Microsimulating Automobile Markets: Evolution of Vehicle Holdings and Vehicle Pricing Dynamics

by Brent Selby and Kara M. Kockelman

Vehicle ownership decisions are central to estimates of emissions, gas tax revenues, energy security, pavement management, and other concerns. This work combines an auction-style microsimulation of vehicle prices and random-utility-maximizing choices, producing a market model for the evolution of new and used personal-vehicle fleets. All available vehicles compete directly, with demand, supply, and price signals endogenous to the model. The framework is described, analyzed, and implemented to show its capabilities in predicting outcomes of varying inputs. Application of the model system using Austin, Texas, survey data over a 20-year period highlight the model's flexibility and reasonable response to multiple inputs, as well as potential implementation issues.

INTRODUCTION

Automobiles dominate the U.S. transportation landscape. Much effort is put into the design of vehicles and the infrastructure they use, directly and peripherally. To understand and anticipate travel patterns, along with emissions, energy use, and gas tax revenues, transportation engineers and planners model vehicle ownership and use decisions. An appreciation of the near- and long-term effects of demographic, economic, and policy changes on vehicle fleet composition allows for more comprehensive planning. Many state, regional, and local transportation agencies must forecast the air quality, greenhouse gas contributions, and fuel tax implications of an evolving transportation landscape. This paper tackles the simulation of vehicle purchase and re-sale decisions via an auction process among individual households in the market for vehicles (new and used).

If a modeler can identify measurable attributes of consumers and producers that propel the buying, selling, scrappage, and use of cars and trucks, they can predict the choices made at an aggregate or disaggregate level using microsimulation. Several researchers have attempted to do this (e.g., Musti and Kockelman 2011, Mohammadian and Miller 2003, and Berkovec 1985) with varying complexity and scope. This work focuses on the choices made when households are offered the option to buy new or used personal vehicles, and the market clearing achieved by auction-driven price fluctuations. Previous works either overlook the used-vehicle market completely or depend on some function for price changes due to vehicle aging. This paper makes explicit the role of user preferences in vehicle price fluctuations through a market auction process, without strong assumptions about supply and demand. The model framework is applied with 5,000 U.S. households to illuminate inputs needed and predictive results.

LITERATURE REVIEW

A number of researchers have sought to model automobile markets. The frameworks depend on the analyst purpose as well as available data and computing power. At the core of most model specifications is a logit choice function to simulate consumer purchases. The transaction models can be summed up as follows: "From a utility-maximizing perspective, when the household's net utility gain from transacting exceeds a threshold, a transaction is triggered" (Mohammadian and Miller 2003, p. 99).

Earlier work by Berkovec (1985) allowed an oligopoly of manufacturers to sell to consumers and consumers to sell to each other or to scrappers. Notably, this included a random repair cost function and a market-clearing requirement in each period. Berkovec and Rust (1985) focused on each household's choice to keep or release a vehicle based on holding duration. These are much simpler than later models but laid useful groundwork, while identifying some important issues in model specification. Berkovec's (1985) model achieved market clearing conditions when the supply from manufacturers and current stock matched the demand by consumers and scrappers. To achieve this, he used a simple supply-demand function that adjusted price for each of 13 vehicle types, with demand summed over all consumers. This is the only model found that established market prices. He included devaluation in a vehicle's "expected capital cost," as a function of its current price and the previous model year's current price without consideration of usage or other heterogeneous trends. In Berkovec and Rust (1985), the depreciation is a simple constant (20% fixed, annual), regardless of year or vehicle type.

Musti and Kockelman (2011) and Mohammadian and Miller (2003) are the best examples of robust, recent models of the vehicle market. Musti and Kockelman (2011) simulated households in the Austin, Texas, region, with demographic and residential attributes evolving over time. There were many levels to their model, including population evolution, vehicle ownership, transaction decisions, and vehicle choice and use. The last sub-model also projected greenhouse gas emissions, but that was not part of the market portion of the simulation. Each year every household had to acquire a vehicle, retire a vehicle, or do nothing. The period ended when this was completed. No market clearing price mechanisms were simulated; exogenous prices were given based on current manufacturer suggested retail prices (MSRPs).

Their transaction model quantified the utility of vehicles owned by each household and available new from manufacturers. Vehicle choice relied on a multinomial logit (MNL) model using stated-preference survey results, neglecting past and current holdings. The households were heterogeneous in their attributes (socioeconomic and geographic) as well as their evolution. While their models simulated vehicle use (among the various fleet-evolution and market-focused models described here), they did not consider devaluation and maintenance at all. Conspicuously missing from their model was the buying and selling of *used* vehicles.

Mohammadian and Miller (2003) undertook a similar, MNL-driven simulation with fewer sub-models, but included an option to both release and acquire a vehicle. Used vehicles released by households in their model essentially vanished, and buyers could choose any model year they wanted, with prices given by exogenous market averages. To account for changes in utility as a result of evolving household attributes, the transaction model controlled for up/down changes in household size and number of workers (as opposed to these attributes' absolute numbers), but lacked home-neighborhood, age, and gender information. Mohammadian and Miller's (2003) choice model strongly depended on previous vehicle types and transaction decisions. Interestingly, they found that unobserved preference heterogeneity was not statistically significant after controlling for previous behaviors. This suggests that differences across decision makers may not be practically useful if information about their current and past vehicle holdings is known.

Mueller and de Haan (2009) constructed a bi-level choice model for new vehicles, randomly presenting consumers a subset of choice alternatives. Notably, it contained a Markov process to carry prior-owned-vehicle attributes (by household) over for new-vehicle choice. Esteban (2007) created a model to investigate the fleet effects of scrappage subsidies. She focused on transaction decisions and found that "a subsidy can induce scrappage even if it pays less for a used car than its without-subsidy price" (2007, p. 26). Since her work focused on national market dynamics, it provides little insight for household-level microsimulation. Emons and Sheldon (2002) gave a very different perspective in their implementation of a "lemons model," focusing only on vehicle attributes, rather than owner attributes. They predicted inspection failures, representative of car quality, based on duration of ownership. No studies in the literature appear to integrate this information with microsimulation of consumer choices.

Berry et al. (1995) presented a method for combined empirical analysis of preference functions, cost functions, aggregate consumer attributes, and product characteristics to derive price estimates, quantities, profits, and consumer welfare. They found their model accurately reproduced actual US markets when changing one parameter at a time, ceteris paribus. Though they only used aggregate inputs and outputs, their approach could be used to feed information to a microsimulation model like those previously mentioned.

Auction Model Microsimulation

Though none of these market models used an auction method, such methods have advantages for pricing and vehicle selection. Products are auctioned, as suggested by Cassady (1967), if they have no standard value, such as antiques. Zhou and Kockelman (2011) used auctions to model real estate markets with various agents. If a property received no bids, the price fell by a certain (small) amount; with multiple bids, the price rose (by a similar amount). The bidding ended when each property hit its (pre-set) minimum price, received a single bid, or hit its (pre-set) maximum price (with a winning buyer randomly selected). Properties in high demand from buyers' experience price increases and those with little demand see prices fall. At or below a minimum threshold price, sellers can be assumed to keep their property. This may be described as a type of alternating double auction market. (See "Auctioning and Market Pricing" section of this paper and Sadrieh 1998, and Gibbons 1992 for more on these markets). Unlike Berkovec's (1985) approach, Zhou and Kockelman's (2011) auction did not require aggregate supply and demand equations.

Vehicle Depreciation, Lifespan, and Holding

Greenspan and Cohen (1999) described an upward trend in vehicle lifespan, with the median age of U.S. personal vehicles just 10 years for 1960 models, and nearly 13 years for 1980 models. DesRosiers (2008) describes heterogeneity in longevity (in Canada) with over 50% of large pickup trucks from 1989 still registered 19 years later, while only 8.2% of subcompacts remain. He shows that the median age for all vehicle types is at least 14 years, with most over 16 years. The 2001 (U.S.) National Household Travel Survey indicates that the average age of vehicles is 8.2 years. National Highway Traffic Safety Administration (Lu 2006) analysis showed that a typical passenger car would travel a lifetime mileage of 152,137 miles, while light trucks would travel 179,954 miles. In terms of holding durations, Emons and Sheldon (2002) found new U.S. vehicles to be held by a household an average period of four to six years.

Consumer Preferences and Decision Making

Three-quarters of respondents in Musti and Kockelman's (2011) survey placed fuel economy in their top three criteria for vehicle selection. However, fuel costs were not statistically significant in the corresponding revealed choice model. (This may be due to sudden changes in fuel price that happened after many of the owned vehicles were purchased.) While Espey and Nair (2005) found the opposite – that consumers did accurately value the savings from lower fuel cost. Bhat et al. (2008) suggested that people value fuel cost less than vehicle purchase cost, but with marginal statistical and practical significance.

Bhat et al. (2008) undertook one of the most comprehensive vehicle-preference studies based on travel surveys in the San Francisco region. They estimated how vehicle type, size, age, and use relate to each owner's socioeconomic attributes, as well as neighborhood attributes and the home's general location within the region. Specifically:

- Older people were more likely to have older vehicles, and younger people were more likely to have newer vehicles;
- Households with higher incomes and/or more workers tended to own fewer older vehicles and used less non-motorized transportation;
- Households in higher density, mixed use, and urban areas held fewer trucks and vans;
- Households in neighborhoods with bike lanes used more non-motorized transportation;
- Race and gender affect vehicle holdings and use; and
- In general, less expensive, bigger (by luggage and seating capacities), more powerful, and lower emission vehicles are preferred, ceteris paribus.

Mohammadian and Miller (2003) predicted the "do nothing" (neither buy nor sell) transaction status with much higher accuracy than any other choice. They found that buy and sell transaction choices were not influenced by the same variables. For example, an increase in the number of household workers seemed to induce a purchase or trade but not reduce the chance of a disposal. However, an increase or decrease in household size improved the chances of trading and disposing, respectively, while not affecting the chances of a purchase.

This work builds on these market and discrete choice concepts to provide a new method for simulation of an automobile market. It draws on several specifications from Musti and Kockelman (2011) fleet simulations, incorporating certain beneficial features of Storchmann's (2004) and Kooreman and Haan's (2006) work. It adds an auction strategy for pricing of used cars not yet available in the literature.

MODEL SPECIFICATION

The model used here includes two MNL models in sequence to predict each household's vehicle fleet from year to year. The first is a once-a-year market entrance model to simulate a household's decision to modify or maintain its "fleet" of personal vehicles. This choice model evaluates the probability that a household will choose to retire a vehicle, acquire a vehicle, or do nothing. The second MNL predicts which vehicle the purchasing/acquiring households will want, among available new and used vehicles. This vehicle choice model runs many times each year, within an auction model, to re-evaluate choices under different price conditions until equilibrium is reached. The objective of this work is to explore the features of such a framework, and examine the results of different context assumptions. The simulation described here was not calibrated as a whole, but rather constructed from previously calibrated models and empirical equations.

Market Entrance and Vehicle Choice Models

The utility model parameters for the market entrance model are based on those from Musti and Kockelman's (2011) transaction model, as given in Table 1. The choices are "acquire," "dispose," or "do nothing" (which serves as the base case). Since these are the only options in the data, a "trade" choice was not available, though it is highly desirable. Some parameter values required adjustment (as discussed in the Results and Conclusions section), since these choice models were calibrated in a different context.

Table 1: MNL Parameter Estimates for Annual Vehicle Transactions

Variable	Coefficient	T-Stat
Acquire (Buy)	-1.8314	-7.33
Dispose (Sell)	-3.7824	-8.96
Number of vehicles in the household x Dispose	0.4077	2.44
Number of workers in a house x Buy	0.2510	2.31
Female indicator x (Acquire, Dispose)	-0.3303	-1.79
Maximum age of vehicle in household x (Acquire, Dispose)	-0.0955	-4.63
Income of household x Do nothing	-2.25E-06	-1.33
Log Likelihood at Constants	-505.37	
Log Likelihood at Convergence	-448.65	
Pseudo R^2	0.3679	
Number of households	640	

(Source: Musti and Kockelman, 2011)

The MNL vehicle choice model estimates the systematic utility of each vehicle available in the market for each household. The model offers nine vehicle choices with distinct body types, fuel costs, and prices, representing the range of the most popular vehicles available in the U.S. Each of these nine vehicle types were offered as new (with set prices and unlimited supply) and competed with any used vehicle put up by sellers. Vehicle and household attributes serve as covariates in the utility expression (Table 2).

The first nine vehicle (and household) attributes shown in Table 2 are not specifically related to used vehicles and so were taken from Musti and Kockelman's (2011) vehicle choice model. In addition to these, four used-vehicle variables were added. Musti and Kockelman's (2011) model did not contain such variables, so these were derived based on other sources (Kooreman and Haan (2006) and Storcheman (2004), as discussed below.

The *Used* indicator x *Income class* level coefficient was approximated such that the lowest income groups are more likely and the highest income groups are very unlikely to choose a used car. The income groups were classified from 1 to 12 with 1 being the lowest (under \$5,000) and 12 being the highest (above \$250,000). At the lower income levels, this has a value in the utility equation close to the difference between two similar body types, making it slightly more probable that a buyer would switch from his/her optimal body type to a similar one if a reasonable used one is available. This was done on a purely intuitive basis, because such used-vehicle data do not exist. At high-income levels, a used car would decrease the utility at a value close to that expected between dissimilar body types, making a used car a very unlikely choice for a household making \$200,000 or more each year.

The next two variables (*Price new x* 10^{-5} *x Used indicator* and *Price new x* 10^{-5} *x exp*(*age* ´ δ)) are based on the price when new and correspond to loss of vehicle value/utility with vehicle age. This is assumed to be universal to all buyers in the market. The values are based on Storcheman's (2004) price depreciation equation, as discussed later. Thus, the negative utility from vehicle aging should generally match the utility difference that comes with paying the initial auction price versus the new price. They will not exactly cancel, however, because different income groups are assumed to value used vehicles differently, and the market model allows prices to vary, as explained in the next section.

Table 2's last variable involves a 100,000-mile (odometer reading) indicator with current price to reflect the nonlinear drop in vehicle value associated with this significant usage milestone. The coefficient is such that the loss of utility will be that of 5% of its monetary value, as suggested by Kooreman and Haan (2006).

Table 2: Vehicle Choice Model Parameters

Variable	Coefficient	t-stat
Fuel cost	-8.514	-2.83
Purchase price (current) x 10^{-5}	-5.57	-3.94
Age of respondent less than 30 indicator x Midsize car	0.3627	2.28
HHsize greater than 4 indicator x SUV	0.8756	3.41
HHsize x Van	0.2895	4.66
Crossover sports utility vehicle (CUV*)	-0.4148	-2.43
Luxury car	-1.121	-3.51
Suburban x SUV	0.2632	1.32
Urban x Midsize car	0.1864	1.21
Used indicator x (Income class - 3)**	-0.3333	-
Price new x 10^{-5} x Used indicator**	5.57	-
Price new x 10^{-5} x exp(age ´ δ)**	-5.23	-
Over 100k miles indicator x Purchase price (current) x 10^{-5}*	-0.2785	-

Note: * CUVs are SUVs with a unit-body car platform. Popular models include the Honda CR-V and Toyota RAV-4.
** denotes variables added to the model of Musti and Kockelman (2009).

Auctioning and Market Pricing

In lieu of neglecting prices or referring to exogenous price functions, the model developed here uses an alternating double auction-based market pricing simulation, similar to that in Zhou and Kockelman (2011) and Sadrieh (1998) – and as described below, for prices of used vehicles (only). Unlike the transaction and vehicle choice models, the auction structure is not a direct simulation of the actions of buyers or sellers in the automobile market. Clearly, the sale of used vehicles directly or through dealers does not have such an open bidding process. Here, an auction bidding methodology is used to simulate prices, based on the preferences of individual buyers and offerings of actual sellers.

The market entrance model selects the (mutually exclusive) buyers and sellers participating in the market each year. The vehicles consist of new vehicles (in unlimited supply, with *fixed* prices) and those to be sold by households making a sell transaction. The buyers are the households making a buy transaction. The rules are such that all buyers must buy an automobile, and all used vehicles (from sellers) must be bought, returned to the selling household, or scrapped.

The alternating double auction is a discrete-time version of the standard ("open outcry") auction. It cycles or alternates between seller bids and buyer bids. Initially, sellers offer their vehicles at an opening bid set at prices (P_0), as described below. Buyers bid at that price on vehicles chosen by the vehicle choice model (i.e., those offering maximum net utility, after reflecting initial offer prices). Buyers act independently, and may only bid on a single (new or used) vehicle at each stage. There is no limit on the number of bids a vehicle can receive. At the beginning of the second cycle, sellers make price adjustments based on the buyers' bids. The sellers will decrease and increase prices of all used vehicles in zero- and two-plus (buyer-) bidder situations, respectively, by a small increment (assumed to be 1% of the vehicle model's price new – or $200 for a $20,000 MSRP vehicle), while single-bid vehicles maintain their current price. The vehicle choice model then runs again, and all remaining buyers put in new bids on those vehicles offering them the greatest (random) utility gain. These cycles continue until all buy decisions have been executed.

If a vehicle's price falls below the scrappage price, it is immediately taken off the market and cannot return. If a vehicle's price reaches its maximum allowed price with more than one bidder, it is given, at that maximum price, to a randomly chosen bidder. A vehicle at maximum price is no longer evaluated by other bidders, but the winning bidder may choose to switch to a different vehicle as prices change. The minimum and maximum prices are set by an arbitrary $[P_0 - 0.15P_0, P_0 + 0.15P_0]$.

For the bidding to end, two conditions must be met: no vehicle may have more than one bidder and no vehicle may have zero bidders if it is at a price greater than its (exogenously set) minimum price. Similar to Zhou and Kockelman (2011), if a vehicle reaches its minimum price without bidders, it is returned to its owner.

The opening auction prices (P_0) of used vehicles are set using the logarithmic depreciation function recommended by Storchmann (2004), where $P_t = P_{new} e^{\alpha+dt}$. Here, P_t is price at year t, P_{new} is new price, and α and δ are depreciation parameters. There is also an additional 5% price drop for vehicles past 100,000 miles, as implied by Kooreman and Haan (2006), and the minimum P_0 is the scrappage price. Though Storchmann's (2004) study included regressions that were model- (and nation-) specific, a single number is used here for all models, for simplicity and because Storchmann (2004) did not include vehicles representing all body types. Only U.S. coefficient values are applied here, as shown in Table 3. Table 3's vehicle models were chosen by Kooreman and Haan because they are very common in the U.S. used-car market. In this study, these values were assumed to be α = -0.05 and δ = -0.175. It should be noted that the Civic and Accord are considered to have some of the lowest depreciation rates among all makes and models. (Lienert 2005, Consumer Reports 2010) Prices of new vehicles are set exogenously, based on MSRPs used in Musti and Kockelman (2011).

Table 3: Parameter Values for Price Depreciation from Storchmann (2004), $P_t = P_{new} e^{\alpha+dt}$

Vehicle Make & Model	α	δ
GM Cadillac Seville	-0.14	-0.163
Toyota Camry	-0.01	-0.168
Honda Accord	0.14	-0.191
Honda Civic	-0.15	-0.172

The Simulation Program

A simulation program was written in MATLAB's m-language, to mimic Austin households making new- and used-vehicle choices over 20 years. The program has a main layer that tracks households and vehicles over time, and a market–level layer that determines prices and vehicle selection in a given year, mimicking the layers of the logit models. The main layer tracks the state of households and vehicles and contains the "market entrance" functions. This includes selecting vehicles and buyers for the market, and updating ownership and other information. The market layer uses the vehicle choice model to determine purchases and runs until market clearance is achieved.

Figure 1: Schematic of the Simulation

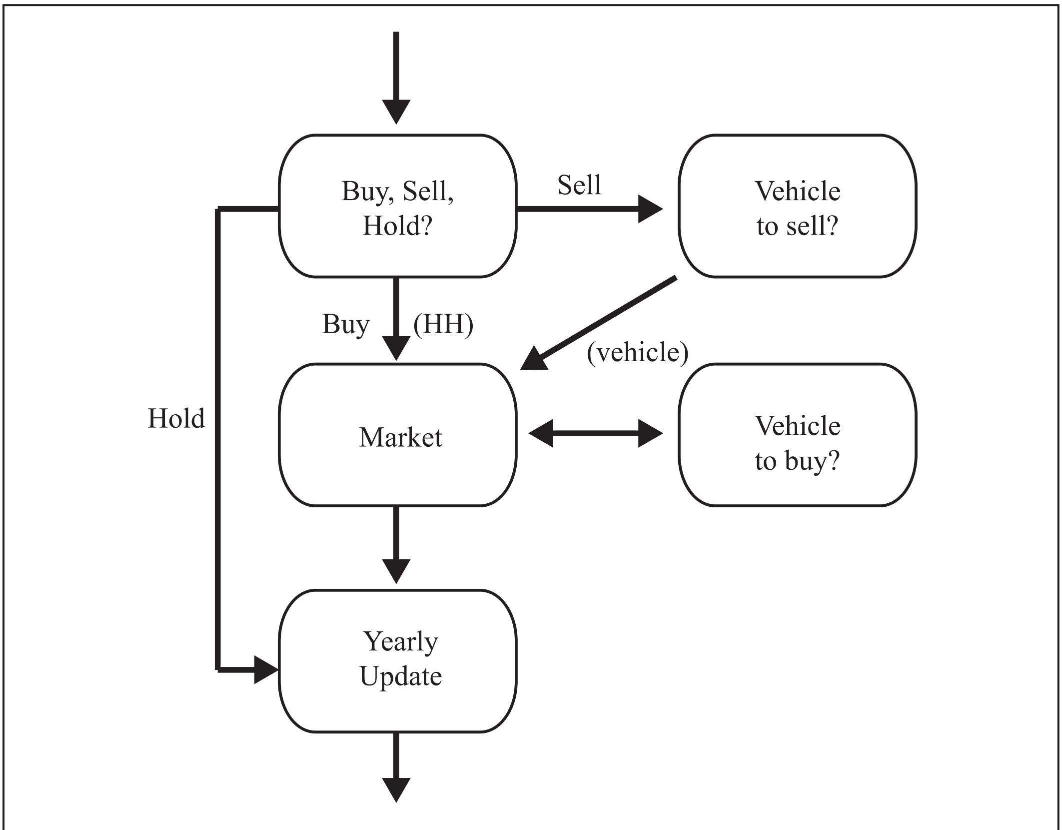


Figure 1 shows the basic flow in one year of the simulation. In the market entrance model, households choose to bypass the market (do nothing), sell a vehicle in the market, or enter it as a buyer. The vehicle choice model selects a vehicle in the household fleet to sell, and this vehicle is put into the market. In the market, vehicles and households are run through the vehicle choice model to determine which automobiles households wish to buy. After the market clears, the yearly update module places vehicles into their new (or old, if unsold) households and updates mileage and vehicle age information. The mileage added on a vehicle in any given year varies by its current owner, who has an associated usage per year, which is given in input data. The yearly mileages are based on averages from the household data and are held constant through the simulation.

The model was run for 20 year-long iterations on a fixed set of households. These households' attributes were not updated over time (to reflect aging individuals and the like), and no households are added or removed (to allow for more straightforward simulation). Such updating is, of course, feasible and useful in the context of real-world applications but beyond the focus of this work. The data used for simulation included 5,000 simulated households generated by duplicating the 637 households (not including those with incomplete data) from Musti and Kockelman's (2011) survey data. Use of 5,000 households allows for a market large enough to function but small enough to easily test. Table 4 provides a summary of these households' attributes (and the specific respondent on the Musti and Kockelman (2011) survey).

Table 4: Summary of Simulated Households' Attributes

	Average	Minimum	Maximum	Std. Dev.
Household Size	2.21	0	7	1.25
Number of Vehicles	1.61	0	5	0.87
Age of HH head (years)	36.8	20	70	15.0
Household Income ($/year)	86,271	5,000	250,000	67,048
Female Indicator	0.36	0	1	0.48
Number of Workers	1.46	0	5	0.85
Miles per Year per Vehicle	10,568	750	42,000	4,687

SIMULATION RESULTS

The simulation successfully ran through 20 years of market decisions among the 5,000 households in 25 to 40 minutes, with each year taking between 20 seconds and 10 minutes. The bidding loops generally took between 20 and 500 iterations, but occasionally required more than 1,000. This volatility can be greatly reduced by limiting repeated, similar-price steps, but was allowed here for simplicity.

Several tests were undertaken to examine the effects of changes in model parameters. One important adjustment was required in Musti and Kockelman's (2011) market entrance model: The value of the coefficient on maximum age of a vehicle in the household's fleet for the buy and sell options was negative (-0.0955), making it less likely that a household would get rid of a vehicle or buy a new one as its oldest vehicle aged. To address the issue of unreasonable holding durations and the resulting vehicle lifespans, a hazard function (for vehicle lifetimes) was added to randomly remove vehicles from households without selling them. This addition allows the model to account for irreparable, stolen, and destroyed vehicles (e.g., via collision or major mechanical failures), with the hazard (risk of vehicle loss) rising with vehicle age (i.e., probability=$1-ae^{b*age-c}$), based on NHTSA statistics (Lu 2006). While more detailed survey data may capture such effects, this exogenous function can fill in the gaps. Selby (2011) describes these changes and variations in user inputs in detail.

Table 5 compares the fleet mix in the high fuel-price and base fuel-price scenarios after 20 years of the simulation. The increased gas prices (at $5, rather than $2.50, per gallon) result in share reductions for large cars and all light trucks (CUVs, SUVs, pickups, and vans). Small share increases were observed in compact and midsize cars, with the majority of the shift going to the subcompact class, which offers the most fuel efficient vehicle type modeled.

Since governments sometimes choose to induce car turnover (thereby improving fleet emissions or safety) by offering scrappage subsidies (e.g., the Obama Administration's "Cash for Clunkers" program or those described in Esteban [2007]), such subsidies are an input parameter of interest. A simulation was done in which the scrappage incentive (per qualifying vehicle) was increased from $500 to $2,500 (for all vehicles). The new scenario encouraged an expected rise in vehicles sold for scrap and a drop in the numbers removed via the hazard function, as seen in Table 6. The average number of auction rounds fell by more than 50%, with vehicles exiting for scrappage more quickly. On average, only one vehicle went unsold every two auctions when the subsidy was offered. Additionally, used-car sales went down 12% (by about 475 vehicles), while new car sales were up 3% (by 225 vehicles). There were slightly more (1.5%) total vehicles (held initially plus purchased during simulation) with the higher scrappage rate offered, and somewhat fewer (-2.2%) purchases made. This may be the result of the removal of low-value cars that had been sold multiple times in the base case but scrapped early on in those with the higher subsidy. The distribution of vehicles' ages in the final simulation year (Year 20) did not change substantially between the cases.

Table 5: Model-Predicted Vehicle Holdings by Type After 20 Years

	Base Case Shares ($2.50/gallon) Year 20	**High-Fuel Cost Scenario Shares** ($5/gallon) Year 20
Subcompact	25.9%	35.0%
Compact	11.0%	11.8%
Midsize	14.6%	14.9%
Large	8.1%	6.8%
Luxury	1.1%	1.2%
CUV	7.0%	6.4%
SUV	6.5%	4.9%
Pickup	8.2%	5.8%
Van	17.4%	13.1%

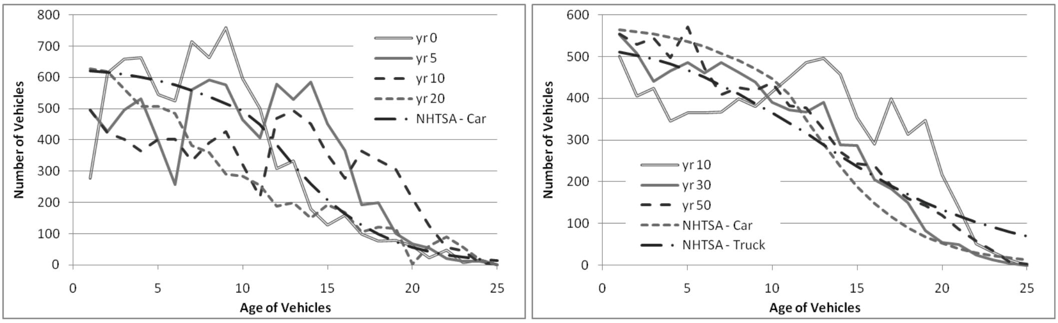
Table 6: Simulation Results for $500- and $2,500-per-Vehicle Scrappage Incentives

	Base Case ($500 Scrappage)		**Scrappage Subsidy** ($2500 Scrappage)	
	Per Year	**Total**	**Per Year**	**Total**
Buyers in Auction	557	11,146	545	10,897
Vehicles in Auction	201	4,023	203	4,053
Auction Rounds	346	6,914	154	3,081
Vehicles Unsold	2	47	1	10
Total Vehicles	15,294		15,517	
New Vehicles Purchased	7,255		7,478	
Used Vehicles Purchased	3,891		3,419	
Vehicles Scrapped	85		624	
Vehicles Removed by Hazard	8,250		7,808	
Average Vehicle Age in Year 20	7.81 yrs		7.95 yrs	

Figure 2 gives vehicle-age distributions at several time points over the simulation, for direct comparison with the NHTSA curves (Lu 2006) for cars and light trucks. It appears that, over the 20-year period, the program is reshaping the synthetic distribution of 5,000 households' vehicles into a smoother function. The rough peaks of the original data are removed by year 20, since those vehicles are all retired and have been replaced via a regular adoption of new vehicles.

Important concerns when running a simulation over a long period of time are the system's equilibrium, encroachment on boundary conditions, and/or cyclical patterns that the program may enter. Fifty-year runs were performed to examine the program's trajectory, and Figure 2 suggests that the model mimics the NHTSA curves (Lu 2006) rather well, which is heartening to see.

Figure 2: Vehicle-Age Distributions for 20-Year and 50-Year Simulations



Note: NHTSA Light Truck Curve Omitted for Readability of the 20-year Image

These various simulations illustrate the framework's flexibility, with results that highlight just a few of the comparisons that can be pursued. Not only can fuel, scrappage incentives, vehicle attributes, and household inputs be changed, but modules can be added without recalibration to incorporate more behavioral sophistication, including household evolution and greenhouse gas emissions estimation.

CONCLUSIONS

This work's results suggest significant potential of auction-style microsimulation for used- and new-car market modeling, while indicating areas for model enhancements. The general modeling approach offers analysts the advantage of determining market prices without requiring explicit supply and demand functions. It also sets all prices and purchase choices simultaneously, for the entire set of market actors (buyers and sellers). This type of model is designed to mimic disaggregate decisions on supply and demand, and microsimulation allows one to incorporate nearly limitless complexity in behavioral processes. With a fluid market and representative groups of buyers and vehicles, the prices and choices may tend toward an optimal set.

The approach taken here, to reflect transactions of used vehicles, extends the approaches taken in previous works – which either ignore such vehicles (e.g., Musti and Kockelman 2011) or assume an external supply of such vehicles (e.g., Mohammadian and Miller 2003). In this model, available used vehicles were compared directly to new vehicles by buyers. By comparing sale vehicle options directly, the model allows individual vehicles to have unique characteristics and avoids the assumption that every model year of a vehicle is for sale in a market. The auction structure sets prices based on the availability of vehicles and the individual preferences of people in the market. Prices and decisions thus react to market conditions such as changes in gas prices. With double gas prices, the model showed the subcompact's share jumping by 10% and the share of all truck types falling by 1% to 5%.

This simulation also suggests some opportunities for model enhancement. First and foremost, households should also be allowed to sell and buy vehicles in the same year – a feature not currently available due to lack of this choice in the survey from which the data is sourced. Consideration of budgetary constraints that many may be under when selecting a vehicle to pursue (and making an offer on that vehicle) would also improve its realism. The market entrance model populates the market with vehicles and buyers based on existing household and fleet attributes, while recognition of actual vehicle prices and availability in the new and used vehicle markets should prove more realistic. Robust data collection would encompass the current holdings and future plans of households, as well as the supply and pricing of vehicles. A shift in the conditions of the new and used markets will induce some to join and discourage others, changing market makeup.

The model used here also provides a history of prices, trades, and other information as outputs but does not use such information itself. A more sophisticated approach could incorporate it into subsequent years' market entrance decisions and pricing schemes. Previous information can provide a starting point for the current year. This would give some measure of continuity, a realistic assumption, from year to year. The effects of new vehicle price negotiation and credit availability may also be useful in future models. The framework presented here is quite flexible, and much can be added without substantive changes, including the evolution of households (e.g., the number, ages, and incomes of household members) and new vehicles (the fuel economy, price, and reliability).

As seen in the results, scrappage prices can affect market and vehicle holdings, with 3% more new cars sold and 12% fewer used vehicles purchased under a higher scrappage incentive. In addition to the price floor for scrappage, a hazard function was used to randomly remove vehicles as they age. This permits early and owner-unexpected exits/losses of vehicles due to a serious crash or other situations. Ideally, this loss should be better integrated with other market decisions (like vehicle use and age) or removed in favor of a more robust market calibration that more clearly models used-car behaviors. Predicting the price accurately depends somewhat on starting at the right point and a great deal on properly calibrating and quantifying the valuation of wear on a vehicle.

Including market pricing and used automobiles is a complicated but presumably central part of modeling a population's evolving vehicle fleet. This paper provides a framework for doing so and requires relatively few parameters for simulation. Additional work is necessary to add robustness and further empirical calibration of all model components.

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