make* Model*Body	Age*Make* Model*Body
R-Squared	0.917	0.933	0.939	0.938	0.948	0.950	0.942
Observations	2,150,821	1,912,499	1,676,461	1,491,405	1,429,164	1,590,089	1,427,728

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

Table 5. The Impact of 10,000-Miles-Driven Discontinuities on Price by Year - Dealer Only

	Dependent Variable: Auction Price for Car Sale						
	2002	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Avg. Discontinuity Size	-160.3	-166.2	-165.9	-165.1	-180.3	-180.4	-176.0
MT 10k miles	-149.8***	-201.0***	-172.0***	-159.9***	-215.8***	-173.5***	-184.5***
	[27.1]	[23.6]	[21.4]	[20.4]	[20.3]	[21.8]	[29.3]
MT 20k miles	-149.2***	-162.6***	-170.2***	-132.5***	-135.9***	-143.7***	-178.3***
	[17.7]	[14.7]	[13.5]	[12.9]	[13.1]	[14.2]	[19.3]
MT 30k miles	-90.5***	-97.2***	-121.8***	-125.5***	-154.0***	-161.7***	-159.2***
	[12.4]	[10.7]	[10.8]	[10.4]	[10.7]	[11.1]	[14.5]
MT 40k miles	-206.1***	-244.7***	-219.3***	-207.9***	-210.5***	-235.6***	-244.3***
	[12.2]	[10.0]	[10.3]	[10.4]	[10.9]	[11.3]	[15.2]
MT 50k miles	-233.7***	-290.4***	-263.6***	-255.5***	-248.7***	-281.8***	-287.6***
	[11.6]	[9.5]	[9.4]	[9.5]	[9.9]	[10.3]	[13.9]
MT 60k miles	-198.5***	-196.9***	-195.8***	-214.0***	-218.3***	-200.8***	-202.2***
	[11.7]	[9.5]	[9.2]	[9.1]	[9.2]	[9.5]	[12.7]
MT 70k miles	-215.7***	-206.2***	-218.0***	-235.2***	-253.2***	-255.3***	-225.2***
	[11.0]	[9.2]	[8.7]	[8.5]	[8.6]	[8.8]	[11.5]
MT 80k miles	-143.2***	-136.3***	-135.7***	-152.5***	-177.7***	-187.8***	-163.1***
	[10.0]	[8.6]	[8.1]	[7.8]	[7.6]	[7.8]	[9.8]
MT 90k miles	-141.4***	-149.7***	-164.4***	-174.2***	-184.5***	-214.4***	-181.5***
	[10.2]	[9.0]	[8.4]	[8.2]	[7.8]	[7.8]	[9.7]
MT 100k miles	-279.2***	-215.7***	-221.9***	-212.9***	-202.0***	-192.4***	-177.4***
	[10.2]	[9.1]	[8.6]	[8.2]	[7.7]	[7.7]	[9.3]
MT 110k miles	-46.6***	-21.1**	-32.9***	-33.6***	-56.7***	-25.3***	-32.9***
	[11.7]	[10.6]	[10.0]	[9.3]	[8.9]	[8.7]	[10.4]
MT 120k miles	-69.6***	-72.1***	-75.5***	-77.3***	-106.3***	-92.4***	-75.6***
	[15.6]	[13.8]	[13.0]	[12.2]	[11.3]	[11.2]	[13.0]
7th-Order Miles Poly	X	X	X	X	X	X	X
Fixed Effects	Age*Make*Model*Body	Age*Make*Model*Body	Age*Make*Model*Body	Age*Make*Model*Body	Age*Make*Model*Body	Age*Make*Model*Body	Age*Make*Model*Body
R-Squared	0.954	0.966	0.965	0.966	0.966	0.968	0.958
Observations	1,447,598	1,542,434	1,751,146	1,893,420	1,851,407	1,796,014	1,201,405

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

Table 6. The Impact of 10,000-Mile Thresholds on Prices by Most Popular Make-Models

	Dependent Variable: Auction Price for Car Sale							
	Ford Taurus	Ford Explorer	Ford Focus	Chevy Impala	Ford F150	Toyota Camry	Chevy Cavalier	Nissan Altima
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Avg. Discontinuity Size	-147.5	-197.2	-105.3	-59.6	-277.4	-109.4	-69.0	-178.5
MT 10k miles	-9.6	-272.2*	-56.4	254.2	-227	78.9	34.1	-102.5
	[84.5]	[161.3]	[75.1]	[175.2]	[160.3]	[136.5]	[93.8]	[121.2]
MT 20k miles	-149.4***	-75.8	-92.0**	-86.1	-151.6**	-107.6*	-68.8	-158.7***
	[33.7]	[64.5]	[45.8]	[77.4]	[68.2]	[61.2]	[60.0]	[54.4]
MT 30k miles	-2.5	-75.5**	-61.8*	-51.8	-218.0***	179.4***	-77.9**	-161.4***
	[21.0]	[38.4]	[31.8]	[43.4]	[59.7]	[37.4]	[36.9]	[41.7]
MT 40k miles	-239.4***	-243.6***	-53	-96.1	-229.5***	-140.1***	-60.1	-141.7***
	[29.7]	[39.7]	[36.2]	[64.4]	[71.8]	[47.9]	[44.7]	[49.2]
MT 50k miles	-257.3***	-278.7***	-90.8**	-126.5**	-328.3***	-331.1***	-57.2	-349.6***
	[28.9]	[43.3]	[39.1]	[56.7]	[74.8]	[51.4]	[45.6]	[56.8]
MT 60k miles	-101.3***	-183.9***	-109.7**	-186.3***	-351.7***	-296.4***	-75	-288.0***
	[27.9]	[48.7]	[43.2]	[52.5]	[86.7]	[53.7]	[48.2]	[64.8]
MT 70k miles	-101.6***	-161.7***	-217.6***	-96.1*	-498.9***	-182.7***	-168.8***	-353.9***
	[26.5]	[50.6]	[42.2]	[49.7]	[89.2]	[56.6]	[45.4]	[65.7]
MT 80k miles	-127.4***	-162.3***	-160.7***	-84.2	-277.2***	-126.2**	-150.3***	-186.6***
	[26.7]	[50.0]	[44.7]	[52.2]	[87.3]	[54.5]	[42.1]	[62.4]
MT 90k miles	-229.3***	-245.0***	-161.4***	-169.2***	-332.9***	-125.9**	-26.4	-226.2***
	[30.2]	[53.4]	[50.4]	[65.6]	[90.2]	[56.6]	[43.1]	[63.1]
MT 100k miles	-361.3***	-423.3***	-143.3**	-97.7	-378.8***	-147.4***	-111.3***	-194.8***
	[31.9]	[55.2]	[55.8]	[71.7]	[90.9]	[55.9]	[41.2]	[60.7]
MT 110k miles	-33.3	42.3	0.7	69.8	20.4	-45.6	-46.1	4.8
	[38.8]	[72.0]	[68.5]	[90.8]	[108.9]	[56.9]	[47.3]	[68.0]
MT 120k miles	-157.3***	-286.4***	-117.6	-44.7	-355.0***	-68.6	-19.8	16.3
	[53.3]	[89.2]	[102.9]	[129.5]	[136.6]	[69.3]	[58.0]	[82.9]
7th-Order Miles Poly	X	X	X	X	X	X	X	X
Fixed Effects	Age*Make*Model*Body	Age*Make*Model*Body	Age*Make*Model*Body	Age*Make*Model*Body	Age*Make*Model*Body	Age*Make*Model*Body	Age*Make*Model*Body	Age*Make*Model*Body
R-Squared	0.882	0.899	0.732	0.796	0.870	0.889	0.722	0.865
Observations	115,624	82,508	60,705	43,045	49,720	58,361	57,520	56,175

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