

# A joint model for vehicle type and fuel type

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## Abstract

In the face of growing concerns about greenhouse gas emissions, there is increasing interest in forecasting the likely demand for alternative fuel vehicles. This paper presents an analysis carried out on stated preference data collected in California, looking at respondent's preferences in a joint vehicle type choice and fuel type choice experiment. Our study recognises the fact that this choice process potentially involves high correlations that an analyst may not be able to adequately represent in the modelled utility components. Importantly, we further hypothesise that the standard Nested Logit model is incapable of capturing the full extent of correlation patterns in such a multi-dimensional choice process, and that a Cross-Nested Logit structure may be more appropriate. Our empirical analysis and a brief forecasting exercise produce evidence to support these suspicions. The findings from this paper are not just of interest in the context of the demand for alternative fuel vehicles but are also relevant for the analysis of multi-dimensional choice processes in general. Finally, an extension shows that additional gains can be made by using mixed GEV structures, allowing for random heterogeneity on top of the flexible correlation structures.

## Introduction

There is increasing interest in the potential demand for alternative fuel vehicles, given not only growing environmental concerns, but also recent volatility in oil prices. There are a number of ways to use alternative fuels, including a mix of alternative and convention fuels in flex fuel and hybrid vehicles, as with ethanol and gasoline or electricity and gasoline, as well as the sole use of alternative fuels, in full electric and compressed natural gas vehicles, for instance. The preferences for different types of fuels are difficult to predict, not least because of the strong relationship between fuel type and other attributes such as performance, annual costs as well as incentives (e.g.

tax breaks). At the same time, there is a very strong link between fuel type and vehicle type, with certain types of fuels being appropriate for specific vehicle types.

With the growing focus on these vehicles, in reducing greenhouse gas emissions, the long expressed interest in modelling the potential consumer response to the introduction of such vehicles should come as no surprise. Examples include Train (1983), Bunch et al. (1993), Train (1993), Golob et al. (1995), Kavalece (1996), Tomkins et al. (1998), Greene (2001), Batley and Toner (2003), Batley et al. (2004), Adler et al. (2004), and Spissu et al. (2009) to name but a few.

In this paper, we discuss work based on the 2008-09 California Vehicle Survey (CVS), aimed at providing input data for the California (light-duty) Conventional and Alternative Fuel Response Simulator (CALCARS) model at the California Energy Commission (CEC). The 2008-09 CVS collected data on both stated and revealed preferences of vehicle owners in California, to forecast their vehicle choice and the use of both conventional and alternative fuel vehicles.

In the present paper, we focus on the stated preference survey component of this work. The survey involved the design of a highly complex survey tool, which included seven fuel types, fifteen vehicle types, and up to eleven level-of-service attributes, such as cost, fuel consumption, fuel availability, refuelling time and acceleration. To reduce the survey complexity, each choice experiment made use of only four alternatives, where this included a reference vehicle and three other vehicles assigned on the basis of a weighting approach. An internet-based survey was used to collect the data, enabling the collection of a very large sample.

The main contribution of the work described here comes in the use of a Cross-Nested Logit (CNL) structure. Earlier empirical work revealed the existence of significant levels of correlation between alternatives sharing the same fuel type as well as between alternatives sharing the same vehicle type. As we discuss in detail in the methodology section, the use of multi-level Nested Logit (NL) structures was not appropriate in this context, and the use of the CNL model was shown to lead to significant gains in model performance as well as the realism of forecasts. Additional gains were obtained by allowing for random taste heterogeneity.

The remainder of this paper is organised as follows. We first describe the survey work carried out for this analysis, followed by methodology discussion, and a presentation of the empirical results and a brief forecasting example. Finally, we present the conclusions of the work.

## Survey Design

Survey data were collected using a two-phase, multi-method approach. The first phase involved a recruitment survey to collect data on revealed preferences (RP) and identify participants planning to purchase a vehicle to recruit for the stated preference survey. The second phase included the stated preference survey with eight vehicle choice exercises.

In the RP survey, respondents were asked to indicate the type of vehicle they are most likely to purchase next for their household; including information about the vehicle type, fuel type, expected fuel efficiency, purchase price, vehicle age, and estimated number of miles the vehicle would be driven annually.

After completing the revealed preference (RP) survey over landline and mobile phones, the respondents were given the option of completing the stated preference (SP) survey using either print or online questionnaires. In both cases, data from the RP survey was used to construct a set of eight stated preference exercises for the SP survey, tailored to the specific individual.

Each stated preference exercise presented respondents with four hypothetical vehicles as alternatives. The first vehicle, or the reference vehicle, was presented as the new or used vehicle the respondent planned to purchase next for their household. The attributes that describe the reference vehicle were consistent with what the respondent reported in the RP survey in terms of vehicle type, fuel type and age, with the remaining attributes varying across choice sets. The next three alternatives were presented as vehicles of different sizes, fuel types and ages. The four vehicles in each exercise were described by a set of ten to twelve attributes, depending on the fuel type presented. Respondents were asked to select the vehicle they would most prefer to purchase based on the attributes presented in each alternative. The values of each attribute varied according to an experimental design (discussed later), requiring respondents to trade off attributes against each other. Figure 1 presents an example of one of the eight stated preference exercises of a hypothetical respondent.

The first two attributes for each alternative were vehicle type and fuel type. A total of fifteen vehicle types and seven fuel types were selected for the exercises. The vehicle type was fixed to the response given in the RP survey for the reference vehicle. For the remaining three alternatives, vehicle type was drawn from one of the following fifteen types:

1. Subcompact car
2. Compact car
3. Mid-size car
4. Large car
5. Sport car or “two door high performance subcompact car”
6. Small cross-utility car or “small wagons with flexible seating”
7. Small cross-utility SUV
8. Mid-size cross-utility SUV
9. Compact SUV
10. Mid-size SUV
11. Large SUV
12. Compact van
13. Large van
14. Compact pick-up truck
15. Standard pick-up truck

While it was possible any vehicle could be selected for the three alternate vehicles, the selection of those vehicles was done using weighted draws based on the respondent’s reference vehicle type. Weighted draws were used because it is expected that respondents will have relatively strong preferences for at least a broad category of vehicles (e.g. small or large), and as a result presenting a respondent with a choice between a reference subcompact car and a large van makes little sense. In that situation, vehicle type would dominate the choice process and little or no information could be gained for the sensitivities to other attributes. On the other hand, completely restricting the different combinations of vehicle types presented to a respondent did not seem appropriate. As a result, a set of weights were developed for each reference vehicle type. With these weights, all vehicle types have a non-zero probability of being included in an exercise, but the probability is higher for those vehicles that are more similar to the reference vehicle type. An especially high weight of approximately 50 percent was used for the reference vehicle type, which ensured that, at least for one pair of alternatives, the relative preference was not influenced by vehicle type. The vehicle types for the three alternative vehicles were drawn without replacement from the list of 15 vehicle types, meaning that, while the reference vehicle was allowed to repeat in one other alternative, allowing respondents to trade off attributes other than vehicle type, no other vehicle types were allowed to repeat across alternatives within a single choice exercise.

For the reference vehicle, fuel type was fixed to the respondent's RP response. The remaining fuel types were drawn from the following list:

1. Standard Gasoline
2. Flex Fuel/E85
3. Clean Diesel
4. Compressed Natural Gas
5. Hybrid-electric
6. Plug-in Hybrid-electric
7. Full Electric

Fuel types for the three alternate vehicles were selected entirely randomly, i.e. not using any weights, thus guaranteeing that all possible combinations were represented roughly evenly. As with vehicle types, fuel types were drawn without replacement, meaning that while the reference vehicle fuel type was allowed to repeat in one of the three alternate vehicles, allowing respondents to trade off attributes other than fuel type, no other fuel types were allowed to repeat across alternatives within a single exercise.

The remaining vehicle attributes were dependent on the vehicle and fuel type. While values for vehicle type and fuel type were selected using weighted and random draws as described above, the values for the remaining attributes varied according to an orthogonal experimental design. The orthogonal design is described in more detail later on.

Many of the vehicle attributes vary around a base value. In the case of purchase price, maintenance cost, miles per gallon equivalent, fuel cost per gallon equivalent, and acceleration, a table with base values was used, representing average values for all vehicles of a particular vehicle type, fuel type and vintage.

The remaining attributes included in the survey were as follows:

- The **vehicle age** was automatically set to *new* for plug-in hybrid electric and full electric vehicles, with variations around the reference vehicle age for other vehicles
- The **purchase price** of the vehicle varied around a base value. For the reference vehicle, the base value is the response given in the RP survey. For the three remaining alternatives, the base value was dependent on a "list price" determined from the combination of vehicle type, fuel type, and vintage, where this was adjusted by the ratio between the indicated price of the reference vehicle in the RP survey and the list price for that vehicle, thus accounting for the possibility that a respondent was considering a higher than average or lower than average price for the reference vehicle. Variations across choice sets are then based on the experimental design.
- There were six **purchase incentive** levels shown in the survey, with the exception of gasoline-powered vehicles, where no incentives were used. Incentives included carpool lane access, free parking, tax credits, reduced tolls and reduced purchase price. Variations across choice sets are then based on the experimental design.
- A base **maintenance cost** per mile for each vehicle was assumed based on the vehicle type, fuel type, and vehicle age. The maintenance cost per mile was multiplied by the reported annual VMT to calculate an annual maintenance cost. Variations across choice sets are then based on the experimental design.
- A base value for **miles per gallon equivalent** was assumed based on the vehicle type, vehicle age, and fuel type. Variations across choice sets are then based on the experimental design.
- The **annual fuel cost** was calculated using the fuel cost in gasoline gallon equivalents, which was a design attribute, the vehicle efficiency in miles per gallon equivalent, and the annual

miles reported in the RP survey. The variation across choices was based on variations in the fuel cost in gasoline gallon equivalents, as specified in the experimental design.

- The **fuel availability, refuelling time, and vehicle range** attributes only applied to full electric and compressed natural gas vehicles, where variations across choice sets for applicable vehicles are then based on the experimental design.
- The **acceleration attribute** was presented as the time it takes to accelerate from zero to 60 miles per hour in seconds. The acceleration of each vehicle was assumed to vary based on the vehicle type, fuel type and vehicle age, and varied according to the experimental design.

The experimental design used for this SP survey was based on an underlying orthogonal design. While several types of designs were considered at the onset, including arguably more advanced efficient designs, it was concluded that, given the complexity of the SP scenarios, an orthogonal design was the most appropriate for this particular application. While efficient designs can be preferable in some situations, the generation of an efficient design requires prior parameter values for all coefficients, as well as a priori decisions in relation to model structure and utility specification, including interactions with socio-demographic variables. While choice between hypothetical options already causes significant problems, further problems arise in the present study as it examines the choice of vehicle types and fuel types. Here, the preferences can be expected to vary across respondents to such an extent – some respondents will strongly prefer compact cars, while others will strongly prefer large SUVs – that it becomes difficult to obtain reliable prior parameter estimates. Additionally, vehicle type and fuel type would have to be directly included in the design, leading to the requirement of generating a very large number of different designs for different combinations of vehicle types and fuel types. These design considerations were not necessary with the approach used in this study, where vehicle types and fuel types were added to the design in a second stage, after generating the base design.

This base design is an orthogonal design of 144 rows, split into 18 blocks of 8 choices. Orthogonal blocking was used to avoid any correlation between the attributes and the blocks (e.g. avoiding the situation where one respondent gets all the high price options). The design contains the levels for ten attributes (the attributes other than vehicle type and fuel type) and four alternatives. The vehicle types and fuel types drawn according to the approach described above were used as inputs for calculating the base values for the levels in this underlying design. In the actual survey, each respondent was presented with one block of eight choice situations. Care was taken to ensure that the 18 different blocks were presented the same number of times and that there was no correlation between sample subgroups and blocks. The choice situations presented to the respondent were constructed on the basis of the set of vehicle type/fuel type combinations drawn for that respondent, and the block of 8 choice situations used from the experimental design for that respondent. The order in which the 8 choice situations from a given block were presented to a respondent was randomized across respondents.

## Modelling methodology

As already alluded to in earlier parts of the paper, the SP data was used to develop discrete choice models belonging to the family of random utility models. For a thorough introduction to such models, see Train (2003). In this section of the paper we first discuss utility function specification, which was identical for all estimated models, followed by a discussion of model structure. At this stage, it is also worth noting that the models used in the present paper exclude respondents from multi-vehicle households.

## Utility specification

An extensive specification search was conducted, leading to the inclusion of the following terms were in the final specification of the utility function:

- Constants for the first three SP alternatives, along with constants for fuel type and vehicle type inertia
- Vehicle type specific constants, with subcompact as the reference vehicle
- Fuel type specific constants, with standard gasoline as the reference fuel
- A constants for vehicles aged 1 or 2 years, and a constant for vehicles aged 3 years or more, with new vehicles as the reference age
- Four incentive constants, with *no incentive* as the reference
- Marginal utility coefficients associated with vehicle price (\$1000s), annual fuel costs (\$1000s), maintenance costs (\$1000s)
- A marginal utility coefficient interacting with vehicle price (\$1000s) and the income category, where seven equally sized income groups were used, and where this linear relationship was justified on the basis of earlier results using income category specific cost coefficients
- Marginal utility coefficients associated with vehicle attributes of miles per gallon equivalent (MPGE), range (miles), acceleration (seconds taken to 60mph)
- Constants associated with the option of plugging in electric vehicles at work and at other locations, and the availability of compressed natural gas at 1 out of 20 stations, with the respective references being home plug-in only, and availability at 1 in 50 stations
- Constants associated with interaction terms for large households and medium-sized vehicles, large households and large-sized vehicles, alternative fuel vehicles and medium-sized vehicles, and alternative fuel vehicles and large-sized vehicles

This specification led to the use of 44 individual parameters. Note that efforts to include refuelling time in the models were unsuccessful.

## Model structure

Although a large number of attributes are used to describe the various alternatives in the SP survey, two of them stand out as main *product* characteristics, namely the vehicle type and the fuel type. Given the nature of the choice scenarios, there are clear grounds to suspect a heightened degree of correlation between two alternatives sharing the same vehicle type or two alternatives sharing the same fuel type. This is even more so the case for two options that are of the same vehicle type and the same fuel type, but vary along some other dimension. To some extent, these correlations can be explained by the inclusion of alternative specific constants, but the degree of variation across respondents in their preference for the different vehicle types and fuel types is potentially so high that a large share of the correlation remains unexplained. However, the use of a random coefficients approach to model the heterogeneity in the vehicle type and fuel type constants across respondents is not an option, given the high number of random terms this would lead to. On the other hand, if the effects of this unobserved correlation are not accounted for, it is likely to lead to unrepresentative substitution patterns. Indeed, assuming that a respondent is interested in purchasing a compact gasoline car and that for some reason, this vehicle becomes unavailable, he or she is arguably more likely to switch to a differently-sized gasoline vehicle (say a sub-compact), than to a vehicle that is of a different fuel type and a different vehicle type. Additionally, there is the possibility that the respondent may more closely evaluate a switch to a differently fuelled compact vehicle (e.g. a hybrid compact) given the similarity in vehicle type. The most basic model, a Multinomial Logit (MNL) model, cannot represent such substitution patterns, and there will be a proportional shift in probability towards all other vehicle type and fuel type combinations.

The typical approach for dealing with such an issue is estimating a Nested Logit (NL) model. For the sake of illustration, let us assume we're in a situation where a respondent has six vehicles to choose from:

- A. Compact gasoline car
- B. Compact hybrid-electric car
- C. Compact gasoline car
- D. Compact gasoline SUV
- E. Compact flex fuel SUV
- F. Compact hybrid-electric car

In this scenario, vehicles A, B, and C share the same vehicle type, as do vehicles D, E, and F. Vehicles A, C, and D share the same fuel type, as do vehicles B and F. Finally, vehicles A and C share the same vehicle type and the same fuel type. This provides ample source for correlation between alternatives. Various possible NL structures arise, as illustrated in Figure 2. In the first structure, we use a nesting by vehicle type approach, hence accounting for the correlation between options that share the same type of vehicle. As an example, if vehicle A was to become unavailable (or less attractive say due to a price increase), a respondent previously interested in this vehicle may be more likely to shift his/her interest to vehicles B or C than to vehicles D, E, or F. The second figure shows the corresponding two-level NL structure using nesting by fuel type. Here, we allow for heightened correlation between vehicles A, C, and D, and between vehicles B and F. It is a likely outcome that both structures reveal heightened substitution patterns between alternatives sharing the same vehicle type, or those sharing the same fuel type. This leads to a requirement for a structure that can jointly accommodate the two substitutions. A possible approach in this context comes in the use of a three-level NL structure, such as the one shown in the third example in Figure 2, first nesting by vehicle type, and then by fuel type. It can immediately be seen that another option, not shown here, is to nest first by fuel type, and then by vehicle type. The model structure in Figure 2 still allows for correlation between the different compact cars, and for correlation between the different compact SUVs. Additionally, it allows for even higher correlation between the two gasoline cars, i.e. options A and B. However, given the ordering of the nesting levels, the model is unable to account for the correlation between two options sharing the same fuel type but being of different vehicle type. As an example, we would expect options B and F to be closer substitutes for each other, but the model treats their errors as completely independent. The issue here is that when using a multi-level NL model for multi-dimensional choice processes, the full correlation can only be accommodated along the highest dimension of nesting in the tree, an issue that was to our knowledge first discussed by Hess & Polak (2006) in an air travel behaviour context.

The solution put forward by Hess & Polak (2006) is to use a CNL structure (cf. Vovsha, 1997), as illustrated in Figure 3, for the present scenario. Here, we make use of two separate vehicle type nests and three separate fuel type nests, with each alternative falling into one vehicle type nest and one fuel type nest<sup>1</sup>. In the resulting structure, we have correlation between those alternatives sharing the same vehicle type (i.e. A, B, C, and D, E, F), and vehicles sharing the same fuel type (i.e. A, C, D, and B, F), with even higher correlation for those alternatives sharing the same vehicle type as well as the same fuel type (i.e. A and C).

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<sup>1</sup> On a technical aside, the CNL specification works by allocating an alternative by different proportions into different nests, collapsing back to a NL model when all allocation parameters are equal to 1, i.e. an alternative belongs into one nest one. In the present context, the allocation parameters were all fixed to a value of 1/2, meaning that an alternative belongs to one vehicle type nest and one fuel type nest. The estimation of actual values for the two non-zero allocation parameters for each alternative would have been very difficult due to the high degree of non-linearity and would arguably not have provided any further benefits from an interpretation perspective.

## Specification of choice set

With the above approach of characterising alternatives along two dimensions, we obtain 105 combinations of vehicle types and fuel types. With the survey making use of four separate SP alternatives, and each alternative potentially taking on one of those 105 combinations, the model implementation actually made use of four sets of 105 utility functions, i.e. a total of 420 alternatives, of which exactly four were available in each choice situation

## Model estimation

All model estimation and forecasting work reported in this paper were carried out using BIOGEME (Bierlaire, 2005), which is easily capable of dealing with such a large CNL structure. One further point needs addressing. The data used in this survey contains multiple observations for each respondent, potentially leading to correlations amongst choices for the same respondent. In the present work, this was not recognised in the modelling work for two reasons. The use of a random coefficients approach was not practical for computational reasons (the estimated models already took several hours without this added complication) and the use of the Jackknife approach (see e.g. Ortúzar, 1997) is not supported by BIOGEME, the only software well versed at estimating the complex model structure used in this paper. From this perspective, some of the estimates with a lower degree of significance should be treated with caution, given the possible underestimation of standard errors resulting from a cross-sectional estimation on repeated choice data.

## Empirical results

The estimation results for the different discrete choice models are summarised in Table 1 for the main results and Table 2 for the nesting parameters for the NL and CNL models. Our first observation is that the NL model using nesting by fuel type gives us an improvement in model fit over the MNL model by 12.43 units in log-likelihood (LL), which is highly significant, coming at the cost of just six additional parameters. These additional parameters are nesting parameters which we will return to below. Similarly, the NL model using nesting by vehicle type improves LL (compared with MNL) by 18.74 units, at the cost of 11 additional parameters. This is highly significant, as is the 34.93 unit improvement for the CNL model (compared with MNL), at the cost of 17 additional parameters. Finally, a likelihood ratio test cannot be used in this case to compare the CNL model to the NL due to the extra constraint on one of the nesting parameters in the CNL model, but the adjusted  $\rho^2$  measure shows a small additional improvement.

Actual estimation results in Table 1, with a few exceptions, show very similar parameter estimates across the four models, with the real differences between the models becoming apparent later on in the forecasting exercise. Going through the various estimates in turn, the values for the three constants suggest some allegiance to the reference alternative, along with a small amount of reading left to right impact. Further evidence of inertia is given by the two following estimates, showing that respondents are highly likely to choose a vehicle of their initially intended vehicle type and to a slightly lesser extent the same fuel type. Without attempting to read too much into the various vehicle type and fuel type constants, the large negative values for the CNG and full electric vehicles do stand out, suggesting that additional incentives/improvements are required to increase the attractiveness of such vehicle given the low baseline preference. There is clear evidence of decreasing attractiveness with increasing age, while the various incentives have a positive impact on utility. All different cost components lead to reductions in utility, though the vehicle price sensitivity is reduced as income increases. Better acceleration, longer range, better fuel efficiency and improved fuel availability all have positive impacts on utility, while large households show the expected preference for larger vehicles, and the attractiveness of alternative fuel vehicles reduces with vehicle size.



We next turn our attention to the nesting parameters, which explain the correlation between alternatives grouped together in a nest, where these parameters, shown in Table 2, are constrained to be between 0 and 1, with lower values meaning higher correlation. The base value of 1 equates to an absence of correlation (as in a MNL model) and for this reason, the t-ratios are calculated with respect to a base value of 1 rather than 0. Looking first at the model using nesting by fuel type, we observe that the nesting parameter for full electric vehicles has collapsed to a value of 1, indicating no heightened correlation between different full electric vehicles. In addition, the values for the nesting parameters for three other fuel types, namely Flex Fuel/E85, Clean Diesel, and Compressed Natural Gas, are close to 1 and not significantly different from 1, suggesting that only low levels of correlation arise in these contexts. However, high correlation is observed between different gasoline cars, and also between different hybrid-electric cars, suggesting in each case the presence of heightened substitution patterns and greater fuel type *allegiance*. In the model using nesting by vehicle type, a number of nesting parameters once again collapse to a value of 1, while high correlation is, for example, observed in the Small cross-utility SUV nest and the Compact pick-up truck nest. Overall, the picture in the CNL model is the combination of the NL results, with the exception that we now observe high correlation in the Flex Fuel/E85 nest, and that the nesting parameter for the Compressed Natural Gas, already close to 1 in the NL model, has now collapsed to a value of 1.

## Forecasting example

A brief forecasting exercise produces a final illustration of the differences between the various models estimated in this paper. Clearly, rescaling of the model outputs and correction of the constants would be required before undertaking any forecasting for the purposes of guiding policy makers (cf. Louviere et al., 2000), but the aim of this example is purely illustrative.

In this forecasting exercise, all 105 combinations of fuel type and vehicle type are available to a single respondent. We further assume that this respondent currently owns a subcompact gasoline vehicle, has an annual mileage of 13,500, and comes from a household falling into the average income category and four or fewer members. Finally, we assume that this respondent is solely interested in new cars. Our forecasting exercise starts by working out the probabilities for the 105 combinations of vehicle type and fuel type, with the four different models estimated in this paper. Next, we assume that following a government policy intervention, there is a reduction in the cost of Plug-in Hybrid Electric vehicles (fuel type 6) by \$4,000, on the condition that they also fall into the Subcompact car, Compact car or Mid-size car categories (vehicle types 1, 2, and 3).

Table 3 presents the changes in probabilities that arise as a result of this change in the attribute for these three vehicles. In the MNL model, we observe an equal increase in the probabilities for the three concerned vehicles, where this is drawn proportionally from all remaining vehicles as a result of the independently distributed errors and the resulting absence of unmodelled correlation in this model. In the model nested by fuel type, we observe a bigger increase in the probability for the three vehicles than in the MNL model, but, with more of the increase in probability drawn from the remaining Plug-in Hybrid Electric vehicles than other fuel types. The overall increase in the probability for Plug-in Hybrid Electric options, across vehicle type, is far less marked. Both of these effects are consistent with intuition. However, the changes in this model draw proportionally from all other non Plug-in Hybrid Electric Vehicles, independently of the fuel type, which may again not be completely realistic.

In the model nested by vehicle type, we observe a bigger draw away from those options with the same vehicle type but with different fuel types (i.e. all non “Plug-in Hybrid Electric” subcompact, compact and mid-size cars). However, we also observe that the actual changes are different across

the first three vehicle types. This results from different levels of correlation in these nests, with higher correlation leading to higher competition. With the nesting parameter (cf. Table 2) being lowest in the mid-size car nest, followed by the compact car and the subcompact car nests, the changes are also largest in that order. This model correctly recognises that a larger share of the draw will come from other options in the same vehicle type categories, such that the increase in the overall share for the three vehicle types is less marked than in the first two models. However, the model doesn't recognise the fact that a bigger draw will also come from other Plug-in Hybrid Electric vehicles. Indeed, for a given vehicle type, all the different fuel types are affected in the same way, including in the case of Plug-in Hybrid Electric. This overstates the overall increase for the probability of that fuel type, especially when compared to the model using nesting by fuel type. Finally, while due to aggregation, the overall changes (i.e. when grossing up across categories) are similar in the CNL and MNL models, the model arguably gives a more intuitively meaningful representation of the changes in probabilities of individual vehicle type and fuel type combinations, with bigger reductions in probabilities for those alternatives that either are of the "Plug-in Hybrid Electric" fuel type or are of the "Subcompact car", "Compact car" or "Mid-size car" vehicle type.

## Extensions to GEV mixture models

As an additional extension, we estimated four mixture equivalents of the models reported in Table 1, namely a Mixed MNL model, a Mixed NL model using nesting by fuel type, a Mixed NL model using nesting by vehicle type, and a mixed CNL model. The results are summarised in Table 4. These models took significantly longer to estimate, with the Mixed CNL model taking over a week to converge; as such, these highly complex models are even more difficult to use in practice, but provide further insights into behaviour by allowing for random taste heterogeneity on top of the complex correlation structure. In our mixture models, we allowed for random heterogeneity in six marginal utility coefficients, namely the three cost components (fuel cost, maintenance cost, and vehicle price), and three performance indicators (acceleration, range, and miles per gallon equivalent). The results show that all four models lead to very substantial increases in model fit compared to their fixed coefficient counterparts, as a result of allowing for the random taste heterogeneity. The actual performance of the different models is very similar, but the implied behaviour is very different across models. Along with the earlier discussed differences in terms of substitution patterns, which are largely carried over into the mixture analogues, there are also differences in the retrieved degree of random taste heterogeneity (expressed in Table 4 in the form of the coefficient of variation). Here, we observe, overall, a drop in the degree of heterogeneity once we accommodate the correlation structure, which would highlight confounding between these two phenomena in the simple Mixed MNL model. Additionally, the two Mixed NL models are more similar to each other in terms of the retrieved heterogeneity, than is the case for the Mixed CNL model.

## Conclusions

This paper is a modelling analysis of vehicle type and fuel type choices of California consumers, captured through a stated preference survey. In this experiment, respondents were faced with a number of scenarios that presented them with a choice between four vehicles, of varying vehicle and fuel types.

The main aim of the present paper was to investigate the prevalence of correlation along these two dimensions of choice, i.e. the influence of unmodelled components on the choice processes specific to given vehicle and fuel types with heightened likelihood of substitution between options of the same vehicle type or the same fuel type.

Our theoretical discussions show how the standard approach for dealing with such correlation, namely a Nested Logit model, may not be appropriate, as it is unable to capture the full extent of correlation along both the vehicle type and the fuel type dimension. Instead we suggest the use of a Cross Nested Logit model structure, and show how this model offers better performance in estimation and produce substitution patterns that are more in line with a priori expectations.

The authors recognise that, especially in the context of large scale forecasting systems, the use of these model structures may not be currently possible due to its computational requirements, leaving practitioners with the option to incorporate any such correlations in the modelled utility components of the more basic models such as MNL. However, advanced nesting structures remain an important avenue for future applied work. The use of advanced GEV mixtures is of course even more demanding, where the mixed GEV structures estimated here are amongst the most complex estimated to date.

In closing, it should also be mentioned that, in the present paper, we have solely investigated the correlation between alternatives sharing the same vehicle type, and the same fuel type. But there may also be correlations between vehicles of different but similar type, such as compact and sub-compact cars, and incorporating such cross-type correlation is an important area for future work.

## Acknowledgements

This paper uses data collected for a project commissioned by the California Energy Commission. The opinions expressed in this paper are those of the authors and do not necessarily reflect the views or policies of the California Energy Commission. The first author acknowledges the financial support of the Leverhulme Trust in the form of a *Leverhulme Early Career Fellowship*.

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Table 1: Estimation results for different discrete choice models

		MNL		NL fuel		NL vehicle		CNL	
LL		-7681.257		-7668.826		-7662.514		-7646.331	
par		44		50		55		61	
adj. rho^2		0.262		0.263		0.263		0.264	
		est.	t-rat.	est.	t-rat.	est.	t-rat.	est.	t-rat.
Constants	Vehicle A constant	0.849	13.54	0.51	7.05	0.664	10.38	0.409	5.54
	Vehicle B constant	0.157	3.48	0.154	3.61	0.147	3.62	0.143	3.63
	Vehicle C constant	0.0403	0.87	0.0451	1.03	0.0319	0.77	0.0361	0.9
	Vehicle Type Inertia	0.988	21.74	0.933	20.08	1.18	21.15	1.09	18.77
	Fuel Type Inertia	0.209	2.89	0.585	6.42	0.177	2.79	0.465	4.72
Vehicle type	Subcompact car	0	-	0	-	0	-	0	-
	Compact car	-0.143	-1.54	-0.144	-1.62	-0.109	-1.16	-0.111	-1.3
	Mid-size car	0.246	2.6	0.23	2.56	0.247	2.59	0.238	2.76
	Large car	-0.128	-1	-0.097	-0.81	-0.213	-1.65	-0.162	-1.28
	Sport car	0.0289	0.25	0.0632	0.57	-0.0243	-0.21	0.00135	0.01
	Small cross-utility car	0.424	3.97	0.393	3.9	0.41	3.85	0.396	3.93
	Small cross-utility SUV	0.29	2.38	0.302	2.64	0.258	2.16	0.274	2.21
	Mid-size cross-utility SUV	0.141	1.04	0.153	1.18	0.0793	0.6	0.0988	0.75
	Compact SUV	0.433	3.22	0.422	3.32	0.369	2.8	0.389	2.85
	Mid-size SUV	0.319	2.37	0.306	2.41	0.241	1.8	0.262	2.34
	Large SUV	0.443	2.82	0.424	2.91	0.343	2.16	0.363	2.52
	Compact van	0.0405	0.28	0.0463	0.35	-0.0232	-0.16	-0.00283	-0.02
	Large van	-0.591	-3.22	-0.538	-3.14	-0.618	-3.49	-0.551	-3.08
	Compact pick-up truck	0.0277	0.22	0.0377	0.32	0.00316	0.03	0.0291	0.25
	Standard pick-up truck	-0.0608	-0.48	-0.0364	-0.31	-0.159	-1.24	-0.0999	-0.76
Fuel type	Standard Gasoline	0	-	0	-	0	-	0	-
	Flex Fuel/E85	0.304	3.64	0.297	3.6	0.271	3.66	0.314	4.19
	Clean Diesel	0.301	2.37	0.241	1.92	0.268	2.36	0.214	1.87
	Compressed Natural Gas	-2.15	-2.05	-2.2	-2.11	-1.7	-1.89	-1.9	-2.03
	Hybrid-electric	0.197	2.32	0.176	2.1	0.188	2.53	0.171	2.29
	Plug-in Hybrid-electric	0.538	7.74	0.509	7.42	0.467	7.54	0.445	7.42
	Full Electric	-2.86	-3.72	-3	-3.92	-2.4	-3.59	-2.64	-3.79
Age	1 or 2 years old	-0.209	-3.32	-0.193	-3.25	-0.187	-3.35	-0.174	-3.24
	3 or more years old	-0.426	-8	-0.397	-7.94	-0.404	-8.56	-0.384	-8.68
Incentives	HOV lane use	0.0606	1.02	0.0699	1.2	0.0424	0.8	0.0472	0.88
	Free parking	0.0446	0.74	0.0443	0.76	0.0362	0.68	0.0306	0.58
	\$1,000 tax credit	0.185	3.09	0.181	3.13	0.16	3.02	0.157	3.09
	\$1,000 reduced purchase price	0.0706	1.18	0.0687	1.17	0.0543	1.01	0.0561	1.04
Costs	Vehicle price	-0.0744	-14.19	-0.0702	-13.89	-0.0689	-14.06	-0.0653	-13.87
	Vehicle price * income cat	0.00684	6.52	0.00663	6.76	0.00629	6.56	0.00618	6.78
	Fuel costs	-0.158	-4.92	-0.158	-5.06	-0.136	-4.51	-0.133	-4.37
	Maintenance costs	-0.0579	-3.11	-0.0546	-3.13	-0.0525	-3.2	-0.0481	-3.05
Performance, efficiency, and fuel availability	MPGE	0.0241	8.52	0.025	8.97	0.0212	8.23	0.0224	8.46
	Range	0.285	1.48	0.292	1.52	0.213	1.29	0.242	1.41
	Acceleration (seconds to 60mph)	-0.0406	-5.33	-0.0393	-5.5	-0.0375	-5.61	-0.0357	-5.55
	Plug-in at work and other locations (EV)	0.123	0.94	0.119	0.92	0.123	1.11	0.118	1.05
	1 in 20 Stations (CNG)	0.329	2.23	0.324	2.21	0.306	2.37	0.31	2.25
Other	Large HH - Medium vehicles	0.395	2.97	0.401	3.21	0.384	2.91	0.36	2.84
	Large HH - Large vehicles	0.728	4.33	0.693	4.4	0.72	4.27	0.659	4.07
	Alt Fuel - Medium vehicles	0.0884	1.21	0.0633	0.9	0.0853	1.28	0.0564	0.74
	Alt Fuel - Large vehicles	-0.137	-1.26	-0.154	-1.48	-0.154	-1.55	-0.161	-1.52

Table 2: Estimation results (part 2)

		NL (fuel type)		NL (vehicle type)		CNL	
		est.	t-rat. (1)	est.	t-rat. (1)	est.	t-rat. (1)
Fuel type	Standard Gasoline	0.68	-8.76	-	-	0.40	-8.45
	Flex Fuel/E85	0.76	-0.51	-	-	0.08	-436.40
	Clean Diesel	0.82	-1.27	-	-	0.80	-0.86
	Compressed Natural Gas	0.90	-0.18	-	-	0.97	-0.02
	Hybrid-electric	0.56	-4.82	-	-	0.46	-5.66
	Plug-in Hybrid-electric	0.74	-4.83	-	-	0.60	-4.82
	Full Electric	1.00	-	-	-	1.00	-
Vehicle type	Subcompact car	-	-	0.90	-1.11	0.81	-1.33
	Compact car	-	-	0.72	-7.18	0.53	-10.88
	Mid-size car	-	-	0.71	-7.54	0.48	-9.63
	Large car	-	-	1.00	-	1.00	-
	Sport car	-	-	1.00	-	1.00	-
	Small cross-utility car	-	-	0.77	-2.11	0.65	-2.31
	Small cross-utility SUV	-	-	0.61	-6.52	0.37	-16.47
	Mid-size cross-utility SUV	-	-	0.75	-1.92	0.66	-1.14
	Compact SUV	-	-	0.68	-2.11	0.15	-38.82
	Mid-size SUV	-	-	0.77	-2.40	0.60	-2.73
	Large SUV	-	-	0.76	-0.77	0.40	-3.85
	Compact van	-	-	1.00	-	1.00	-
	Large van	-	-	0.63	-2.91	0.47	-4.28
	Compact pick-up truck	-	-	0.71	-2.35	0.39	-5.64
	Standard pick-up truck	-	-	1.00	-	1.00	-

Table 3: Forecasting example

MNL								
Vehicle type	Fuel type							Total
	1	2	3	4	5	6	7	
1	-1.28%	-1.28%	-1.28%	-1.28%	-1.28%	17.55%	-1.28%	9.88%
2	-1.28%	-1.28%	-1.28%	-1.28%	-1.28%	17.55%	-1.28%	9.88%
3	-1.28%	-1.28%	-1.28%	-1.28%	-1.28%	17.55%	-1.28%	9.88%
4	-1.28%	-1.28%	-1.28%	-1.28%	-1.28%	-1.28%	-1.28%	-8.94%
5	-1.28%	-1.28%	-1.28%	-1.28%	-1.28%	-1.28%	-1.28%	-8.94%
6	-1.28%	-1.28%	-1.28%	-1.28%	-1.28%	-1.28%	-1.28%	-8.94%
7	-1.28%	-1.28%	-1.28%	-1.28%	-1.28%	-1.28%	-1.28%	-8.94%
8	-1.28%	-1.28%	-1.28%	-1.28%	-1.28%	-1.28%	-1.28%	-8.94%
9	-1.28%	-1.28%	-1.28%	-1.28%	-1.28%	-1.28%	-1.28%	-8.94%
10	-1.28%	-1.28%	-1.28%	-1.28%	-1.28%	-1.28%	-1.28%	-8.94%
11	-1.28%	-1.28%	-1.28%	-1.28%	-1.28%	-1.28%	-1.28%	-8.94%
12	-1.28%	-1.28%	-1.28%	-1.28%	-1.28%	-1.28%	-1.28%	-8.94%
13	-1.28%	-1.28%	-1.28%	-1.28%	-1.28%	-1.28%	-1.28%	-8.94%
14	-1.28%	-1.28%	-1.28%	-1.28%	-1.28%	-1.28%	-1.28%	-8.94%
15	-1.28%	-1.28%	-1.28%	-1.28%	-1.28%	-1.28%	-1.28%	-8.94%
Total	-19.16%	-19.16%	-19.16%	-19.16%	-19.16%	37.31%	-19.16%	

NL (fuel type)								
Vehicle type	Fuel type							Total
	1	2	3	4	5	6	7	
1	-1.23%	-1.23%	-1.23%	-1.23%	-1.23%	19.92%	-1.23%	12.12%
2	-1.23%	-1.23%	-1.23%	-1.23%	-1.23%	19.92%	-1.23%	12.12%
3	-1.23%	-1.23%	-1.23%	-1.23%	-1.23%	19.92%	-1.23%	12.12%
4	-1.23%	-1.23%	-1.23%	-1.23%	-1.23%	-3.79%	-1.23%	-11.23%
5	-1.23%	-1.23%	-1.23%	-1.23%	-1.23%	-3.79%	-1.23%	-11.23%
6	-1.23%	-1.23%	-1.23%	-1.23%	-1.23%	-3.79%	-1.23%	-11.23%
7	-1.23%	-1.23%	-1.23%	-1.23%	-1.23%	-3.79%	-1.23%	-11.23%
8	-1.23%	-1.23%	-1.23%	-1.23%	-1.23%	-3.79%	-1.23%	-11.23%
9	-1.23%	-1.23%	-1.23%	-1.23%	-1.23%	-3.79%	-1.23%	-11.23%
10	-1.23%	-1.23%	-1.23%	-1.23%	-1.23%	-3.79%	-1.23%	-11.23%
11	-1.23%	-1.23%	-1.23%	-1.23%	-1.23%	-3.79%	-1.23%	-11.23%
12	-1.23%	-1.23%	-1.23%	-1.23%	-1.23%	-3.79%	-1.23%	-11.23%
13	-1.23%	-1.23%	-1.23%	-1.23%	-1.23%	-3.79%	-1.23%	-11.23%
14	-1.23%	-1.23%	-1.23%	-1.23%	-1.23%	-3.79%	-1.23%	-11.23%
15	-1.23%	-1.23%	-1.23%	-1.23%	-1.23%	-3.79%	-1.23%	-11.23%
Total	-18.46%	-18.46%	-18.46%	-18.46%	-18.46%	14.26%	-18.46%	

NL (vehicle type)								
Vehicle type	Fuel type							Total
	1	2	3	4	5	6	7	
1	-1.69%	-1.69%	-1.69%	-1.69%	-1.69%	17.80%	-1.69%	7.67%
2	-2.40%	-2.40%	-2.40%	-2.40%	-2.40%	22.27%	-2.40%	7.88%
3	-2.64%	-2.64%	-2.64%	-2.64%	-2.64%	22.23%	-2.64%	6.42%
4	-1.32%	-1.32%	-1.32%	-1.32%	-1.32%	-1.32%	-1.32%	-9.27%
5	-1.32%	-1.32%	-1.32%	-1.32%	-1.32%	-1.32%	-1.32%	-9.27%
6	-1.32%	-1.32%	-1.32%	-1.32%	-1.32%	-1.32%	-1.32%	-9.27%
7	-1.32%	-1.32%	-1.32%	-1.32%	-1.32%	-1.32%	-1.32%	-9.27%
8	-1.32%	-1.32%	-1.32%	-1.32%	-1.32%	-1.32%	-1.32%	-9.27%
9	-1.32%	-1.32%	-1.32%	-1.32%	-1.32%	-1.32%	-1.32%	-9.27%
10	-1.32%	-1.32%	-1.32%	-1.32%	-1.32%	-1.32%	-1.32%	-9.27%
11	-1.32%	-1.32%	-1.32%	-1.32%	-1.32%	-1.32%	-1.32%	-9.27%
12	-1.32%	-1.32%	-1.32%	-1.32%	-1.32%	-1.32%	-1.32%	-9.27%
13	-1.32%	-1.32%	-1.32%	-1.32%	-1.32%	-1.32%	-1.32%	-9.27%
14	-1.32%	-1.32%	-1.32%	-1.32%	-1.32%	-1.32%	-1.32%	-9.27%
15	-1.32%	-1.32%	-1.32%	-1.32%	-1.32%	-1.32%	-1.32%	-9.27%
Total	-22.61%	-22.61%	-22.61%	-22.61%	-22.61%	46.42%	-22.61%	

CNL								
Vehicle type	Fuel type							Total
	1	2	3	4	5	6	7	
1	-1.52%	-1.48%	-1.54%	-1.45%	-1.53%	19.05%	-1.46%	10.10%
2	-2.70%	-3.17%	-2.25%	-1.44%	-2.56%	24.78%	-1.52%	11.11%
3	-3.57%	-4.46%	-2.74%	-1.69%	-3.38%	26.15%	-1.57%	8.88%
4	-1.20%	-1.20%	-1.20%	-1.20%	-1.20%	-2.23%	-1.20%	-9.99%
5	-1.20%	-1.20%	-1.20%	-1.20%	-1.20%	-2.64%	-1.20%	-10.10%
6	-1.20%	-1.20%	-1.20%	-1.20%	-1.20%	-3.54%	-1.20%	-10.10%
7	-1.20%	-1.20%	-1.20%	-1.20%	-1.20%	-3.57%	-1.20%	-10.10%
8	-1.20%	-1.20%	-1.20%	-1.20%	-1.20%	-2.77%	-1.20%	-9.99%
9	-1.20%	-1.20%	-1.20%	-1.20%	-1.20%	-5.71%	-1.20%	-12.12%
10	-1.20%	-1.20%	-1.20%	-1.20%	-1.20%	-2.98%	-1.20%	-10.10%
11	-1.20%	-1.20%	-1.20%	-1.20%	-1.20%	-3.05%	-1.20%	-10.10%
12	-1.20%	-1.20%	-1.20%	-1.20%	-1.20%	-2.23%	-1.20%	-9.99%
13	-1.20%	-1.20%	-1.20%	-1.20%	-1.20%	-2.78%	-1.20%	-9.99%
14	-1.20%	-1.20%	-1.20%	-1.20%	-1.20%	-3.56%	-1.20%	-10.10%
15	-1.20%	-1.20%	-1.20%	-1.20%	-1.20%	-2.11%	-1.20%	-9.99%
Total	-22.19%	-23.52%	-20.94%	-18.98%	-21.87%	32.83%	-18.96%	

Table 4: Summary of results for Mixed GEV models

	Mixed MNL	Mixed NL (fuel)	Mixed NL (vehicle)	Mixed CNL
Model fit for base model	0.262	0.263	0.263	0.264
Model fit for mixture model	0.314	0.314	0.316	0.316
<b>Coefficient of variation</b>	<b>Mixed MNL</b>	<b>Mixed NL (fuel)</b>	<b>Mixed NL (vehicle)</b>	<b>Mixed CNL</b>
Acceleration	2.68	2.54	2.46	1.97
Range	12.18	9.39	9.75	5.45
Miles per gallon equivalent	6.88	6.92	6.64	7.49
Fuel cost	1.82	1.91	2.08	1.65
Maintenance cost	1.50	0.14	0.44	1.25
Price	1.00	1.02	1.00	1.08



## 2008 California Vehicle Survey



If the following vehicle options were available to you, which would you choose?  
Please carefully examine all the attributes of each vehicle and then select the one you will most likely purchase by filling in the circle below your choice.

Vehicle Choice 1	Vehicle A	Vehicle B	Vehicle C	Vehicle D
<b>Vehicle type</b>	Midsized car	Compact SUV	Midsized car	Compact van
<b>Fuel type</b>	Gasoline	Natural Gas (NGV)	Plug-in Hybrid (PHEV)	Clean Diesel
<b>Age of vehicle</b>	New (2009)	New (2009)	New (2009)	New (2009)
<b>Purchase price</b>	\$29,400	\$36,600	\$31,100	\$20,900
<b>Incentive</b>	--	--	\$1,000 tax credit	--
<b>MPG or equivalent</b>	29 MPG	15 MPG	60 MPG	31 MPG
<b>Fuel cost per year</b>	\$1,090	\$1,950	\$780	\$1,170
<b>Fuel availability</b>		1 in 50 stations		
<b>Refueling time</b>		10 Minutes at station, 4 hours at home		
<b>Driving range</b>		300 Miles		
<b>Maintenance cost per year</b>	\$460	\$370	\$350	\$550
<b>Acceleration (0-60 mpg)</b>	10.2 seconds	11 seconds	8 seconds	11.8 seconds
<b>Select One:</b>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Figure 1: Example Stated Preference Exercise

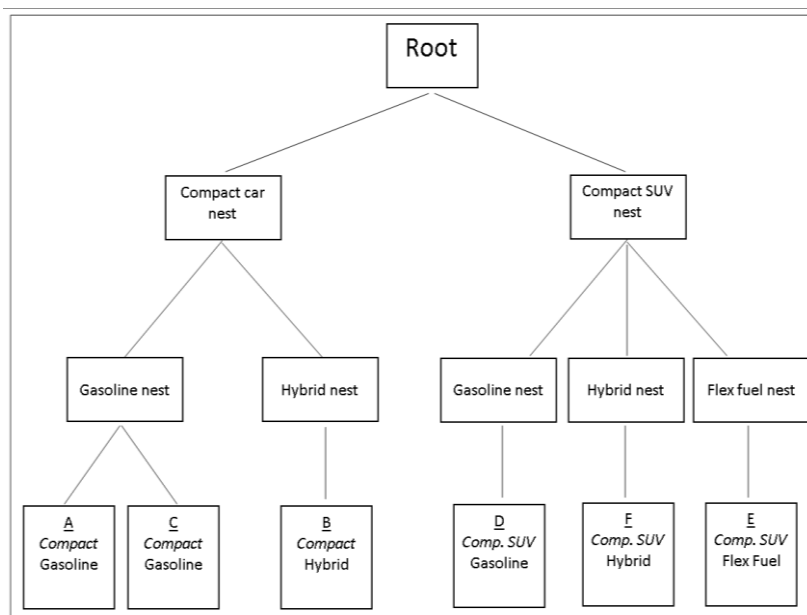
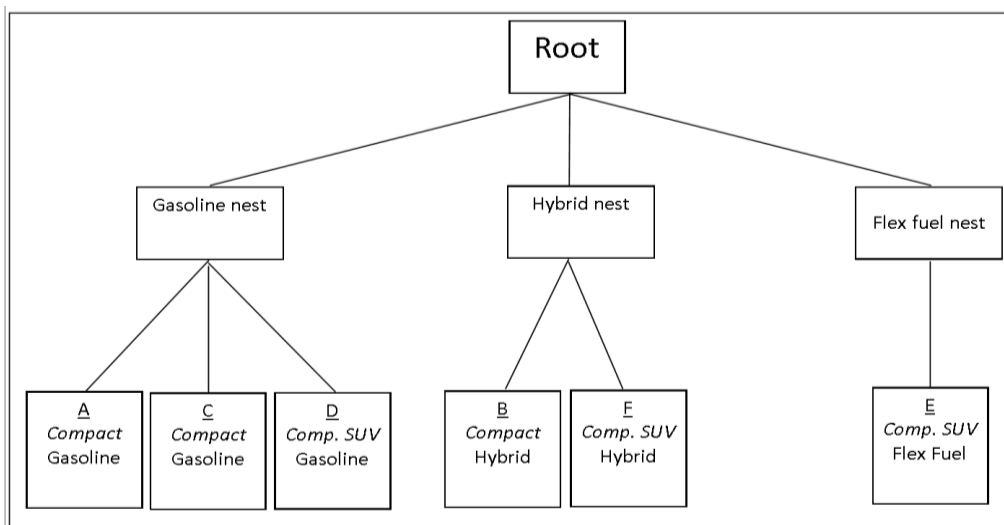
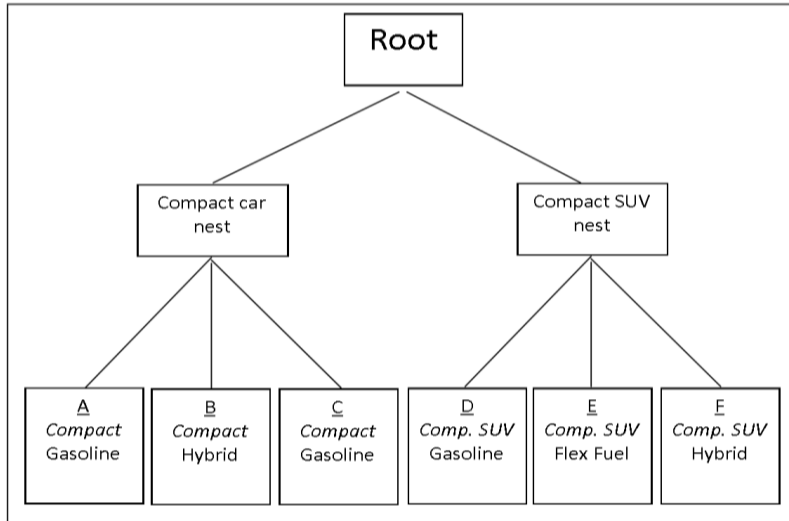


Figure 2: Different possible NL structures

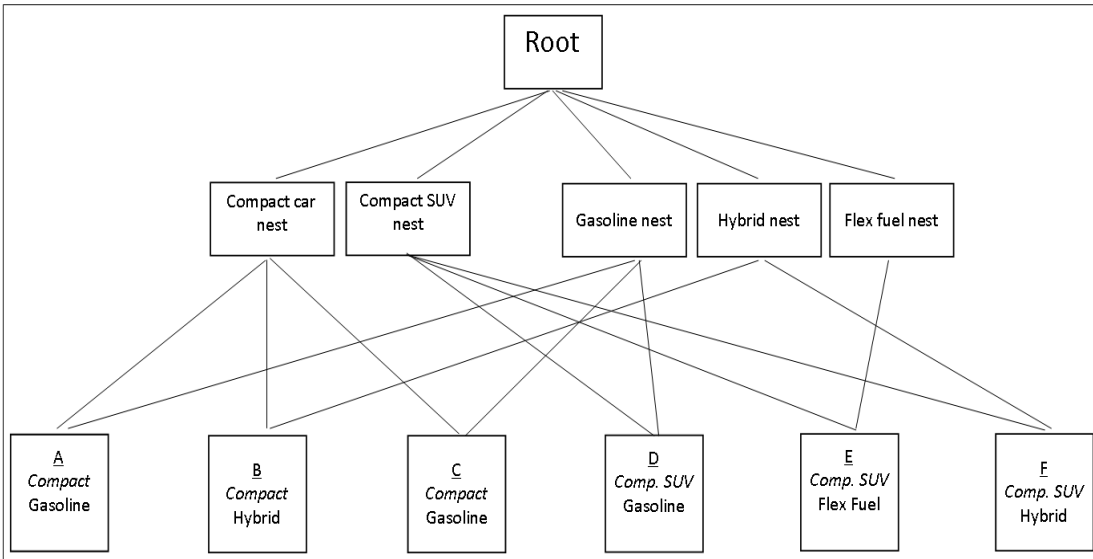


Figure 3: CNL structure