ON THE IMPLICATIONS OF USING COMPOSITE VEHICLES IN CHOICE MODEL PREDICTION

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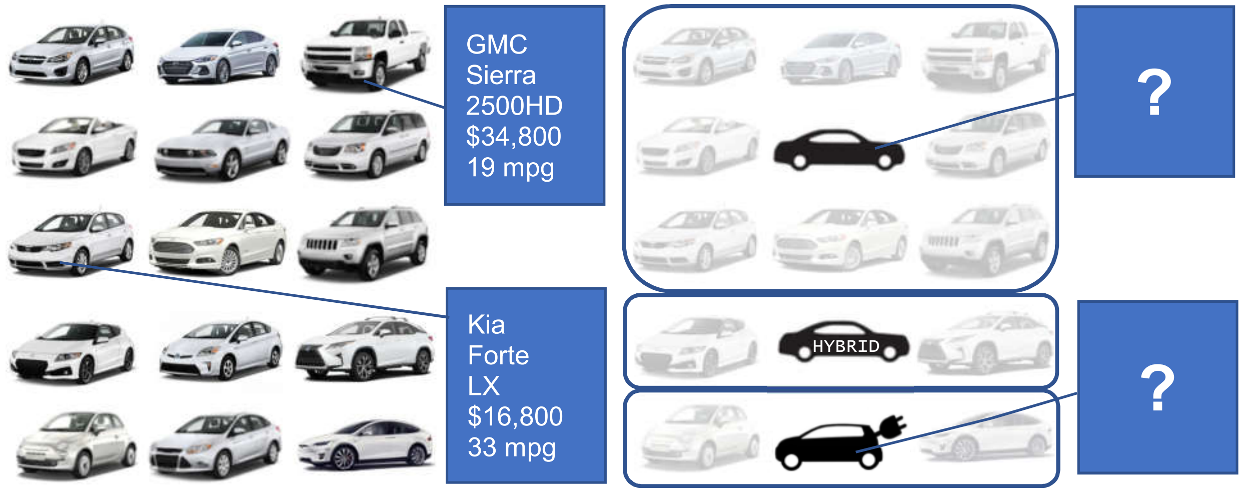
GRAPHICAL ABSTRACT



HIGHLIGHTS

- Choice modelers often use composites to represent groups of alternatives, but this practice may introduce arbitrary changes to choice-share predictions.
- We find that composite specification can cause more variation in predicted shares than parameter uncertainty in models without alternative-specific constants (ASCs).
- We find that ASCs can mitigate or eliminate this variation in some, but not all, counterfactual scenarios.
- We identify correction factors for models using composites to predict choice shares in counterfactual scenarios consistent with those from corresponding models that use disaggregated elemental alternatives.

ABSTRACT
Vehicle choice modelers often use composite alternatives, which are simplified representations of a larger, diverse group of vehicle options—a practice known as choice set aggregation. Although this practice has been justified by computational tractability and data constraints, it can introduce arbitrary changes to choice-share predictions. We isolate and characterize the implications of using composite vehicles for choice prediction, given exogenously determined model parameters. We first identify correction factors needed for composite models to predict choice shares that are consistent with those from models that use the full set of disaggregated elemental alternatives. We then assess the distortion of choice-share predictions under various composite specifications and partial corrections using two case studies based on models in the literature used in transportation and energy policymaking: (1) we examine a logit model without alternative-specific constants (ASCs) and find that the distortion in share predictions due to composite specification is substantial and can be larger than variation due to parameter uncertainty; (2) we examine counterfactual predictions of a nested logit model with ASCs based on the NEMS and LVChoice models and find that composite models using ASCs can mitigate or eliminate distortion in some, but not all, counterfactual scenarios. In particular, the distortion is larger when the scenario significantly affects the differences in elemental membership or utility heterogeneity between composite groups. We provide explicit correction factors for composite models with and without ASCs that can be used to take advantage of the tractability of composite models while ensuring that their choice-share predictions exactly match those of their corresponding elemental models in counterfactual and forecasting scenarios.

Keywords: choice set aggregation, aggregation of alternatives, vehicle choice model, composite vehicles, multinomial logit, nested logit, mixed logit

1 INTRODUCTION

Discrete choice models are widely used to estimate consumer preferences for transportation options and to simulate choices under various scenarios. For example, vehicle choice models (VCMs) can be used to predict how vehicle sales might respond to a subsidy program (Greene et al., 2005) or how well alternative-fuel vehicles may sell given improvements in their performance (Stephens et al., 2014). These predictions are used in counterfactual policy studies (Bento et al., 2009; Goldberg, 1998; Greene et al., 2005; Jacobsen, 2013), as well as projections and forecasts (Brownstone et al., 2000; Liu and Lin, 2017).

Vehicle choice models vary considerably in the level of detail at which they represent the market. Some studies represent alternatives in a choice set at a granular level of detail (Brooker et al., 2015; Bunch and Brownstone, 2013; Greene and Liu, 2012; Klier and Linn, 2012). These alternatives are known as *elemental* alternatives[1] (Ben-Akiva and Lerman, 1985), and we refer to models that represent the choice set using elemental alternatives as "elemental models". For example, in Brooker et al. (2015), the US automotive market is represented by over 400 alternatives at the make-model-trim level (e.g.: GMC Sierra 2500HD, Kia Forte LX, etc.). Other models use *composite* alternatives, which represent groups of elemental alternatives (e.g.: grouped by size class, technology, and/or fuel type) (Bento et al., 2009; Brownstone et al., 2000; Goldberg, 1998; Xie and Lin, 2017). The use of composites in choice modeling is also known as choice set aggregation[2], which is one of several methods to reduce the choice set (Ben-Akiva and Lerman, 1985; McFadden, 1978). We refer to models that represent the choice set using composites as "composite models". For example, the VCMs in the National Energy Modeling System (NEMS) (EIA, 2010) and the related LVChoice model (Birky, 2012), which are used to inform policymaking, aggregate vehicles by fuel type (e.g.: gasoline, electric, etc.) and vehicle class (e.g.: small car, large SUV, etc.). Each group of vehicles of a specific fuel type and vehicle class is modeled using a single generic composite vehicle whose attributes are intended to represent the group. As a result, the market of alternatives is represented by a dramatically reduced choice set of only 45 composite vehicle alternatives in LVChoice. Figure 1 shows an illustrative example of how granular elemental alternatives are grouped and represented using composites in VCMs.

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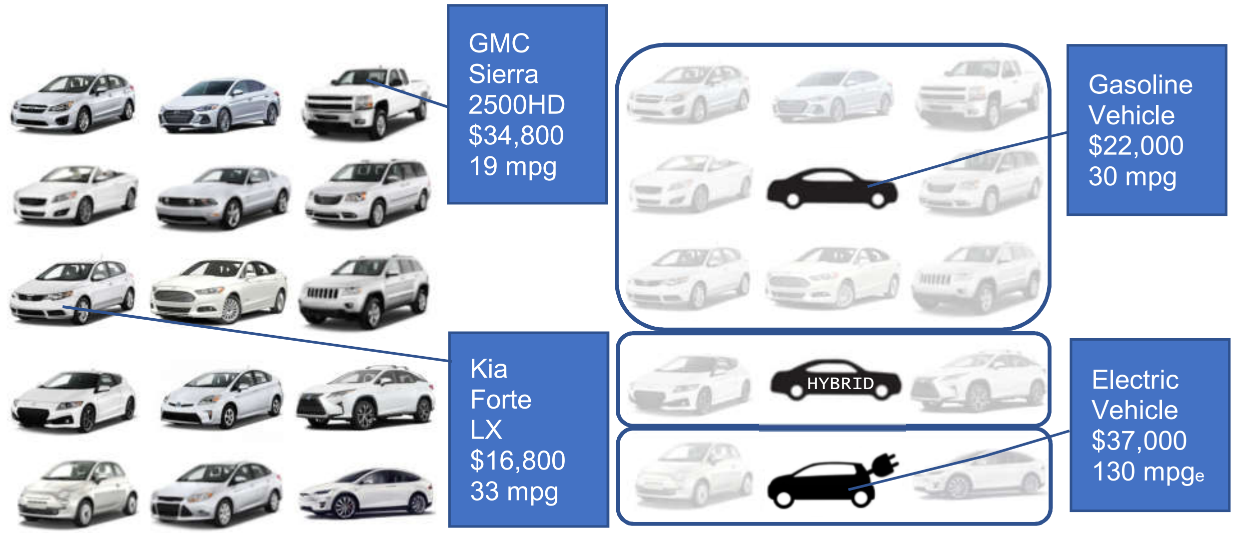
[1] More precisely, we define an *element* as a product profile (vector of attributes) that represents a group of alternatives with identical observed attributes (e.g.: a red Ford Focus SE and a blue Ford Focus SE have identical observed attributes if color is not observed) and a *composite* as a product profile that represents a group of alternatives that differ in observed attributes (e.g.: the Ford Focus SE and Ford Focus ST differ on price and fuel economy). See the literature review section for more detail.

[2] Choice set aggregation, or aggregation of alternatives, should not be confused with the aggregation of individual consumers into groups. To avoid possible confusion, we primarily refer to the "use of composites" instead of "aggregation".



(a) These elemental alternatives represent the market at the disaggregated make-model-trim level.

(b) These composite alternatives represent the market at the aggregated fuel-type level.

Figure 1: Examples of choice sets using (a) elemental alternatives, and (b) composite alternatives (adapted from manufacturer website images, with permission).

Some studies use composite vehicles in the process of estimating model parameters, while other studies use composite vehicles only for predicting choice shares. We label these the “explanatory literature” and the “predictive literature,” respectively, following Haaf et al. (2016). Table 1 provides a detailed comparison.

In the explanatory literature, parameter estimation is often conducted on composite vehicles because sales data are typically not available at the disaggregated elemental level; however, there is concern that the use of composites can cause an “aggregation bias” for model parameters, and researchers have worked to quantify and mitigate this bias (Brownstone and Li, 2017; Habibi et al., 2017; Spiller, 2012; Wong et al., 2018). Researchers in other domains—particularly spatial and locational choice—also find that the use of composites affects both model estimation and subsequent prediction results (Haener et al., 2004; Parsons and Hauber, 1998; Parsons and Needelman, 1992).

In contrast, the predictive literature focuses on simulating choice shares under a range of scenarios. This literature adopts parameter estimates from other studies or using expert judgment (e.g.: willingness-to-pay and elasticity estimates that are presumed to be unbiased). Applications and examples of these models are shown in **Error! Reference source not found.** and Table 2.[3] Many of these studies choose to use composites to model counterfactual and forecast scenarios. Here, the implications of choice set aggregation are decoupled from the issue of parameter bias. The predictive literature lacks studies characterizing the influence of composite vehicles on choice predictions, so it is not known how much this practice might be arbitrarily influencing results.

[3] Vehicle choice models in the predictive literature are frequently used for policy analysis, as summarized in Table 1. Several scholars summarize advantages of this approach for supporting policy decisions in a choice model peer review for the US Environmental Protection Agency (SRA International et al., 2012).

We focus on the predictive literature to isolate the effect of composites on prediction, and we address the following research questions:

1. How does the use of composite alternatives in place of elemental alternatives affect VCM choice predictions in theory and in practice?
2. How much does composite specification distort predictions relative to other sources of error, uncertainty, or variation?
3. How might composites be specified to produce choice predictions that match a corresponding elemental model?

We begin by reviewing the variety of choice set aggregation practices used in the literature. We then develop theory regarding the use of composites in choice prediction for several types of choice models and identify "correction factors"[4] that allow composite models to predict choice shares that are consistent with those from corresponding elemental models. We then construct two case studies simulating choice predictions for elemental and composite choice sets based on VCMs used in the literature and in policymaking. In these case studies, we analyze the variation in simulation results due to differences in composite specification and compare it to variation in simulation results caused by other sources of uncertainty and variation in VCMs.

[4] The term "correction factor" indicates that the composite model is "corrected" to match a corresponding elemental model, following the terminology in the literature (Ben-Akiva and Lerman, 1985). It does not imply that the corresponding elemental model itself is "correct" or that choice predictions from the elemental model would necessarily match observations.

Table 1: Types of Vehicle Choice Modeling Literature that Use Composite Alternatives

	Explanatory literature	Predictive literature
Objective	Estimate model parameters that explain preferences and choices, and in some studies, use the resulting model to predict choice share in counterfactual scenarios	Predict choice share in counterfactual scenarios and/or forecasts
Method	Estimate preference parameters $\boldsymbol{\beta}$ by fitting a choice model to observed choices	Simulate choice shares P_k for a range of scenarios by computing market shares with a choice model
Process	$\mathbf{x}_{k0}, s_k \rightarrow \boldsymbol{\beta}, \xi_k$ $\mathbf{x}_{kt}, \boldsymbol{\beta}, \xi_k \rightarrow P_{kt}$ (some studies)	$\mathbf{x}_{k0}, s_k, \boldsymbol{\beta} \rightarrow \xi_k$ (some studies) $\mathbf{x}_{kt}, \xi_k, \boldsymbol{\beta} \rightarrow P_{kt}$
Source of preference parameters $\boldsymbol{\beta}$	Estimated using $\mathbf{x}_{k0}, s_k$	Exogenous (literature/expert-informed) based on willingness to pay for attributes and price elasticities
Source of ASC ξ	Estimated simultaneously	Calibrated post-hoc to observed shares s_k in a baseline scenario
Correction factors used in utility specification of composite	Size factor sometimes included. Heterogeneity factor not used, except in literature comparing different composite specifications (bottom row). Can be approximated.	Size factor (or variant) often included. Heterogeneity factor not used. May require computation of elemental utilities and elemental ASCs or can be approximated.
Sample literature using composite alternatives	Goldberg (1998); Brownstone et al. (2000); Train & Winston (2007); Bento et al. (2009); Shiau et al. (2009); Jacobsen (2013)	Michalek et al. (2004); EIA (2010); Birky (2012); Greene et al. (2014); Xie & Lin (2017)
Sample literature using elemental alternatives	Klier & Linn (2012); Bunch & Brownstone (2013); Whitefoot et al. (2017)	Greene et al. (2005); Bunch et al. (2011); Greene & Liu (2012); Whitefoot & Skerlos (2012); Brooker et al. (2015)
Example applications	Analyses of impacts and effects of fuel economy standards (Goldberg, 1998; Klier & Linn, 2012; Bunch & Brownstone, 2013; Jacobsen, 2013), gasoline taxes (Bento et al., 2009), automotive industry competitiveness (Train & Winston, 2007)	DOE VTO program analysis (Stephens et al., 2014), NRC Transitions to Alternative Vehicles & Fuels study (Greene et al., 2014), EIA Annual Energy Outlook (Lynes et al., 2017), EPA and DOT evaluating potential use of VCMs in regulatory rulemaking (Helfand et al., 2015; SRA International et al., 2012)
Literature comparing between models with different composite specifications	*Vehicle choice*: Spiller (2012); Habibi et al. (2017); Wong, Brownstone, & Bunch (2018) *Spatial choice*: Parsons & Needelman (1992); Feather (1994); Kaoru et al. (1995); Ferguson & Kanaroglou (1997); Parsons & Hauber (1998); Haener et al. (2004)	This study

Notes: $\mathbf{x}_{kt}$: vehicle attributes of composite alternative *k* in scenario *t*, s_k: observed market share of composite alternative *k*, P_{kt}: predicted choice share of composite alternative *k* in scenario *t*.
Refer to Haaf et al. (2016) for further discussion regarding explanatory and predictive literature.
Refer to Table 2 for further detail and references regarding specific studies that use correction factors.

2 LITERATURE REVIEW

Several recent studies have characterized the effects of specific modeling assumptions on vehicle choice model predictions, such as utility specification, functional form, preference heterogeneity, and error distribution (Haaf et al., 2016, 2014; Helfand et al., 2015; Klier and Linn, 2012; Stephens, 2014; Stephens et al., 2017). We focus on the effects of choice set aggregation and the use of composites.

Before reviewing the literature on composites, it is instructive to explicitly define the terms composite and elemental alternatives, as the use of these terms varies across the literature. For the purposes of this study, we define an *element* as a product profile (vector of attributes) that represents a group of alternatives with identical observed attributes and a *composite* as a product profile that represents a group of alternatives that differ in observed attributes. Whether a product profile at a given level of detail is considered an element or a composite depends on the observed attributes included in the utility function of the choice model. For example, many vehicle choice models include attributes such as price and fuel economy. Vehicle descriptions at the make-model level (e.g.: Ford Focus) describe groups of variants (e.g.: Ford Focus SE, Ford Focus ST, etc.) that differ substantially in price and fuel economy, so we classify a choice model using alternatives at the make-model level as using composites. In contrast, if a choice model described vehicles at the make-model-trim level (e.g.: Ford Focus SE) within which all variants of each profile (e.g.: red Ford Focus SE, blue Ford Focus SE, etc.) have the same price and fuel economy, then we classify it as using elements. However, if the "color" attribute were to be added as an attribute in the utility function of this choice model, then the make-model-trim level would be considered to be at the composite level because each profile represents a group of alternatives that varies in one of the observed attributes (color).[5]

2.1 Use of Composites in Vehicle Choice Models

Table 2 demonstrates how much VCMs used for counterfactual analysis or forecasting can vary in the level of detail at which they represent the market. VCMs in the top section of Table 2 represent the automotive market using only tens or hundreds of composite alternatives based on combinations of size class, powertrains, and fuel type—creating simplified and abstracted representations of the market. Each composite represents many design variants in the real market. On the other end of the spectrum, VCMs in the bottom section of Table 2 simulate hundreds or thousands of vehicle alternatives at the make-model-engine or make-model-trim level to represent a much more detailed set of design variants in the market.

There are several reasons why a modeler may choose to represent vehicle alternatives as composites. One reason is computational costs and tractability (Brownstone et al., 2000; Goldberg, 1998; McFadden, 1978). Increasing computational power in recent years has somewhat mitigated this need. However, computational constraints may still force modelers to use composites when the VCM is integrated with an interdependent supply-side model that

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[5] In vehicle choice modeling practice, make-model-trim profiles and series-subseries profiles are not necessarily strictly elements, because each represents a group of variants that differ in options packages (e.g.: premium stereo, navigation system) that affect observed attributes (e.g.: price). Nevertheless, the make-model-trim level and the series-subseries level are typically treated as elements in practice (any variation in observed attributes of alternatives below these levels is typically ignored) due to limited data availability, and we follow this convention here.

iteratively determines the attributes of vehicle options and their sales (Bunch et al., 2011; Goldberg, 1998; Jacobsen, 2013; Shiau et al., 2009).

Other reasons modelers use composites are data constraints and a desired level of resolution in predictions. For example, modelers may lack data to specify attributes for each elemental alternative in a future scenario (Helfand et al., 2015) and may only be interested in predictions made at a composite level to focus on their research question of interest or to avoid a sense of false precision (Greene and Liu, 2012). Modelers also may not be willing to predict market shares in detail and may prefer to stay abstract in their predictions, citing the politically sensitive and controversial nature of manufacturer-level predictions (Keefe, 2014; Xie and Lin, 2017). Finally, modeling the market entry or exit of specific design variants may not be within the scope of research (Klier and Linn, 2012).

Choice set aggregation can also be used to deal with commonality in unobserved attributes of elemental alternatives that would conflict with the assumption of independent and identically distributed error terms in logit models. This is discussed in more detail by McFadden (1978).

Despite the advantages of using composites discussed above, there are several arguments against their use. Composite alternatives are abstractions with hypothetical attributes that are not actually available on the market and therefore may inaccurately represent choices. In the locational choice literature, Kanaroglou and Ferguson (1996) argue that elemental alternatives are the “fundamental disaggregate units considered by choice-makers in the decision process” while composites are often defined out of necessity but do not correspond with consumer choices. Haener et al. (2004) describe the disaggregate version of their choice model to be closer to how they believe decisions are made. In vehicle choice, Spiller (2012) and Wong, Brownstone, & Bunch (2018) both describe composites as “misspecification” of the “true” choice set.

Furthermore, the use of composites may ignore the heterogeneity of their underlying elemental alternatives, which may be important to model explicitly, especially for vehicle choice (Greene and Liu, 2012; Spiller, 2012). The consumer vehicle market includes a large amount of vehicle design variation, and there is uncertainty in future technology, fuel-type, and segment availability and popularity. Baum and Luria (2016) describe recent shifts towards higher-end, more luxurious, and heavier design variants in the automotive market. Wong et al. (2018) cite increasing variation in fuel economy and other attributes in recent years due to fuel price variations, stringent fuel economy standards, and technological advances. Composites may inadequately reflect the impact of scenarios or policies that affect passenger vehicle options heterogeneously, such as those based on fuel economy or battery capacity. Several studies (Brooker et al., 2015; Bunch and Brownstone, 2013; Greene and Liu, 2012; Klier and Linn, 2012; Whitefoot and Skerlos, 2012) cite this as motivation to simulate at an elemental level.[6]

[6] For example, Brooker et al. (2015) argue that the Toyota Prius hybrid, a particularly high-selling vehicle, would be inadequately represented by a generic composite hybrid vehicle. Other examples of elemental alternatives driving the sales of the composite category, particularly alternative-fuel vehicles: the BMW i3 extended-range electric vehicle with a 100-mile electric range plus gasoline range extender and the Tesla Model S 85 electric vehicle with a 300-mile range and no extender may not be well represented by the composites in LVChoice and earlier versions of the NEMS model (Birky, 2012; Greene and Chin, 2000), which include a Plug-In Hybrid Electric Vehicle (PHEV) with a 40-mile range and EVs with 100- and 200-mile ranges.

Table 2: Examples of Vehicle Choice Models that Predict Counterfactual or Future Market Shares Using Different Representations of the US Light-Duty Vehicle Market

Publication [*Model Name*]	Number of Simulated Alternatives	Granularity of Alternatives	Type of Choice Model[a]	Source of Preference Parameters [b]	Source of ASCs[b]	Correction Factors
a) Vehicle Choice Models Simulating at Composite Level with Aggregation						
Michalek, Papalambros, & Skerlos (2004)	**5-20**	5-10 makes x 1-2 models each	L	Exo	–	–
Shiau, Michalek, & Hendrickson (2009)	**10**	10 makes (mid-size only)	MXL	Est	–	–
Greene, Park, & Liu (2014) [*LAVE-Trans*]	**10**	5 fuel types x 2 size classes	NL	Exo	Cal	Size
Xie & Lin (2017) [*MA3T variant*]	**12-28**	(3 fuel economy variants + 4 fuel types) x 4 size classes	NL	Exo	Cal	Size
Goldberg (1998)	**18**	9 size classes x 2 origins	NL	Est	–	–
Brownstone, Bunch, & Train (2000)	**26-37**	12 sizes x 4 fuel types x 2 origins x 2 cost levels	L & MXL	Est	Est	Size
Liu & Lin (2017) [*MA3T variant*]	**20**	10 fuel types x 2 size classes	NL	Exo	Cal	Size
Brownstone et al. (1996)	**36**	14 size classes x 4 fuel types	L & NL	Est	Est	–
Birky (2012) [*LVChoice*]	**45**[c]	9 fuel types x 5 size classes	NL	Exo	Cal	Size
Vyas et al. (2012) [*SimAGENT*]	**54**	9 body types x 6 vintages	MDC EV	Est	Est	–
Bento et al. (2009)	**59**	7 makes x 10 size classes x 5 ages	MXL	Est	–	–
Levinson et al. (2017) [*ParaChoice*]	**100**	20 fuel types x 5 size classes	NL	Exo	Cal	Size
EIA (2010) [*NEMS CVCC*]	**132**[c]	11 fuel types x 12 size classes	NL	Exo	Cal	Size
Train & Winston (2007)	**200**	Make/model	MXL	Est	Est	Size
Harrison et al. (2007) [*NERA NVMM*]	**200+**	Make/model	NL	Exo	Cal	–
Goldberg (1995)	**228**	Make/model	NL	Est	–	–
Jacobsen (2013)	**287**	7 makes x 10 size classes x 5 ages	MXL	Est	–	–
Bunch & Mahmassani (2009) [*CARBITS 2*]	**350**	12 sizes x prestige x model years	L & NL	Est	Cal	Size
b) Vehicle Choice Models Simulating at Elemental Level (or with Minimal Aggregation)						
Brooker et al. (2015) [*ADOPT*]	**400+**	Make/model/trim/engine options	MXL	Est	Cal	–
Whitefoot & Skerlos (2012)	**473**	Make/model/engine	L	Exo	Cal	–
Whitefoot, Fowlie, & Skerlos (2017)	**471**	Make/model/engine	MXL	Est	Est	–
Bunch et al. (2011) [*CARBITS 3*]	**800+**	Make/model/engine	NL	Est	Cal	–
Greene et al. (2005)	**831**	Make/carline/configuration	NL	Exo	Cal	–
Greene (2009)	**867**	Make/model/engine	NL	Exo	Cal	–
Greene & Liu (2012) [*CVCM for EPA*]	**~1000**	Make/model/configuration	NL	Exo	Cal	–
Bunch & Brownstone (2013) [*model for DOT Volpe*]	**1213**	Make/model/nameplate	NL	Est	Est	–
Klier & Linn (2012)	**1819**	Make/model/engine x model years	NL	Est	Est	–

Notes: In this table, the models in which preference parameters are estimated prior to simulation fall into the explanatory literature category, and the models where the parameters are exogenously determined and/or calibrated fall into the predictive literature category.
[a] L: Multinomial Logit; MXL: Mixed Logit; NL: Nested Logit; MDCEV: Multiple Discrete-Continuous Extreme Value
[b] Exo: exogenous; Est: estimated; Cal: calibrated
[c] These models simulate each size class in its own separate choice model, and so there are only 9-11 fuel type composites in the choice model simulations for each assumed market segment.

2.2 Composite Specification

Modelers using composites must make assumptions about how they are specified. Composites are commonly specified using the arithmetic average or sales-weighted average of the attributes of their constituent elemental alternatives. However, while the use of averages to represent composites may be intuitive, the choice set aggregation literature has described a need for modelers to "correct" such models by accounting for the group size and utility heterogeneity of the elemental alternatives being represented by composites (Ben-Akiva and Lerman, 1985; Kitamura et al., 1979; Lerman, 1975; McFadden, 1978).[7] These correction factors serve to align composite model results with corresponding elemental model results.

In practice, though, composite VCMs vary in how they specify composites, and no consistent application of correction factors has emerged in the literature. Goldberg (1998) and Jacobsen (2013) use composites with average attributes and no correction factors. Leiby and Rubin (1997) and Greene and Chin (2000) derived a "Make-Model Availability" (MMA) factor that is meant to represent the "value of diversity of choice" to the consumer and has subsequently been widely used in other VCMs used in policymaking (Birky, 2012; EIA, 2010; Greene et al., 2014; Greene and Liu, 2012; Liu and Lin, 2017). Brownstone et al. (2000) and Train and Winston (2007) include the number of vehicle models in their utility specifications, describing it as a factor accounting for "product line externality," while Wolinetz and Axsen (2016) include the number of electric vehicle model offerings as part of an "availability constraint." Tables 1 and Table 2 show summaries of correction factor usage in the literature.

In this paper, we show how composites affect choice-share predictions through both mathematical derivation and simulation case studies. We explicitly identify the correction factors that allow composite models to be consistent with elemental-model choice predictions, thereby allowing modelers to exploit the advantages of composite models while eliminating the discrepancies between composite and elemental choice predictions.

[7] Later studies (Feather, 1994; Ferguson and Kanaroglou, 1997; Haener et al., 2004; Kaoru et al., 1995; Parsons and Needelman, 1992) examined how composite use and correction factors could affect spatial and locational choice model results. We note that while spatial and locational choices may be sufficiently described by composites with the average attributes of carefully defined homogeneous groups of geographically proximate elemental choices, the vehicle market of make-model-trim alternatives may not be adequately modeled by composites without accounting for group size and heterogeneity. Wong et al. (2018) and Brownstone and Li (2017) analyzed various specifications, including the McFadden (1978) approximate correction factor on parameter estimation results but not on predicted choice probabilities. Habibi et al. (2017) also compare several specifications and correction factors but focus on the impact on estimation. Refer to Table 1 for a summary.

3 THEORY

We examine a general discrete choice model containing a set of composite vehicle alternatives $\mathcal{K}$ and compare its predicted choice probabilities to those of a corresponding choice model containing the set of elemental vehicle alternatives $\mathcal{J}$. Each composite alternative, $k \in \mathcal{K}$, represents a subset of the elemental alternatives $\mathcal{J}_k \subseteq \mathcal{J}$. The subsets $\mathcal{J}_k\ \forall k \in \mathcal{K}$ partition the set $\mathcal{J}$ ($\cup_{k\in\mathcal{K}} \mathcal{J}_k = \mathcal{J}$ and $\mathcal{J}_k \cap \mathcal{J}_{k'} = \emptyset\ \forall k \in \mathcal{K}, k' \in \mathcal{K}\backslash k$). We define P_j to be the predicted market-level probability of consumers choosing alternative j, or predicted choice share. The choice shares predicted by the composite model $P_k\ \forall k \in \mathcal{K}$ will vary depending on how the attributes of the composites are specified (e.g.: average or sales-weighted average of the attributes of the subsumed elements). We define ΔP_k as the difference between a given composite model's predicted choice probability P_k and the sum of the elemental model's predicted choice probabilities for the alternatives that k represents, $\sum_{j\in\mathcal{J}_k} P_j$. Specifically,

$$\Delta P_k = P_k - \sum_{j\in\mathcal{J}_k} P_j \tag{1}$$

This difference provides a metric for comparing composite model specifications used in the predictive literature, and we examine some conditions under which $\Delta P_k = 0$.[8] We begin with models that exclude alternative-specific constants (ASCs) and later generalize to those that include ASCs.

3.1 Models Without Alternative-Specific Constants (ASCs)

Studies using choice models that lack ASCs include Goldberg (1998), Bento et al. (2009), Shiau et al. (2009), and Jacobsen (2013). For a general random-utility discrete-choice model without ASCs, consumers choose the alternative with the highest utility. The utility u_j of each alternative j can be separated into two components: $u_j = v_j + \varepsilon_j$. The first term v_j is the consumer utility derived from vehicle attributes observed by the modeler, henceforth referred to as observed utility.[9] The second term ε_j represents unobserved random error. Given v_j for all alternatives and a distribution for ε_j, the choice share P_j ($\Pr(u_j \geq u_{j'}\ \ \forall j' \in \mathcal{J})$) can be computed with a multidimensional integral for the elemental choice set $\mathcal{J}$ and for the composite choice set $\mathcal{K}$:

$$P_j = \int_{\epsilon_j=-\infty}^{\infty} \left(\int_{\epsilon_1=-\infty}^{v_j-v_1+\epsilon_j} \dots \int_{\epsilon_J=-\infty}^{v_j-v_J+\epsilon_k} f_{\mathrm{J}}(\boldsymbol{\epsilon}) d\epsilon_{\neg j} \right) d\epsilon_j;\quad P_k = \int_{\epsilon_k=-\infty}^{\infty} \left(\int_{\epsilon_1=-\infty}^{v_k-v_1+\epsilon_k} \dots \int_{\epsilon_K=-\infty}^{v_k-v_K+\epsilon_k} f_{\mathrm{K}}(\boldsymbol{\epsilon}) d\epsilon_{\neg k} \right) d\epsilon_k \tag{2}$$

where $K = |\mathcal{K}|, J = |\mathcal{J}|$, $f_{\mathrm{K}}(\boldsymbol{\epsilon})$ is the probability density function for the vector of random error terms in the composite model, $f_{\mathrm{J}}(\boldsymbol{\epsilon})$ is the probability density function for the vector of random error terms in the elemental model, and $\neg$ represents "all except", so that $d\epsilon_{\neg k} = d\epsilon_K d\epsilon_{K-1} \dots d\epsilon_{k+1} d\epsilon_{k-1} \dots d\epsilon_2 d\epsilon_1$, and $d\epsilon_{\neg j} = d\epsilon_J d\epsilon_{J-1} \dots d\epsilon_{j+1} d\epsilon_{j-1} \dots d\epsilon_2 d\epsilon_1$. The difference between the composite and elemental model choice-share predictions ΔP_k for generic error distribution

[8] As we will see, $\Delta P_k = 0$ when the appropriate "correction factors" are used in the composite utilities.

[9] For simplicity of illustration, consumer heterogeneity, including consumer-specific attributes such as demographic information that would affect utility, is ignored here.

assumptions is computed using Eq.(1) and Eq.(2). This expression provides a measure of the inconsistency between the elemental model and any given composite model specification.

To find a composite model specification that is consistent with the elemental model for a given error distribution assumption, we set $\Delta P_k = 0 \; \forall k \in \mathcal{K}$ and solve for the utility of the composite[10]. For the particular cases where both the elemental model and the composite model are specified as logit, nested logit, or mixed logit, a closed-form expression or kernel solution exists. We derive each of these cases in Appendix A and summarize results in Table 3. The solutions share a similar form for the utility of the composite involving the Logarithm of the Sum of the Exponential (LSE) of the utilities of the elemental alternatives. The LSE specification can be decomposed, as shown by McFadden (1978) and by Ben-Akiva and Lerman (1985),[11] into (1) the base composite utility (often an average or weighted average of the elements represented by the composite), (2) the group "size correction factor," which is a factor that accounts for the number of elements represented by the composite, and (3) the "heterogeneity correction factor[12]," which is a factor that accounts for differences in utility of elemental alternatives from the base composite utility. When both of these correction factors are combined with the base composite utility, they are mathematically equivalent to the LSE and therefore predict choice probabilities from the composite model that are consistent with those that the elemental model would predict for the corresponding group of vehicles. As shown in Table 2, while some vehicle choice models have applied a size correction factor (or a variant), no vehicle choice model using composites in the predictive literature has applied these correction factors in full[13]. We characterize the implications of this practice.

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[10] A solution may or may not exist, depending on the pair of assumptions about the error term distributions. As demonstrated in Parsons and Needelman (1992) based on McFadden (1978), a solution consistent with random utility maximization exists where both error terms are iid Type I Extreme Value.

[11] The size and heterogeneity correction factors were first discussed and derived by Lerman (1975), McFadden (1978), and Ben-Akiva and Lerman (1985) for logit and nested logit models. In this paper, we extend the derivation to make explicit how these concepts apply to mixed-logit models and to models that include ASCs.

[12] The exponential function in the heterogeneity correction factor emphasizes alternatives in $\mathcal{J}_k$ with higher utility. Ben-Akiva and Lerman (1985) observe that the derivative of the heterogeneity correction factor shows sensitivity to elemental alternatives with high choice probabilities.

[13] One study in the explanatory literature, Habibi et al. (2017), does use full correction factors to make predictions, but focuses on comparing parameter estimates.

Table 3: Composite Specifications for Models Without ASCs to Produce Share Predictions Consistent with a Corresponding Elemental Model

	Observed utility of composites required for $\Delta P_k = 0\ \forall k \in \mathcal{K}$	Base composite utility[14,15]	Size correction factor	Heterogeneity correction factor
Logit	$v_k = \ln\left(\sum_{j\in\mathcal{J}_k} \exp(v_j)\right) = \bar{v}_k + \ln(n_k) + \ln(b_k)$	$\bar{v}_k = \boldsymbol{\beta}'\bar{\mathbf{x}}_k$	$n_k = \lvert\mathcal{J}_k\rvert$	$b_k = \dfrac{\sum_{j\in\mathcal{J}_k} \exp\left(\boldsymbol{\beta}'(\mathbf{x}_j - \bar{\mathbf{x}}_k)\right)}{n_k}$
Nested Logit	$v_k = \lambda_k \ln\left(\sum_{j\in\mathcal{J}_k} \exp\left(\frac{v_j}{\lambda_k}\right)\right) = \bar{v}_k + \lambda_k \ln(n_k) + \lambda_k \ln(b_k)$	$\bar{v}_k = \boldsymbol{\beta}'\bar{\mathbf{x}}_k$	$n_k = \lvert\mathcal{J}_k\rvert$	$b_k = \dfrac{\sum_{j\in\mathcal{J}_k} \exp\left(\frac{\boldsymbol{\beta}'(\mathbf{x}_j - \bar{\mathbf{x}}_k)}{\lambda_k}\right)}{n_k}$
Mixed Logit	$\tilde{v}_k = \ln\left(\sum_{j\in\mathcal{J}_k} \exp(\tilde{v}_j)\right) = \tilde{\bar{v}}_k + \ln(n_k) + \ln(\tilde{b}_k)$	$\tilde{\bar{v}}_k = \tilde{\boldsymbol{\beta}}'\bar{\mathbf{x}}_k$	$n_k = \lvert\mathcal{J}_k\rvert$	$\tilde{b}_k = \dfrac{\sum_{j\in\mathcal{J}_k} \exp\left(\tilde{\boldsymbol{\beta}}'(\mathbf{x}_j - \bar{\mathbf{x}}_k)\right)}{n_k}$

Notes: Derivations are available in Appendix A and B. v: "observed utility," utility derived from attributes observed by the modeler; $\bar{v}_k$: base composite utility; λ: nest parameter, which reflects the degree of independence in unobserved utility among alternatives in the nests; $\mathbf{x}$: vector of vehicle attributes; $\bar{\mathbf{x}}_k$: vector of attributes of the composite alternative; $\boldsymbol{\beta}$: vector of consumer preference parameters. For the case of mixed logit (which includes latent-class logit as a special case), the model parameters are random variables and therefore the base composite utility and the heterogeneity correction factor are also random variables. We identify random variables with the ~ symbol. $\tilde{\boldsymbol{\beta}}$: random vector of consumer preference parameters, which may be continuous (e.g.: normal) or discrete (e.g.: different values for individual consumer segments, as in latent-class models).

[14] We show the case where utility is linear-in-parameters for illustration. Note that when utility is linear in parameters, a composite alternative defined using the average value for each attribute will have average utility. Other utility models could be used so long as the heterogeneity correction factor is adjusted accordingly.

[15] In the literature, the base composite's attribute vector is often calculated as an average or weighted average ($\bar{\mathbf{x}}_k = \sum_{j\in\mathcal{J}_k} w_j \mathbf{x}_j / n_k$, where the w's are some weights e.g.: sales of each alternative) (Goldberg, 1998; Bento et al., 2009). However, in other models, the base composite's attributes are based on other methods or expert judgment, for example in the case of forecasts (EIA, 2010). The correction factors apply for any specification of $\bar{\mathbf{x}}_k$.

3.2 Models With Alternative-Specific Constants (ASCs)

Many vehicle choice models (Brownstone et al., 2000; Bunch et al., 2011; Train and Winston, 2007; Xie and Lin, 2017) use ASCs, which are utility parameters estimated for each choice alternative. Each alternative's ASC can be thought of, under certain conditions, as representing the average utility across consumers that is associated with the alternative's unobserved attributes. With ASCs, the utility for each choice alternative in the model is represented by $u_j = \boldsymbol{\beta}'\mathbf{x}_j + \xi_j + \varepsilon_j$. In the literature and in practice, ASCs are determined by two different approaches: (1) by estimating them together with other parameters and (2) by fitting them post-hoc as calibration constants (Haaf et al., 2016). VCMs in the explanatory literature typically estimate ASCs simultaneously with other choice model parameters as part of an effort to control for omitted variable bias (Guevara, 2015; Haaf et al., 2016; Klier and Linn, 2012; Train and Winston, 2007; Whitefoot et al., 2017), whereas VCMs in the predictive literature use post-hoc calibration to estimate ASCs as calibration constants (Birky, 2012; Greene et al., 2005; Xie and Lin, 2017). The correction factors we present are agnostic about the approach of estimating ASCs. In the literature, ASCs have been estimated/calibrated for elemental alternatives using elemental sales data (which we refer to as E-ASCs) as well as for composite alternatives using composite-level sales data (C-ASCs). Refer to Tables 1 and 2 for examples.

To differentiate the baseline scenario in which ASCs are estimated or calibrated to existing sales data from the counterfactual or forecast scenario where shares are predicted, we introduce the subscript $t \in \mathcal{T}$ and define $t = 0$ as the baseline scenario where observed shares are available and ASCs are estimated ($t \neq 0$ implies a counterfactual or forecast scenario). Similar to our procedure in the previous section, to find a composite model specification that is consistent with the elemental model, we set $\Delta P_{kt} = 0\ \ \forall k \in \mathcal{K},\ t \in \mathcal{T}$ and solve for the utility of the composite for the cases of logit, nested logit, and mixed logit when E-ASCs and C-ASCs are present. Derivations are provided in Appendix C, and the results are summarized in Table 4.

Here, the LSE solution is decomposed into a base composite utility and correction factors that are functions of both the E-ASCs and the C-ASCs.[16] For any E-ASCs and C-ASCs determined by any method, these correction factors will adjust the composite model to make predictions consistent with the elemental model. To be meaningful, the E-ASCs are generally estimated or calibrated using observed data, but any value for the C-ASCs will do. A convenient choice when constructing a new composite model is to set $\xi_k = 0\ \ \forall k \in \mathcal{K}$ and simplify the equations in Table 4 accordingly, but for models that have already been calibrated at the composite level, the general correction factors in Table 4 allow a modeler to adjust the composite specification so that choice probabilities are consistent with an associated elemental model. This is advantageous, for example, when counterfactual or forecast scenarios involve computationally intensive operations where the use of composites can reduce computation time or when sensitivity analysis for forecasts is more tractable with fewer parameters.

[16] For simplicity, we show ASCs as being estimated in the baseline scenario $t = 0$ using observed choices and assumed constant across counterfactual and forecast scenarios (no scenario subscript). Some models make projected adjustments to ASCs for forecast scenarios (e.g.: Birky, 2012; EIA, 2010). This practice is discussed by Haaf et al. (2016) and Stephens et al. (2017). The correction factors in Table 4 hold for any choice of ASCs for any scenario.

Table 4: Composite Specifications for Models With ASCs to Produce Share Predictions Consistent With a Corresponding Elemental Model

	Observed utility of composites required for $\Delta P_{kt} = 0\ \forall k \in \mathcal{K}, t \in \mathcal{T}$	Base composite utility[14,15]	Size correction factor	Heterogeneity[17] correction factor
Logit	$v_{kt} = \ln\left(\sum_{j\in\mathcal{J}_{kt}} \exp(v_{jt} + \xi_j)\right) - \xi_k = \bar{v}_{kt} + \ln(n_{kt}) + \ln(b_{kt}) - \xi_k$	$\bar{v}_{kt} = \boldsymbol{\beta}'\bar{\mathbf{x}}_{kt} + \xi_k$	$n_{kt} = \lvert\mathcal{J}_{kt}\rvert$	$b_{kt} = \frac{\sum_{j\in\mathcal{J}_{kt}} \exp\left(\boldsymbol{\beta}'(\mathbf{x}_{jt} - \bar{\mathbf{x}}_{kt}) + (\xi_j - \xi_k)\right)}{n_{kt}}$
Nested Logit	$v_{kt} = \lambda_{kt} \ln\left(\sum_{j\in\mathcal{J}_{kt}} \exp\left(\frac{v_{jt} + \xi_j}{\lambda_{kt}}\right)\right) - \xi_k = \bar{v}_{kt} + \lambda_{kt}\ln(n_{kt}) + \lambda_{kt}\ln(b_{kt}) - \xi_k$	$\bar{v}_{kt} = \boldsymbol{\beta}'\bar{\mathbf{x}}_{kt} + \xi_k$	$n_{kt} = \lvert\mathcal{J}_{kt}\rvert$	$b_{kt} = \frac{\sum_{j\in\mathcal{J}_{kt}} \exp\left(\frac{\boldsymbol{\beta}'(\mathbf{x}_{jt} - \bar{\mathbf{x}}_{kt}) +}{\lambda_{kt}}\right.}{n_{kt}}$
Mixed Logit	$\tilde{v}_{kt} = \ln\left(\sum_{j\in\mathcal{J}_{kt}} \exp(\tilde{v}_{jt} + \xi_j)\right) - \xi_k = \bar{\tilde{v}}_{kt} + \ln(n_{kt}) + \ln(\tilde{b}_{kt}) - \xi_k$	$\bar{\tilde{v}}_{kt} = \tilde{\boldsymbol{\beta}}'\bar{\mathbf{x}}_{kt} + \xi_k$	$n_{kt} = \lvert\mathcal{J}_{kt}\rvert$	$\tilde{b}_{kt} = \frac{\sum_{j\in\mathcal{J}_{kt}} \exp\left(\tilde{\boldsymbol{\beta}}'(\mathbf{x}_{jt} - \bar{\mathbf{x}}_{kt}) + (\xi_j - \xi_k)\right)}{n_{kt}}$

Notes: Derivations are available in Appendix C. ξ_j: Elemental-Alternative-Specific-Constant (E-ASC) (estimated or calibrated to observed choice data in scenario $t = 0$); ξ_k: Composite-Alternative-Specific-Constant (C-ASC) (may take any value (e.g.: zero) or be estimated or calibrated to observed choice data in scenario $t = 0$)[16]; $\bar{v}_{kt}$: base utility of composite k in scenario t[14,15]; λ: nest parameter, which reflects the degree of independence in unobserved utility among alternatives in the nests; $\mathbf{x}$: vector of vehicle attributes; $\bar{\mathbf{x}}_k$: vector of attributes of the composite alternative; $\boldsymbol{\beta}$: vector of consumer preference parameters. $\tilde{\boldsymbol{\beta}}$: random vector of consumer preference parameters, which may be continuous (e.g.: normal) or discrete (e.g.: different values for individual consumer segments, as in latent-class models)

[17] Heterogeneity correction factor here in Table 4 refers to heterogeneity of observed utility including E-ASC (in contrast to heterogeneity correction factor for models without ASC)

For the typical case where ASCs are fit to data from a single market,[18] the ASCs can reduce share error for both the elemental model and the composite model to zero in the baseline scenario $t = 0$. But, importantly, these ASCs do not necessarily lead to the same result in counterfactual or forecast scenarios. Specifically, we define:

$$\Delta s_{j0} = P_{j0} - s_{j0} \quad \forall j \in \mathcal{J} \tag{3}$$

$$\Delta s_{k0} = P_{k0} - s_{k0} = P_{k0} - \sum_{j \in \mathcal{J}_k} s_{j0} \quad \forall k \in \mathcal{K} \tag{4}$$

Where s_{j0} is the observed share of alternative j in scenario $t = 0$; Δs_{j0} is the difference between predicted elemental choice probabilities and observed choice shares for alternative j in scenario $t = 0$, and Δs_{k0} is the difference between predicted composite choice probabilities and observed choice share for composite k in scenario $t = 0$. Choice share for composite k is defined as the sum of the observed shares for the alternatives represented by composite k.

Calibration of ξ_j enforces that $P_{j0} = s_{j0}$ (and therefore $\Delta s_{j0} = 0$) $\forall j \in \mathcal{J}$. Similarly, if the composite model is independently calibrated to sales data at the composite level, such as in Birky (2012), calibration of ξ_k enforces that $P_{k0} = \sum_{j \in \mathcal{J}_k} s_{j0}$ and $\Delta s_{k0} = 0$ $\forall k \in \mathcal{K}$. Because both the elemental model and the composite model are calibrated to match the same baseline scenario sales data, they will have consistent choice probabilities in that scenario: $\Delta P_{k0} = 0$. But without complete correction in the composite model, the elemental and composite models with ASCs may nevertheless produce different choice probabilities in counterfactual or forecast scenarios: $\Delta P_{kt} \neq 0$.

Table 5 summarizes these implications, and Figure 2 summarizes the comparison of the roles of E-ASCs, C-ASCs, and correction factors: E-ASCs and C-ASCs force the elemental model and composite model choice shares, respectively, to match the observed market shares (and therefore match one another) in the baseline scenario where ASCs are determined, whereas the correction factors ensure that the elemental model and composite model match one another for all scenarios.

Table 5: Summary of the Implications of ASCs and Correction Factors

		Baseline scenario	Counterfactual scenario
Without ASCs	Without complete correction	$\Delta P \neq 0$	$\Delta P \neq 0$
	With complete correction	$\Delta P = 0$	$\Delta P = 0$
With ASCs	Without complete correction	$\Delta P = 0$	$\Delta P \neq 0$
	With complete correction	$\Delta P = 0$	$\Delta P = 0$

[18] In some models, ASCs for alternatives that appear in multiple observed markets (e.g.: model years or choice sets) are held constant across those markets to estimate ASCs as fixed effects and control for omitted variables (Guevara, 2015). We focus our narrative here on the case of a single market, where ASCs provide enough degrees of freedom to allow choice model shares to match observed shares and can be used in conjunction with instrumental variables to control for omitted variables (Haaf et al., 2016).

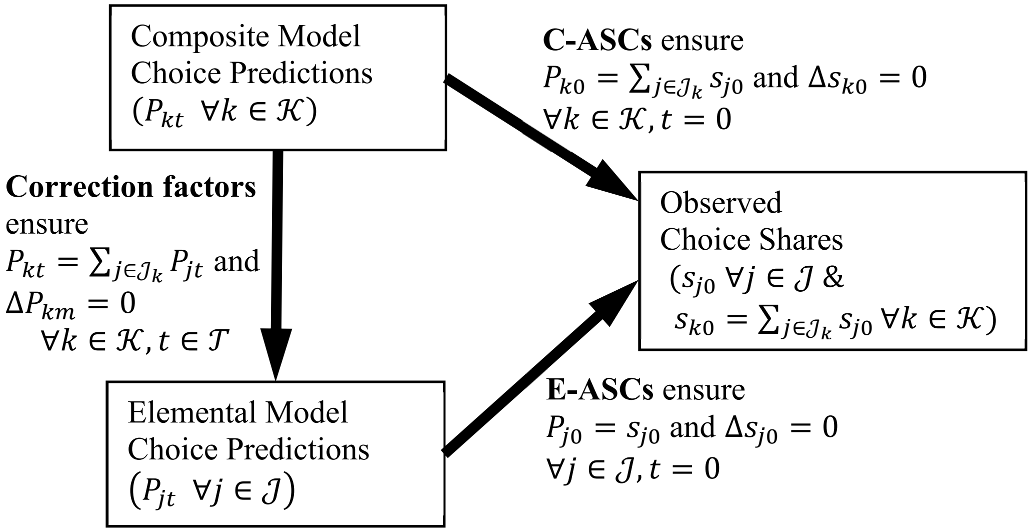

Figure 2: Illustration of the roles of correction factors, E-ASCs, and C-ASCs in choice modeling. Arrows indicate the direction of adjustment, so that the predictions from the model at each arrow's tail are adjusted to match those from the models at the arrow's head.

Our correction factors, which extend prior work to explicitly address models with ASCs, allow models with vehicle composites to produce choice shares consistent with a corresponding model with elemental alternatives, even in counterfactual or forecast scenarios.

4 SIMULATION CASE STUDIES

To characterize the impact of composite specification on choice modeling predictions in practice, we construct two case studies. In Case 1, we isolate the effect of composite specification on choice model share prediction for a simple logit model without ASCs and compare its magnitude relative to parameter uncertainty. In Case 2, we construct a nested logit model based on the NEMS and LVChoice models, with and without ASCs, and we explore the effect of the use of composites and correction factors on counterfactual predictions. We compute choice probabilities using a series of models that predict choice shares using different specifications of the utility of composite vehicles. These model specifications are listed in Table 6.

Table 6: Model Specifications in Case Study Simulations

Composite Model Specification	Components Included in the Utility of the Composite
C1a	Base composite utility using the arithmetic averages of constituent vehicle utilities ($\bar{v}_k = \sum_{j \in \mathcal{J}_k} v_j / n_k$)
C1w	Base composite utility using sales-weighted averages ($\bar{v}_k = \sum_{j \in \mathcal{J}_k} w_j v_j / n_k$)
C2a	Base composite utility based on arithmetic averages plus the size correction factor (Table 3, 4)

C2w	Base composite utility based on sales-weighted averages plus the size correction factor (Table 3, 4)
C3	Base composite utility with both size and heterogeneity correction factors (Table 3, 4) (results for this specification are independent of how the base composite utility is specified)
Other Model Specifications	
E	Elemental: choice set composed of disaggregated elemental alternatives at the make-model-trim level and their attributes. The set of elemental alternatives are based on the model-year 2014 vehicles tracked by *IHS Polk* with more than 100 sales in California.

Both case studies concentrate on choice shares for various fuel-types in the small car market in California. Fuel-type groupings for composites are based on the classification scheme in LVChoice and include gasoline vehicles, diesel vehicles, hybrid electric vehicles (HEVs), plug-in hybrid vehicles with a ~10-mile electric range (PHEV10), PHEVs with a ~40-mile[19] range (PHEV40), and fully electric vehicles (EVs). Sales and attribute data are from *IHS Polk* and *Wards Automotive Yearbook*, respectively, for model-year 2014 new car registrations in California.

4.1 Case 1 – Logit Without ASCs

In Case 1, we use a multinomial logit model with a functional form that includes price, fuel economy, 0-60 mph acceleration time, and vehicle footprint (wheelbase multiplied by track width), following Whitefoot and Skerlos (2012). We exclude ASCs to isolate the effect of composites on the model's ability to capture choice predictions using observed attributes. Utility parameters are defined based on the midpoint of the willingness-to-pay ranges and the price elasticity of demand found by Whitefoot and Skerlos (2012).

[19] The PHEV40 composite group is meant as a classification covering PHEVs with a large range and is not strictly limited to PHEVs with exactly 40 mi of all-electric range. For 2014, this included the Ford C-Max Energi SEL with 20 mi, Cadillac ELR with 37 mi, and Chevrolet Volt with 38 mi.

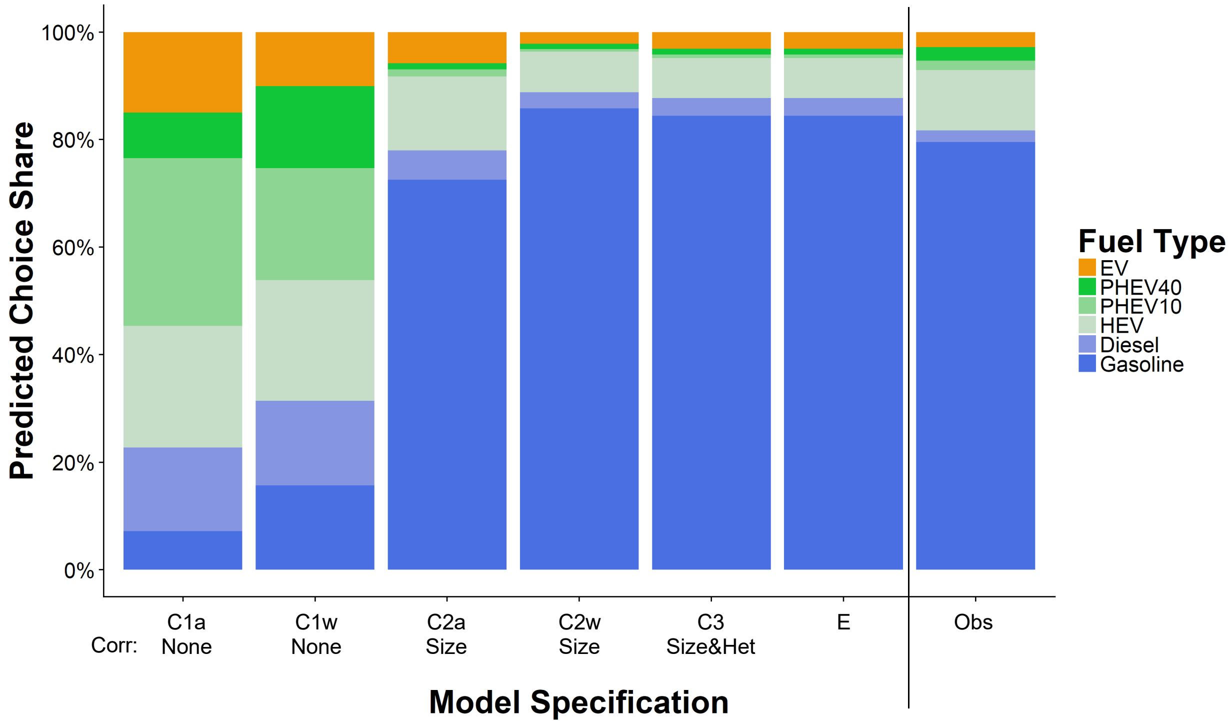

Figure 3: Case 1 simulated choice shares by fuel type for the 2014 California new small car market under different specifications for the utility of composites as defined in Table 4. "Corr" refers to correction factors included in the model specification; "Size" and "Het" refer to the size and heterogeneity correction factors, respectively. The rightmost column "Obs" shows observed (not simulated) sales of 2014 vehicles.

Figure 3 shows that choice-share predictions significantly differ depending on how the composites are specified. When using only arithmetic means to specify composites (C1a), choice predictions deviate dramatically from the benchmark elemental model results (E). Shares of alternative-fuel vehicles, each of which represent few elemental variants, are much larger in the composite model, and shares of gasoline vehicles, which represent many diverse elemental variants, are much smaller. Using sales-weighted-average composites (C1w) reduces the deviations only slightly. We find that including the size correction factor (C2a) improves predictions considerably, but differences in the choice shares are still substantial. For example, shares of HEVs and EVs in this composite specification (14% and 6%, respectively) are still much larger than the elemental model (7% and 3%, respectively). Gasoline vehicle share is substantially smaller in the composite model compared to the elemental model (72% instead of 84%). Compared to arithmetic averages, sales-weighted average composites with the size correction (C2w) achieved predictions much closer to the benchmark, but they overpredict gasoline vehicles and underpredict HEVs and EVs relative to the elemental model. When the appropriate heterogeneity correction factor from Table 2 is included in model specification C3, the predictions successfully replicate the benchmark results. This is expected because using the appropriate correction factors is equivalent to the LSE solution for each composite group, resulting in choice probabilities that match the elemental model results.

These results show that the use of composites and correction factors can substantially impact choice-share predictions. We also observe that, in this particular case study, the elemental model predictions of choice shares are much closer to observed shares than the predictions from the uncorrected composite models. This implies that, if we were to use ASCs in this case study for the uncorrected composite model, the ASCs would play a larger role in share predictions relative to the vehicle attributes we consider than they would when the elemental model is used. Hence, the use of composites without correction factors can significantly influence how much share predictions are driven by observed versus unobserved attributes. Whether unobserved attributes play a larger role in the uncorrected composite model or the elemental model depends, of course, on which model predicts actual shares more closely with no ASCs. We would expect this to vary from case to case. We further explore the role of ASCs in Case 2.

We then examine how the magnitude of the effect of composite specification on choice probabilities compares to other sources of model error or uncertainty. We do so by repeating the Case 1 simulation with a range of utility parameter estimates. A total of 1000 sets of preference parameters are drawn from independent uniform distributions based on the interval containing all estimates of willingness-to-pay and price elasticities of demand across the literature reviewed in Whitefoot and Skerlos (2012), which reflect the uncertainty in estimated preference parameters arising from differences in data, estimation methods, and model specification across studies. We examine the magnitude of variation of these outputs due to parameter uncertainty and compare it to the variation due to different composite definitions.

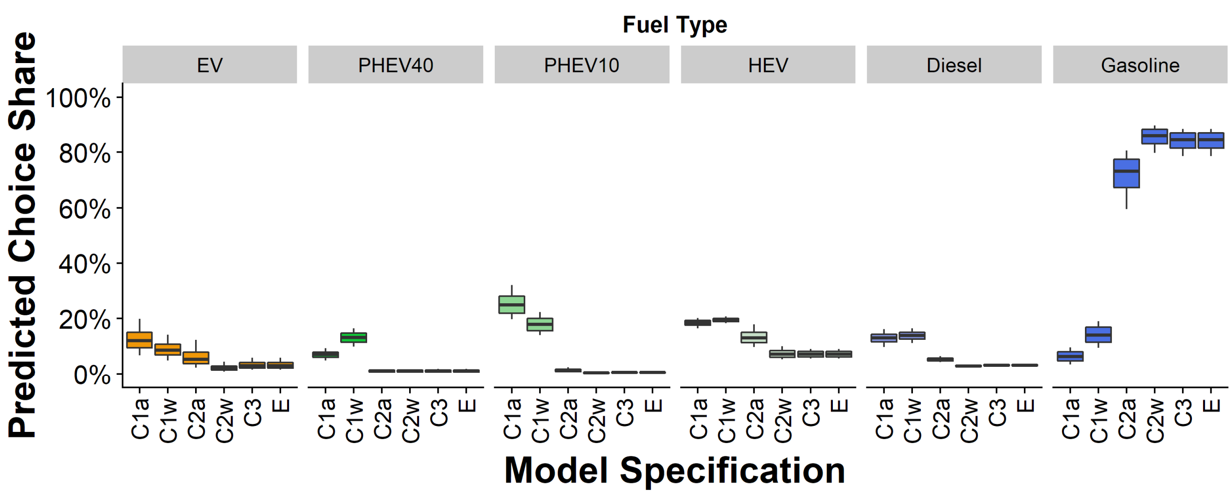

Figure 4: Simulated choice shares of each fuel type in the 2014 California new small car market, using different specifications for the utility of composites as defined in Table 4 and 1000 sets of preference parameters drawn from ranges in the literature (Whitefoot and Skerlos, 2012). Boxes denote interquartile range and whiskers denote 5th and 95th percentiles.

Figure 4 shows the magnitude of choice-share variation for each fuel-type over the distribution of parameter values $\boldsymbol{\beta}$. For example, the box plot on the far left shows the variation in the share of EVs predicted by the model using the arithmetic average composite specification over the 1000 draws of the parameter values $\boldsymbol{\beta}$ from ranges in the literature. This box plot shows that the median share of EVs predicted by this composite model (C1) is 12%, and the 5% and 95% percentiles of the uncertainty distribution are 7% share and 20% share, respectively.

Looking across the box plots, we observe that variation due to composite specification (comparing C1, C2, and C3 with E, the elemental model within the same fuel type) is often larger than variation due to parameter uncertainty (the spread of each box plot). For example, the share of EVs predicted by the elemental model is 2-6% (median of 3%). These results suggest that composite specification can cause substantial share prediction variation that can be greater than variation due to parameter uncertainty. Further details of these results are discussed in Appendix D.

4.2 Case 2 – Nested Logit With ASCs

In Case 2, we investigate the effect of using composites on VCM simulations of counterfactual scenarios based on VCMs used to inform policymaking. We construct a nested logit specification with ASCs based on LVChoice (Birky, 2012), a VCM used by the Department of Energy and the National Petroleum Council to simulate market shares of alternative-fuel vehicles under different scenarios. LVChoice uses the same utility specification and parameters as the VCM in the NEMS CVCC model used by the Energy Information Administration (EIA) (Birky, 2012; EIA, 2010). Further details of the model used in Case 2 are in Appendix E. Following LVChoice and NEMS, we treat vehicle size classes as separate nested logit models representing isolated markets and consumer segments.

Similar to Case 1, in Case 2 we simulate choice shares using a series of composite model specifications (C1, C2, C3), as well as a benchmark disaggregated elemental model (E). In Case 2, we specify composite vehicles using sales-weighted averages based on the attributes and sales of constituent elemental alternatives in 2014 and drop the "w" from the labels for simplicity of notation. Composites are defined at the sub-fuel type level based on the classification scheme used in LVChoice and NEMS. In the elemental model, make-model-trim level alternatives are added as members of each sub-fuel type in a 3-level nested logit model. This model structure is shown in Figure 5.

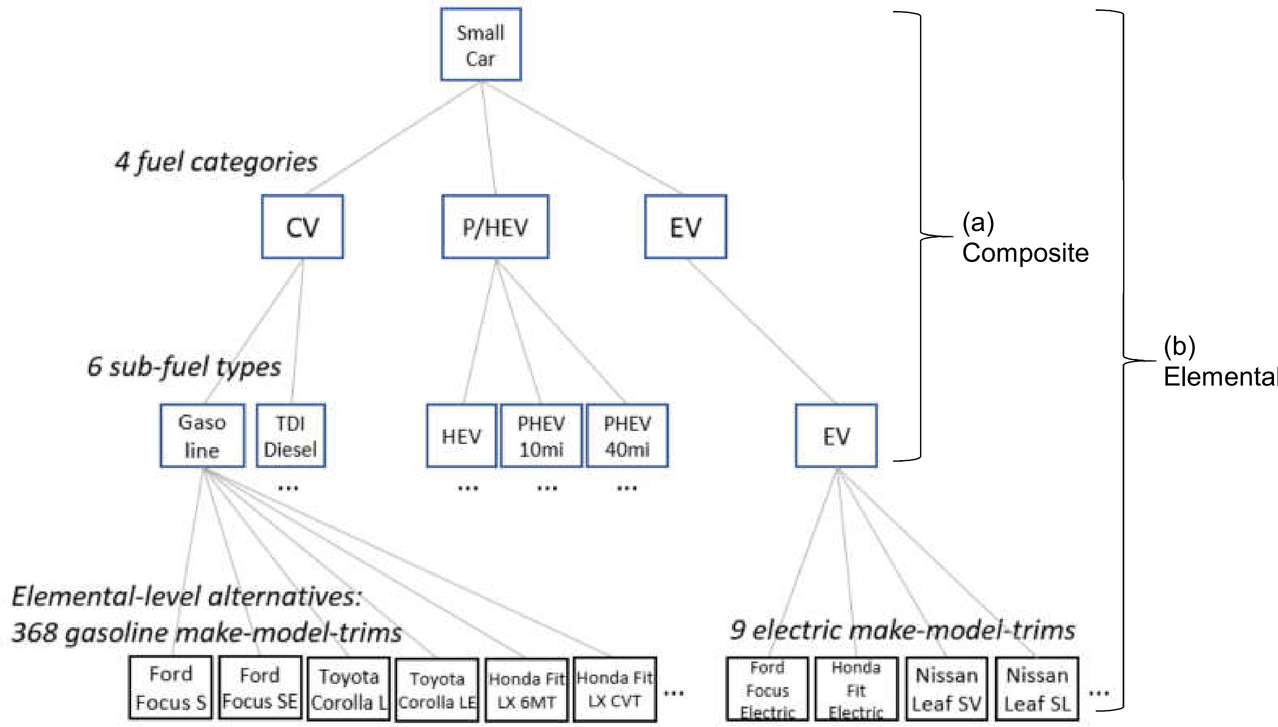

Figure 5: Structure of the (a) composite model and (b) elemental model used in Case 2, based on the structure of LVChoice and NEMS (Birky, 2012; EIA, 2010). CV refers to conventional vehicles; TDI refers to turbo-direct-injection.

In addition to constructing multiple composite models with varying correction factors, we examine results in this case using models with ASCs. We calibrate the ASCs post-hoc, following the common practice in the predictive literature for VCMs (Haaf et al., 2016). Specifically, we adopt the default utility-coefficient parameters in LVChoice and solve for the E-ASCs in the elemental model needed for predicted shares to match observed 2014 market shares. The C-ASCs are similarly calibrated in the composite model using the sum of the observed shares of the elemental alternatives represented by the composite. We present the results from models with and without ASCs for comparison.

We simulate scenarios that are typical of those simulated in the predictive VCM literature in Tables 1 and 2. These scenarios reflect counterfactual or forecasted settings that assume technological and/or policy changes that affect the attributes of the alternatives. We present four scenarios to represent the range of impacts of composite specification on choice share predictions[20]:

(a) The baseline scenario, which includes 2014 US federal and California state subsidy and monetary incentive programs for EVs and PHEVs (all vehicles at 2014 list price, except for EV and PHEV, for which prices were reduced by $4,000-10,000[21]);
(b) A counterfactual scenario in which there are no EV and PHEV subsidies (all vehicles at 2014 list price);

[20] The results of other simulated scenarios can be found in Appendix F.
[21] Data for subsidy amounts for each elemental vehicle were from California Air Resources Board (2017).

(c) A "battery cost reduction" scenario, based on battery cost projections in the EIA Annual Energy Outlook Reference Case between 2014 and 2025 (Lynes, 2017) (baseline scenario with EV and PHEV prices reduced by $300-600/kWh from $600-1200/kWh);[22]
(d) A "battery cost reduction and full EV offerings" scenario, a forecast type scenario based on battery cost reduction in scenario (c) and an increase in the number of EV make-model-trim variants to equal the number of gasoline make-model-trim variants.[23]

Figure 6 summarizes model predictions when ASCs are excluded from the models and when they are included. In both cases, the following composite models are constructed: the uncorrected composite model (C1), the composite model with the size correction factor (C2), and the composite model with both the size and the heterogeneity correction factor (C3), defined in Tables 3 and 4. These specifications follow those used in practice as discussed in section 2.2 and are defined in Table 5.

In the top row of Figure 6, where ASCs are not used, we see that the composite models that are not fully corrected (C1 and C2) are much more sensitive to changes in the counterfactual scenarios than the elemental model. Similar to Case 1, we find that the uncorrected composite models systematically overpredict shares for alternative-fuel vehicles (each of which represents few elemental variants) and underpredict gasoline vehicle share (which represents many elemental variants) relative to the elemental model. As expected, the fully corrected composite model (C3) matches the elemental model in all scenarios.

In the bottom row of Figure 6, where ASCs are used, all models have the same results in the baseline scenario (a) by design. This occurs because all composite and elemental models are calibrated with ASCs to the observed market shares for that scenario (2014 California market shares). As shown in Figure 2, the C-ASCs calibrated to the baseline scenario allow for $\boldsymbol{P_{k0}} = \sum_{j\in\mathcal{J}_k}\boldsymbol{P_{j0}} = \sum_{j\in\mathcal{J}_k}\boldsymbol{s_{j0}}$, regardless of correction. So, the choice shares of all models are therefore identical in the baseline scenario. However, the composite models using ASCs can still produce different share predictions from the elemental model in counterfactual scenarios. In particular, the distortion is related to how differently the counterfactual scenarios affect the size and heterogeneity correction factors for each composite group.

In the counterfactual no-subsidy scenario (b) with relatively minor impact on utility heterogeneity, the distortion introduced by composite specifications without correction factors is negligible when the models use ASCs. In the battery cost reduction scenario (c), prices of elemental PHEVs and EVs within the same fuel-type group are affected differently depending on their battery pack size. This is because the PHEV and EV composite groups include vehicles with a variety of battery sizes. This affects the heterogeneity correction factor for each composite group differently and causes the C1 and C2 models to predict different shares than the fully corrected C3 model and elemental model. In this instance, in scenario (c), the omission of the heterogeneity correction factor led to lower PHEV share (38% instead of 44%) and higher gasoline share (37% instead of 32%) relative to the elemental model. In scenario (d), we combine the battery cost reduction with an increase in the size (number of elements) of the EV composite group to match the size of the gasoline vehicle composite group. Both size and heterogeneity correction factors are shown to impact choice share predictions significantly, with

[22] Range of battery pack cost reduction based on EIA's estimates that depend on pack size and vehicle type (larger $/kWh costs and cost reductions for smaller packs such as in PHEVs).

EV share varying from 21% in C1 without correction to 37% in C2 with only size correction and to 70% with both size and heterogeneity correction, matching the elemental model prediction.[23]

In the literature, model specifications such as C1 and C2 (and variants) have been used for counterfactual simulations in vehicle choice models, while C3 has not (see Table 2 and 2). The use of complete size and heterogeneity correction enables the prediction of choice shares that are consistent with those from the elemental model even in counterfactual scenarios.

[23] For scenario (d), we do not forecast individual EV elements, but, rather, forecast the number of EV elements in the correction factor, following practice in the predictive literature i.e. the user-defined Make-Model-Availability parameter in LVChoice (Birky, 2012) and LAVE-Trans (Greene et al., 2014). We display the elemental results of this case as identical to C3 results because they match by definition, but individual elements were not simulated for this case.

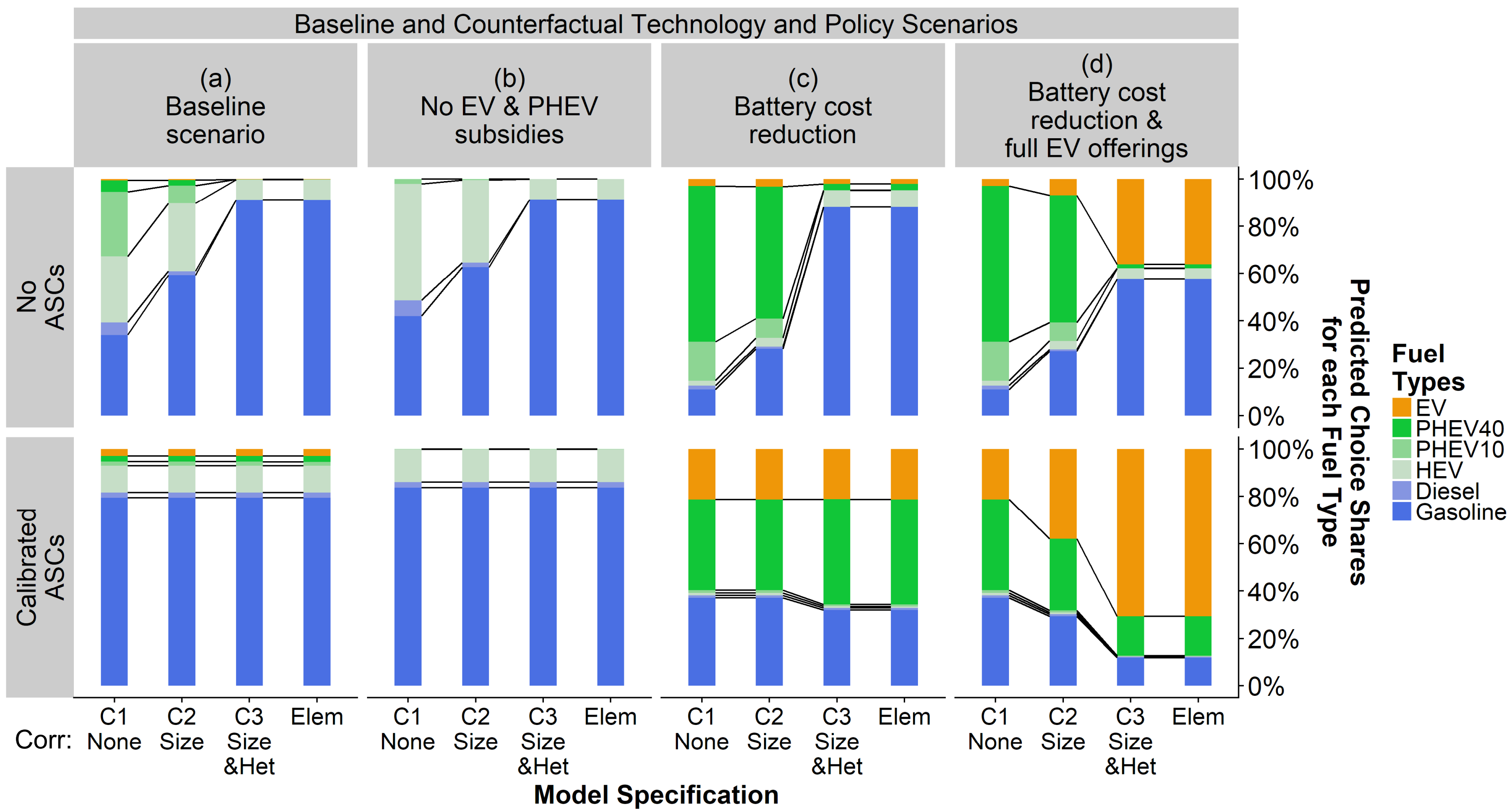

Figure 6: Case 2 simulated choice shares by fuel type for the 2014 California new small car market under (a) baseline and (b)-(d)[20] counterfactual scenarios with different specifications for the utility of composites as defined in Table 6. "Corr" indicates correction factors applied in each case; "Size" and "Het" refer to the size and heterogeneity correction factors, respectively. All composite utilities are defined by the sales-weighted average utilities of their corresponding elements. "Elem" indicates the elemental model (make-model-trim level).

5 CONCLUSION

We find that the common practice of using composites for vehicle choice model predictions can significantly distort choice-share predictions relative to models that use disaggregated elemental alternatives unless appropriate correction factors are used. We identify correction factors for a variety of model forms: multinomial logit, nested logit, and mixed logit—with and without ASCs—given exogenous preference parameters. These correction factors ensure choice-share predictions from composite models are consistent with those from their corresponding elemental models in counterfactual or forecast scenarios.

For our first case study, which excludes ASCs, the distortion of share predictions using a variety of specifications for composites that appear in the literature can be as wide or wider than the variation in share predictions due to uncertainty in preference parameters in the literature. For our second case study, which includes ASCs, composite-model choice shares are consistent with elemental-model choice shares in the baseline scenario where ASCs are calibrated, but they can nevertheless differ in counterfactual or forecast scenarios.

Generally, we find that the magnitude of the distortion introduced by the use of composites depends on several factors. Composite models without correction factors can systematically misrepresent the choice shares when composite groups (1) represent a particularly large or small number of elements, (2) represent a heterogeneous group of elements with utilities that deviate substantially from the utility of the composite, or (3) when composites are used in counterfactual scenarios that affect the number of elements in the group (e.g.: policy increases electric vehicle offerings) or the heterogeneity of utility of the elements in the composite group differently than other composite groups (e.g.: policy increases the spread of electric vehicle prices).

To avoid these distortions, we recommend that vehicle choice modelers using composites apply full correction factors. In many of the cases we examined, the distortions introduced by the use of composites are largely mitigated when the models include ASCs; however, significant distortion can remain in some counterfactual cases even when ASCs are used. To ensure that the distortion is eliminated, full correction factors are needed. This requires data on attributes of elemental alternatives and, for models with ASCs, sales data for elemental alternatives in a baseline scenario. Vehicle attribute and sales data at a detailed level (e.g., make-model-trim and subseries level) are available through databases such as *Wards Automotive* and *IHS Polk*, respectively. Of course, future attributes are not known. Examination of past trends may inform sensitivity analysis for forecasting using composites with fewer parameters (e.g.: $\bar{v}$, $\ln(n)$, $\ln(b)$) than if the attributes of every elemental alternative were to be forecasted (e.g.: Brooker et al., 2015), but more research is needed to characterize the interdependencies of these factors for forecasting. When sales data at the elemental level are too challenging or expensive to obtain, an examination of the correction factors, even when E-ASCs are uncertain, can give the modeler an understanding of the magnitude of distortion the composite specification may cause (for example, sales data at the make-model level can be assigned to elements at the make-model-subseries level using a variety of assumptions, producing a variety of estimates for the ASCs that can be used for robustness checks).

Correction factors can allow modelers to exploit the advantages of composite models, including reduced model complexity and computational cost, without introducing arbitrary distortion to choice-share results caused by specification of the composite. Our analysis focuses on differences between the predictions of models specified with composite vehicles and models specified with vehicle alternatives at the elemental level. We do not characterize how well either model represents the “true” data-generating process of consumer choices (misspecification) or how well model predictions match observed sales. Study of interactions between model misspecification and the use of composites is left for future work.

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GLOSSARY
ASC Alternative-Specific Constant
C-ASC Composite-Alternative-Specific Constant
E-ASC Elemental-Alternative-Specific Constant
EIA Energy Information Administration
EV Electric Vehicle
HEV Hybrid Electric Vehicle
LSE Logarithm of the Sum of the Exponential
MMA Make-Model Availability
NEMS National Energy Modeling System
PHEV Plug-In Electric Vehicle
VCM Vehicle Choice Model

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APPENDIX A: DERIVATIONS FOR ΔP AND FOR ASSOCIATED COMPOSITE SPECIFICATIONS FOR $\Delta P = 0$

In this Appendix, we derive expressions for the utility of the composite such that $\Delta P_k = 0$. For special cases of discrete choice models such as logit, nested logit, and mixed- and latent-class logit, ΔP_k simplifies to expressions that can be solved explicitly, which we derive below.

Multinomial Logit

When both the composite and elemental models are modeled using multinomial logit assumptions, specifically where $f_{\boldsymbol{\varepsilon}}(\boldsymbol{\epsilon}) = \prod_{\varepsilon} e^{-\varepsilon}\exp(-e^{-\varepsilon})$ (iid Type I Extreme Value error distribution), Equation 2 simplifies to:

$$\Delta P_k = \frac{e^{v_k}}{\sum_{\mathcal{k}\in\mathcal{K}} e^{v_{\mathcal{k}}}} - \sum_{j\in\mathcal{J}_k} \frac{e^{v_j}}{\sum_{\mathcal{j}\in\mathcal{J}} e^{v_{\mathcal{j}}}}$$
$$= \frac{(e^{v_k})\left(\sum_{\mathcal{j}\in\mathcal{J}} e^{v_{\mathcal{j}}}\right) - \left(\sum_{j\in\mathcal{J}_k} e^{v_j}\right)\left(\sum_{\mathcal{k}\in\mathcal{K}} e^{v_{\mathcal{k}}}\right)}{\left(\sum_{\mathcal{k}\in\mathcal{K}} e^{v_{\mathcal{k}}}\right)\left(\sum_{\mathcal{j}\in\mathcal{J}} e^{v_{\mathcal{j}}}\right)}$$

where $j, \mathcal{j}$ are indices for elemental alternatives, and $k, \mathcal{k}$ are indices for composite alternatives. To specify composite vehicles that predict the choice shares consistent with those from the elemental model, we set $\Delta P_k = 0$ and solve for v_k:

$$v_k = \ln\left(\sum_{j\in\mathcal{J}_k} e^{v_j}\right) + \ln\left(\frac{\sum_{\mathcal{k}\in\mathcal{K}} e^{v_{\mathcal{k}}}}{\sum_{\mathcal{j}\in\mathcal{J}} e^{v_{\mathcal{j}}}}\right)$$

The second term is the log of the ratio of the sum of exponentiated utilities of all alternatives in the composite model to the sum of the exponentiated utilities of all alternatives in the elemental model. This term can take the value of any arbitrary constant because logit choice probabilities are invariant to a constant shift in utility across all alternatives:

$$\frac{e^{v_k+c}}{\sum_{\mathcal{k}} e^{v_{\mathcal{k}}+c}} = \frac{e^{v_k}e^{c}}{\sum_{\mathcal{k}} e^{v_{\mathcal{k}}}e^{c}} = \frac{e^{v_k}e^{c}}{e^{c}\sum_{\mathcal{k}} e^{v_{\mathcal{k}}}} = \frac{e^{v_k}}{\sum_{\mathcal{k}} e^{v_{\mathcal{k}}}}$$

So, v_k can be simplified to:

$$v_k = \ln\left(\sum_{j\in\mathcal{J}_k} e^{v_j}\right) + d$$

where d is an arbitrary constant. The composite model generates identical choice probabilities for any value of d. If we choose $d = 0$ for simplicity[1], we recover the log-sum-exponential function (LSE) identified by McFadden (1978)[2] and Ben-Akiva and Lerman (1985):

$$v_k = \ln\left(\sum_{j\in\mathcal{J}_k} e^{v_j}\right)$$

This tells us that if we specify composites such that the utility of each composite is equal to the LSE of the elemental alternatives it represents, the composite model will produce the same

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[1] If $v_{\mathcal{k}}$ is defined as $\ln\left(\sum_{j\in\mathcal{J}_k} e^{v_j}\right)$, we see that the quantity $\frac{\sum_{\mathcal{k}\in\mathcal{K}} e^{v_{\mathcal{k}}}}{\sum_{\mathcal{j}\in\mathcal{J}} e^{v_{\mathcal{j}}}} = 1$ and therefore $c = \ln(1) = 0$ is consistent with the derived result.

[2] Described as the “inclusive value”

choice probabilities as the summed choice probabilities of the elemental alternatives each composite represents in the elemental model.

Nested Multinomial Logit

The nested logit model extends the logit model by allowing alternative assumptions about the correlation of errors in subsets of alternatives. The nest parameters λ_k determine the correlation of error terms for alternatives within the same nest, which alters substitution patterns. The grouping of alternatives into nests is analogous to the mapping of elemental alternatives to composite alternatives, and the LSE function as the utility specification for composites derived in the previous section is also equivalent to the closed-form solution for the marginal probability of a choice associated with a certain nest in the nested logit framework (McFadden, 1978), as can be seen in the following derivation.

The predicted choice probability using nested logit can be expressed as the product of a conditional probability (j conditional on nest k) and marginal probability of nest k itself:

$$P_j = P(j|k)P(k)$$

$$= \left(\frac{\exp\left(\frac{v_j}{\lambda_k}\right)}{\sum_{\jmath\in\mathcal{J}_k}\exp\left(\frac{v_\jmath}{\lambda_k}\right)}\right)\left(\frac{\exp\left(\lambda_k \ln\sum_{\jmath\in\mathcal{J}_k}\exp\left(\frac{v_\jmath}{\lambda_k}\right)\right)}{\sum_{\mathscr{k}\in\mathcal{K}}\exp\left(\lambda_\mathscr{k} \ln\sum_{\jmath\in\mathcal{J}_\mathscr{k}}\exp\left(\frac{v_\jmath}{\lambda_\mathscr{k}}\right)\right)}\right)$$

where k is the nest containing alternative j. At the composite level, the choice probability for composite k is:

$$P_k = \frac{\exp(v_k)}{\sum_{\mathscr{k}\in\mathcal{K}}[\exp(v_\mathscr{k})]}$$

Therefore,

$$\Delta P_k = \frac{\exp(v_k)}{\sum_{\mathscr{k}\in\mathcal{K}}[\exp(v_\mathscr{k})]} - \sum_{j\in\mathcal{J}_k}\frac{\exp\left(\frac{v_j}{\lambda_k}\right)\exp\left(\lambda_k \ln\sum_{\jmath\in\mathcal{J}_k}\exp\left(\frac{v_\jmath}{\lambda_k}\right)\right)}{\left(\sum_{\jmath\in\mathcal{J}_k}\exp\left(\frac{v_\jmath}{\lambda_k}\right)\right)\left(\sum_{\mathscr{k}\in\mathcal{K}}\exp\left(\lambda_\mathscr{k} \ln\sum_{\jmath\in\mathcal{J}_\mathscr{k}}\exp\left(\frac{v_\jmath}{\lambda_\mathscr{k}}\right)\right)\right)}$$

Setting the derived expression to zero results in a specification for the composite utility.

$$v_k = \ln\left\{\sum_{\mathscr{k}\in\mathcal{K}}[exp(v_\mathscr{k})]\frac{\exp\left(\lambda_k\, ln\sum_{\jmath\in\mathcal{J}_k} exp\left(\frac{v_\jmath}{\lambda_k}\right)\right)}{\sum_{\mathscr{k}\in\mathcal{K}} exp\left(\lambda_\mathscr{k}\, ln\sum_{\jmath\in\mathcal{J}_\mathscr{k}} exp\left(\frac{v_\jmath}{\lambda_\mathscr{k}}\right)\right)}\right\}$$

$$v_k = \lambda_k \ln\left(\sum_{j\in\mathcal{J}_k}\exp\left(\frac{v_j}{\lambda_k}\right)\right) + \ln\left\{\frac{\sum_{\mathscr{k}\in\mathcal{K}}[exp(v_\mathscr{k})]}{\sum_{\mathscr{k}\in\mathcal{K}} exp\left(\lambda_\mathscr{k}\, ln\sum_{\jmath\in\mathcal{J}_\mathscr{k}} exp\left(\frac{v_\jmath}{\lambda_\mathscr{k}}\right)\right)}\right\}$$

Again, the 2nd term is the same for all k, so we can interpret it to be a constant shift across all alternatives, which does not affect choice probability predictions[3].

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[3] If $v_\mathscr{k}$ is defined as $\lambda_k \ln\left(\sum_{j\in\mathcal{J}_k}\exp\left(\frac{v_j}{\lambda_k}\right)\right)$, we see that the quantity $\frac{\sum_{\mathscr{k}\in\mathcal{K}}[exp(v_\mathscr{k})]}{\sum_{\mathscr{k}\in\mathcal{K}} exp\left(\lambda_\mathscr{k}\, ln\sum_{\jmath\in\mathcal{J}_\mathscr{k}} exp\left(\frac{v_\jmath}{\lambda_\mathscr{k}}\right)\right)} = 1$ and therefore the second term equals zero, which is consistent with the derived result.

$$v_k = \lambda_k \ln\left(\sum_{j\in\mathcal{J}_k} \exp\left(\frac{v_j}{\lambda_k}\right)\right)$$

This is a more general version of the previous result for logit[4].

Mixed Logit and Latent-Class Logit
Further variations of the logit model involve the representation of consumer and preference heterogeneity. In mixed logit (also known as random coefficients logit), there are general continuously distributed random-variable preference parameters, $\widetilde{\boldsymbol{\beta}}$, representing consumer heterogeneity, and ΔP_k can be represented as:

$$\Delta P_k = \int_{\beta=-\infty}^{\beta=+\infty} \left\{\left[\frac{\exp(\widetilde{\boldsymbol{\beta}}'\boldsymbol{x_k})}{\sum_{\hbar\in\mathcal{K}} \exp(\widetilde{\boldsymbol{\beta}}'\boldsymbol{x_{\hbar}})} - \sum_{j\in\mathcal{J}_k} \frac{\exp(\widetilde{\boldsymbol{\beta}}'\boldsymbol{x_j})}{\sum_{\jmath\in\mathcal{J}_k} \exp(\widetilde{\boldsymbol{\beta}}'\boldsymbol{x_{\jmath}})}\right] f(\widetilde{\boldsymbol{\beta}})\right\} d\widetilde{\boldsymbol{\beta}}$$

$$\Delta P_k = \int_{\beta=-\infty}^{\beta=+\infty} \{\Delta P_k(\widetilde{\boldsymbol{\beta}}) f(\widetilde{\boldsymbol{\beta}})\} d\widetilde{\boldsymbol{\beta}}$$

A special case for $\Delta P_k = 0$ would be for the utility of composites for each value of $\widetilde{\boldsymbol{\beta}}$ to be specified by the following expression:

$$v_k = \ln \sum_{j\in\mathcal{J}_k} \exp(\widetilde{\boldsymbol{\beta}}'\boldsymbol{x_j})$$

In latent-class logit, which can be thought of as a special case of mixed logit, consumer preferences are modeled as a discrete distribution and the choice probability integral becomes a summation of logit models using the consumer preferences of each latent class weighted by the probability of each latent class. For example, with a discrete distribution of preference coefficients represented by $\boldsymbol{\beta_i}$ for consumer class *i*, and their proportions represented by $f(\boldsymbol{\beta_i})$ where $\sum_i f(\boldsymbol{\beta_i}) = 1$, the predicted choice probability collapses into:

$$P_j = \sum_i \left\{\frac{\exp(\boldsymbol{\beta_i}'\boldsymbol{x_j})}{\sum_{\jmath\in\mathcal{J}_k} \exp(\boldsymbol{\beta_i}'\boldsymbol{x_{\jmath}})} f(\boldsymbol{\beta_i})\right\}$$

$$P_k = \sum_i \left\{\frac{\exp(\boldsymbol{\beta_i}'\boldsymbol{x_k})}{\sum_{\hbar\in\mathcal{K}} \exp(\boldsymbol{\beta_i}'\boldsymbol{x_{\hbar}})} f(\boldsymbol{\beta_i})\right\}$$

Therefore,

$$\Delta P_k = P_k - \sum_{j\in\mathcal{J}_k} P_j$$

$$\Delta P_k = \sum_i \left\{\frac{\exp(\boldsymbol{\beta_i}'\boldsymbol{x_k})}{\sum_{\hbar\in\mathcal{K}} \exp(\boldsymbol{\beta_i}'\boldsymbol{x_{\hbar}})} f(\boldsymbol{\beta_i})\right\} - \sum_{\jmath\in\mathcal{J}_k} \sum_i \left\{\frac{\exp(\boldsymbol{\beta_i}'\boldsymbol{x_j})}{\sum_{\jmath\in\mathcal{J}_k} \exp(\boldsymbol{\beta_i}'\boldsymbol{x_{\jmath}})} f(\boldsymbol{\beta_i})\right\}$$

$$\Delta P_k = \sum_i \left\{\left[\frac{\exp(\boldsymbol{\beta_i}'\boldsymbol{x_k})}{\sum_{\hbar\in\mathcal{K}} \exp(\boldsymbol{\beta_i}'\boldsymbol{x_{\hbar}})} - \sum_{j\in\mathcal{J}_k} \frac{\exp(\boldsymbol{\beta_i}'\boldsymbol{x_j})}{\sum_{\jmath\in\mathcal{J}_k} \exp(\boldsymbol{\beta_i}'\boldsymbol{x_{\jmath}})}\right] f(\beta_i)\right\}$$

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[4] In logit, the random error components of utility are assumed to be uncorrelated, with the nest parameter $\lambda_k = 1\ \forall k$

$$\Delta P_k = \sum_i \{\Delta P_{ik} f(\boldsymbol{\beta_i})\}$$

Similar to the mixed-logit case, the condition $\Delta P_k = 0$ here can be fulfilled for latent-class logit in a special case where each $\Delta P_{ik} = 0 \ \forall \ i$. This would require that the utility of composites for each consumer class *i* be specified by the LSE expression unique to each consumer class:

$$v_{ik} = \ln \sum_{j \in \mathcal{J}_k} \exp(\boldsymbol{\beta_i}' \boldsymbol{x_j})$$

This ensures that each $\Delta P_{ik} = 0$ and therefore $\Delta P_k = 0$. This special case solution implies that zero deviations in predictions between the composite and elemental level within each consumer class.

APPENDIX B: DECOMPOSITION OF LSE AND DERIVATION OF CORRECTION FACTORS THAT ALLOW $\boldsymbol{\Delta P = 0}$

McFadden (1978), Ben-Akiva and Lerman (1985), and Parsons and Needelman (1992) show that in the logit and nested-logit cases with no ASCs, the LSE expression for the utility of composite alternatives can be decomposed into a function of a base composite utility $\bar{v}_k$ (often defined as the average utility of its constituent elemental alternatives[5]) and two correction factors: "size," the number of elements in the group of elemental alternatives being represented by the composite alternative, and "heterogeneity," a function that accounts for differences in utility of elemental alternatives from the base composite utility[6]. We show this decomposition for nested logit first, which is general to logit (where $\lambda_k = 1 \ \forall k$). We then extend this derivation to mixed-logit and latent-class logit.

$$v_k = \lambda_k \ln\left(\sum_{j \in \mathcal{J}_k} \exp\left(\frac{v_j}{\lambda_k}\right)\right)$$

$Let \ v_j = \bar{v}_k + (v_j - \bar{v}_k)$. Then,

$$v_k = \lambda_k \ln\left(\sum_{j \in \mathcal{J}_k} \exp\left(\frac{[\bar{v}_k + (v_j - \bar{v}_k)]}{\lambda_k}\right)\right)$$

$$= \lambda_k \ln\left(\sum_{j \in \mathcal{J}_k} \left\{\exp\left(\frac{\bar{v}_k}{\lambda_k}\right) \exp\left(\frac{v_j - \bar{v}_k}{\lambda_k}\right)\right\}\right)$$

[5] In the literature, the base composite's attribute vector is often calculated as an average or weighted average ($\bar{\mathbf{x}}_k = \sum_{j \in \mathcal{J}_k} w_j \mathbf{x}_j / n_k$, where the w's are some weights e.g.: sales of each alternative) (Goldberg, 1998; Bento et al., 2009). However, in some models, the base composite's attributes are based on other methods or expert judgment, for example in the case of forecasts (EIA, 2010). The correction factors apply for any specification of $\bar{\mathbf{x}}_k$.

[6] The exponential function in the heterogeneity correction factor amplifies the positive differences between the utility of the elemental alternatives and the base composite utility and shrinks the negative differences. Therefore, the heterogeneity correction factor is weighted towards the differences in utility of elemental alternatives with positive and higher differences. Ben-Akiva and Lerman (1985) observe that the derivative of the heterogeneity correction factor shows sensitivity to elemental alternatives with high choice probabilities.

$$= \lambda_k \ln\left(\exp\left(\frac{\bar{v}_k}{\lambda_k}\right)\sum_{j\in\mathcal{J}_k}\left\{\exp\left(\frac{v_j-\bar{v}_k}{\lambda_k}\right)\right\}\right)$$

$$= \bar{v}_k + \lambda_k \ln\left(\sum_{j\in\mathcal{J}_k}\left\{\exp\left(\frac{v_j-\bar{v}_k}{\lambda_k}\right)\right\}\right)$$

$$= \bar{v}_k + \lambda_k \ln\left(\sum_{j\in\mathcal{J}_k}\left\{\exp\left(\frac{v_j-\bar{v}_k}{\lambda_k}\right)\frac{1}{n_k}n_k\right\}\right)$$

$$= \bar{v}_k + \lambda_k \ln(n_k) + \lambda_k \ln\left(\frac{1}{n_k}\sum_{j\in\mathcal{J}_k}\left\{\exp\left(\frac{v_j-\bar{v}_k}{\lambda_k}\right)\right\}\right)$$

$$\lambda_k \ln\left(\sum_{j\in\mathcal{J}_k}\exp\left(\frac{v_j}{\lambda_k}\right)\right) = \bar{v}_k + \lambda_k \ln(n_k) + \lambda_k \ln(b_k)$$

This shows how the size and heterogeneity correction factors can be added to the base composite utility to recover the LSE quantity and maintain zero deviation between the elemental and composite predictions.

We can generalize to mixed logit and latent-class logit, where $\lambda_k = 1\ \forall k$ and the model parameters $\widetilde{\boldsymbol{\beta}}, \tilde{v},$ and $\tilde{b}$ are continuously distributed random variables. We show the case where utility is linear-in-parameters for illustration. Note that when utility is linear-in-parameters, a composite alternative defined using the average value for each attribute will have average utility. Other utility models could be used so long as the heterogeneity correction factor is adjusted accordingly.

For mixed logit, the LSE can be decomposed:

$$\tilde{v}_k = \ln\sum_{j\in\mathcal{J}_k}\exp\left(\widetilde{\boldsymbol{\beta}}'\boldsymbol{x_j}\right)$$

$$= \widetilde{\boldsymbol{\beta}}'\overline{\boldsymbol{x}}_{\boldsymbol{k}} + \ln(n_k) + \ln\left(\frac{\sum_{j\in\mathcal{J}_k} exp\left(\widetilde{\boldsymbol{\beta}}'(\boldsymbol{x}_j - \overline{\boldsymbol{x}}_k)\right)}{n_k}\right)$$

For latent-class logit, the LSE can also be decomposed:

$$v_{ki} = \ln\sum_{j\in\mathcal{J}_k}\exp\left(\boldsymbol{\beta_i}'\boldsymbol{x_j}\right)$$

$$= \boldsymbol{\beta_i}\overline{\boldsymbol{x}}_{\boldsymbol{k}} + \ln(n_k) + \ln\left(\frac{\sum_{j\in\mathcal{J}_k} exp\left(\boldsymbol{\beta_i}'(\boldsymbol{x}_j - \overline{\boldsymbol{x}}_k)\right)}{n_k}\right)$$

This shows that there are correction factors unique to each consumer class i that would allow for the composite utilities perceived by each consumer class to equal the LSE specification and therefore result in composite choice share predictions that do not deviate from their corresponding elemental model's predictions.

APPENDIX C: DERIVATIONS FOR ΔP, COMPOSITE SPECIFICATIONS, AND CORRECTION FACTORS IN MODELS USING ASCS

In Appendices A and B, for models without ASCs, we have shown the composite utility specifications and correction factors necessary for the choice model predictions to match the elemental results. In models with ASCs, the elemental model is defined differently, where the utility for each choice alternative in the model is represented by:

$$u_{jm} = v_{jm} + \xi_j + \varepsilon_{jm}$$

The following shows the derivation for ΔP_{km}, which measures the differences between the choice share predictions of composite models that use C-ASCs and their corresponding elemental models that use E-ASCs, for all scenarios m. We then establish the composite specification required for $\Delta P_{km} = 0$.

From the result of Appendix A, we found that in logit-type models, composites specified by the LSE of its constituent elemental utilities result in $\Delta P_k = 0$. We generalize this to obtain correction factors that are appropriate for models with ASCs and for all scenarios m. Instead of needing the composite utility v_k to equal the LSE of elemental utilities v_j, the composite utility in scenario m plus the C-ASC, $v_{km} + \xi_k$, will need to equal the LSE of the elemental base utilities plus their E-ASCs, $v_{jm} + \xi_j$ in order for $\Delta P_{km} = 0$. We show the derivation and decomposition here for nested logit, which can be generalized to logit and mixed logit in a similar manner as in Appendix A and B.

$$(v_{km} + \xi_k) = \lambda_{km} \ln\left(\sum_{j \in \mathcal{J}_k} \exp\left(\frac{v_{jm} + \xi_j}{\lambda_{km}}\right)\right)$$

$Let\ v_{jm} = \bar{v}_{km} + \left(v_{jm} - \bar{v}_{km}\right)$ and $\xi_j = \xi_k + \left(\xi_j - \xi_k\right)$. Then,

$$(v_{km} + \xi_k) = \lambda_{km} \ln\left(\sum_{j \in \mathcal{J}_k} \exp\left(\frac{\left[\bar{v}_{km} + \left(v_{jm} - \bar{v}_{km}\right) + \xi_k + (\xi_j - \xi_k)\right]}{\lambda_{km}}\right)\right)$$

$$= \lambda_{km} \ln\left(\sum_{j \in \mathcal{J}_k} \left\{\exp\left(\frac{\bar{v}_{km}}{\lambda_{km}}\right) \exp\left(\frac{\xi_k}{\lambda_{km}}\right) \exp\left(\frac{v_{jm} - \bar{v}_{km} + \xi_j - \xi_k}{\lambda_{km}}\right)\right\}\right)$$

$$= \lambda_{km} \ln\left(\exp\left(\frac{\bar{v}_{km}}{\lambda_{km}}\right) \exp\left(\frac{\xi_k}{\lambda_{km}}\right) \sum_{j \in \mathcal{J}_k} \left\{\exp\left(\frac{v_{jm} - \bar{v}_{km} + \xi_j - \xi_k}{\lambda_{km}}\right)\right\}\right)$$

$$= \bar{v}_{km} + \xi_k + \lambda_{km} \ln\left(\sum_{j \in \mathcal{J}_k} \left\{\exp\left(\frac{v_{jm} - \bar{v}_{km} + \xi_j - \xi_k}{\lambda_{km}}\right)\right\}\right)$$

$$= \bar{v}_{km} + \xi_k + \lambda_{km} \ln\left(\sum_{j \in \mathcal{J}_k} \left\{\exp\left(\frac{v_{jm} - \bar{v}_{km} + \xi_j - \xi_k}{\lambda_{km}}\right) \frac{1}{n_{km}} n_{km}\right\}\right)$$

$$= \bar{v}_{km} + \xi_k + \lambda_{km} \ln(n_{km}) + \lambda_{km} \ln\left(\frac{1}{n_{km}} \sum_{j \in \mathcal{J}_k} \left\{\exp\left(\frac{v_{jm} - \bar{v}_{km} + \xi_j - \xi_k}{\lambda_{km}}\right)\right\}\right)$$

$$\lambda_{km} \ln\left(\sum_{j\in\mathcal{J}_k} \exp\left(\frac{v_{jm}+\xi_j}{\lambda_{km}}\right)\right) = (\bar{v}_{km}+\xi_k) + \lambda_{km}\ln(n_{km}) + \lambda_{km}\ln(b_{km})$$

We observe that the composite correction factors are valid for any choice of ξ_k, as long as the same quantity is included in the heterogeneity correction factor. ξ_k is typically determined from previously estimated or calibrated ξ_k, which is the standard practice in models using ASCs simulating counterfactual or future choice shares in scenario *m* (Haaf et al., 2016).

APPENDIX D: ADDITIONAL DETAIL ON CASE 1 RESULTS

To visualize the deviation between various composite models and the elemental model, we transform the data in Figure 4 to show differences with the elemental model, ΔP_k. Specifically, we compute the difference between the composite and elemental share predictions for each composite model specification, conditional on each draw of $\boldsymbol{\beta}$. These are plotted in Figure A1. We find that the results for ΔP_k for most composite specifications and fuel types are statistically significantly different from zero. This indicates that the deviations between the composite and elemental models are statistically significant when accounting for variation in parameter values across the literature (the EV composites with size correction are exceptions where the range of deviations do cross zero).

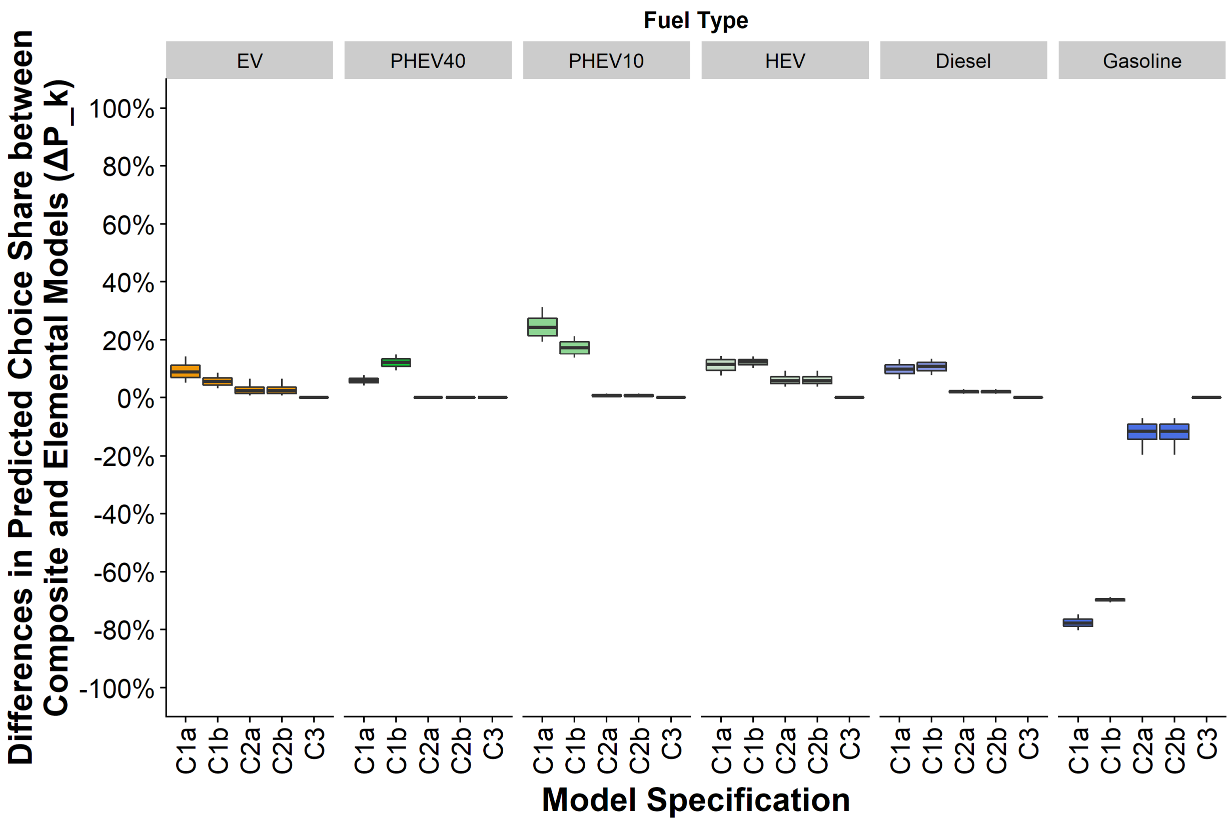


Figure A1: Differences in simulated choice shares of each fuel type for each composite specification as defined in Table 4 and the benchmark elemental model over 1000 sets of preference parameters drawn from ranges in the literature (Whitefoot and Skerlos, 2012). Boxes denote interquartile range and whiskers denote 5th and 95th percentiles.

Figure A1 shows the distribution of the differences between the composite and elemental models across the 1000 draws of $\boldsymbol{\beta}$. For example, the far-left box plot (C1a for EV) shows that the median difference between the arithmetic-average composite model and the elemental model predictions for EV choice shares is 6%. It also shows that the 5% and 95% percentile differences in prediction between the composite and elemental models across different draws of $\boldsymbol{\beta}$ are 1% and 16%, respectively. This figure illustrates that the composite models without correction tend to overpredict the share of AFV composites (which represent few elemental alternatives) and underpredict the share of gasoline vehicles (for which there are many diverse elemental alternatives), and that this variation is robust to different values of $\boldsymbol{\beta}$ in the literature. Comparing Figure A1 to Figure 4 provides an additional way to compare the importance of composite specification. For example, using the arithmetic-average composite model modifies gasoline vehicle share predictions by 72-80% relative to the elemental model (C1a for Gasoline in Figure A1), while parameter uncertainty alone only results in a 12% spread between the 5^{th} and 95^{th} percentiles in gasoline share predictions from the elemental model (E for Gasoline in Figure 4).

APPENDIX E: CASE 2 MODEL DETAILS

We use a nested logit utility specification and model structure based on that used in LVChoice, which itself is based on EIA NEMS CVCC (version AEO 2010). We use the preference parameters, adjusted for inflation, from the "coef" worksheet in the LVChoice Excel workbook (Birky, 2012) downloaded from https://www.anl.gov/energy-systems/project/light-duty-vehicle-consumer-choice-model-lvchoice. These are reprinted below. We interpret the use of "technology set generalized cost coefficient" to be analogous to setting the nested logit parameter to be 0.5 (i.e. vehicle price parameter / technology set gen. cost = 0.00065/0.00131 = 0.5) based on documentation in Birky (2012) and Greene and Liu (2012).

The attributes and parameters in the utility specification are as follows:

Parameter	Small Car	parameter units
Vehicle Price	-0.00131	1990$
Fuel Cost	-0.62159	1990 cents/mile
Range	-155.398	miles
Acceleration, 0-60 mph	-0.28482	seconds
Luggage Space	2.355299	index to conventional, 0-1.0
Battery Replacement Cost	-0.00082	1990$
Maintenance Cost	-0.00397	1990$/yr
Make/Model Availability	0.3	index to conventional, 0-1.0
Fuel Availability Coefficient 1	-9.81375	index to gasoline, 0-1.0
Fuel Availability Coefficient 2	-20.149	index to gasoline, 0-1.0
Home Refueling for Evs	0.66045	dummy, 0 or 1
Multi-Fuel General. Cost	-2.98935	na
Technology Set Gen. Cost	-0.00065	na

Source: Birky (2012)

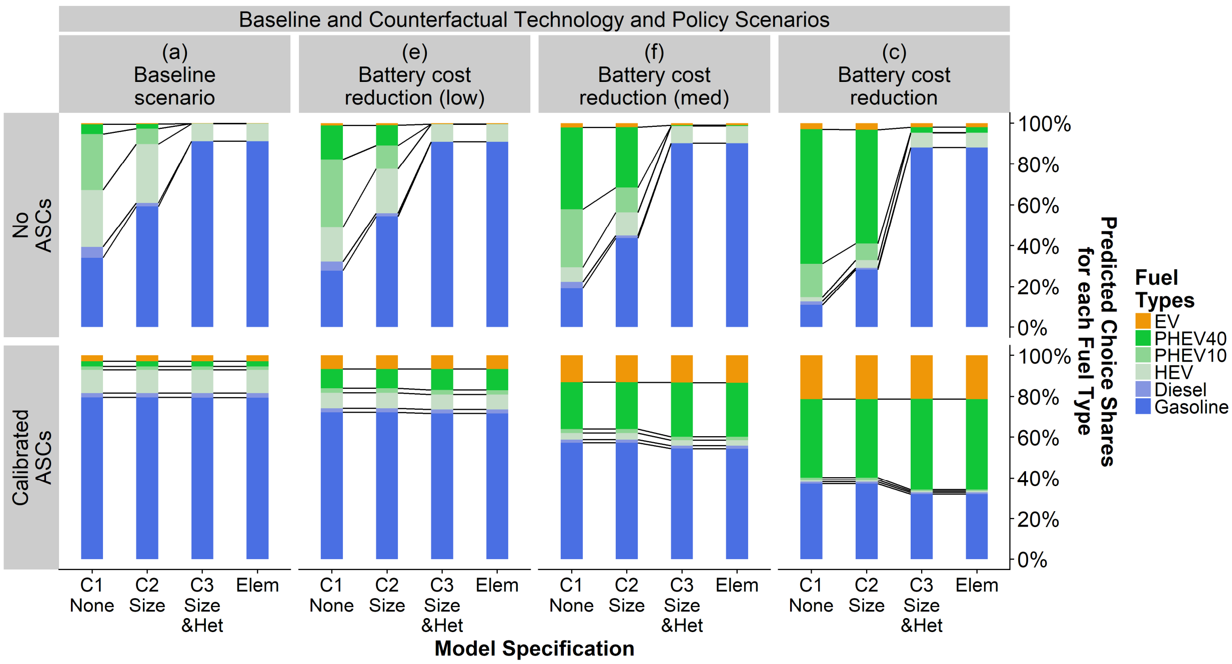
The set of elemental alternatives was based on *IHS Polk* at the make/series/subseries level. Attribute data from *Wards Automotive* were matched to these elemental alternatives. For attributes not available from *Wards Automotive*, default values from LVChoice for the year 2014 were used. *IHS Polk* sales data were used for sales weighting and E-ASC calibration.

APPENDIX F: ADDITIONAL SIMULATION RESULTS FROM CASE 2

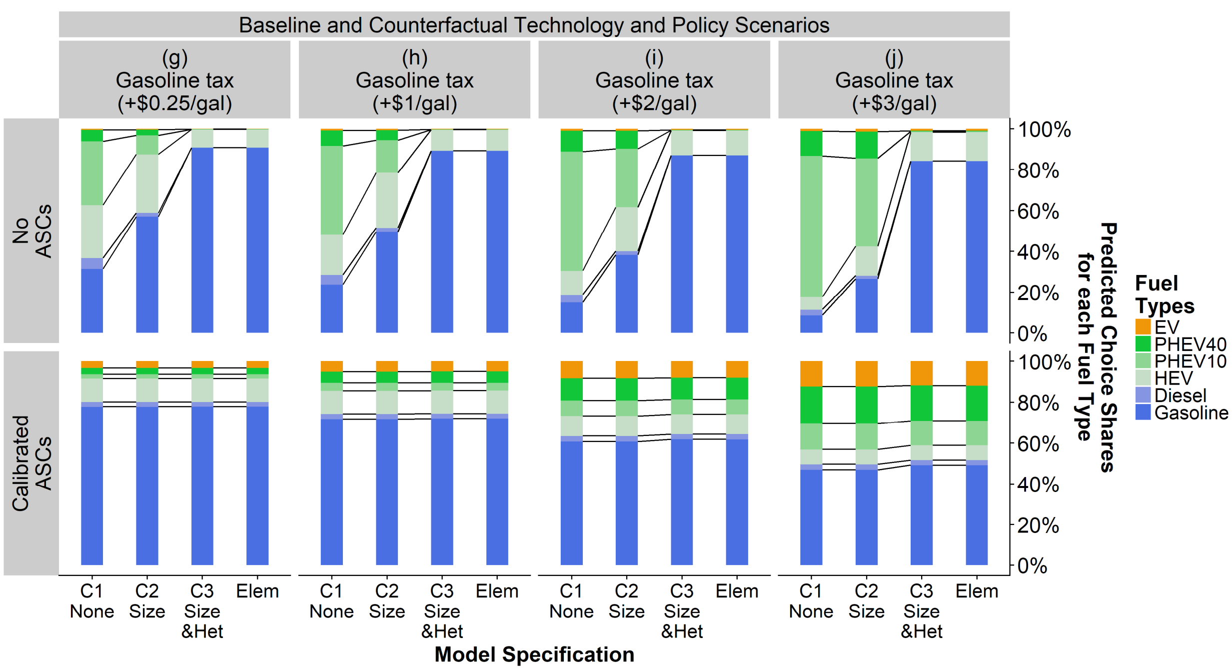
We present a broader set of counterfactual scenarios simulated for Case 2. These scenarios are based on those tested in the predictive VCM literature in Tables 1 and 2. The full list of scenario details are as follows:

(a) The baseline scenario, which includes 2014 US federal and California state subsidy and monetary incentive programs for EVs and PHEVs (all vehicles at 2014 list price, except for EV and PHEV, for which prices were reduced by $4,000-10,000[7]);
(b) A counterfactual scenario in which there are no EV and PHEV subsidies (all vehicles at 2014 list price);
(c) A "battery cost reduction" scenario, based on battery cost projections in the EIA Annual Energy Outlook Reference Case between 2014 and 2025 (Lynes, 2017) (baseline scenario with EV and PHEV prices reduced by $300-600/kWh from $600-1200/kWh[8]);
(d) A "battery cost reduction and full EV offerings" scenario, a forecast type scenario based on battery cost reduction in scenario (c) and an increase in the number of EV make-model-trim variants to equal the number of gasoline make-model-trim variants.[23]
(e) Battery cost reduction scenario with EV and PHEV prices reduced by $100-200/kWh
(f) Battery cost reduction scenario with EV and PHEV prices reduced by $200-400/kWh
(g) Gasoline tax scenario with gasoline prices increased by $0.25/gal
(h) Gasoline tax scenario with gasoline prices increased by $1/gal
(i) Gasoline tax scenario with gasoline prices increased by $2/gal
(j) Gasoline tax scenario with gasoline prices increased by $3/gal
(k) Gas-guzzler fee scenario with prices of below-average fuel economy vehicles increased by $1000/0.01 gallons per mile (GPM)
(l) Gas-guzzler fee scenario with prices of below-average fuel economy vehicles increased by $3000/0.01 GPM
(m) Gas-guzzler fee scenario with prices of below-average fuel economy vehicles increased by $5000/0.01 GPM
(n) Rebate scenario with prices of above-average fuel economy vehicles increased by $1000/0.01 GPM
(o) Rebate scenario with prices of above-average fuel economy vehicles increased by $3000/0.01 GPM
(p) Rebate scenario with prices of above-average fuel economy vehicles increased by $5000/0.01 GPM
(q) Fee-bate scenario with a $500/0.01 GPM fee or rebate pivoted around average fuel economy
(r) Fee-bate scenario with a $1000/0.01 GPM fee or rebate pivoted around average fuel economy
(s) Fee-bate scenario with a $3000/0.01 GPM fee or rebate pivoted around average fuel economy

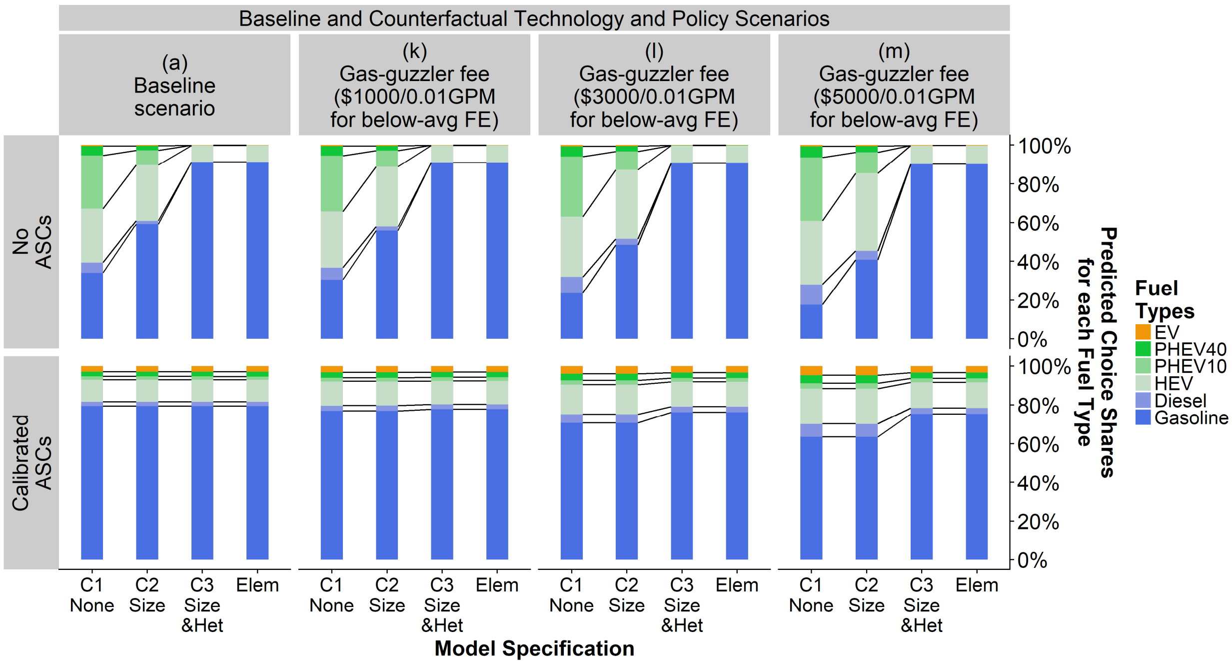
[7] Data for subsidy amounts for each elemental vehicle were from California Air Resources Board (2017).
[8] Range of battery pack cost reduction based on EIA's estimates that depend on pack size and vehicle type (larger $/kWh costs and cost reductions for smaller packs such as in PHEVs).

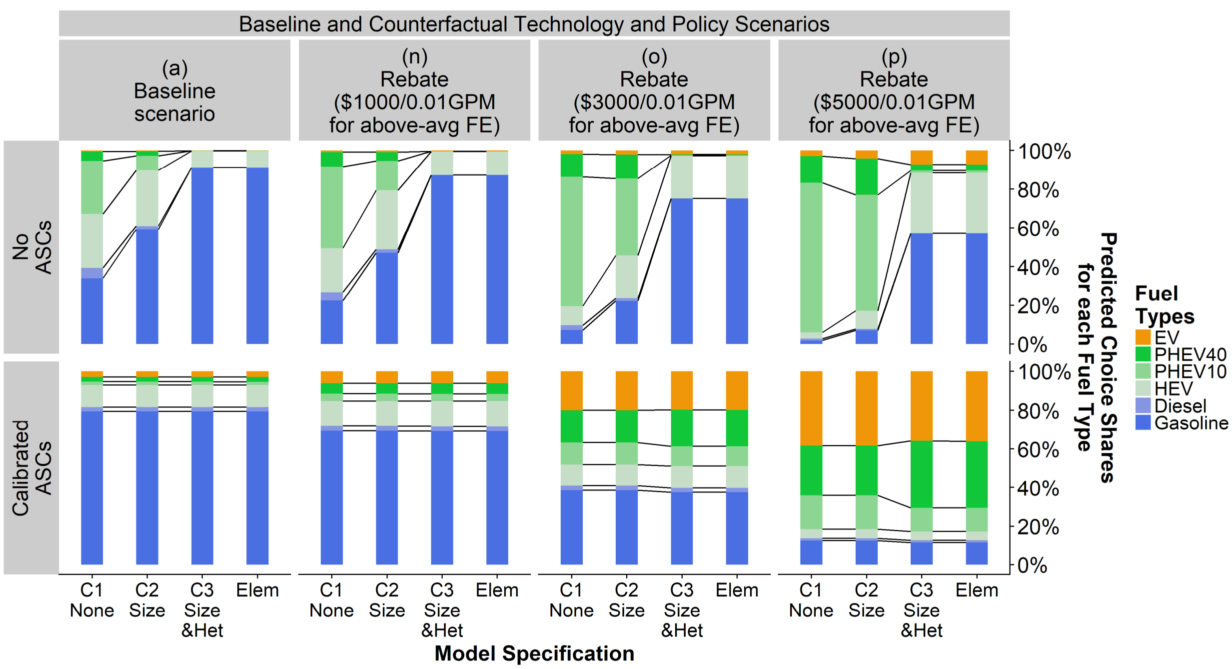


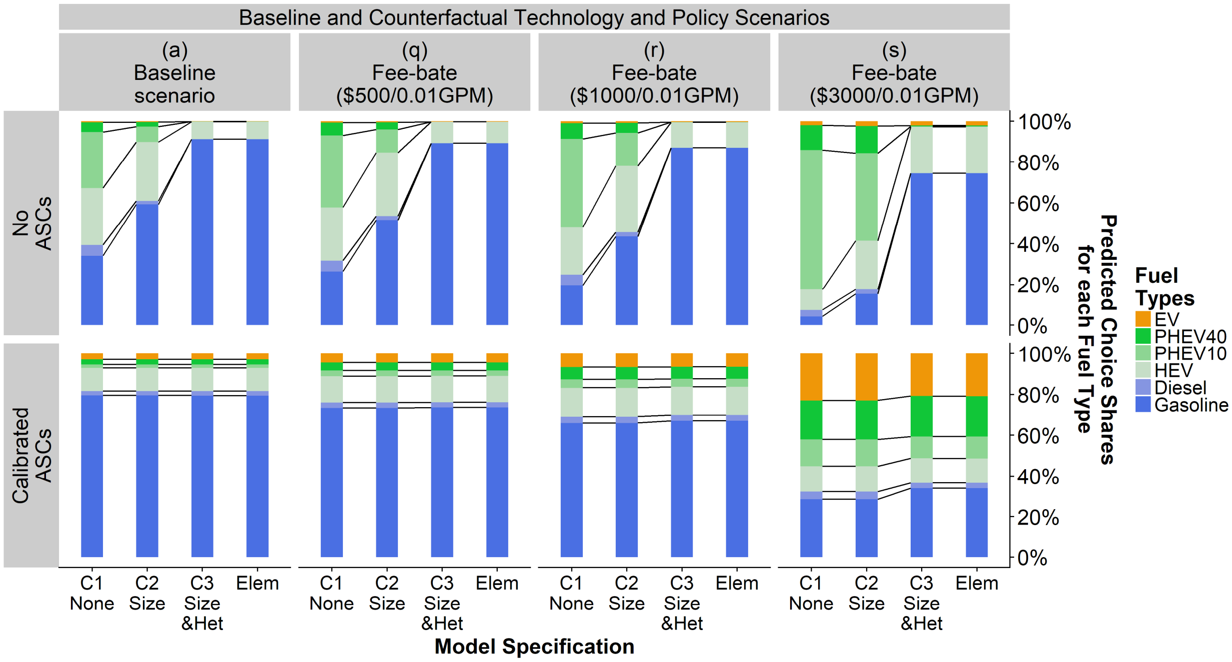
Baseline and Counterfactual Technology and Policy Scenarios
(a) Baseline scenario
(e) Battery cost reduction (low)
(f) Battery cost reduction (med)
(c) Battery cost reduction
No ASCs
Calibrated ASCs
100%
80%
60%
40%
20%
0%
Predicted Choice Shares for each Fuel Type
Fuel Types
EV
PHEV40
PHEV10
HEV
Diesel
Gasoline
C1 None
C2 Size
C3 Size &Het
Elem
Model Specification



Baseline and Counterfactual Technology and Policy Scenarios
(g) Gasoline tax (+$0.25/gal)
(h) Gasoline tax (+$1/gal)
(i) Gasoline tax (+$2/gal)
(j) Gasoline tax (+$3/gal)
No ASCs
Calibrated ASCs
100%
80%
60%
40%
20%
0%
Predicted Choice Shares for each Fuel Type
Fuel Types
EV
PHEV40
PHEV10
HEV
Diesel
Gasoline
C1 None
C2 Size
C3 Size &Het
Elem
Model Specification


Baseline and Counterfactual Technology and Policy Scenarios
(a)
Baseline
scenario
(k)
Gas-guzzler fee
($1000/0.01GPM
for below-avg FE)
(l)
Gas-guzzler fee
($3000/0.01GPM
for below-avg FE)
(m)
Gas-guzzler fee
($5000/0.01GPM
for below-avg FE)
No
ASCs
Calibrated
ASCs
100%
80%
60%
40%
20%
0%
Predicted Choice Shares
for each Fuel Type
Fuel
Types
EV
PHEV40
PHEV10
HEV
Diesel
Gasoline
C1
None
C2
Size
C3
Size
&Het
Elem
Model Specification


Baseline and Counterfactual Technology and Policy Scenarios
(a)
Baseline
scenario
(n)
Rebate
($1000/0.01GPM
for above-avg FE)
(o)
Rebate
($3000/0.01GPM
for above-avg FE)
(p)
Rebate
($5000/0.01GPM
for above-avg FE)
No
ASCs
Calibrated
ASCs
100%
80%
60%
40%
20%
0%
Predicted Choice Shares
for each Fuel Type
Fuel
Types
EV
PHEV40
PHEV10
HEV
Diesel
Gasoline
C1
None
C2
Size
C3
Size
&Het
Elem
Model Specification



Generally, counterfactual scenarios with increasing deviation from the baseline scenario (left to right) carry larger distortions in the predicted shares in the composite models without full correction (C1, C2) from the predicted result from elemental model (E). Scenarios that affect the utility heterogeneity of each fuel type (composite group) differently also lead to prediction mismatch (i.e. gas-guzzler tax affecting the set of elemental gasoline vehicle alternatives but not the electric vehicles, causing a change in ln(b) for the gasoline composite but not the electric composite).