

Automobile Maintenance Costs, Used Cars, and Adverse Selection

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1 Introduction

Since Akerlof's (1970) seminal work on "lemons" markets, economists have been investigating how the lack of information on product quality affects the decision to sell durable goods. Engers, Hartmann, and Stern (2004b) (EHSb) finds, in a dynamic setting with sufficient heterogeneity in tastes, the trade-inhibiting effects of private information are less severe than previously thought. New-car owners whose utility falls rapidly with declines in quality maintain them well and yet sell them soon after buying them. On the other hand, new-car owners whose utility does not fall rapidly with declines in quality hold them for long periods and maintain them poorly. The unobservable heterogeneity in car quality that drives selling decisions is not constant, specific to a car, but rather varies across owners of the same car. This suggests that the lemons problem is due to individual owners' decisions rather than manufacturers'.

EHSb shows theoretically how the owner's maintenance decision determines unobservable car quality and influences the decision to sell. In equilibrium, the owner will not incur maintenance expenditures to raise a car's quality if he intends to sell it. Because quality is unobservable, he will be unable to pass the costs onto potential buyers. The literature has yet to substantiate empirically that it is the maintenance decision and not another decision by the owner that drives the decision to sell. Because of data limitations, EHSb does not examine empirically the link between maintenance and selling. Using a different dataset, this paper tries to clarify the role unobserved maintenance expenditures plays in the selling decision. Our results suggest that unobserved maintenance costs do not affect selling decisions.

We estimate a model of the household decision to sell (scrap) a vehicle as a function of the household's characteristics, the vehicle's age and changes in maintenance costs as predicted by the car's characteristics. The methodology decomposes changes in car costs into observed and unobserved components and

measures how much each component explains the decision to sell. A significant effect of unobserved components would suggest a lemons effect in the selling decision. Our results indicate there is no lemons effect due to unobservable maintenance expenditures as commonly assumed.¹

The empirical analysis uses the Consumer Expenditure Survey which tracks households' expenditures on cars. For each car, we observe make, model, and age. Total expenditures on maintenance for all vehicles owned by the household are given as well. Finally, the survey provides information on the household's income, whether the household lives in an urban setting, and the number of drivers per car. This demographic information allows us to control for differences in vehicle operating costs that vary by household characteristics.

The detailed survey of household expenditures on passenger vehicles allows us to create operating cost profiles by brand and age. This is of value for those studying automobile-related issues such as the scrapping or the buying and selling decision. For example, households compare the vehicle's scrap price against the cost of maintaining the vehicle in working condition when deciding if to scrap, and consumers compare the utility flows minus the operating costs of alternative vehicles when deciding whether to buy and sell. Thus, understanding how costs vary by brand across a vehicle's lifetime is useful in researching these issues.

The layout of the paper is as follows: Section 2 summarizes the literature on the selling and scrapping of durable goods. Section 3 describes the data used to estimate a vehicle's maintenance cost as function of its product characteristics as well as the owner's characteristics. Section 4 discusses the results of the cost regressions. Section 5 presents a model of the decision to sell (scrap) and the methodology to decompose the costs into observed and unobserved components to identify if a lemons effect exists in the selling decision. Finally, Section 6 discusses the results and their implications for identifying the role maintenance expenditures play in selling decisions.

2 Literature Review

In order to understand what drives consumers to sell their cars, one must understand the household's decision to buy and sell durable goods. These goods are consumed over many periods and are often resold. They are imperfect substitutes for new ones; their qualities depreciate over time and at different rates. Consumers' willingness to hold onto these goods as they depreciate varies with consumer preferences for quality.

The literature on buying and selling of durable goods can be classified into two groups based on assumptions made about the way information is distributed

¹Both Fabel and Lehmann (2002) and Engers Hartmann, and Stern (2004b) define quality as a function of the owner's maintenance effort that is unobserved by potential buyers. This modeling of quality as owner-determined is consistent with optimal asset durability and retirement/scrappage literatures. See, for example, Schmalensee (1974), Parks (1979), Rust (1985), and Nelson and Caputo (1997).

in the market. The first group of models assumes complete information available to buyers and sellers. This strand of the literature focuses on the role quality deterioration plays in households' purchasing decisions. Rust (1985) provides a general theoretical model of stochastic degradation. It endogenizes the selling decision and allows for heterogeneous preferences for product quality. In stationary equilibrium, consumers hold durable goods for one period and repeatedly purchase the same quality grade. Konishi and Sandfort (2002) introduces a transaction cost for replacing a good. Now there is an incentive for consumers to hold durable goods across multiple quality grades in order to economize on transaction costs. As a result, in equilibrium, some consumers continue holding their durable goods despite the depreciated quality. Alternatively, Sandfort (1999) motivates consumer holding of durable goods across quality grades by introducing a time cost spent in search for replacement.

In contrast, the second strand of the literature focuses on how information problems affect the decision to hold onto one's car as it depreciates. Akerlof (1970) argues that adverse selection may entirely shut down the market for second-hand durables. When Hendel and Lizzeri (1999a, 1999b) extend the model to a dynamic setting, they conclude that asymmetric information reduces the amount of trade in equilibrium, but never shuts it down. EHSb reaches similar conclusions when it allows for multiple trades for a given good. Finally, Hendel, Lizzeri, and Siniscalchi (2003) extends the model to allow sales histories to signal car quality. It contrasts how efficient different types of selling contracts - leasing, resale, and rental - sort output and quality across consumers.

None of the models in either strand of the literature can answer (empirically) the question: is it the maintenance decision or another decision by the owner that determines unobservable car quality and drives selling decision? The first strand does not address how unobservable quality affects selling decisions, an important feature of the used car market. With the exception of the theoretical model in EHSb, the second strand assumes the rate of quality depreciation (and consequently its effect on the selling decision) is exogenous to the model. As a result, these models cannot identify if it is the owner's maintenance decision that influences the selling decision.

Unlike the literature on buying and selling of durable goods, both the optimal asset durability literature and the retirement/scrappage literature have endogenized the maintenance decision to explore its role in the selling and scrap-age decision. In the optimal asset durability literature, maintenance expenditures are found to influence the deterioration and depreciation rates. Both Schmalensee (1974) and Parks (1979) theoretically show that the rate of depreciation depends on the expected price of an asset and the cost of maintenance. Schmalensee demonstrates that when purchase prices are higher, consumers want to maintain the quality of the good, thereby reduce the rate of capital deterioration. Parks extends the model to allow for changes in asset prices. As consumers' expectations about future prices rise, they also increase their maintenance to reduce the rate of deterioration. Nelson and Caputo (1997) tests the theoretical implications of Parks' model. Using data on aircraft, it observes that depreciation rates respond to the price of maintenance as well as fuel costs

and price of new and used aircraft. This leads one to question the assumption that depreciation rates are exogenous.

Several papers in the scrappage and replacement investment literature also have established the importance of maintenance expenditures in the decision to scrap a durable good. Walker (1968) finds that the decision to scrap a vehicle depends on its age, its condition, the cost of repair and reconditioning, and the expected resale price in its age bracket. Parks (1977) allows the probability of scrappage also to depend on the car's make, vintage, and price relative to auto repair costs. When controlling for this additional factors, it observes the scrappage probability rises as the price of the car falls relative to the cost of repairing the vehicle. Alberini, Harrington, and McConnell (1996, 1998) constructs a similar model of the scrappage decision but uses disaggregated data to make predictions. Finally, Hamilton and Macauley (1998) attributes the increase in car longevity (i.e., lower scrappage rate) observed over the last 30 years to the reduction in the cost of maintaining a car.

EHSb considers elements of the three literatures described above. First, it endogenizes the maintenance decision. Consumers have the choice to incur maintenance costs to raise the car's unobservable quality. Second, this choice enters the household's decision on whether to keep the car or sell it and purchase another one. Consumers compare the utility flows from owning the car versus the costs of operating the car. The selling decision also depends on the vintage, age, make and model versus other available car options. Finally, buying and selling decisions are made under asymmetric information.

EHSb uses this model to investigate if unobservable heterogeneity in car quality explains how long consumers own their cars. It observes significant unobserved heterogeneity in the timing of selling of cars. The unobserved heterogeneity terms are not positively correlated over all owners of a given car, suggesting that the manufacturer does not induce the "lemonness" of cars. Instead, the results indicate a negative correlation between the unobserved heterogeneity terms for the first owner and subsequent owners of the car, suggesting that the "lemonness" of the car is a function of decisions made by the original owner.

The EHSb theoretical model postulates that the maintenance decisions by the first owner alter the car's unobservable quality and consequently the rate at which it is sold by subsequent owners. Because of strong preferences for quality, car aficionados continue maintaining the quality of their cars (despite the difficulty of passing on the costs of higher quality to potential buyers). They also sell them quickly in order to enjoy the utility flows of new vehicles. Consumers whose utility does not drop as rapidly with a drop in car quality do not maintain their cars as well the car aficionados. When they finally sell their cars, they tend to be lemons and subsequent owners try to sell them quickly once they observe the true quality. Because of lack of data, EHSb does not establish empirically that it is maintenance expenditures that explain the correlation in the unobservable heterogeneity terms across owners after the first one. This paper tries to clarify the role unobserved maintenance expenditures plays in selling decisions and determine if it is the source of the asymmetric information problem in the car market.

This paper estimates a model of the household decision to sell (scrap) as a function of the household’s characteristics, the vehicle’s age, and changes in maintenance costs as predicted by the car’s characteristics. The value of selling (or scrapping) the car depends on its age and observed and unobserved maintenance costs. A car is sold when the unobserved value of selling is positive. As with the scrappage literature, the owner scraps the car if the scrap value is greater than the difference between the value of the working vehicle and the cost to repair the vehicle. If the unobserved components of maintenance expenditures explain selling decisions, this suggests a lemons effect in the used car market.

3 Data

The Consumer Expenditure Survey (CEX), administered by the Bureau of Labor Statistics, tracks household spending on a variety of items including expenditures on automobile related items. It is a rotating panel in which each household (a family or a single consumer) is interviewed at most four times. Every quarter, twenty-five percent of the sample is replaced with new households.

For each household, the survey records expenditures on maintenance, car insurance, gasoline and oil, licensing and registration fees, and other miscellaneous expenses. The figures reported are aggregated over all vehicles owned by the household. The survey also collects information on the stock of vehicles owned by the household, providing detailed information on each vehicle’s make, model, and year. All of the information is collected on a quarterly basis.

Because expenditures are aggregated across a household’s stock of vehicles, two restrictions are placed on the sample. First, since we are focusing on passenger vehicles, a quarterly observation for a household is included in our sample only if it does not own a truck, van, or motorcycle in that quarter. Second, for our cost regressions, the sample was restricted to households that did not buy or sell a car in that quarter. This is because the CEX does not indicate at what date the household incurs the expenses. As a result, one is unable to decompose household expenses when the household’s stock of vehicles is changing within a quarter.

Additional restrictions are placed on the dataset to suit our estimation needs. First, a quarterly observation for a household is included only if each of the household’s passenger cars is manufactured by one of the automakers listed in Table 1. Some of the manufacturer brand names have been combined for simplicity. We aggregate Cadillac and Lincoln into “American Luxury,” Infiniti and Lexus into “Japanese Luxury,” and Audi, BMW, Jaguar, Mercedes-Benz, Porsche, and Saab into “European Luxury.” Honda and Acura vehicles are consolidated into one brand category as well as Mitsubishi and Eagle vehicles. Rarer brands like Peugeot, Isuzu, and Kia are combined to form the “Other” category. Second, we include only vehicles that were manufactured after 1985 because, in related work, we merge these data with Kelly Blue Book price data, which are available only back to 1986. Table 2 provides information on the age

distribution of the vehicles included in the sample.

Brand	# Obs	Brand	# Obs	Brand	# Obs
Buick	1159	Mazda	538	Subaru	287
Chevrolet	2132	Mercury	753	Toyota	1641
Chrysler	466	Mitsubishi	279	Volkswagen	281
Dodge	862	Nissan	1006	Volvo	192
Ford	2565	Oldsmobile	1148	American Luxury	640
Geo	273	Plymouth	513	European Luxury	343
Honda	1923	Pontiac	1136	Japanese Luxury	61
Hyundai	277	Saturn	247	Other	60

Notes:

1. “American Luxury” includes Cadillac and Lincoln.
2. “European Luxury” includes Audi, BMW, Jaguar, Mercedes Benz, Porsche, and Saab.
3. “Japanese Luxury” includes Infinity and Lexus.
4. “Other” includes Isuzu, Kia, and Peugeot.

Age	# Obs	Age	# Obs	Age	# Obs
1 Year	3014	5 Years	2020	10 Years	715
2 Years	2293	6 Years	1732	11 Years	524
3 Years	2172	7 Years	1432	12 Years	328
4 Years	2216	8 Years	1225	13 Years	5657
		9 Years	965		

Given these restrictions, the sample consists of 34126 interviews of 14171 households between 1988 and 1999. Table 3 reports the sample moments of the data. The average household in the sample owns 1.2 cars with four households owning six vehicles. Quarterly household expenditures on car related items vary from as little as \$0 to as high as \$10999 (in 1999 dollars). Finally, the median age of the cars in the sample is 5 years. This is 1 to 2 years younger than the median age of cars operating in the U.S. in the last two decades (Ward’s Automotive Yearbook, 2001).²

²The distribution of vehicle age differs for two reasons. First, the sample of households in the CEX is not representative of the U.S. without using population weights. Because we do not use these weights, we lose any correlation between household characteristics, such as income and family size, and the true distribution of vehicle age. Second, we drop from the sample any household that own a vehicle produced before 1986 because we only had price data for these model-years. Therefore, this sample criterion truncates the distribution of vehicle age, especially earlier in the sample period.

We also observe some demographic information for each household. Ninety-four percent of the households live in an urban area. The average household has 1.66 drivers. Almost 10 percent have at least three drivers in the household, with 1 household having 8 drivers. Because we observe the household's stock of vehicles, we calculate the number of drivers per vehicle. This captures some of the variation in vehicle expenses across households due to driving intensity. In the sample constructed, 61% of the households have 1 driver per vehicle owned and about 5% have at least 3 drivers per vehicle.

Variable	Mean	Std Dev
Vehicle Characteristics		
Age	4.96	2.98
Household Characteristics		
Income (in \$1000)	38.5	31.2
Urban	0.94	0.24
# of Drivers	1.66	0.74
# of Drivers per car	1.41	0.65
# of Cars owned	1.24	0.48
Total Real Quarterly Expenditures on Vehicles	475.40	498.56
# Observations (household quarters)	34126	
# Households	14171	
No. of Vehicles Owned by Households	18782	

The household's income bracket is the final demographic variable observed. We match these discrete data with continuous income information from the Current Population Survey. From these survey data, we construct the mean income for each income bracket in every year of the sample. The average income for households in the sample is \$38545. Household income is observed to be as high as \$120685 and as low as \$1652.

4 Cost Regressions

Automobile cost profiles are created to determine if unobservable spending on vehicles drives selling decisions. In this section, we present the methodology used to decompose household automobile spending by brand and age. Several alternative specifications are tested. Furthermore, coefficients for each of the specifications are estimated using three different regression techniques, one of which controls for bias due to outliers and another that controls for a potential bias due to selection. After establishing which model and regression technique best predicts household spending, we discuss the results and their implications for understanding how costs vary by brand and age. Finally, we explore how cost per mile changes across a vehicle's life and how this affects our interpretation of our results.

4.1 Methodology

Let c_{it} be total maintenance expenditure of household i in quarter t . Let d_{itmjs} be a dummy for whether the m th car owned by household i in quarter t is a brand j car of age s . Let

$$n_{itj}^b = \sum_{m,s} d_{itmjs}$$

be the number of cars of brand j owned by i at t ,

$$n_{its}^a = \sum_{m,j} d_{itmjs}$$

be the number of cars of age s owned by i at t , and

$$n_{itjs}^{ab} = \sum_m d_{itmjs}$$

be the number of cars of age s of brand j owned by i at t .

We estimate a variety of different specifications of cost. The first specification is

$$c_{it} = \gamma_0 + \sum_j \gamma_j^b n_{itj}^b + \sum_s \gamma_s^a n_{its}^a + \sum_{j,s} \gamma_{js}^{ab} n_{itjs}^{ab} + \gamma_t + e_{it} \quad (1)$$

with appropriate exclusions necessary for identification.³ Also, we consider two specifications allowing for model-year effects. Let

$$n_{itjy}^{bc} = \sum_m d_{itmjy}$$

be the number of cars of brand j and model-year (manufacture year) y owned by household i at time t , and

$$n_{ity}^c = \sum_j n_{itjy}^{bc}$$

be the sum over brands. Then two specifications with model-year effects are

$$\begin{aligned} c_{it} = & \gamma_0 + \sum_j \gamma_j^b n_{itj}^b + \sum_s \gamma_s^a n_{its}^a + \sum_{j,s} \gamma_{js}^{ab} n_{itjs}^{ab} + \sum_y \gamma_y^c n_{ity}^c \\ & + \sum_{j,y} \gamma_{jy}^{bc} n_{itjy}^{bc} + \gamma_t + e_{it} \end{aligned} \quad (2)$$

and

$$c_{it} = \gamma_0 + \sum_j \gamma_j^b n_{itj}^b + \sum_s \gamma_s^a n_{its}^a + \sum_{j,s} \gamma_{js}^{ab} n_{itjs}^{ab} + \sum_y \gamma_y^c n_{ity}^c + \gamma_t + e_{it}, \quad (3)$$

³We also replace the interaction terms in equation (1) with spline effects (with nodes at 5 and 11 years of age) to reduce the number of parameters to estimate. Restrictions implied by the spline specification are rejected.

again with appropriate exclusions necessary for identification. Once a single brand, age, and model-year are treated as bases, all remaining coefficients are identified. As before, we replace the interaction terms in equation (2) with spline effects (with nodes at model-year 1991 and 1997).

All coefficients are estimated with ordinary least squares (OLS), quantile regression, and an adjusted quantile regression method that controls for selection bias. Relative to quantile regression, OLS gives undue weight to outliers. As Berkovec (1985) suggests, a selection bias problem may emerge because cars that suddenly require large maintenance expenditures may be sold or scrapped. Dropping observations where households sell or scrap vehicles may bias the estimates. We control for this by assuming that the maintenance cost associated with a car just sold (or scrapped) had it not been sold (or scrapped) is B where B is a large outlier. If we add these outliers to the data and estimate the model with quantile regression, then assuming that the cost is B is equivalent to assuming the cost is larger than the median cost of cars with the same observable characteristics. Thus, the adjusted quantile regression estimates make an “upper bound” assumption about the maintenance costs associated with cars sold or scrapped.

4.2 Results

Table 4 reports parameter estimates for the three different specifications for cost: equation (1) with brand-age spline effects, equation (2) with brand-age and brand-model-year spline effects, and equation (3) with brand-age spline and model-year effects.⁴ There are 34126 observations, and so almost all coefficient estimates are significant at standard levels. Because there are too many variables to report, only coefficients for the brand and age variables (but not the interactive terms nor the spline terms) are listed. There are 24 car brands, so we show only a subset of “representative brands:” Buick for American non-luxury; Honda for Japanese non-luxury; Volkswagen for European non-luxury; and the three luxury brands. We also report a subset of “representative ages” to demonstrate how costs vary by vehicle age. Finally, only the OLS parameter estimates are given. This simplifies the discussion of which specification best matches the data. Then, once this is established, we discuss the merits of the three alternative regression techniques, OLS, quantile regression, and adjusted quantile regression, that were used to estimate coefficients.

⁴Variations of these three cost specifications are estimated as well. For example, one of the regression specifications includes brand-age interaction terms as well as brand-model spline effects.

Variable	Equation 1	Equation 2	Equation 3
Constant	42.43** (16.87)	-4.96 (17.80)	42.86** (16.78)
Brand Effects			
Buick	-145.68** (34.43)	-130.11** (38.034)	-150.33** (32.32)
Honda	-84.77** (32.48)	-64.42* (38.10)	-82.57** (32.37)
Volkswagen	-82.47** (39.14)	-43.75 (44.20)	-66.05* (39.01)
American Luxury	-148.92** (38.89)	-196.59** (46.68)	-142.20** (38.80)
Japanese Luxury	-18.38 (80.81)	-57.96 (91.96)	-76.91 (80.62)

The demographic variables influence household automobile expenses similarly irrespective of the specification used. Namely, living in an urban area raises expenditures approximately \$50. This captures the higher prices households pay for automobile related items in urban areas. Each additional driver per vehicle raises household expenditures approximately \$30. The greater intensity in driving induces households to spend more on their vehicles.

According to equation (1)'s specification for cost, automobile expenditures rise by \$330 for every three year old vehicle a household owns (holding constant its brand and model-year). Vehicle costs rise with age, first peaking around age 5, dropping in year 7, steadily rising until year 10, and then dropping again. This observed fluctuation in spending across vehicle age is as expected. In the first five years, most routine maintenance work is minor such as tune-ups and oil changes. Then, around the fifth year, depending on driving intensity, vehicles require more expensive, more labor intensive routine maintenance work such as replacing of the timing belts and servicing the transmission.⁵ The more expensive routine maintenance work is incurred again 5 years later.

When one controls for model-year effects as in the second and third specification, the magnitude of the age effect drops across all vehicle ages. The drop is even greater when the model-year effect is modeled to be constant across brands of the same model-year. This implies that the age effects in equation (1) pick up some of the variation in automobile expenses across model-year.

⁵For example, one replaces the timing belts and services the transmission around 60000 miles. If the average household drives 12000 miles in a year, then these maintenance activities are done approximately every 5 years. (Ward's Motor Vehicle Facts and Figures)

Table 4 (continued)			
Variable	Equation 1	Equation 2	Equation 3
Age Effects			
Age 3	329.82** (32.16)	305.07** (37.34)	271.13** (32.72)
Age 4	367.59** (32.46)	353.64** (37.56)	312.79** (32.96)
Age 5	390.35** (33.11)	386.36** (38.15)	343.12** (33.61)
Age 7	388.37** (32.77)	371.46** (37.89)	346.55** (33.28)
Age 10	454.07** (35.02)	414.77** (39.72)	418.57** (35.42)
Age 12	366.87** (39.22)	327.59** (43.48)	336.55** (39.45)
Age 13	248.89** (51.83)	224.33** (55.13)	225.99** (51.69)
Adjusted R^2	0.130	0.136	.137

Notes:

1. Numbers in parentheses are standard errors.
2. Single starred items are statistically significant at the 10% level, and double starred items are statistically significant at the 5% level.
3. The variables associated with the brand effects are, for example, the number of Buick vehicles that the household owns in the relevant quarter.
4. The variables associated with the age effects are, for example, the number of vehicles the household owns in the relevant quarter that are 3 years old.
5. The “European Luxury” variable is the base brand, and thus all brand coefficients are relative to it.

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Returning to equation (1)’s specification for cost, we find that automobile expenditures drop by \$146 for every Buick a household owns (regardless of its age and model-year).⁶ On the other hand, each additional Honda a household owns only lowers expenditures by \$85. We predict Hondas are more expensive to maintain than Buicks under all three specifications for costs. This prediction counters our initial priors. It is commonly believed that Hondas are of higher quality, and one has to spend less to maintain these vehicles. However, the estimated coefficients are consistent with the data. Households that own only one vehicle (and thus all expenses can be attributed to that vehicle) spend on

⁶The cost of operating a vehicle is positive when one takes into account age of the vehicle and all terms interacted with brand

average \$81 more on their Hondas than on their Buicks.⁷ This can be explained by the fact that the CEX tracks what households spend on their vehicles and not what they should spend on their vehicles to maintain car quality. The unexpected cost of Hondas relative to Buicks may suggest that Hondas have a high resale value (i.e., low depreciation rate) because the households who purchase them spend more on maintaining their vehicles, and thus, once they sell them, the cars are of higher quality.⁸

As is evident in Table 4, the magnitude of the additional costs varies by the specification used. When one controls for model-year effects, the additional cost of a non-luxury vehicle is higher. The reverse is true for luxury vehicles. Thus, without model-year effects, one underestimates (overestimates) the expenses associated with owning an additional non-luxury (luxury) vehicle.

Although the magnitude of the effects may change with specifications, all three specifications have similar predictions for ranking of relative costs across brands and vehicle ages. We choose the second specification, the one that includes both brand-age and brand-model-year spline effects, to decompose household expenditures on automobiles. However, we restrict brand-age effects to be the same within American non-luxury brands (i.e., Chevrolet, Chrysler, Dodge, Ford, Geo, Mercury, Oldsmobile, Plymouth, Pontiac, and Saturn), within Japanese non-luxury brands, and within European non-luxury brands to save on degrees of freedom.⁹ This allows identification of how automobile expenses vary across age and model-year with more precision. Thus, the rest of the discussion will focus on the results based on the second specification for cost.

The brand and age coefficients by themselves provide limited information because of all of the interacted variables. Combining the coefficients, however, allows us to quantify the marginal effect of adding another vehicle to the household's stock. For example, operating a 7 year old 1992 Honda (holding all else constant) lowers a household's expenditures by \$42 dollars.¹⁰ This is \$60 higher than if one operates a Buick of the same vintage and age. As discussed previously, this result is consistent with the data. Households with one vehicle spend more on their 7 year old Hondas than Buicks for every model-year with exception of the 1988 model-year. As expected, the luxury vehicles are substantially

⁷Expenditures on Hondas verses Buicks when controlling for age and model year are examined later in this section.

⁸Alternatively, one might argue that Hondas are more costly to maintain; imported vehicles have more expensive parts and higher labor costs because there are fewer shops qualified to repair them. Yet, Hondas (and many other non-luxury Japanese vehicles) are different from other import vehicles like BMWs and Volvos. Hondas have a sizeable market presence in the U.S. On average, Hondas alone account for 9% of the car market over the sample period. This is higher than for the total imported luxury market. Furthermore if one combines Honda, Nissan, and Toyota, the market share is almost a quarter of U.S. sales. Their high popularity has increased the supply of shops to repair them, making their maintenance costs similar to domestic vehicles'.

⁹When we allow for a complete set of brand specific age interactions, all coefficients become statistically insignificant.

¹⁰The factors held constant are the non-interacted age effect, the household's demographic variables, and the stock and composition of the other vehicles owned by the household.

more expensive to maintain and operate.

Table 5 Additional Automobile Expenses of Owning a Variety of Branded Vehicles						
Brand Name	OLS Parameter Estimates					Marginal Effect
	Brand Effect	Brand Interaction Effects				
		Age (node 1)	Age (node 2)	Model-Year (node 1)	Model-Year (node 2)	
Buick	-130.11** (38.04)	-17.66** (3.95)	11.64** (4.41)	3.74** (1.61)	11.64** (1.03)	-102.87
Honda	-64.42* (38.10)	-21.92** (4.63)	20.01** (5.17)	3.45** (1.93)	11.79** (1.38)	-42.42
American Luxury	-196.59** (46.68)	-30.45** (10.41)	13.84 (9.82)	26.53 (5.03)	10.80** (4.28)	22.12
European Luxury	0.00	-44.45** (14.29)	22.47* (12.76)	24.54** (7.61)	6.33 (5.43)	7.91

Notes:

1. Coefficients are for a 1992 vehicle that is 7 years old.
2. The coefficient on European Luxury is defined to be zero for identification purposes.
3. Numbers in parentheses are standard errors.
4. Single starred items are statistically significant at the 10% level, and double starred items are statistically significant at the 5% level.
5. The marginal cost of owning another vehicle of given brand is the sum of the brand effects and the brand-age and brand-model spline effects. It can be represented as

$$\gamma_j^b + \gamma_{js}^{ab,1} \tau_1^s + \gamma_{js}^{ab,2} (s - \tau_1^s) + \gamma_{jy}^{bc,1} \tau_1^m + \gamma_{jy}^{bc,2} (m - \tau_1^m)$$

where $\tau_1^s = 5$ (node 1 for brand-age spline effects), $\tau_1^m = 6$ (node 1 for brand-model-year spline effects), $\gamma_{js}^{ab,1}$ and $\gamma_{js}^{ab,2}$ are first and second brand-age spline slopes, $\gamma_{jy}^{bc,1}$ and $\gamma_{jy}^{bc,2}$ are first and second brand-model-year spline slopes, $m = 12$ (1992 model-year), and $s = 7$ (age).

Table 6 Additional Cost of Owning Honda Vehicles					
Age	OLS Parameter Estimates				Marginal Effect
	Age	Age Interaction Effects			
		Node 1	Node 2	Node 3	
3 Years	305.07** (37.34)	-21.92** (4.63)			239.31
5 Years	386.36** (38.15)	-21.92** (4.63)			276.76
7 Years	371.46** (37.89)	-21.92** (4.63)	20.01** (5.17)		301.88
10 Years	414.77** (39.72)	-21.92** (4.63)	20.01** (5.17)		405.22
12Years	327.59** (43.48)	-21.92** (4.63)	20.01** (5.17)	12.33 (32.72)	350.38

Notes:

1. Numbers in parentheses are standard errors.
2. Single starred items are statistically significant at the 10% level, and double starred items are statistically significant at the 5% level.
3. The marginal cost of owning another Honda of a given age is the sum of the brand and brand-age spline effects. It can be represented as

$$\begin{aligned} & \gamma_j^a + 1 (s < 6) \gamma_{js}^{ab,1} s + 1 (6 \leq s < 12) \left[\gamma_{js}^{ab,1} \tau_1^s + \gamma_{js}^{ab,2} (s - \tau_1^s) \right] \\ & + 1 (12 \leq s) \left[\gamma_{js}^{ab,1} \tau_1^s + \gamma_{js}^{ab,2} (\tau_2^s - \tau_1^s) + \gamma_{js}^{ab,3} (s - \tau_2^s) \right] \end{aligned}$$

where $\tau_1^s = 5$ and $\tau_2^s = 11$ are node 1 and node 2 for brand-age spline effects, and s is the age of the vehicle.

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The brand coefficients suggest that automobile-related expenditures fall when households add to their stock of vehicles. These figures, however, hold constant the vehicle's age and thus do not reflect the total additional costs associated with both age and brand name simultaneously. Table 6 reports the additional costs of operating another Honda vehicle at various ages. The costs associated with age are positive and large enough to outweigh the additional costs associated with brand name alone. This is true for all brands. The variation in costs across alternatively aged vehicles is important to prospective buyers. They compare each car's full cost (sticker price plus discounted operating costs) when deciding which vehicle to purchase.

The previous tables provide insight on household expenditures for a particular model-year and/or vehicle age. We also have constructed graphs to

demonstrate that those results still hold for other model-years and vehicle ages. There are 24 car brands, so we show only a subset of “representative brands.” For each representative brand, we show two figures and six curves. The first figure, labeled “Age Effects,” shows how total maintenance cost changes with age given the coefficient estimates from the specification in equation (1). For a particular brand j , this graphs $\hat{\gamma}_0 + \hat{\gamma}_j^b + \hat{\gamma}_s^a + \hat{\gamma}_{js}^{ab}$ as s varies from 1 to 13. There are three different sets of estimates: OLS estimates, quantile regression estimates, and adjusted quantile regression estimates. The second, labeled “Model Year Effects,” shows how model-year effects change over time with the coefficient estimates from the specification in equation (3). This graphs $\hat{\gamma}_y^c$ as y varies from 1987 to 1999.

The first cost pattern, displayed in Figures 1 and 2, is the “Buick” pattern. Buick car maintenance costs rise with age until age 10 and then fall. Adjusting for selection has no economically significant effect on the shape of the curve. While such a pattern may seem implausible, Pickrell and Schimek (1999) and Engers, Hartmann, and Stern (2004a) (EHSa) suggest that the cost reductions may be due to significant reductions in usage of the car, thus requiring lower maintenance costs. Also, insurance costs decline with age. Model-year effects generally rise with year, and selection correction has no economically significant effect. Vehicles have become more expensive to maintain as engines have become more sophisticated. Much of the routine maintenance work that was once considered simple can no longer be done at home. Servicing newer models requires more training and specialized equipment. By construction, the other American non-luxury brands, Chevrolet, Chrysler, Dodge, Ford, Geo, Mercury, Oldsmobile, Plymouth, Pontiac, and Saturn, follow the “Buick pattern.”

The next pattern, displayed in Figures 3 and 4, is the “Honda” pattern. The Honda age and model-year effects are similar to the “Buick” pattern. By construction, other brands following the “Honda” pattern are Hyundai, Mazda, Mitsubishi, Nissan, Subaru, and Toyota.

The “Volkswagen” pattern, displayed in Figures 5 and 6, is somewhat different from the “Buick” and “Honda” pattern. There is still an increase in cost followed by a reduction around age 10 but only for the OLS estimates. For the quantile estimates and the adjusted quantile estimates, the cost reduction disappears and is replaced by a leveling off of cost. However, this does not look like a selection effect as the quantile estimates and the adjusted quantile estimates are very similar. Possibly Volkswagen owners, unlike other brand owners, do not significantly reduce the amount they drive their vehicles as their vehicles age. As a result, their expenditures do not drop with age but level off. Model-year effects generally decline (in contrast to the “Buick” and “Honda” model-year effects) except for an increase in late years using the adjusted quantile estimates. By construction, Volvo follows the same pattern. As with all vehicles, engines in Volkswagens and Volvos have become more sophisticated over the years and thus are more costly to maintain. Still, we observe model-year effects declining after 1993. This suggests that variation in car quality across model-years dominates the increase in costs due to technological advancements. For example,

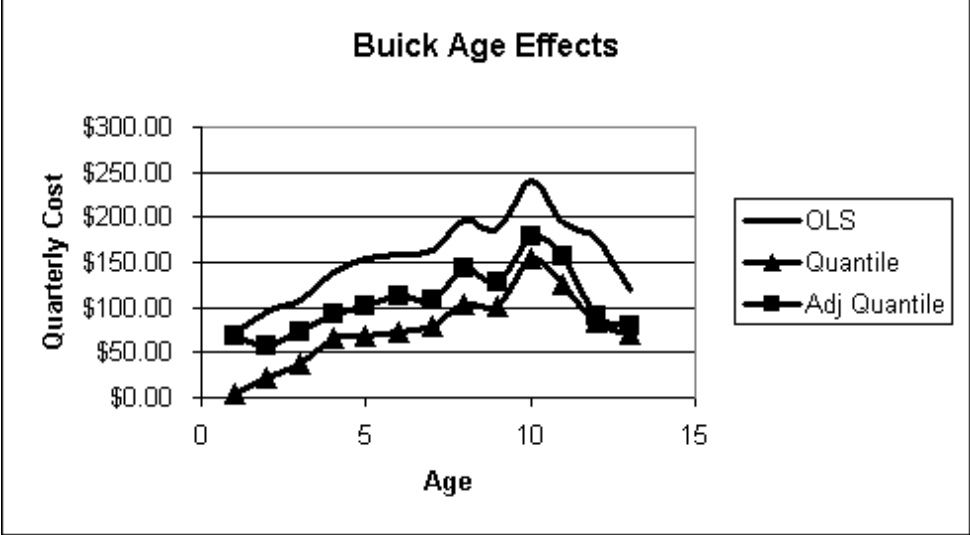


Figure 1:

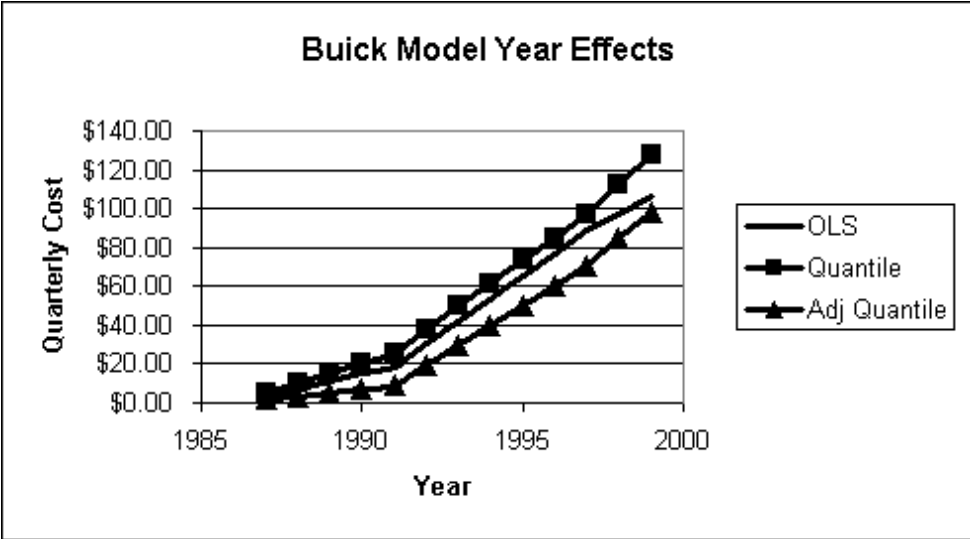


Figure 2:

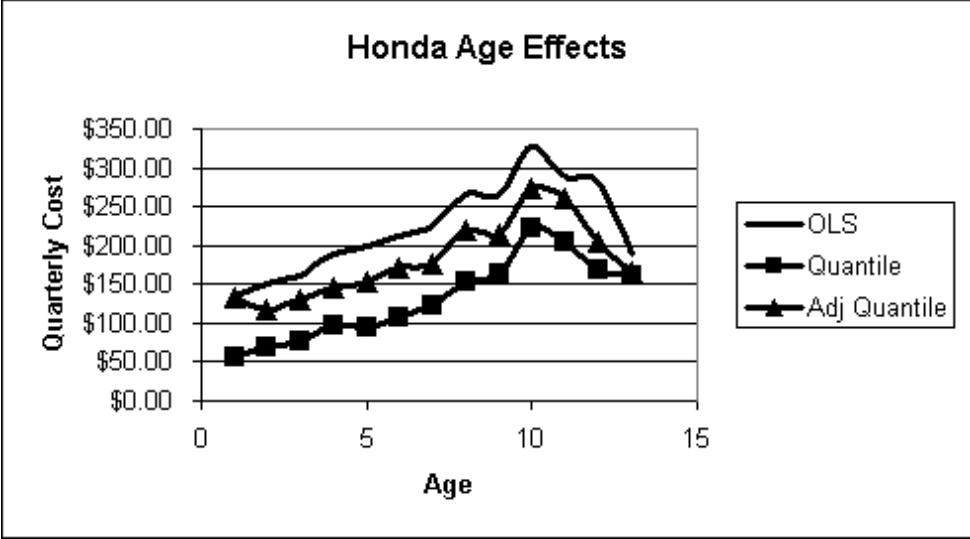


Figure 3:

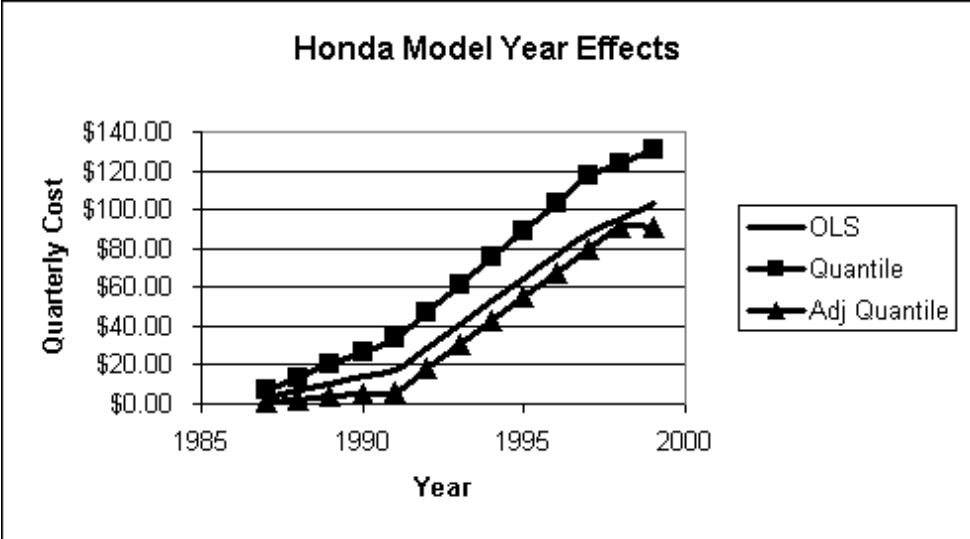


Figure 4:

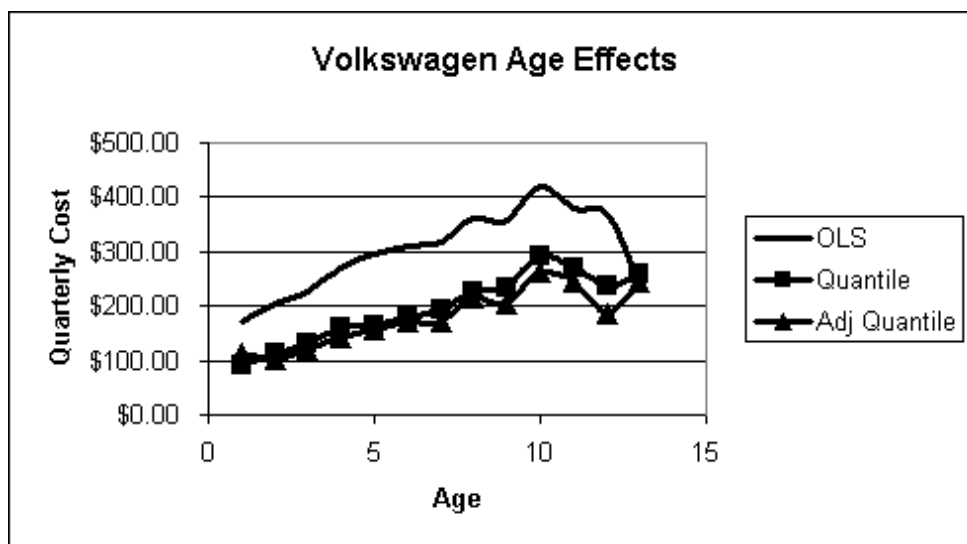


Figure 5:

Volkswagen had difficulties with its production process in the late 1980s and early 1990s.¹¹ Quality of their vehicles rose (i.e., fewer reported car problems) when these production problems were addressed, potentially lowering the costs of operating a Volkswagen.

The “American Luxury” pattern, displayed in Figures 7 and 8, is generally rising though there are some large fluctuations in age effects in later years probably due to small sample sizes. The three age effect curves have similar shapes. The model-year effects are all rising though second order effects differ with the inclusion of selection correction.

The “Japanese Luxury” pattern, displayed in Figures 9 and 10, is generally rising, both in age effects and model-year effects. Here, the selection correction has a large effect on the estimated increase in age effects and model-year effects.

The “European Luxury” pattern, displayed in Figures 11 and 12, is generally rising in age effects with a modest reduction after age 10. This is true for all three estimates. The model-year effects rise until 1997 and then fall dramatically, especially for the selection corrected estimates.

While the effects of selection correction on age and model-year profiles are mixed, the selection effect on brand effects, displayed in Figures 13 and 14, is quite clear. In all but two cases (Mercury and Toyota), quantile estimates and

¹¹Volkswagen shifted production from their unprofitable plant in the U.S. to Mexico in mid-1988. They also faced a series of assembly plant and supplier strikes in their Brazil production plants. Finally, Volkswagen was still working through the aftereffects of a 1991 shake-up of mid-level management two years later (Ward’s Automotive Yearbook, various editions).

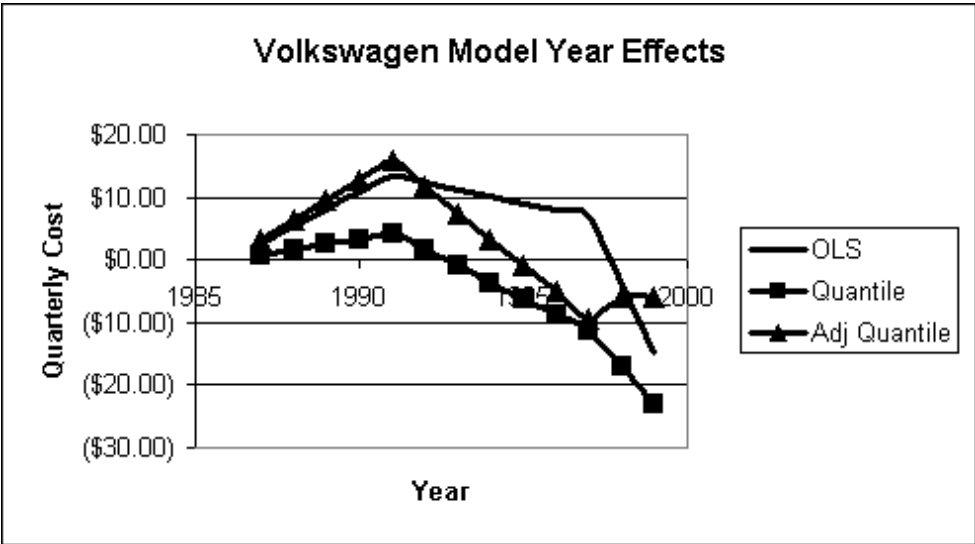


Figure 6:

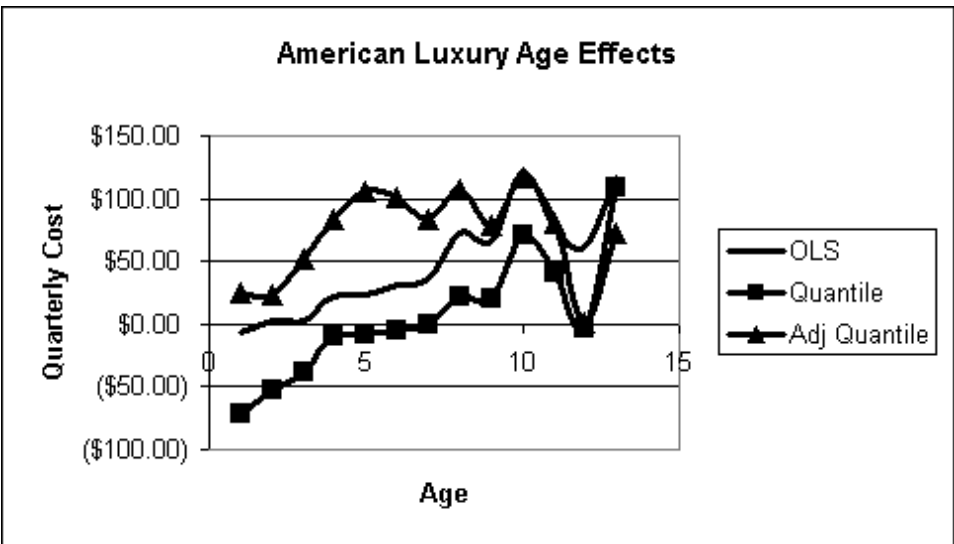


Figure 7:

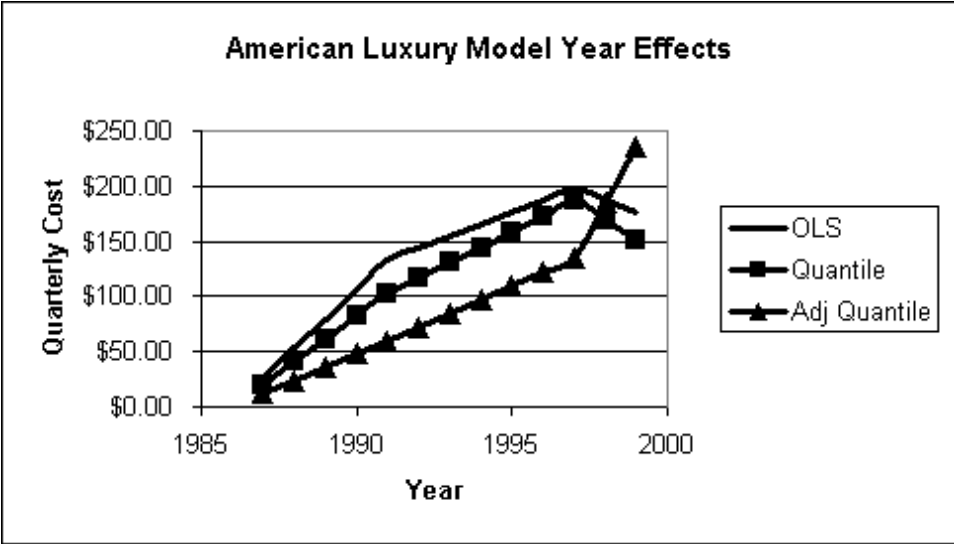


Figure 8:

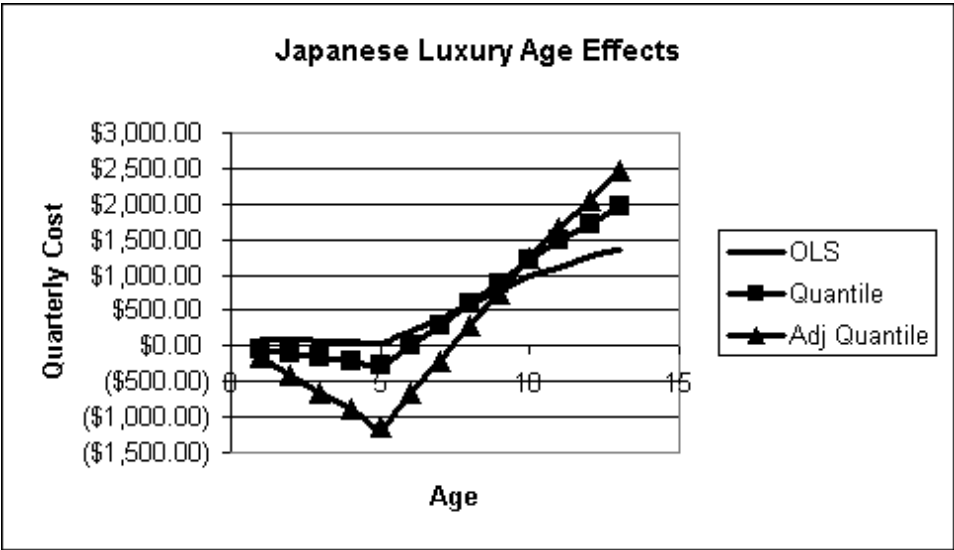


Figure 9:

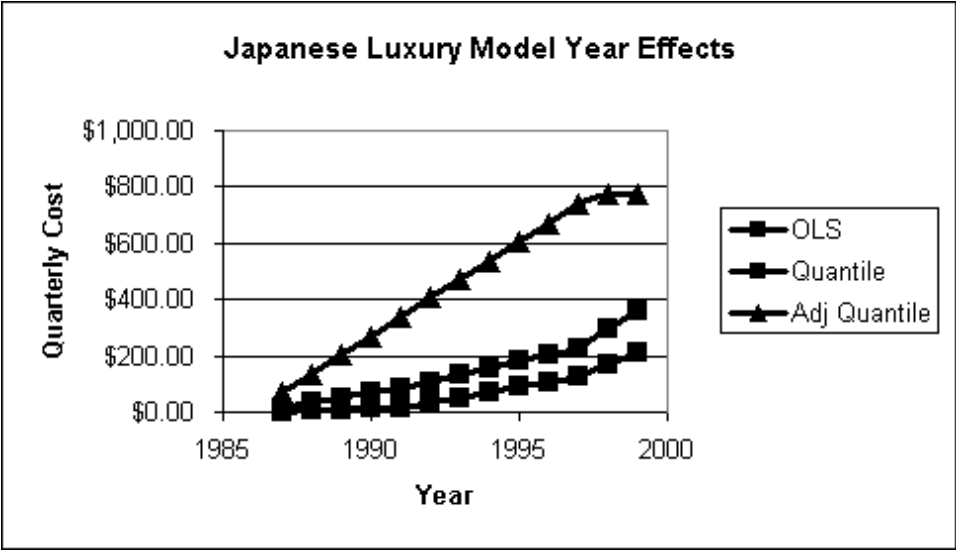


Figure 10:

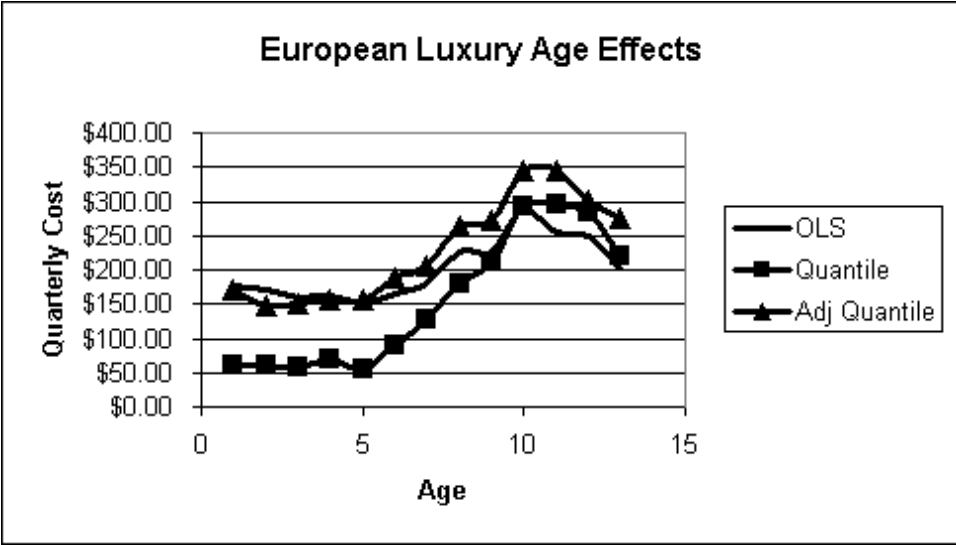


Figure 11:

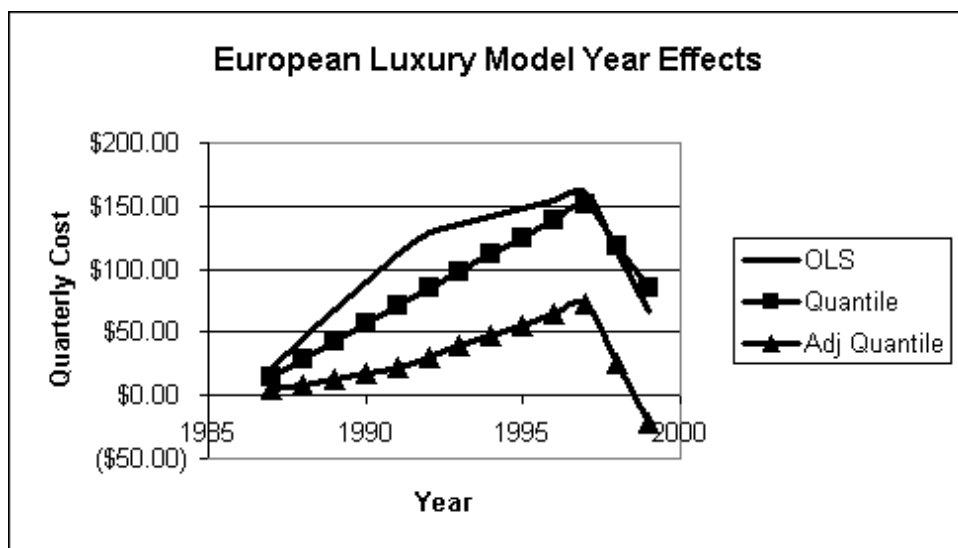


Figure 12:

adjusted quantile estimates of brand effects are larger than OLS estimates. In almost all cases, quantile estimates are larger than adjusted quantile estimates.

In the next section, we use the predicted observed and unobserved costs to explain the household’s decision to sell a vehicle. The estimates based on the quantile regression technique are chosen over the other two. This estimation method is robust with respect to the existence of outliers in the cost data. But, unlike the adjusted quantile technique, it does not correct for a selection bias problem. For both the American and Japanese non-luxury vehicles, correcting for a selection bias problem does not change the shape of either the age or model-year curves. This is also true for European vehicles with the exception of the late model non-luxury ones. The selection correction does affect the pattern of costs across model-year for the “American Luxury” vehicles. The quantile regression estimates are consistent with observations at the aggregate level that operating costs have been rising at a decreasing rate for vehicles produced between 1989 and 2001 (Ward’s Automotive Yearbook, 2001).¹² Finally, even though the selection correction affects the pattern of costs across model-year for the “American Luxury” vehicles, its predictions are not consistent with aggregate data. Operating costs have been rising over time at a decreasing rate for vehicles produced between 1989 and 2001. This pattern is predicted with the quantile regression. Thus, the quantile regression was chosen either

¹²Ward’s Automotive Yearbook does not report this information for vehicles produced before 1989. Despite lacking data on all model-years, we still expect operating costs to rise across all model-years in the sample.

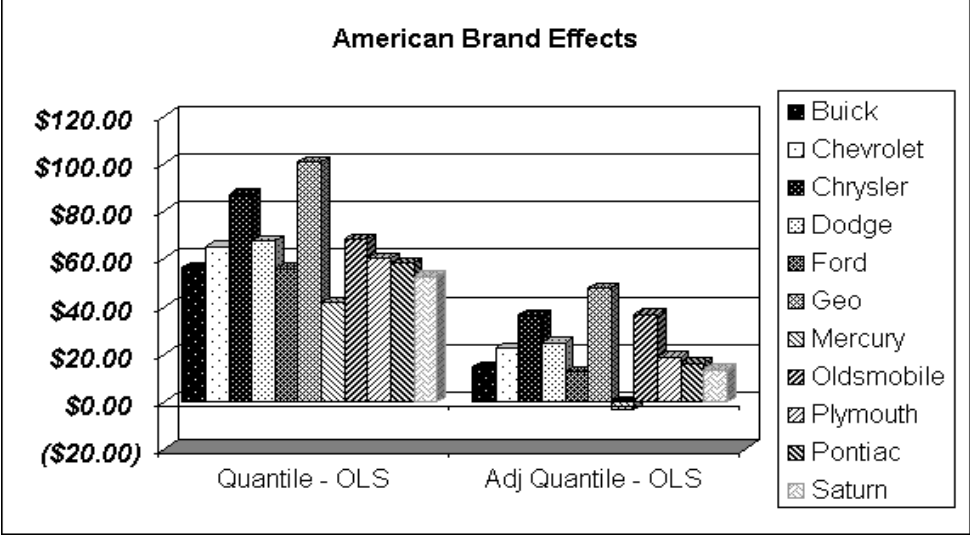


Figure 13:

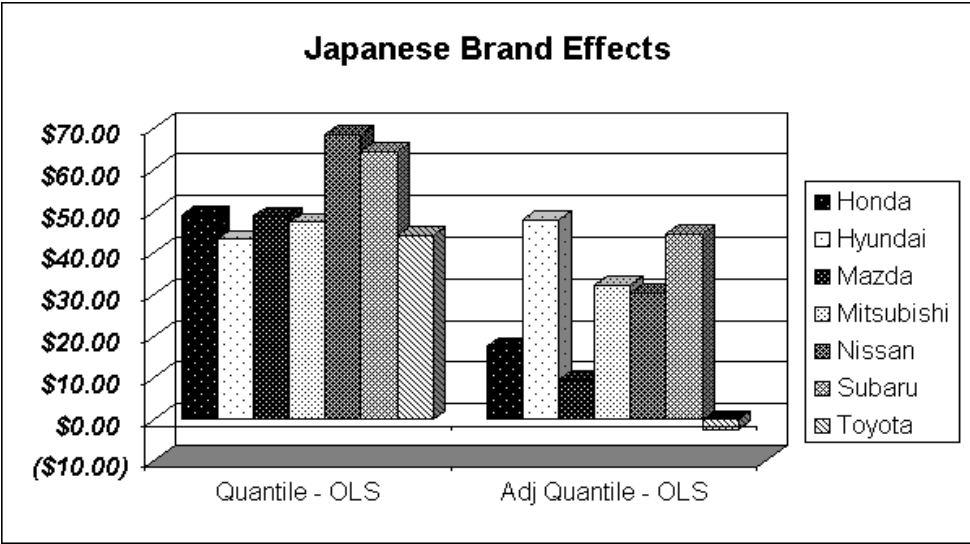


Figure 14:

because correcting for the selection error does not change the pattern of costs or it changes it in a way that is not consistent with the patterns observed using aggregate data.

4.3 Changes in Cost per Mile

It is well known that used car prices decline with the age of the car (see, for example, EHSa). A simple model of car prices would suggest

$$\pi_{js} = u_{js} - c_{js} + \delta\pi_{js+1}$$

where π_{js} is the (average) price of a brand j car at age s , u_{js} is the average dollar value of the flow of services, c_{js} is the maintenance cost, and δ is a one period discount factor. Either u_{js} must ultimately be declining in s or c_{js} must ultimately be increasing in s to explain π_{js} declining in s . In fact, the estimated cost curves suggest that for most brands, cost is increasing up until about ten years of age. At that point, with a few exceptions, costs start to decline. Thus, it would be difficult for changes in maintenance cost to explain used car prices, especially late in a car's life. Furthermore, for all cases there are no steep increases in cost after the first year. Thus, cost can not explain the steep decline in the price of a car in the first year.

Another possibility is that u_{js} is declining in s . If a good proxy for u_{js} is mileage, then evidence in Pickrell and Schimek (1999) and EHSa is consistent with such a story. Furthermore, while cost per quarter may be declining with age, maybe cost per mile is not. Using the structural estimates of the effects of aging on miles driven in EHSa, we can construct a brand-specific age profile of miles driven per year. We can combine this with our estimates of how maintenance costs change with age to construct a profile of how maintenance costs per mile change with age. In EHSa, we find that miles driven per year decline with age. So a significant part of the downturn in maintenance costs visible in Figures 1, 3, 5, and 11 can be explained by reductions in usage of the car. For example, Figure 15 shows that, while cost per quarter decline significantly for Buicks after age 10, cost per mile declines as well but by a much smaller amount. In fact, for most brands,¹³ while cost per quarter declines after age 10, cost per mile plateaus but does not decline.

5 Sales

Now that we have established the shape of the cost profiles by brand and age, we can proceed to examine whether unobserved automobile costs drive selling decisions. In this section, we present a model of the decision to sell (or scrap) as

¹³Cost per quarter year and cost per mile, disaggregated by brand is available for all brands at <http://faculty.virginia.edu/stevenstern/resint/empiofstf/carcosts/carcosts.html>. Brands with plateauing cost per mile include Chevrolet, Plymouth, Pontiac, Saturn, Ford, Mercury, Chrysler, Dodge, Japanese Luxury, and Nissan. The other brands have slowly declining cost per mile.

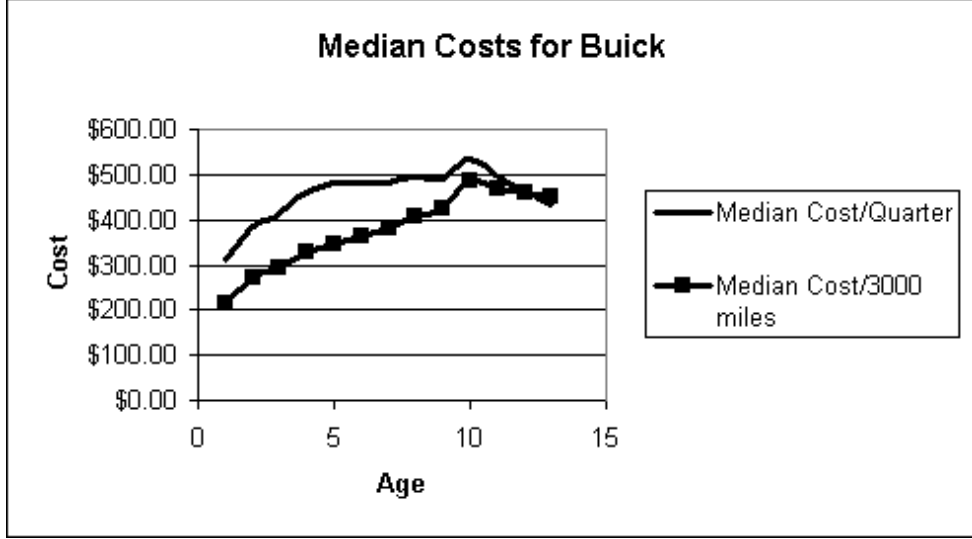


Figure 15:

a function of the vehicle's age, observed and unobserved costs, and interactive terms. The methodology to decompose the costs into observed and unobserved components is described. If we were to find that unobserved costs predict selling behavior, this would be evidence of adverse selection in the used car market.

5.1 Methodology

Let p_{ijt}^* be the net value to household i of selling (or scrapping) car j at time t . Let

$$\begin{aligned}
 p_{ijt}^* = & \beta_0 + \xi_{b_{ijt}} + \beta_1 \Delta c_{ijt}^o + \beta_2 \Delta c_{ijt}^u + \beta_3 a_{ijt} + \beta_4 1(a_{ijt} \geq 5) a_{ijt} \quad (4) \\
 & + \beta_5 a_{ijt} \Delta c_{ijt}^o + \beta_6 1(a_{ijt} \geq 5) a_{ijt} \Delta c_{ijt}^o + \beta_7 a_{ijt} \Delta c_{ijt}^u + \\
 & \beta_8 1(a_{ijt} \geq 5) a_{ijt} \Delta c_{ijt}^u + \varepsilon_{ijt}
 \end{aligned}$$

where b_{ijt} is the brand of car j , c_{ijt}^o is the component of total cost of car j at time t predicted by observed car characteristics (predicted cost from our cost regression), c_{ijt}^u is the component of total cost of car j at time t orthogonal (unobserved) to observed car characteristics (the residual from our cost regression),

$$\Delta c_{ijt}^k = c_{ijt-1}^k - c_{ijt-2}^k$$

for $k = o, u$, a_{ijt} is the age of car j at time t , and ε_{ijt} is a random error, $\varepsilon_{ijt} \sim iidN(0, \sigma_\varepsilon^2)$.¹⁴ Without loss of generality, we can set $\sigma_\varepsilon^2 = 1$ (because

¹⁴We also considered specifying equation (4) in terms of c_{ijt-1}^o and c_{ijt-1}^u rather than Δc_{ijt}^o and Δc_{ijt}^u . However, such a specification would require household and car specific

we observe only a discrete indicator of p_{ijt}^*). It will be useful to rewrite equation (4) as

$$p_{ijt}^* = P_{ijt}^* (\Delta c_{ijt}^u) + \varepsilon_{ijt}$$

where

$$\begin{aligned} P_{ijt}^* (\Delta c_{ijt}^u) &= \beta_0 + \xi_{b_{ijt}} + \beta_1 \Delta c_{ijt}^o + \beta_2 \Delta c_{ijt}^u + \beta_3 a_{ijt} + \beta_4 1(a_{ijt} \geq 5) a_{ijt} \\ &\quad + \beta_5 a_{ijt} \Delta c_{ijt}^o + \beta_6 1(a_{ijt} \geq 5) a_{ijt} \Delta c_{ijt}^o + \beta_7 a_{ijt} \Delta c_{ijt}^u \\ &\quad + \beta_8 1(a_{ijt} \geq 5) a_{ijt} \Delta c_{ijt}^u. \end{aligned}$$

Let p_{ijt} be an indicator of whether household i sells car j at time t ,

$$p_{ijt} = 1(p_{ijt}^* > 0).$$

We observe

$$\{x_{i1t}, x_{i2t}, \dots, x_{iJ_{it}}, \Delta c_{it}^u\}_{t=1}^T$$

for each household i where $x_{ijt} = (b_{ijt}, a_{ijt}, p_{ijt}, \Delta c_{ijt}^o)$, J_{it} is the number of cars household i owns at time t , and

$$\Delta c_{it}^u = \sum_{j=1}^{J_{it}} \Delta c_{ijt}^u.$$

Note, in particular that we do not observe Δc_{ijt}^u for each car j . If we assume that

$$\begin{aligned} \Delta c_{ijt}^u &= \alpha_{it} + \eta_{ijt}, \\ \alpha_{it} &\sim iidN(0, \sigma_\alpha^2), \\ \eta_{ijt} &\sim iidN(0, \sigma_\eta^2), \end{aligned}$$

then the probability of observing $\{p_{i1t}, p_{i2t}, \dots, p_{iJ_{it}t}\}$ conditional on $\{x_{i1t}, x_{i2t}, \dots, x_{iJ_{it}t}, \Delta c_{it}^u\}$ is

$$\begin{aligned} L_{it} &= \int \dots \int \prod_{j=1}^{J_{it}} \Phi(P_{ijt}^*(\Delta c_{ijt}^u))^{p_{ijt}} [1 - \Phi(P_{ijt}^*(\Delta c_{ijt}^u))]^{1-p_{ijt}} \cdot \quad (5) \\ &\quad \frac{1}{\sigma_\alpha} \phi\left(\frac{\Delta c_{it}^u - \sum_{j=1}^{J_{it}} \eta_{ijt}}{J_{it} \sigma_\alpha}\right) \frac{1}{\sigma_\eta} \phi\left(\frac{\eta_{ijt}}{\sigma_\eta}\right) d\eta_{ijt} \end{aligned}$$

where $\Phi(\cdot)$ is the standard normal distribution function and $\phi(\cdot)$ is its density.

random effects and an idiosyncratic effect with serial correlation. Without serial correlation, the household would have no reason to consider past shocks to cost in the present decision. This parameters of the proposed specification would be difficult to identify with the data available.

We can simulate equation (5) easily as

$$\tilde{L}_{it} = \frac{1}{R} \sum_{r=1}^R \prod_{j=1}^{J_{it}} \Phi(P_{ijt}^* (\Delta c_{ijt}^{ur}))^{p_{ijt}} [1 - \Phi(P_{ijt}^* (\Delta c_{ijt}^{ur}))]^{1-p_{ijt}} \frac{1}{\sigma_\alpha} \phi\left(\frac{\alpha_{it}^r}{\sigma_\alpha}\right)$$

where η_{ijt}^r is a pseudorandom draw of η_{ijt} from $N(0, \sigma_\eta^2)$,

$$\begin{aligned} \Delta c_{ijt}^{ur} &= \alpha_{it}^r + \eta_{ijt}^r, \\ \alpha_{it}^r &= \frac{\Delta c_{it}^u - \sum_{j=1}^{J_{it}} \eta_{ijt}^r}{J_{it}}. \end{aligned}$$

We can improve precision of the simulator using antithetic acceleration (Geweke 1988).

The log simulated likelihood function is

$$\log L = \sum_{i,t} \log L_{it}.$$

The value of $\theta = (\beta_0, \beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \sigma_\alpha, \sigma_\eta)$ that maximizes $\log L$ is the maximum simulated likelihood estimator (MSLE) of θ , and a consistent estimate of its covariance matrix is

$$\hat{C}(\hat{\theta}) = \left[\frac{1}{IT} \sum_{i,t} \frac{\partial \log L_{it}}{\partial \theta} \frac{\partial \log L_{it}}{\partial \theta'} \right]^{-1}$$

where I is the number of families.¹⁵

5.2 Results

Table 7 reports descriptive statistics for observed and unobserved costs using the estimates from the figures presented in Section 4 using the quantile regression estimates.¹⁶ The standard deviation of unobserved cost is 4.1 times the standard deviation of observed cost. While some of unobserved cost may be observable by a potential owner, the results still suggest that there is the potential for a large lemons effect. However, raw correlations show that observed cost is significantly negatively correlated with sales (i.e., it may be difficult to sell a used car with known maintenance problems), and unobserved cost has no correlation with sales.

¹⁵While the MSLE is consistent only if $R \rightarrow \infty$ as $I \rightarrow \infty$, a number of papers (e.g., Börsch-Supan and Hajivassiliou 1993) shows that, even with moderate values of R , MSLE performs very well.

¹⁶Moments from the OLS estimates are trivially different.

Table 7 Descriptive Statistics			
Variable	Mean	Std Dev	Correlation with Sales
Δ Observed Cost	0.004	0.071	-0.184
Δ Unobserved Cost	-0.003	0.290	0.040
# Cars	1.40	0.656	0.125
Age	4.55	2.98	0.032
Sales (3rd quarter)	0.020	0.139	
Sales (4th quarter)	0.022	0.148	
# Sales Opportunities		16094	
# Households		7459	

Notes:

1. Costs are measured in \$1000/year units.

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The structural estimates in Table 8 are consistent with the raw correlations.¹⁷ Observed cost has a significant negative effect on the probability of selling a car, and unobserved cost has no significant effect. Results also indicate that the vehicle’s age (excluding how age affects operating costs) is not an important, nor significant factor in household’s selling decisions. Age interacted with observed costs influences selling behavior. As the vehicle ages, each additional dollar of automobile related expenses the household incurs reduces the likelihood of selling even more. This is to be expected. Vehicles that require more observed maintenance are more difficult to sell and older vehicles are known to require more maintenance as their quality has deteriorated with age. Age also is observed to shift this relationship between selling and costs. Vehicles that are over 5 years of age are more likely to be sold than ones under the age of 5 years for any given increase in observed costs.¹⁸

Even though variation in unobservable costs does not explain selling behavior, there still exists significant variation in unobservable costs across families (with the same demographics and vehicle stock) and across the vehicles those families own. The standard deviation of the household-specific unobserved costs is almost two times as large as the standard deviation of the vehicle-specific unobservable costs. They are both statistically different from zero. Neither variation in unobserved spending across households or the cars they own explains selling behavior in the used car market. This suggests that there is not a significant lemons problem associated with unobserved spending on automobiles as commonly assumed.

¹⁷Estimates based on data from OLS cost regressions are trivially different from the quantile regression estimates.

¹⁸The age node is set to 5 years because the average number of years people keep their new car is between 4 and 4.5 years.

Table 8 Quantile Regression Parameter Estimates			
Variable	Estimates	Variable	Estimates
Constant	-1.027** (0.059)	American (not luxury)	0.069 (0.055)
Δ Observed Cost	-0.855* (0.512)	European Luxury	0.241** (0.087)
Δ Unobserved Cost	-0.111 (0.231)	European (not luxury)	0.146* (0.081)
Age	0.004 (0.011)	Japanese Luxury	0.263* (0.166)
Age*1 (Age \geq 5)	0.006 (0.009)	Japanese (not luxury)	0.105* (0.056)
Age* Δ Observed Cost	-0.742** (0.116)	$\log \sigma_\alpha$	-1.434** (0.009)
Age*1 (Age \geq 5) * Δ Observed Cost	0.501** (0.127)	$\log \sigma_\eta$	-2.014** (0.035)
Age* Δ Unobserved Cost	0.073 (0.093)		
Age*1 (Age \geq 5) * Δ Unobserved Cost	-0.039 (0.070)	χ^2_5 for brand effects	10.8*
American Luxury	0.000	\log Likelihood	-10453.7

Notes:

1. There are 14918 observations.
2. American Luxury is the excluded brand.
3. Numbers in parentheses are standard errors.
4. Double starred items are statistically significant at the 5% level.
5. The χ^2_5 statistic corresponds to the null hypothesis that all of the brand effects are zero against the general alternative.

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The brand effects reveal insights about the used car market as well. Turnover rates vary across brands. European and Japanese vehicles are more likely to be sold than American luxury vehicles, while American luxury and non-luxury vehicles are equally likely. We can interpret our results in terms of the Hendel and Lizzeri (1999) model. Under adverse selection, vehicles with greater product variability have lower volume of trade and steeper decline in prices. This relationship between turnover rates and price declines is found in the U.S. market. American vehicles, vehicles that are least likely to be sold, have the

greatest declines in log prices (EHSa).^{19,20} Consumers are more likely to trade vehicles whose quality they are more certain about, whose quality that has less variability. This is also consistent with our previous finding that vehicles with known maintenance problems (i.e., unreliable brands) are more difficult to sell. Together this provides evidence that adverse selection drives trade patterns in the used car market. But, from above, we conclude the source of this adverse selection is not unobserved maintenance expenditures.

6 Conclusions

Previous studies find evidence that the lemons problem in the used car market is due to individual owners' decisions rather than manufacturers'. Using data that track household spending on vehicles, this paper tries to clarify if the owner's maintenance decision (as commonly assumed) is the source of the market failure. Our model allows us to identify if the selling decision is driven by unobservable maintenance costs.

First, we estimate alternative specifications of how automobile-related expenses vary by the vehicle's age, brand, and model-year. We find that the quantile regression specification that is robust to outliers best predicts household spending on vehicles. Interestingly, correcting for a selection bias problem does not qualitatively affect the cost predictions. For most models, we observe costs rising with age until age 10 and then falling. This is consistent with Pickrell and Schimek (1999) and EHSa. Costs decline with significant reduction of car usage, thus requiring less maintenance. Costs also are found to rise with model-year, implying that the increase in vehicle costs due to technological advances dominates changes in car maintenance due to variation in car quality across model-year. Unexpectedly, we find that households spend more on their Hondas than their Buicks. One reason Hondas may have a high resale price is that the people who have initially purchased them spend more to maintain them, and thus they are of higher quality when sold. This result suggests that it is important to model the household's car portfolio choice.

After estimating the cost structure, we model the household's decision to sell as a function of the vehicle's age and changes in costs as predicted by the car's characteristics. We decompose changes in costs into observed and unobserved components and measure how much each component explains the decision to sell. The predicted pattern of trade supports the assertion that the used car market suffers from adverse selection. Results indicate that observed costs have a significant negative effect on the probability of selling a car, while unobserved costs are found to have no effect. This suggests that, contrary to popular belief,

¹⁹Price data were collected for 1986 through 1997 4-door sedan models or appropriate base models over the period between 1986 and 2000.

²⁰The Hendel and Lizzeri (1999) argument depends on European and Japanese vehicles being of higher quality initially than American vehicles. Rankings in the J.D. Power & Associates Initial Quality Study - the industry benchmark for new vehicle quality - suggest this to be true. European and Japanese vehicles routinely dominate the top spots in the survey, while American vehicles often receive below average rating.

there is no significant lemons effect due to unobservable maintenance expenditures. Thus, the owner's maintenance decision is not the source of any market failure observed in the used car market.

References

- [1] Akerlof, George (1970). "The Market for 'Lemons': Quality Uncertainty and the Market Mechanism." *Quarterly Journal of Economics*. 84(3): 488-500.
- [2] Alberini, Anna, Winston Harrington, and Virginia McConnell (1996). "Estimating An Emissions Supply Function From Accelerated Vehicle Retirement Programs." *Review of Economics and Statistics*. 78(2): 251-265.
- [3] Alberini, Anna, Winston Harrington, and Virginia McConnell (1998). "Fleet Turnover and Old Car Scrap Policies." *Resources for the Future Discussion Paper 98-23*.
- [4] Berkovec, James (1985). "New Car Sales and Used Car Stocks: A model of the Automobile Market." *Rand Journal of Economics*. 16(2): 195-214.
- [5] Börsch-Supan, Axel and Vassilis Hajivassiliou (1993). "Smooth Unbiased Multivariate Probability Simulators for Maximum Likelihood Estimation of Limited Dependent Variable Models." *Journal of Econometrics*. 58(3): 347-68.
- [6] Engers, Maxim, Monica Hartmann, and Steven Stern (2004a). "Mileage and Used Car Prices." Unpublished manuscript.
- [7] Engers, Maxim, Monica Hartmann, and Steven Stern (2004b). "Are Lemons Really Hot Potatoes?" Unpublished manuscript.
- [8] Fabel, Oliver and Erik E. Lehmann (2002). "Adverse Selection and Market Substitution by Electronic Trade." *International Journal of Economics of Business*. 9(2): 175-193.
- [9] Geweke, John (1988). "Antithetic Acceleration of Monte Carlo Integration in Bayesian Inference." *Journal of Econometrics*. 38(1/2): 73-89.
- [10] Hamilton, Bruce and Molly Macauley (1998). "Competition and Car Longevity." *Resources for the Future Discussion Paper 98-20*.
- [11] Hendel, Igal and Alessandro Lizzeri (1999). "Adverse Selection in Durable Goods Markets." *American Economic Review*. 89(5): 1097-1115.
- [12] Hendel, Igal and Alessandro Lizzeri (2002). "The Role of Leasing under Adverse Selection." *Journal of Political Economy*. 110(1): 113-143.

- [13] Hendel, Igal, Alessandro Lizzeri, and Marciano Siniscalchi (2003). “Efficient Sorting in a Dynamic Adverse Selection Model.” Unpublished manuscript.
- [14] Konishi, Hideo and Michael Sandfort (2002). “Existence of Stationary Equilibrium in the Markets for New and Used Durable Goods.” *Journal of Economic Dynamics and Control*. 26(6): 1029-1052.
- [15] Nelson, Randy and Michael Caputo (1997). “Price Changes, Maintenance, and the Rate of Depreciation.” *Review of Economics and Statistics*. 79(3): 422-430.
- [16] Parks, Richard (1977). “Determinants of Scrapage Rates For Postwar Vintage Automobiles.” *Econometrica*. 45(5): 1099-1115.
- [17] Parks, Richard (1979). “Durability, Maintenance, and the Price of Used Assets.” *Economic Inquiry*. 17(2): 197-217.
- [18] Pickrell, Don and Paul Schimek (1999). “Growth in Motor Vehicle Ownership and Use: Evidence from the Nationwide Personal Transportation Survey.” *Journal of Transportation and Statistics*. 2(1): 1-17.
- [19] Rust, John (1985). “Stationary Equilibrium in a Market for Durable Assets.” *Econometrica*. 53(4): 783-805.
- [20] Sandfort, Michael (1999). “A Dynamic Structural Analysis of Consumer Demand for Automobiles in Sydney, Australia, 1981-1985.” Unpublished manuscript.
- [21] Schmalensee, Richard (1974). “Market Structure, Durability, and Maintenance Effort.” *Review of Economic Studies*. 41(2): 277-287.
- [22] Walker, Franklin (1968). “Determinants of Auto Scrapage.” *Review of Economics and Statistics*. 50(4): 503-506.
- [23] Ward’s Communications. *Ward’s Automotive Yearbook*. Southfield, MI, various editions.
- [24] Ward’s Communications (2000). *Ward’s Motor Vehicle Facts and Figures*. Southfield, MI.