TESTING A MODEL OF CONSUMER VEHICLE PURCHASES

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ABSTRACT

Consumer vehicle choice models have been estimated and used for a wide variety of policy simulations. Infrequently, though, have predicted responses from these models been tested against actual outcomes. This paper tests a model developed for the U.S. Environmental Protection Agency that is intended to estimate the impacts of changes in vehicle prices and fuel economy. It is a nested logit with a representative consumer and 5 layers: the buy/no buy decision, passenger versus cargo versus ultra-prestige vehicle, vehicle classes, subdivision of those classes into standard and prestige vehicles, and then individual vehicles. It is calibrated to vehicle purchases in model year (MY) 2008. Vehicle changes between MY and 2010 are then used to make predictions, and those predictions are compared to actual outcomes in MY 2010. The research suggests that the model may predict better when its inputs are aggregated than when they are as disaggregated as possible, though further work is needed to assess the model's predictive abilities.

Testing a Model of Consumer Vehicle Purchases

Estimating and simulating purchase patterns of consumer vehicles have significant policy relevance because of the contributions of vehicles to air pollution, including greenhouse gas (GHG) emissions, and because of the importance of the auto sector to the U.S. economy. A large literature has examined the impacts on vehicle sales and fleet mix of such questions as impacts of fuel economy standards and pollution taxes (e.g., Goldberg 1998, Whitefoot and Skerlos 2011, Jacobsen forthcoming) and feebates (e.g., Greene 2009), competitiveness of the U.S. auto industry (Train and Winston 2007), and market acceptability of alternative-fuel vehicles (e.g., Brownstone et al. 1996). The U.S. Environmental Protection Agency has been exploring the use of vehicle choice models for use in analyzing the impacts of its vehicle GHG/fuel economy regulations.

Almost unstudied, though, is the effectiveness of these models in predicting market responses to changed circumstances. The models, commonly econometrically estimated, are used for prospective simulation purposes. Rarely, though, have researchers used their models to examine situations where model results could be compared to reality.

It seems evident that the utility of these models for estimating policy impacts should depend on their effectiveness in predicting those impacts. In addition, models in general have limitations, based on factors such as the purposes for which they are designed, and the data, computational, or funding limitations in developing them. Deciding the use of consumer vehicle choice modeling in policy analysis, then, should be informed by assessing the utility and limits of these models.

This paper presents initial results of comparing predictions from a consumer vehicle choice model (CCM) with actual market results. The model used here was developed by Greene and Liu for the U.S. Environmental Protection Agency (2012) specifically to predict changes in total sales and fleet mix associated with GHG/fuel economy standards. This paper assesses the model's predictions of model year (MY) 2010 vehicle sales based on a calibration to MY 2008 sales. In this preliminary assessment, we find that the level of aggregation used in the dataset affects the results, with more aggregated data producing somewhat better results than more detailed data.

Background

The magnitude of the auto industry in the U.S. economy and the importance of its role in international trade and environmental protection have led to a large literature examining the market for light-duty vehicles. Dozens of articles have been written that analyze the impacts of various policies on consumer vehicle purchases. Helfand and Wolverton (2011) review this literature, though the literature continues to expand (e.g., Bento et al. 2012; Allcott 2013). As noted above, these models have been used to examine policy scenarios of many kinds, including international trade, industrial organization, and environmental requirements.

In most of these papers, the quality of the model is based on the econometric analysis: if the analysis meets theoretical and statistical requirements, and the results include expected and statistically significant coefficients on variables, then the model is suitable for policy analysis. Researchers commonly use their models for simulation of counter-factual situations based on the best estimates of the baseline situation. As a result of such practices, for instance, Goldberg (1998) found that a gas tax of 780%, 80 cents per gallon in 1989, would be necessary to achieve the same fuel savings as fuel economy standards, while Jacobsen (forthcoming) finds much lower gasoline taxes would achieve the same effects as fuel economy standards.[1]

Despite their widespread use for policy simulation, these models have typically not been validated for their ability to predict vehicles sales in response to new circumstances. That is, rarely have their predictions been tested against real-world outcomes, to see if they can in fact predict out of sample. One exception is Pakes et al. 1993, who (as summarized in Berry et al. 1995):

> used our model's estimates to predict the effect of the 1973 gas price hike on the average MPG of new cars sold in subsequent years. We found that our model predicted 1974 and 1975 average MPG almost exactly. . . . However, by 1976 new small fuel efficient models began to be introduced and our predictions, based on fixed characteristics, became markedly worse and deteriorated further over time.

Another exception is Heckmann et al. (2013), who use data from MY 2004-6 vehicles to estimate a number of different econometric models, and test their predictions against MY 2007 vehicle sales. They find that models scoring better with a goodness-of-fit metric perform better in predictions; the specific metric chosen is not important, and neither is the structural specification (nested, mixed, or plain logit). More covariates also improves predictive ability. With no information – that is, assuming all vehicles have the same market share of 0.42% -- 70% of share predictions have errors greater than 0.2%; with the best models, only 30% of share predictions exceed that criterion.

This paper adds to that literature by performing a validation exercise using a consumer vehicle choice model developed for the U.S. Environmental Protection Agency (EPA). As will be discussed, the results presented here are preliminary and subject to revision. The following section describes that model.

[1] These models are not directly comparable. Unlike Goldberg's model, Jacobsen's model takes into account the used vehicle fleet and the amount that vehicles are driven. Because a gasoline tax affects existing vehicles as well as new vehicles, it saves fuel across the fleet. In contrast, a fuel economy standard affects only new vehicles.

The Model[2]

As mentioned, the model used here was developed by Greene and Liu for EPA (2012) specifically to predict changes in total sales and fleet mix associated with GHG/fuel economy standards. It is a nested logit with a representative consumer and 5 layers, as described in Figure 1. The first layer constitutes the buy/no buy decision. Next it distinguishes between passenger vehicles, cargo vehicles, and ultra-prestige vehicles. It is important to note that passenger vehicles include sport-utility vehicles and minivans, although many of these vehicles are considered light-duty trucks for regulatory purposes. Consumers commonly consider these to be passenger vehicles; it is more likely, for instance, that people consider an SUV to be a substitute for a large or midsize car than for a pickup truck. Because the model is meant to reflect consumer decision processes, it was considered appropriate to nest SUVs and minivans as passenger vehicles rather than cargo vehicles. Ultra-prestige vehicles are defined purely by price exceeding $75,000.

The model separates those passenger and cargo vehicles into standard and prestige vehicles (with prestige determined by price), and then individual vehicles. See Figure 1 and Table 1 for further detail. The model is calibrated to sales by individual model in a base year through use of each vehicle's price and fuel economy. The price and fuel economy are used to estimate an effective price; when that effective price is combined with the price slope for that vehicle's nest, the constant term for that vehicle is the value that results in matching the initial sales volume.

Vehicle sales are predicted to change in response to changes in net vehicle price, where the change in net vehicle price is calculated as the increase in vehicle cost associated with technologies to reduce GHGs, less a share of the future fuel savings associated with those

[2] This section draws heavily from Greene and Liu (2012).

technologies. Greene (2010) found highly varied estimates in the literature of consumer willingness to pay (WTP) for additional fuel economy in the vehicle purchase decision, with a number of studies showing WTP less than the expected value of future fuel savings, and others showing overvaluation. The CCM allows a user to choose the number of years of expected fuel savings that vehicle buyers are believed to consider in their purchase decisions, as well as the future fuel prices and discount rate they might use for those calculations.

The model is designed to interact with EPA's technology-cost model, the Optimization Model for reducing Greenhouse Gases from Automobiles (OMEGA), that seeks cost-effective combinations of technologies to achieve GHG standards. Iteration between the CCM and OMEGA can be used to estimate whether sufficient technology is added to vehicles to bring fleets into compliance with standards, after consumer responses are taken into account.

The demand elasticities in the model for each vehicle nest are not estimated from an original data set, but rather are based on reviewing estimates in the literature. This approach has advantages and disadvantages. It allows for synthesis of the results from multiple analyses, and professional judgment about whether the values are appropriate. It also can be viewed as combining results from different studies, where the differences in the studies may have implications for the value. Table 2 provides the elasticities used in the analysis and the studies on which they are based.

A few limitations of the model are identifiable even before any simulations are run. Some of these limitations arise from the model being designed to be calibrated to an existing fleet and then to estimate deviations from that initial calibration. The model thus does not account for or macroeconomic shocks that might affect either total sales or changes in fleet mix independent of GHG standards, the introduction or departure of vehicles in the fleet, changes in consumer preferences, or manufacturer changes in other vehicle characteristics (such as acceleration). For the purposes for which the model was built, these need not be major limitations. The model was designed for static, same-year analysis of the effects on vehicle sales of adding costly but fuel-saving technologies; that is, it was intended to compare vehicle sales with and without costly but fuel-saving technologies for a single fleet of vehicles. In principle, then, changes in the economy, demographics, or the fleet over time should not affect the ability of the model to predict, because it is predicting against a static counter-factual. However, the baseline of no standards and the counter-factual of meeting the standards do not exist in the same year. As a result, the model is here being tested for its ability to predict between two model years. As will be discussed further, the years for which we currently have data involve the beginning and the depths of the Great Recession, whose effects may swamp any predictive abilities of the model. This limitation is therefore an issue for this method of testing the model.

Other limitations are associated with the use of nested logit. For instance, as Train (2009) notes, "only differences in utility matter." As a result, an equal change in all vehicle prices (e.g., $1000) would lead to no change in market shares for vehicles, although $1000 has a much bigger impact on the price of an economy car than that of a luxury car. (It would change total sales.) The nested logit also puts limitations on demand elasticities for the nests: responsiveness to price must be highest at the individual-vehicle level, and decrease at each higher nest. The model includes a validation step to ensure that these limitations are achieved.

Method

This paper compares the model's predictions of changes in fuel prices and changes in fuel economy standards in MY 2010, relative to MY 2008 vehicles, to those that occurred during MY 2010. The approach is to calibrate the model to MY 2008 vehicle sales; provide the model with changes in each vehicle's fuel economy and price between MY 2008 and 2010; and use those changes to predict sales in MY 2010. Those predictions are then compared to actual sales in 2010. Though the Great Recession clearly had a significant effect on the vehicle market during this time, it is also a period of fuel price swings and changes in vehicle characteristics that should be reflected in the modeling results. This period thus provides an opportunity for an initial review of the model's ability to predict changes in the vehicle fleet.

Data requirements to calibrate the model include the vehicle's price, fuel economy, and sales in MY 2008; to make the predictions, the model needs the change in price and the fuel economy in going from MY 2008 to MY 2010 vehicles. These data come from market data assembled by EPA and the Department of Transportation for its analysis of GHG standards for MYs 2017-25 (U.S. Environmental Protection Agency and Department of Transportation 2012). The initial datasets each contain over 1000 vehicles, including some vehicles with the same name but, for instance, different engines. To run the consumer vehicle choice model, each MY 2008 vehicle needed to be matched with its MY 2010 counterpart. The change in vehicle fuel economy and the change in price (manufacturer's suggested retail price), along with changes in fuel prices, would provide the basis for changes in vehicle sales.

The list of vehicles in MY 2008 does not match up with the list for MY 2010 in a straightforward way, however. Vehicles enter and exit the market between any two model years; indeed, Saab dropped out of the market entirely during this time. This paper uses two methods to address this problem. In the first, aggregation by vehicles, multiple trim levels (for instance, two-door vs. four-door versions of a vehicle) of each vehicle are combined through sales-weighting. This approach allows matching of most of the individual vehicle models. In the second, aggregation by class, all vehicles are aggregated, by manufacturer, to the classes of the vehicle choice model (see Table 1 for those classes).

Tables 3 and 4 provides the summary statistics for these two methods compared to the whole fleets. Both cases permit matching of over 90% of the vehicles in either model year, though aggregating by class allows for representation of somewhat more vehicles. In the analyses presented here, vehicles that were not matched were dropped from the analysis. In future work, we plan to consider alternative approaches to handle vehicles that either disappear or join the market between two years.

Table 4 shows that the two forms of aggregation lead to small differences in fleet characteristics. Aggregating by class matches slightly better on weighted average price, but aggregating by vehicle matches slightly better on average fuel economy. Differences in shares among passenger, cargo, and ultra-prestige vehicles are less than one percent in all cases.

As discussed earlier, the effective vehicle price in the model is the vehicle's purchase price, plus some share of the expected lifetime fuel consumption of the vehicle. Expected lifetime fuel consumption is based on a vehicle's fuel economy (the "label" value),[3] average vehicle miles traveled over a vehicle's lifetime, fuel prices taken from the Energy Information Administration's Annual Energy Outlook, a discount rate specified by the user, and a number of years of fuel consumption that a consumer considers in purchasing a vehicle, also specified by the user. The results that follow are based on a 3% discount rate and 5 years of fuel consumption.[4] Future work will include experimentation with different assumptions for these latter two values.

[3] The value on the fuel economy label is based on a different test method than that used for compliance with fuel economy standards. The label value, typically lower than that used for compliance, is considered to be closer to the fuel economy that a driver will experience. In addition, it is information a consumer is likely to have available when considering a new vehicle.

[4] In the results presented here, the model incorporates different fuel prices starting in 2008 than in 2010.

Results

Tables 5 and 6 provide an overview of results for the two methods of aggregation. Note that the "actual" market results in the tables omit the vehicles that were not matched between the model years, and thus were excluded from the modeling exercise. This approach assesses the model against all vehicles included in the modeling exercise, rather than the entire population of vehicles. Because each aggregated dataset included a slightly different set of vehicles, the "actual" results are not the same when aggregating by vehicle compared to aggregating by class.

Both methods do poorly in predicting total vehicle sales. This result is not a surprise, given the model years studied here and the model's function. As discussed above, the model is not designed to predict future vehicle sales based on future changes; instead, it is intended for comparisons within a model-year of vehicles with and without fuel-saving technologies. Sales in MY 2010 were heavily affected by the Great Recession, which the model, calibrated to MY 2008, would not be able to take into account. Both forms of aggregation predict increases in vehicle sales, a result that must be due to decreases in effective prices (price plus a portion of future fuel consumption) between the two years.

Both forms of aggregation correctly predict increases in fuel economy, though the actual increase in fuel economy is greater than that predicted in either form of aggregation. This effect may, again, perhaps be due to the influence of the Great Recession: people may have switched to less expensive vehicles, which, at this time, may have been more fuel-efficient than more expensive vehicles. There may be other explanations for this result as well. Perhaps, for instance, people accounted for more future fuel consumption in their purchase decisions than these model runs allowed. Exploring the role of fuel consumption in consumer purchase decisions is another avenue for future analyses.

Although the model did not correctly estimate vehicle sales, perhaps it does better in forecasting consumer shifts across vehicle classes in response to changes in price and fuel economy. At a high level, the two methods of aggregation produced opposite results directionally for the shares of passenger, cargo, and ultra-prestige vehicles: aggregation by vehicle implied a switch from passenger vehicles to cargo vehicles, with aggregation by class showing what actually happened, a relative increase in passenger vehicles. These shifts are small: the actual full market share in passenger vehicles went from about 86% to 88% (see Table 4), though either form of aggregation used a slightly smaller share of passenger vehicles. Both aggregations may have omitted slightly more passenger vehicles than cargo or ultra-prestige vehicles, perhaps reflecting a greater tendency of passenger vehicles to be redesigned in ways that make them hard to link across years.

In predicting shares of the 19 vehicle classes included in the vehicle choice model, aggregation by class correctly estimated the direction of shifts in more cases (14 out of 19 classes) than did aggregation by vehicle (10 out of 19 classes) (see Tables 7 and 8). Most of the shifts in market shares are small, though: in most cases (13 for aggregation by class, 14 for aggregation by vehicle), the predicted market share is within 1 percent of the actual market share. (Average market share of each class would be 100/19 = 5.26%.) With mostly small changes in market shares, it may be difficult to distinguish the quality of modeling performance from a general tendency for market shares not to change very much.

For both aggregations, the largest class is Midsize Cars and Station Wagons. This class also experienced a relatively large shift in shares between 2008 and 2010, from about 14% to 18-19%. Both forms of aggregation not only missed the magnitude of this shift, but even missed the direction. It is not possible to say from which classes people switched (other than the obvious point that people generally switched from classes where shares went down). The relatively inaccurate performance for this large class may suggest that it could be useful to experiment with adjusting the demand elasticity for it. With another large class, Compact and Small Station Wagons, both forms of aggregation resulted in the right direction for shares, but did not capture the magnitude. For Subcompacts, both models got the magnitude (about 2%) of the market shift about right, but in the wrong direction. Whether these flawed predictions represent a problem in the model or a change in preferences related to the recession cannot be determined.

In sum, there is some evidence that aggregating by class may lead to somewhat better performance than aggregating by vehicle. It is not a surprise that the model did not predict the reduction in sales due to the recession. It shows some but not strong ability to predict changes in market shares. Given that most changes in market shares are small, it may be difficult to identify them. On the other hand, the model did not do well in predicting shifts in two of the larger vehicle classes, Compact and Midsize Cars (and Station Wagons). Additional work, potentially with additional model years of data, may be needed to understand better the ability of the EPA model to estimate changes in vehicle purchases.

Conclusion

Consumer vehicle choice models are commonly used to simulate the effects of counter-factual situations; they have been tested against reality much less frequently. This paper adds to, and seeks to encourage, that literature by testing the ability of a model developed for the U.S. Environmental Protection Agency to predict responses to changes in vehicles made between MY 2008 and MY 2010. This work finds few definitive answers, though it suggests that conducting the analysis with more aggregated data may provide greater success, at least qualitatively, than more detailed input sets.

The results presented here suggest that further work is desirable. For instance, it would be valuable to get additional years of data. Do predictions of responses to vehicles in future model years follow the same pattern as in MY 2010? Or might it predict better for non-recession years, or worse for years further in the future? It may be possible to adjust various model parameters to develop better estimates of shifts in vehicle classes; if those adjustments work for predicting MY 2010 market shares, would they work as well for other years? In addition to use of additional model years of data, it may be useful to consider other criteria for success in modeling than whether predicted market shares fall within 1 percent of actual shares, or move directionally together.

Perhaps the major lesson learned so far is that conducting a validation exercise is a significant challenge. As discussed in the paper, the U.S. EPA's model is static, designed to evaluate changes in vehicles within a model year rather than over time. There is no obvious way to test the model for the manner for which it was designed, because only one vehicle fleet exists in the U.S. in a year; no counter-factual exists. Models that incorporate demographic factors may be better suited to testing across time; on the other hand, when they are ultimately used for simulation purposes, such models require projections of those demographic factors, which may not be of great reliability. Across time, any model has to face the fact that vehicles, even manufacturers, enter and exit the market. Whitefoot et al. (2013) seek to endogenize manufacturer and consumer decisions simultaneously; whether such efforts will reflect actual market movements is yet to be seen. We hope that this paper stimulates more research on the ability of consumer vehicle choice models to predict market changes.

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TABLE 1. Vehicle Class Definition in the Consumer Vehicle Choice Model

CVCM Class	No. of Configurations[1]	Corresponding EPA Class
1. Prestige[2] Two-Seaters	27	Two Seaters
2. Prestige Subcompact Cars	49	Subcompact Cars, Minicompact Cars
3. Prestige Compact Cars and Small Station Wagons	71	Compact cars, Small Station Wagons
4. Prestige Midsize Cars and Station Wagons	66	Midsize Cars, Midsize Station Wagons
5. Prestige Large Cars	17	Large Cars
6. Two-Seater	26	Two Seaters
7. Subcompact Cars	58	Subcompact Cars, Minicompact Cars
8. Compact Cars and Small Station Wagons	82	Compact Cars, Small Station Wagons
9. Midsize Cars and Station Wagons	100	Midsize Cars, Midsize Station Wagons
10. Large Cars	29	Large Cars
11. Prestige SUVs	109	SUVs
12. Small[3] SUVs	17	SUVs
13. Midsize SUVs	72	SUVs
14. large SUVs	137	SUVs
15. MiniVans	19	MiniVans
16. Cargo/Large Passenger Vans	42	Cargo Vans, Passenger Vans
17. Small Pickup Trucks	49	Small Pickup Trucks
18. Standard Pickup Trucks	67	Standard Pickup Trucks
19. Ultra Prestige Vehicles[3]	93	See the definition (note 4) below

Notes:

(1) Number of configurations is the number of configurations which a CVCM class contains. It is not an attribute of the model itself, but specific to the vehicle data base to which the model is calibrated: a configuration is a record in the data base and a CVCM class consists of multiple records.

(2) Prestige and non-prestige classes are defined by vehicle price: the prestige are vehicles whose prices are higher than or equal to unweighted average price in the corresponding EPA class, and vice versa for non-prestige vehicles. E.g., Prestige Two-Seater class is the set of relatively expensive vehicle configurations in EPA class of two seaters with prices higher than or equal to the unweighted average price of EPA two seaters.

(3) Non-prestige SUVs are divided into small, midsize and large SUVs by vehicle's footprint (small: footprint <43; midsize: 43<=footprint<46; large: footprint>=46)

(4) Ultra Prestige class is defined as the set of vehicles whose prices are higher than or equal to $75,000.

TABLE 2. Own Price Elasticities of New Vehicle Demand in the Literature

		Own Price Elasticity of Demand	Values Used in Calibration
Choice of Configuration			
	Small	Berry et al. (1995): -6.4 for Mazda 323; Eftec (2008): -4.5	-5
	Midsize	Berry et al. (1995): -4.8 for Nissan Maxima; Eftec (2008): -5.4	-5
	Large	Berry et al. (1995): -4.8 for Honda Accord; Eftec (2008): -3.6	-5
	Luxury	Berry et al. (1995): -3.1 for Lexus LS400; Eftec (2008): -4.0	-3.5
	Sport	Eftec (2008): -1.6	-3.5 for two seaters
Choice of Make/Model	Average	Bordely (1993):-3.6; Goldberg (1995): -3.3; Goldberg (1998):-3.1;	
	Small	Bordley (1993): -3.4; Goldberg (1995): -3.5	-4
	Midsize	Bordley (1993): -3.3; Goldberg (1995): -4.6; Goldberg (1996,1998):-4	-4
	Large	Bordley (1993): -3.8; Goldberg (1995): -4.7; Goldberg (1996,1998):-4	-4
	Luxury	Bordley (1993): -3.7; Goldberg (1995): -2; Goldberg(1996):-1.2;	-2
	Sport	Bordley (1993): -4.2; Goldberg (1995): -1.4; Goldberg(1996,1998):-1.2	-2 for two seaters
	Truck	Goldberg (1995): -3.1�	
	Van	Goldberg (1995): -4.5�	
Choice of Market segment	Small	Bordley (1993):-1.9; Kleit (2002):-2.8; Cambridge (2008): -1.8	-3
	Midsize	Bordley (1993):-2.3; Kleit (2002):-3.5; Cambridge (2008): -1.3	-3
	Large	Bordley (1993):-3; Kleit (2002):-4.5; Cambridge (2008): -2.8	-3
	Luxury	Bordley (1993):-2.4; Kleit (2002):-1.7; Cambridge (2008): -3.5	-2.2
	Sport	Bordley (1993):-3.4; Kleit (2002):-2.3; Cambridge (2008): -1.8	-1.3 for two seaters
	Truck	Kleit (2002):-3 for small truck, -1.5 for large truck	
	SUV	Kleit (2002):-3 for small suv, -2 for large suv	
	Van	Kleit (2002):-2.4	
Choice to Buy a New Veh or Not		ranged from -0.8 to -1 Levinsohn(1988), Kleit (1990), McCarthy (1996,1998), Goldberg (1998)	-0.8
	Small	Berry et al. (1995): -6.4 for Mazda 323; Eftec (2008): -4.5	-5
	Midsize	Berry et al. (1995): -4.8 for Nissan Maxima; Eftec (2008): -5.4	-5
	Large	Berry et al. (1995): -4.8 for Honda Accord; Eftec (2008): -3.6	-5
	Luxury	Berry et al. (1995): -3.1 for Lexus LS400; Eftec (2008): -4.0	-3.5
	Sport	Eftec (2008): -1.6	-3.5 for two seaters

Table 3. Summary Statistics of Baseline and Aggregated Fleets

	2008			2010		
	Baseline	**Fleet Aggregated by Vehicle**	**Fleet Aggregated by Class**	**Baseline**	**Fleet Aggregated by Vehicle**	**Fleet Aggregated by Class**
Total number of unique vehicles	1302	524*	145**	1171	524*	145**
Total vehicle sales	13,851,761	12,976,766	13,573,775	11,190,180	10,199,188	10,648,871
% Total vehicle sales captured in the final matching process	--	94%	98%	--	91%	95%

*108 unmatched vehicles include manufacturers or vehicles manufactured in one year but not in the other. These are dropped in the results that follow.
**Two manufacturers (Spyker/Saab, Tesla) had sales in 2008 but not 2010. In 36 occasions, a manufacturer had sales in a vehicle class in one year but not in the other. These are dropped in the results that follow.

Table 4. Additional Summary Statistics

	MY 2008 Actual	MY 2008 aggr. by vehicle	MY 2008 aggr. by class	MY 2010 Actual	MY 2010 aggr. by vehicle	MY 2010 aggr. by class
Total sales (millions)	13.9	13.0	13.6	11.2	10.2	10.6
Weighted avg. price	$27,873	$27,702	$27,850	$26,767	$26,624	
Min price	$11,783	$11,783	$13,646	$9,970	$11,923	
Max price	$1.7M	$1.7M	$254,533	$1.7M	$1.7M	
Weighted avg. fuel economy	26.2	26.3	25.7	28.4	28.3	
Min FE	12.0	12.0	15.2	12.0	12.0	
Max FE	65.8	65.8	49.5	70.8	70.8	
Share passenger	86.3%	85.7%	86.0%	87.8%	86.8%	87.2%
Share cargo	12.8%	13.4%	13.1%	11.6%	12.7%	12.1%
Share ultra-prestige	0.9%	0.9%	0.9%	0.7%	0.5%	0.7%

Table 5. Results with Aggregation by Vehicle

	MY 2008	MY 2010 Predicted	MY 2010 Actual	Directional Agreement?	% Dif. bet. Pred. & Actual (volumes)
Total Sales	12,976,766	13,280,540	10,199,188	N	26%
Weighted Avg. Fuel Economy	26.3 mpg	27.5 mpg	28.3 mpg	Y	-3%
Share passenger	85. 7%	85.0%	86.8%	N	24%
Share cargo	13.4%	14.0%	12.7%	N	36%
Share ultra-prestige	0.9%	1.0%	0.5%	N	81%

Table 6. Results with Aggregation by Class

	MY 2008	MY 2010 Predicted	MY 2010 Actual	Directional Agreement?	% Dif. bet. Pred. & Actual (volumes)
Total Sales	12,976,766		10,648,872	N	26%
Weighted Avg. Fuel Economy	26.3 mpg	26.9 mpg			
Share passenger	85. 7%	86.3%	87.1%	Y	25%
Share cargo	13.4%	12.8%	12.1%	Y	31%
Share ultra-prestige	0.9%	0.9%	0.7%	Y	54%

Table 7. Class Shifts for Aggregation by Vehicle

Market Shares by Vehicle Class	MY 2008	MY 2010 Predicted	MY 2010 Actual	Diff < 1%	Directional Agreement?
Prestige Two-Seater	0.56%	0.52%	0.28%	Y	Y
Prestige Subcompact	2.00%	1.93%	1.36%	Y	Y
Prestige Midsize & Station Wagon	3.78%	3.53%	2.96%	Y	Y
Prestige Large	6.71%	6.18%	5.51%	Y	Y
Two-Seater	0.29%	0.28%	0.10%	Y	Y
Large Car	3.14%	2.12%	2.24%	Y	Y
Prestige SUV	9.57%	9.26%	8.67%	Y	Y
Minivan	4.72%	4.95%	4.81%	Y	Y
Cargo Pickup Small	2.80%	2.28%	2.44%	Y	Y
Prestige Compact & Sm Stat Wagon	2.93%	3.23%	2.83%	Y	
Midsize SUV	2.20%	1.65%	2.41%	Y	
Large SUV	10.04%	9.98%	10.21%	Y	
Cargo / large passenger van	0.10%	0.08%	0.17%	Y	
Ultra Prestige	0.90%	0.98%	0.54%	Y	
Compact and Small Station Wagon	9.16%	9.42%	12.90%		Y
Subcompact	7.50%	8.66%	5.86%		
Midsize Car and Station Wagon	13.88%	13.40%	18.83%		
Small SUV	9.19%	9.93%	7.84%		
Cargo Pickup Standard	10.53%	11.63%	10.05%		
19 Classes				14 Y	10 Y

Table 8. Class Shifts for Aggregation by Class

Market Shares by Vehicle Class	MY 2008	MY 2010 Predicted	MY 2010 Actual	Diff < 1%	Directional Agreement?
Prestige Two-Seater	0.51%	0.47%	0.26%	Y	Y
Prestige Compact & Sm Stat Wagon	2.76%	2.93%	3.29%	Y	Y
Prestige Midsize & Station Wagon	4.26%	3.83%	3.13%	Y	Y
Two-Seater	0.28%	0.28%	0.10%	Y	Y
Large Car	2.45%	1.47%	2.04%	Y	Y
Midsize SUV	2.10%	1.19%	1.11%	Y	Y
Large SUV	9.62%	9.03%	9.57%	Y	Y
Minivan	4.67%	4.88%	4.96%	Y	Y
Cargo / large passenger van	0.25%	0.22%	0.16%	Y	Y
Cargo Pickup Small	2.68%	2.40%	2.33%	Y	Y
Ultra Prestige	0.94%	0.90%	0.67%	Y	Y
Prestige SUV	9.84%	10.26%	9.48%	Y	
Cargo Pickup Standard	10.15%	10.20%	9.64%	Y	
Prestige Large	7.25%	5.35%	2.88%		Y
Compact and Small Station Wagon	9.49%	10.85%	16.45%		Y
Small SUV	9.75%	12.52%	9.87%		Y
Prestige Subcompact	2.20%	3.24%	1.79%		
Subcompact	6.62%	8.77%	4.35%		
Midsize Car and Station Wagon	14.20%	11.21%	17.90%		
19 Classes				13 Y	14 Y

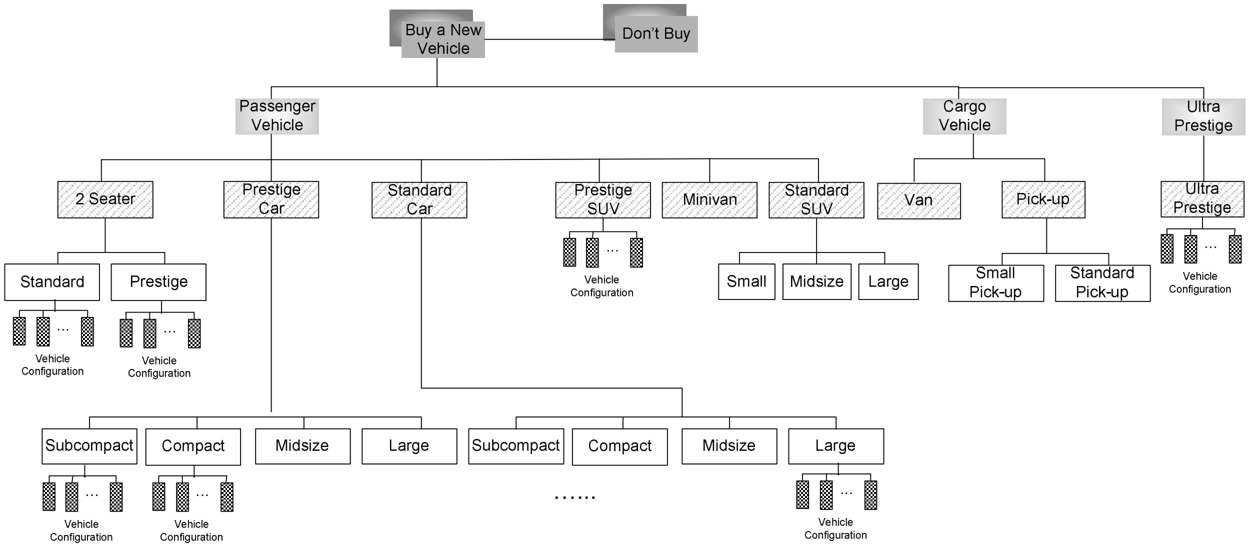

Figure 1. Nested Multinomial Logit Structure of Consumer Choice Model

Note: "Standard" is synonymous with "Non-Prestige"