Integrated modelling of consumer choice, producer decisions, and policy design in the automotive market

with applications in engineering design,

policy analysis, and energy, transportation, and environment

Submitted in partial fulfillment of the requirements

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in

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Next, I’d like to express my deepest gratitude to three categories of supporters: CMU and EPP, my academic home and family; my academic and professional community; and my family. Over the last 4.5 years, I’ve learned and grown a lot – intellectually, professionally – but even more importantly, personally and mentally. I struggled a lot, but at every step, I was supported by the following people and organizations:

CMU and EPP, my academic home and family

“It takes a village to raise a PhD” - modified African proverb

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My academic and professional community

> *"If I have seen further, it is by standing on the shoulders of giants" - popularly attributed to Newton (1675), who likely borrowed it from Bernard of Chartres (1159), as recorded by John of Salisbury (1159)*

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My work was only possible by building on the work of countless scholars and contributors, past and present. During my PhD, I had a knack for finding recent contributions to the literature similar to what I had thought I had "discovered." While somewhat stressful, I am grateful this helped me avoid "Columbus[1]" existing results. I'm grateful for peer researchers, peer reviewers, editors, conference and summer school organizers for their roles in a system where I could learn the latest and best understanding and then build on it and contribute to it.

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[1] https://www.npr.org/sections/codeswitch/2014/07/06/328466757/columbusing-the-art-of-discovering-something-that-is-not-new

For better or worse, Twitter has been a big part of my life, and I am grateful for the large and diverse set of Twitter communities that I'm part of, such as: #energytwitter, #econtwitter, #hiddencurriculum #phdchat #acwri #academictwitter, #Rstats #tidyverse, transport twitter, Tesla twitter, climate twitter, Canadian twitter, Asian-American twitter, mental health and wellness twitter, …

Family

"Can't live with them, can't live without them" - popular saying

My mom, dad, and sister have been supporting me my whole life, in direct and indirect ways, in spirit and in sacrifice. I'm truly grateful that we've continued to connect during my PhD.

I did get married during my PhD, as my EPP classmates like to joke about. My life partner Dolly has supported me through everything and for a very long time now. We've been learning and growing together. She became a doctor before I started here, and then she completed a Master's degree while I was still here, so I'm only just caught up.

And last but not least, lately I've been learning how important gratitude (for others, self, everything) and self-compassion is, so I'd like to thank and appreciate myself: past me, present me, and future me.

Abstract

In this thesis, I explored and investigated consumer choice modeling, optimal engineering design, and technology-specific policy simulation in three studies. In the first study (Chapter 2), "On the Implications of Using Composite Vehicles in Choice Model Prediction," I investigated the issues of choice set representation in choice modeling methodology. I derived composite correction factors for logit-class models that can help reconcile differences in modeling results in composite-level and elemental-level models. I then demonstrated cases where correction factors may be useful. This contributed to an improved understanding of how competitor representation affects choice predictions. In the second study (Chapter 3), "Implications of Competitor Representation on Optimal Engineering Design," I investigated profit-maximizing engineering design models that integrate choice models for demand. Specifically, I studied how competitor representation can affect the trade-off between cost and benefit of design change. I derived a closed-form expression for the marginal cost and benefit relationship for the level of an attribute under optimal design assuming a latent-class or mixed logit (random-coefficients logit) demand model. I used this to characterize the impact of competitor representation in a case study of optimal automotive design. In the third study (Chapter 4), "The dynamic costs and benefits of a technology-forcing policy nested in a broader performance standard: the case of ZEV and CAFE," I addressed the complexity of dynamic effects and nested policy interaction in automotive energy and environmental policy. I focus on two policies: Zero-Emission Vehicle (ZEV) mandates and Corporate Average Fuel Economy / Greenhouse Gas (CAFE/GHG) standards. I simulated consumer, producer, and government decisions in a model with explicit technological change, dynamic learning-by-doing spillover effects, policy interaction effects, and endogenous fleet standard setting via cost-benefit analysis. I demonstrated the potential impacts of ZEV mandates: potential net social benefit or net social cost, depending on key factors and parameters. I identified these key factors and quantified the trade-offs that may inform ZEV and CAFE/GHG fleet standard policy-making.

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Chapter 1: Introduction

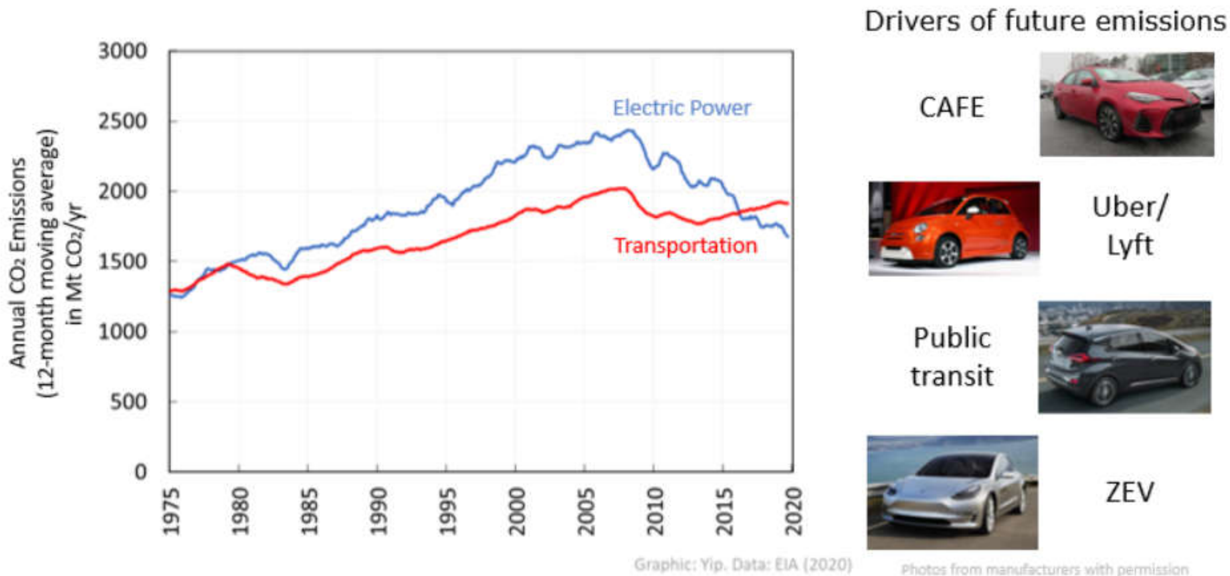


Figure 0.1: Landscape of automotive-related CO_2 emissions in the United States.

In 2016, the transportation sector in the United States surpassed the electric power sector to become the highest-emitting sector of CO_2 emissions (EIA, 2017). While emissions from electric power have mainly been reduced via adoption of new technologies and cleaner fuels by large firms at the power plant level, emissions from transportation, particularly from the light duty vehicle segment, have grown steadily. Pollution from light duty vehicles depend not only on technological advances, but also on a complex mix of consumer choice, automaker decisions, and policy design. The latest fuel efficiency and electric vehicle (EV) technologies promise to help reduce light duty vehicle emissions, but the impact of these technologies is limited to their success in the marketplace. While many automakers have now announced commitments to electrify their product portfolios (Greentech Media, 2018), it was only a few years ago when EVs were mostly known in the industry as "compliance cars," cars that were likely sold at losses in order for automakers to meet regulatory quotas (Green Car Reports, 2014). In response to market demand and regulatory changes, Ford and GM recently decided to drop smaller and fuel-efficient sedans from their lineups to focus on SUVs and trucks (Automotive News, 2018), which will likely add to the trend of increasing emissions. In a similar way, many transportation energy and environmental policies also depend on consumer and producer behavior. Governments have aimed to reduce emissions with policies such as Corporate Average Fuel Economy and Greenhouse Gas (CAFE/GHG) standards, EV tax credits, and Zero Emission Vehicle (ZEV) mandates, but their success also relies on automaker responses and consumer adoption.

To help understand the roles of consumers, producers, and government in the light duty vehicle segment, researchers have developed methods to model demand, supply, and policy. Vehicle choice models are widely used to simulate consumer purchase decisions in economic and policy analyses, such as the Department of Energy (DOE)'s assessment of public investment in vehicle technology R&D programs (Stephens, Birky, & Ward, 2014) and the Energy Information Administration (EIA)'s Annual Energy Outlook scenario projections (EIA, 2018). And in academic studies, automaker design and pricing choices are modeled as profit maximization and design optimization problems, with consideration of consumer demand via choice modeling (Wassenaar & Chen, 2003). Policy options are typically modeled as scenarios with exogenous parameters that affect producer and consumer decisions (Shiau, Michalek, & Hendrickson, 2009; Whitefoot, Fowlie, & Skerlos, 2017) but can also be modeled endogenously. All of these modeling methods involve assumptions that may have implications that are not well understood. Model specifications vary significantly in the literature and they can lead to drastically different model outcomes with different implications. This presents a need to understand and characterize the implications of model specification.

This thesis contains three body chapters, each for a study. Figure 0.2 is a representation of how each study investigates and applies various methods for modeling automotive demand, supply, and policy.

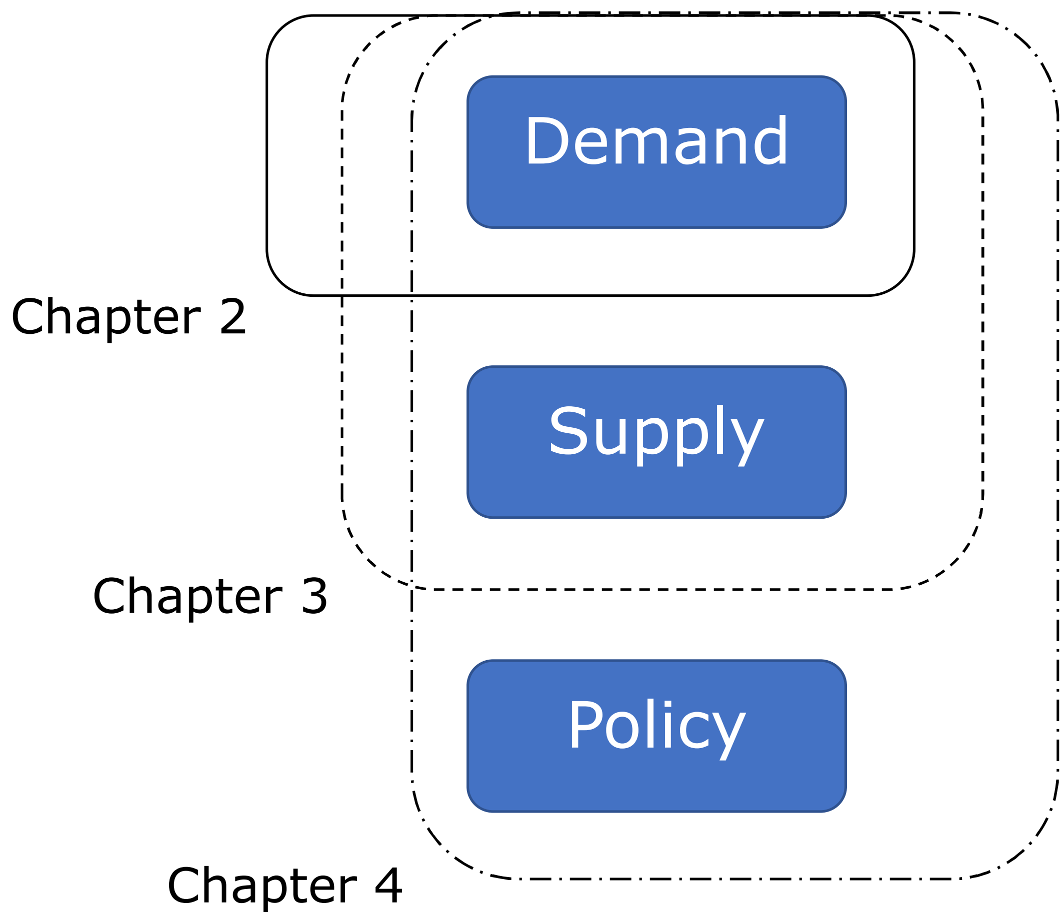


Figure 0.2: Coverage of the chapters/studies in this thesis.

The first two studies of this thesis investigate a specific model specification issue in choice modeling – how the modeler represents the available choice set alternatives in the market. In the first study, I focus on modeling demand (in several exogenous policy scenarios) and examine how, when, and why different specifications for the alternatives produce different predictions about consumer choice. In the second study, I expand the modeling scope to consider both consumer and producer decisions and investigate how different representations of competing alternatives affect producer design and pricing decisions under profit maximization. In both studies, with theory and case studies, I demonstrate how to reconcile observed differences in modeling results with new specifications involving “correction factors.” Both studies 1 and 2 build on the literature evaluating the suitability of choice models for policy analysis and engineering design.

In the third study, I expand the modeling scope further to study the role of energy and environmental policy in the light duty automotive market. The most economically efficient policy would typically involve taxing and subsidizing externalities directly (Parry, Walls, & Harrington, 2007), but the presence of multiple, dynamic, and complex externalities, as well as political considerations mean that an assortment of potentially sub-optimal policies are implemented in practice, making them relevant and important to study. I focus on modeling the various dynamic and interacting impacts of two types of such policies: fleet-level Corporate Average Fuel Economy and Greenhouse Gas standards (CAFE/GHG), which regulates the fuel economy and emissions intensity of new light duty vehicle sales, and Zero-Emissions Vehicle (ZEV) mandates, a technology-forcing policy that requires a proportion of new light duty vehicle sales to meet ZEV criteria.

To set the tone of the thesis, I provide a few quoted words of wisdom[2] applicable to research:

"Research is what I am doing when I don't know what I am doing"
- von Braun (1957), who may or may not have been quoting Einstein

""Once the rockets are up,
who cares where they come down?
That's not my department,"
says Wernher von Braun."
- Lyrics from Lehrer (1965), based on von Braun (1976)

[2] RT ≠ endorsement - that is to say, the opinions expressed in the quotes here and throughout the thesis should not necessarily be interpreted as the official policy or position of the thesis author.

Chapter 2: On the Implications of Using Composite Vehicles in Choice Model Prediction

This study was co-authored with Jeremy Michalek and Kate Whitefoot and was published in Transportation Research Part B: Methodological in 2018[3].

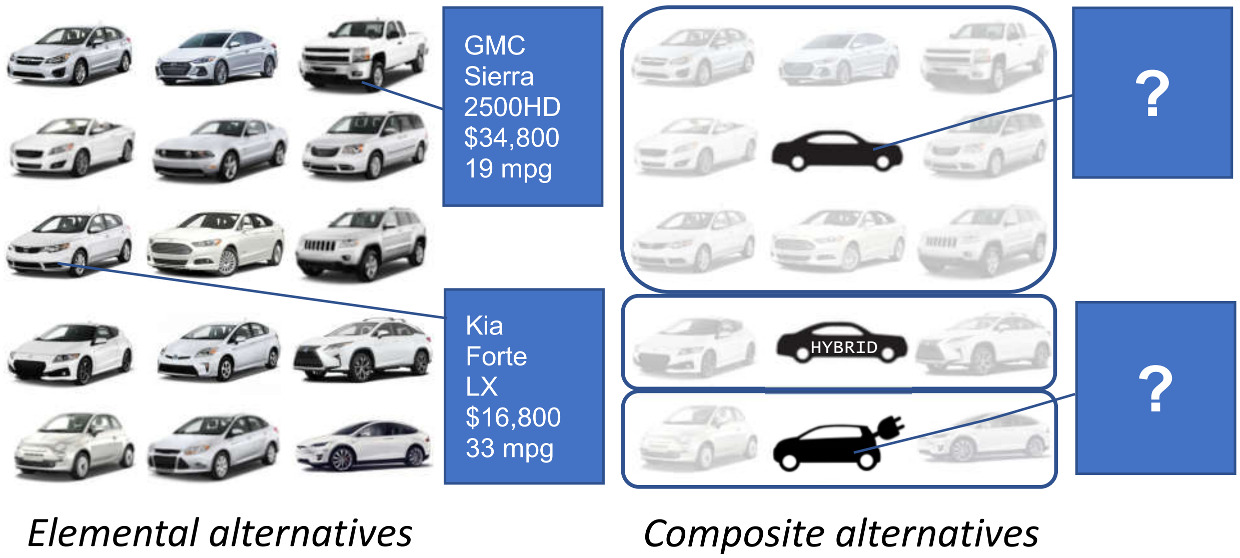
"Variety is the spice of life" - Cowper (1785)

The environmental impact and economic cost of transportation policy like fuel economy standards depend critically on consumer behavior. But consumer choice predictions have shown to be sensitive to model specification (Haaf, Michalek, Morrow, & Liu, 2014). There is a need to understand and characterize the sources of uncertainty and variation in choice model predictions. This first study investigates a key model specification issue in discrete choice modeling: the representation of the alternatives in the marketplace.

Choice modelers often use *composites* to represent groups of alternatives, but this practice may introduce arbitrary changes to choice-share predictions. In this study, we evaluate the impacts of the use of composites on choice-share prediction. We do this to produce insight into modeling limitations and biases and to provide guidance on minimizing or eliminating discrepancies. 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 and demonstrate correction factors for models using composites to predict choice shares in counterfactual scenarios consistent with those from corresponding models that use disaggregated elemental alternatives.

[3] Yip, A. H. C., Michalek, J. J., & Whitefoot, K. S. (2018) "On the implications of using composite vehicles in choice model prediction," *Transportation Research Part B: Methodological*, v116, p163-188. 10.1016/j.trb.2018.07.011

1. Graphical Abstract



2. 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.

3. 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

4. **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[4] (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[5], 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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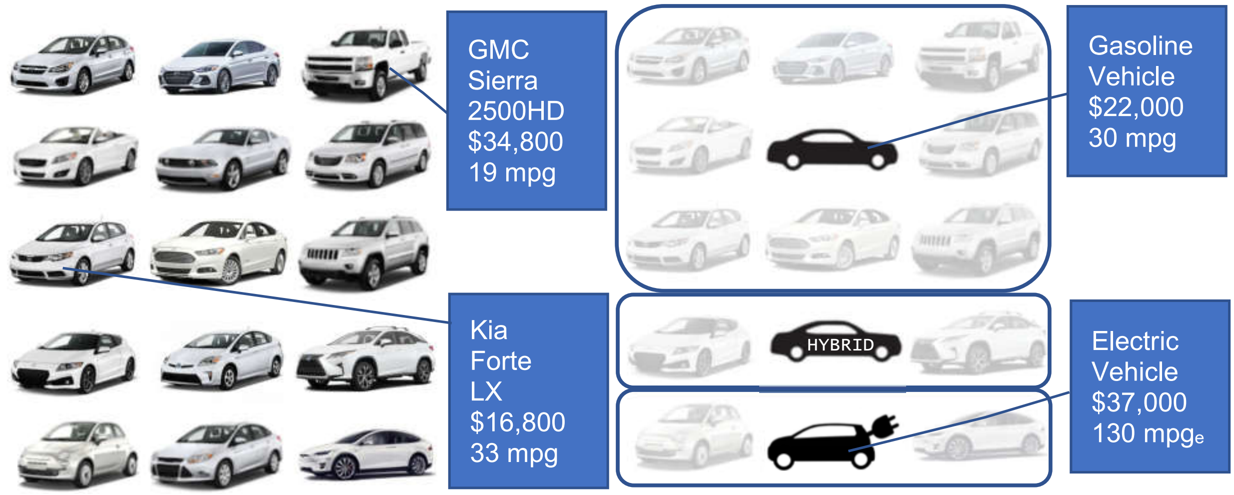
[4] More precisely, we define an *element* as a product profile (vector of attributes) that represents a group of alternatives with identical observed attributes (e.g.: a red Ford Focus SE and a blue Ford Focus SE have identical observed attributes if color is not observed) and a *composite* as a product 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.

[5] 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 Tables 1 and 2.[6] 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.

[6] 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"[7] 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.

[7] 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.

5. 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).[8]

5.1. 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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[8] 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.[9]

[9] 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	MDCEV	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.

5.2. 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).[10] 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 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.

6. 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

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[10] 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.

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 $\Delta P_k = 0$.[11] We begin with models that exclude alternative-specific constants (ASCs) and later generalize to those that include ASCs.

6.1. 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.[12] 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 ($\Pr\left(u_j \geq u_{j'}\ \ \forall j' \in \mathcal{J}\right)$) 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 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

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

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

composite[13]. 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),[14] 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[15]," 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[16]. We characterize the implications of this practice.

[13] 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.

[14] 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.

[15] 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.

[16] 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[17,18]	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).

[17] 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.

[18] 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 $\bar{\mathbf{x}}_k$.

6.2. 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.[19] 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.

[19] 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[17,18]	Size correction factor	Heterogeneity[20] 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	$v_{kt} = \lambda_{kt} \ln\left(\sum_{j\in\mathcal{J}_{kt}} \exp\left(\frac{v_{jt} + \xi_j}{\lambda_{kt}}\right)\right) - \xi_k$ $= \bar{v}_{kt} + \lambda_{kt}\ln(n_{kt}) + \lambda_{kt}\ln(b_{kt}) - \xi_k$	$\bar{v}_{kt} = \boldsymbol{\beta}'\bar{\mathbf{x}}_{kt} + \xi_k$	$n_{kt} = \lvert\mathcal{J}_{kt}\rvert$	$b_{kt} = \frac{\sum_{j\in\mathcal{J}_{kt}} \exp\left(\frac{\boldsymbol{\beta}'(\mathbf{x}_{jt} - \bar{\mathbf{x}}_{kt}) + (\xi_j - \xi_k)}{\lambda_{kt}}\right)}{n_{kt}}$
Mixed Logit	$\tilde{v}_{kt} = \ln\left(\sum_{j\in\mathcal{J}_{kt}} \exp(\tilde{v}_{jt} + \xi_j)\right) - \xi_k$ $= \tilde{\bar{v}}_{kt} + \ln(n_{kt}) + \ln(\tilde{b}_{kt}) - \xi_k$	$\tilde{\bar{v}}_{kt} = \tilde{\boldsymbol{\beta}}'\bar{\mathbf{x}}_{kt} + \xi_k$	$n_{kt} = \lvert\mathcal{J}_{kt}\rvert$	$\tilde{b}_{kt} = \frac{\sum_{j\in\mathcal{J}_{kt}} \exp\left(\tilde{\boldsymbol{\beta}}'(\mathbf{x}_{jt} - \bar{\mathbf{x}}_{kt}) + (\xi_j - \xi_k)\right)}{n_{kt}}$

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 $t = 0$)[19]; $\bar{v}_{kt}$: base utility of composite k in scenario t[17,18]; 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)

[20] 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,[21] 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	$\Delta P = 0$	$\Delta P = 0$

[21] 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).

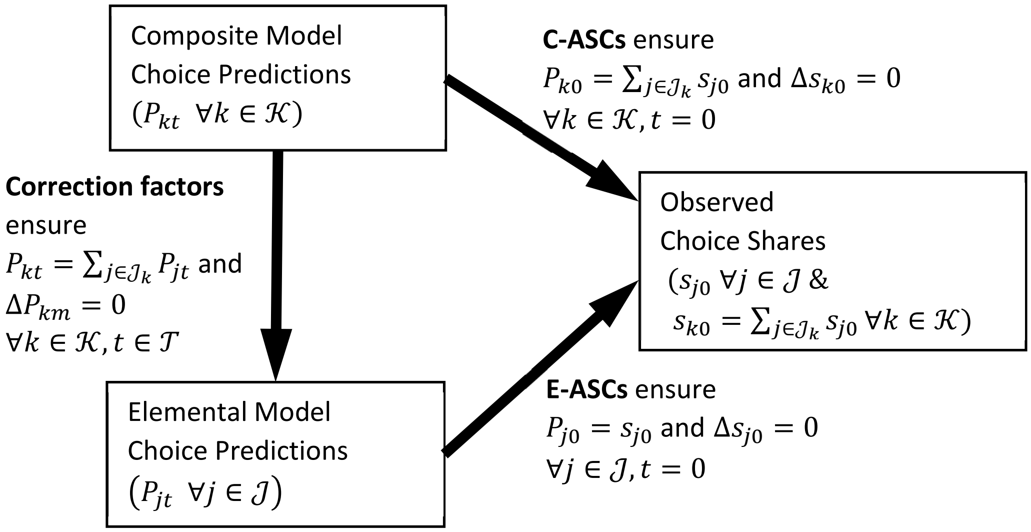

Figure 2: Illustration of the roles of correction factors, E-ASCs, and C-ASCs in choice modeling. Arrows indicate the direction of adjustment, so that the predictions from the model at each arrow's tail are adjusted to match those from the models at the arrow's head.

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.

7. 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[22] 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.

7.1. 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).

[22] 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.

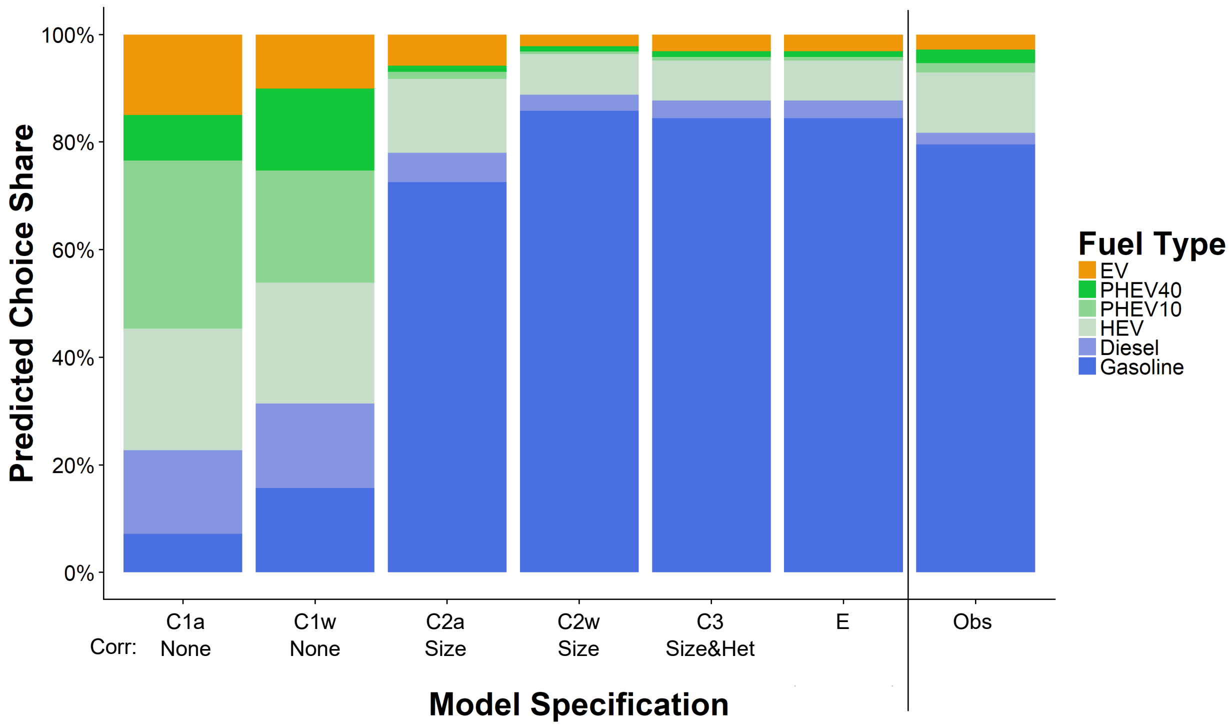

Figure 3: Case 1 simulated choice shares by fuel type for the 2014 California new small car market under different specifications for the utility of composites as defined in Table 4. "Corr" refers to correction factors included in the model specification; "Size" and "Het" refer to the size and heterogeneity 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.

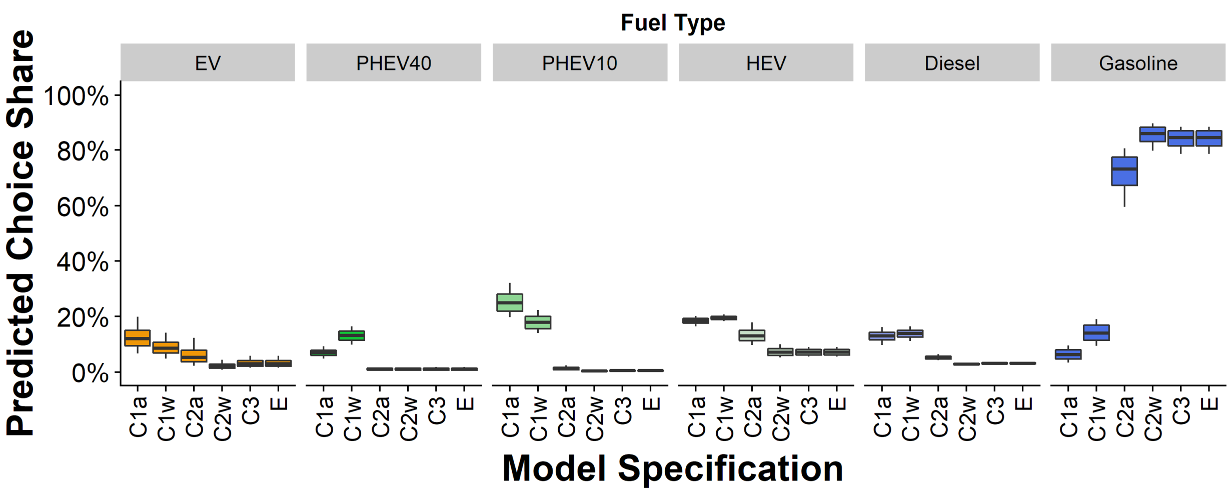

Figure 4: Simulated choice shares of each fuel type in the 2014 California new small car market, using different specifications for the utility of composites as defined in Table 4 and 1000 sets of preference parameters drawn from ranges in the literature (Whitefoot and Skerlos, 2012). Boxes denote interquartile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

7.2. 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.

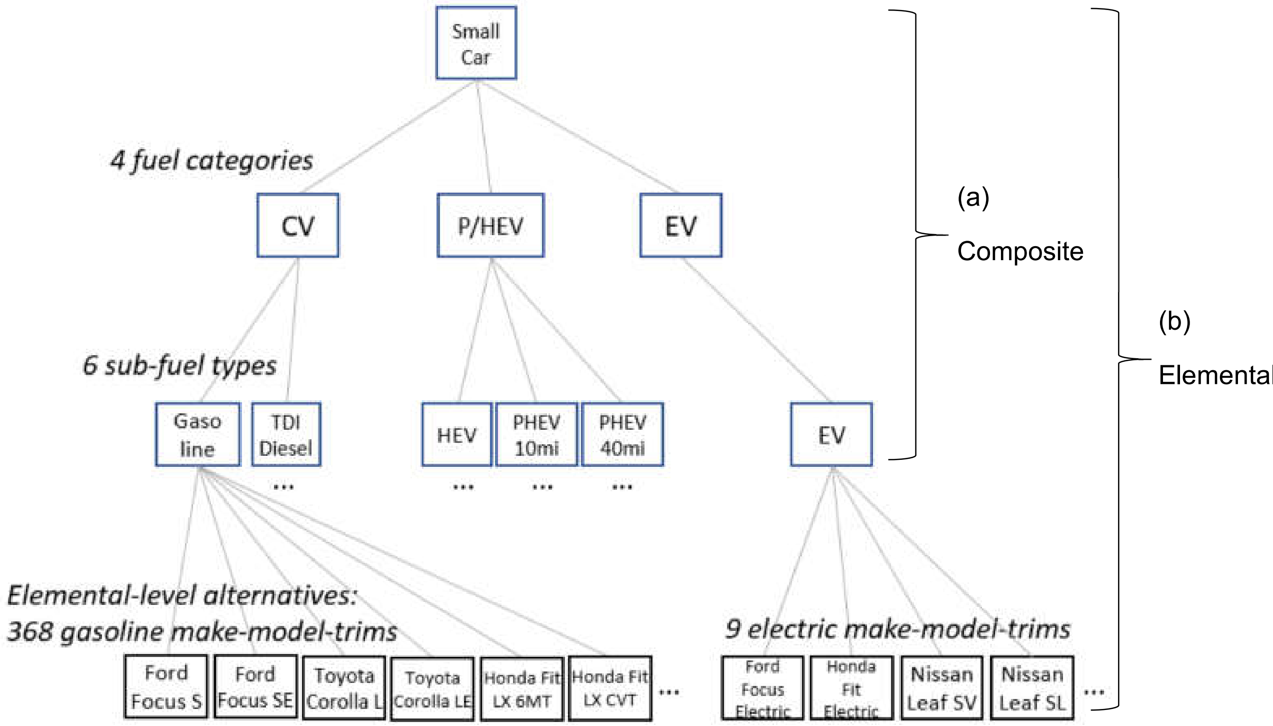

Figure 5: Structure of the (a) composite model and (b) elemental model used in Case 2, based on the structure of LVChoice and NEMS (Birky, 2012; EIA, 2010). CV refers to conventional vehicles; TDI refers to turbo-direct-injection.

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[23]:

(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[24]);
(b) A counterfactual scenario in which there are no EV and PHEV subsidies (all vehicles at 2014 list price);

[23] The results of other simulated scenarios can be found in Appendix F.
[24] 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);[25]
(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.[26]

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 $P_{k0} = \sum_{j\in\mathcal{J}_k} P_{j0} = \sum_{j\in\mathcal{J}_k} s_{j0}$, 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 EV share varying from 21% in C1 without correction to 37% in C2 with only size correction and

[25] 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).

to 70% with both size and heterogeneity correction, matching the elemental model prediction.[26]

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 Tables 1 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.

[26] 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.

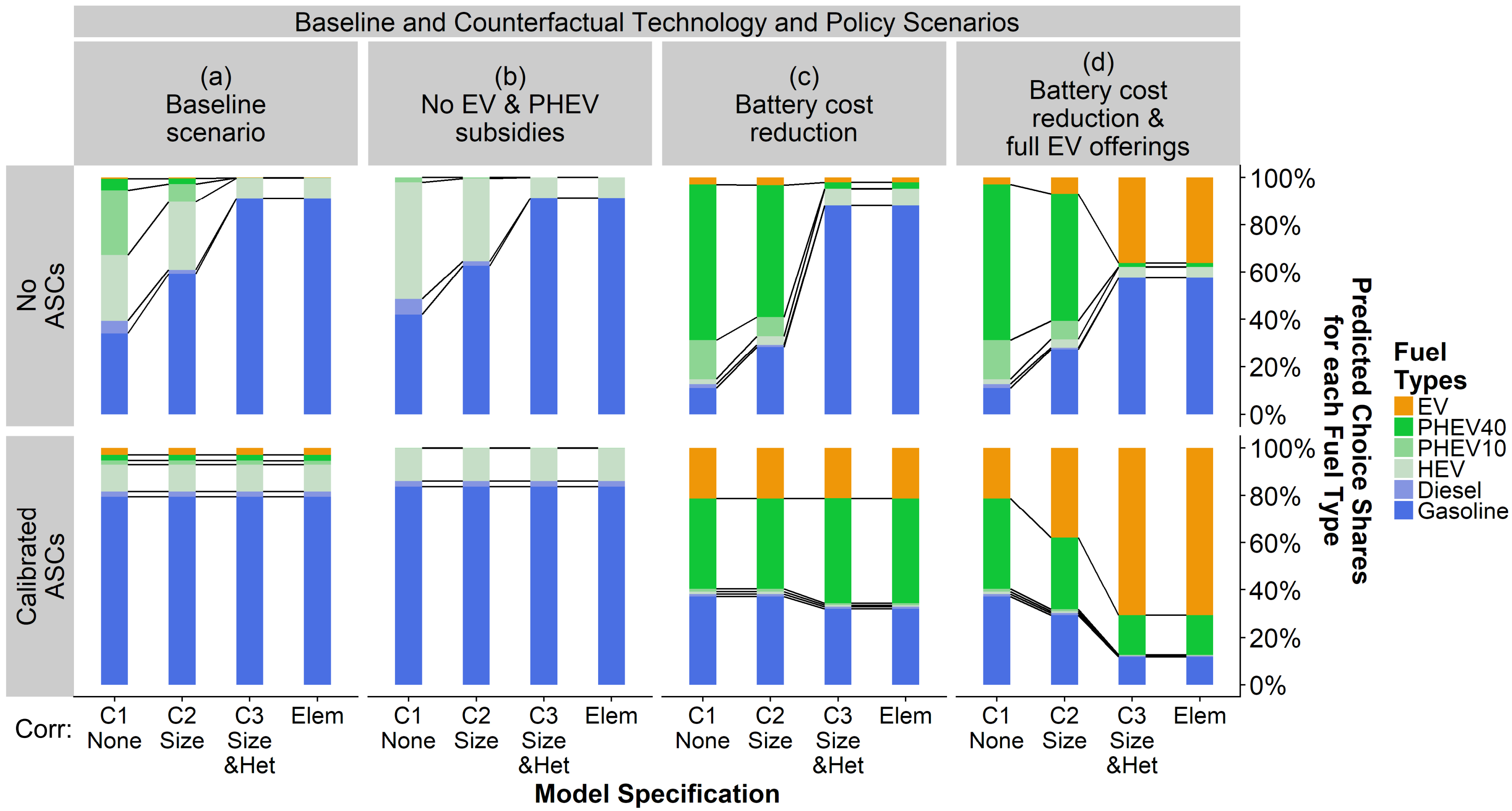

Figure 6: Case 2 simulated choice shares by fuel type for the 2014 California new small car market under (a) baseline and (b)-(d)[20] counterfactual scenarios with different specifications for the utility of composites as defined in Table 6. "Corr" indicates correction factors applied in each case; "Size" 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).

8. 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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10. 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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12. Supplementary Material and Appendices

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:

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

where $j, \mathscr{j}$ are indices for elemental alternatives, and $k, \mathscr{k}$ 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:

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

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:

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

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[27], we recover the log-sum-exponential function (LSE) identified by McFadden (1978)[28] 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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[27] If $v_{\mathscr{k}}$ is defined as $\ln\left(\sum_{j\in\mathcal{J}_k} e^{v_j}\right)$, we see that the quantity $\frac{\sum_{\mathscr{k}\in\mathcal{K}} e^{v_{\mathscr{k}}}}{\sum_{\mathscr{j}\in\mathcal{J}} e^{v_{\mathscr{j}}}} = 1$ and therefore $c = \ln(1) = 0$ is consistent with the derived result.

[28] 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:

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

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

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,

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

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

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

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

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[29].

[29] 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 $\frac{\sum_{\mathscr{k}\in\mathcal{K}}[exp(v_{\mathscr{k}})]}{\sum_{\mathscr{k}\in\mathcal{K}} exp\left(\lambda_{\mathscr{k}}\, ln\sum_{\mathscr{j}\in\mathcal{J}_{\mathscr{k}}} exp\left(\frac{v_{\mathscr{j}}}{\lambda_{\mathscr{k}}}\right)\right)} = 1$ 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[30].

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:

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

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

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:

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

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:

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

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

Therefore,

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

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

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

[30] 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[31]) 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[32]. 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,

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

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

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[31] 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 $\bar{\mathbf{x}}_k$.

[32] 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.

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

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

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

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

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

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

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

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

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

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).

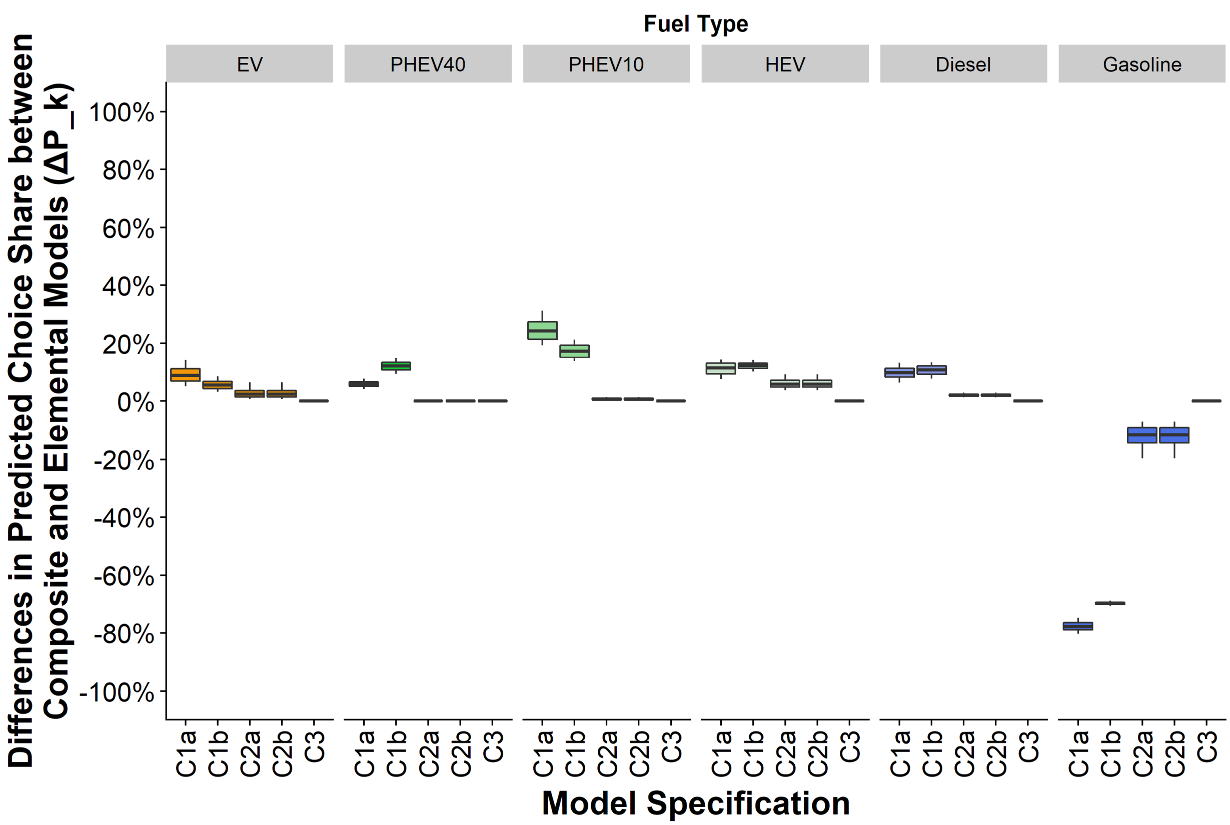

Figure A1: Differences in simulated choice shares of each fuel type for each composite

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 5th and 95th 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[33]);
(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[34]);
(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.[26]
(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

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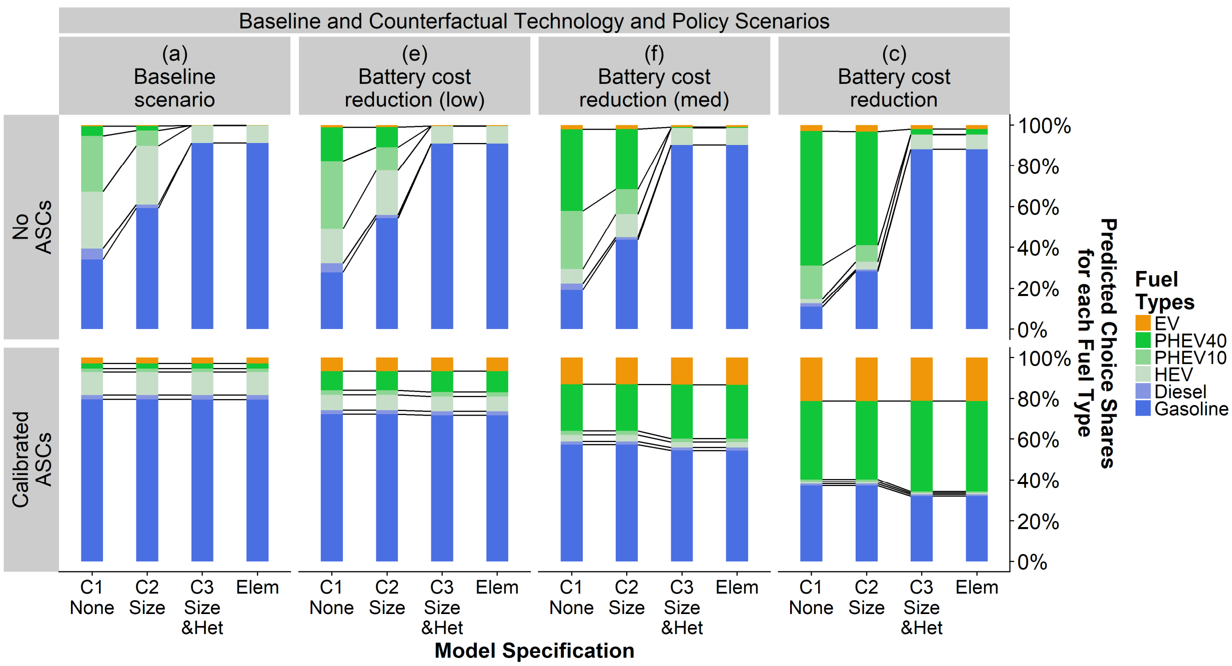
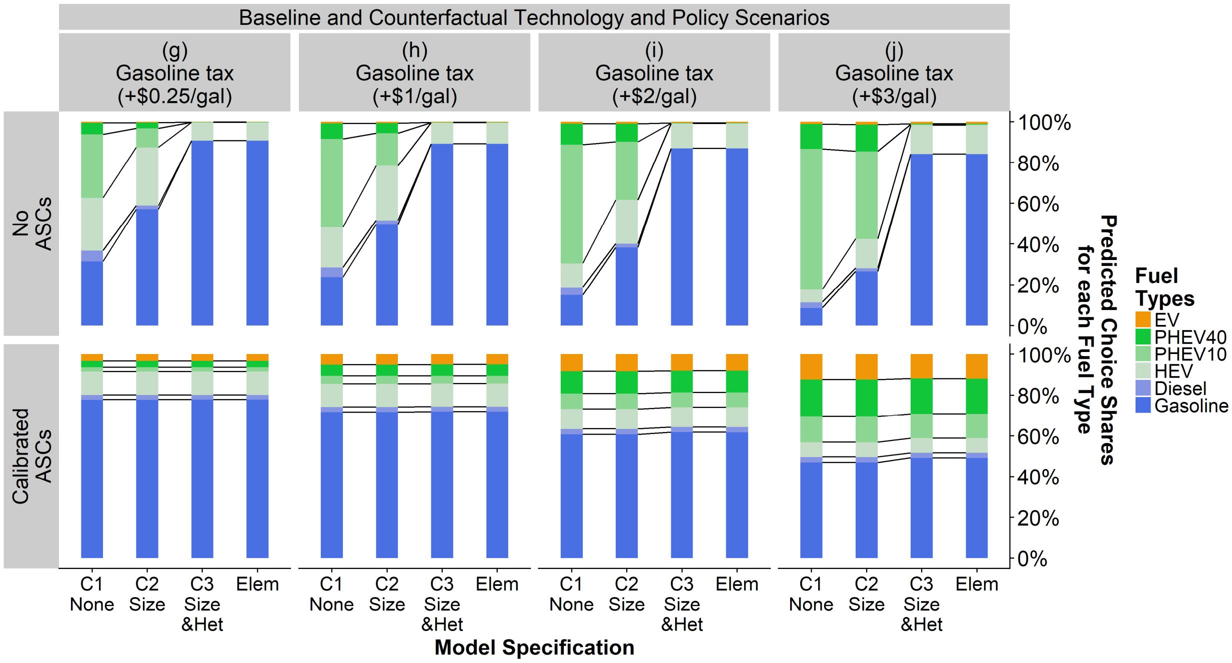
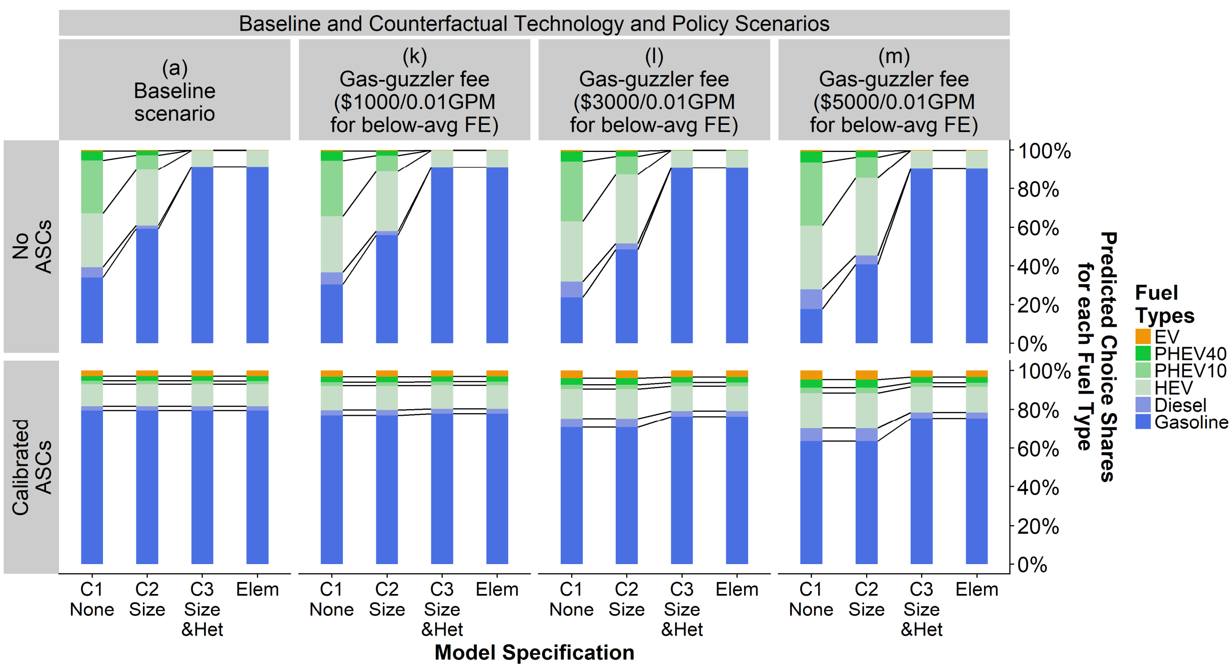
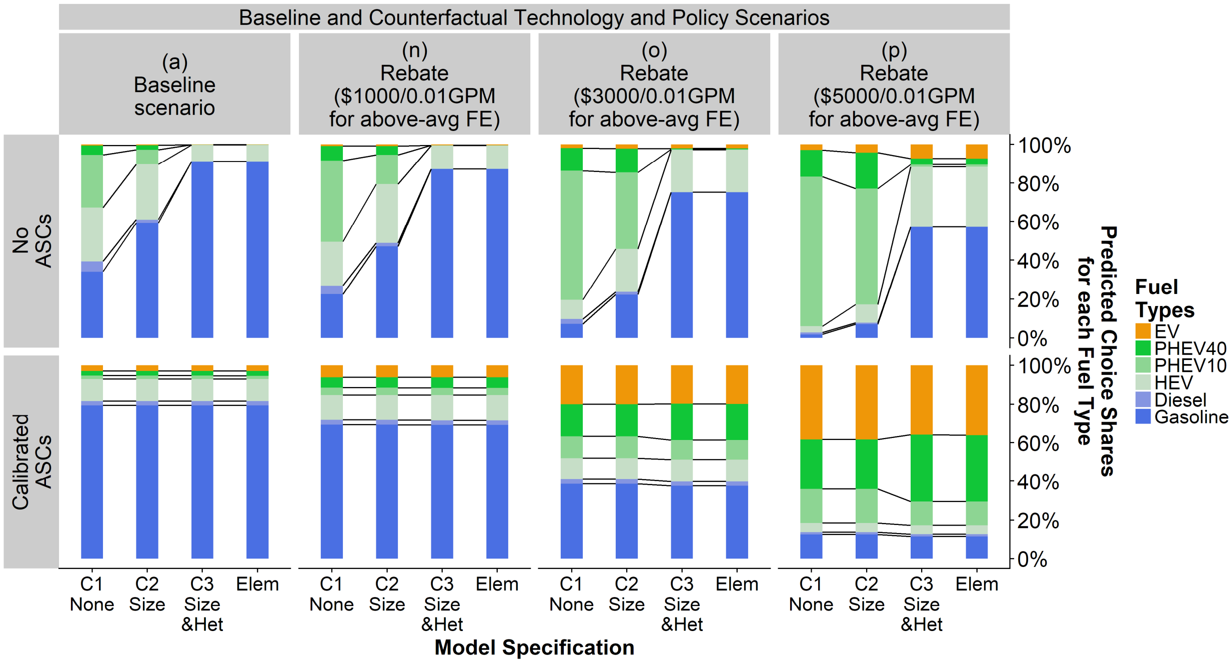
[33] Data for subsidy amounts for each elemental vehicle were from California Air Resources Board (2017).
[34] Range of battery pack cost reduction based on EIA's estimates that depend on pack size and vehicle type (larger $/kWh costs and cost reductions for smaller packs such as in PHEVs).

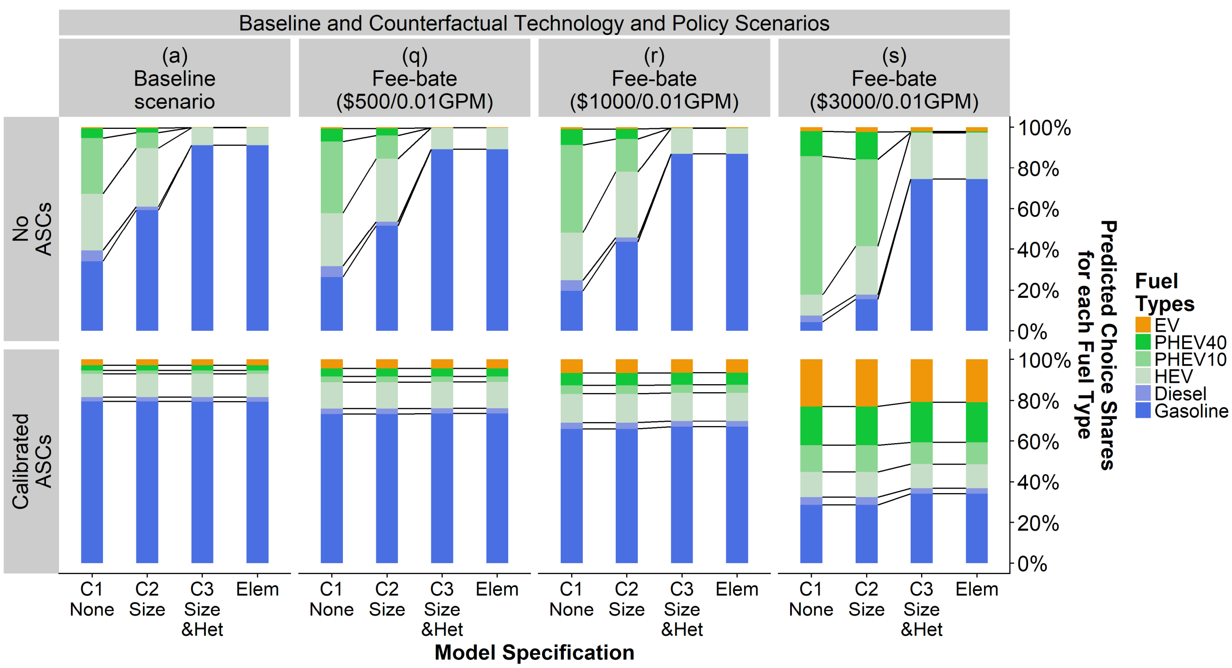
(n) Rebate scenario with prices of above-average fuel economy vehicles increased by $1000/0.01 GPM
(o) Rebate scenario with prices of above-average fuel economy vehicles increased by $3000/0.01 GPM
(p) Rebate scenario with prices of above-average fuel economy vehicles increased by $5000/0.01 GPM
(q) 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




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%
C1 None
C2 Size
C3 Size &Het
Elem
Model Specification
Predicted Choice Shares for each Fuel Type
Fuel Types
EV
PHEV40
PHEV10
HEV
Diesel
Gasoline


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%
C1 None
C2 Size
C3 Size &Het
Elem
Model Specification
Predicted Choice Shares for each Fuel Type
Fuel Types
EV
PHEV40
PHEV10
HEV
Diesel
Gasoline





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).

Chapter 3: Implications of Competitor Representation on Optimal Engineering Design

This study was co-authored with Jeremy Michalek and Kate Whitefoot. It was recently presented at the 2019 International Design Engineering Technical Conferences, published in conference proceedings[35], and will be submitted to the Journal of Mechanical Design.

> *"An optimist sees a glass that's half full; a pessimist sees a glass that's half empty; an engineer sees a glass that's twice as big as it needs to be." - old engineering joke, first online by Crowder (1990), according to Popik (2015)*

In this study, we investigate optimal design models that integrate choice models for demand and how competitor representation can affect the trade-off between cost and benefit of design change. We derived a closed-form expression for the marginal cost and benefit relationship for the level of an attribute under optimal design assuming a latent-class or mixed logit demand model. We used this to characterize the impact of competitor representation in optimal design models.

[35] Yip, A. H. C, Michalek, J. J., Whitefoot, K. S. Implications of Competitor Representation on Optimal Design. ASME 2019 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference Proceedings. Vol 2A. Paper No. DETC2019-98114. 10.1115/DETC2019-98114

Abstract

We investigate the effect of competitor product representation on optimal design results in profit-maximization studies. Specifically, we study the implications of replacing a large set of "elemental" product alternatives available in the marketplace with a reduced set of selected competitors or "composite" alternatives, as is common in the literature. We derive first-order optimality conditions and show that optimal design (but not price) is independent of competitors under the logit and nested logit models (where preference coefficients are homogeneous), but optimal design results may depend on competitor representation in latent class and mixed logit models (where preference coefficients are heterogeneous). In a case study of automotive powertrain design using mixed logit demand, we find optimal acceleration performance changes when competitors are modeled using a small set of composite alternatives rather than the full set. The magnitude of this change depends on the specific form and parameters of the cost and demand functions assumed and it ranged from 0% to 5% across a primary range of parameter assumptions in our case study and up to 20% when using a wider range. We find that the magnitude of the change in optimal design variables induced by competitor representation in our case study increases with the heterogeneity of preference coefficients across consumers and changes with the curvature of the cost function. We show that correction factors can recover optimal solutions of the elemental competitor model while requiring only a small set of composite competitors to represent the market.

Keywords: optimal design, competitor, logit, nested logit, mixed logit, composite, elemental, heterogeneity

1. Introduction

The engineering literature on design for market systems integrates consumer choice models within optimal design problems to determine the most profitable product designs and positioning among competing product offerings [1–7]. The optimal design outcomes in these models can be sensitive to choice model specification generally [2,6–9]. However, the implications of competitor representation on optimal design has not been systematically studied.

In optimal design studies, competing products are represented with different practices and at varying levels of detail. Table 1 summarizes examples of competitor representation in the design for market systems literature. In some studies, competing products are specified at a granular level, and their attributes correspond to those of the near-complete range of real-world products. For example, Choi et al. [10] represent the market of pain relievers with 14 existing brands and types. Morrow et al. [11] include 443 specific automotive design variants at the make-model-engine-option level representing the new car market in the US. In other studies, competing products are represented with a select number of hypothetical products meant to span the options available in the market. For example, Kwak and Kim [12] specify three competing products: a high-, mid-, and low-spec computer; Shiau and Michalek [3] assume four competing products in the weight scales market; Besharati et al. [13] assume that there are three competitive products in the angle grinder market; and Shin and Ferguson [14] assume three cars and three MP3 players that compete with the product under design. In some studies, only a subset of real-world competing alternatives is modeled, based on product segmentation, popularity in the market, and/or proximity to the product under design. For example, in both Shiau et al. [15] and Wassenaar et al. [16], competitors for a mid-size car under design were specified by a choice set with 10-12 other specific mid-size cars of different brands and designs. The choice model formulation in these two studies exclude options in different size segments such as compact car and SUV, even though survey data shows that many consumers consider vehicles of different size segments when purchasing a vehicle [17]. In these latter two types of studies, there is an implicit recognition that the actual market consists of many products (more than the 3-7 represented in these examples) but that it would be impractical or infeasible to include all of them in the choice model.

TABLE 1: Examples of Competitor Representation in the Design for Market Systems Literature[36]

Study (author, year)	Market	Number of competing alternatives	Type of competitor representation
Shin & Ferguson, 2016 [14]	Cars	3	Hypothetical
Shin & Ferguson, 2016 [14]	MP3 players	3	Hypothetical
Kwak & Kim, 2012 [12]	Computers	3	Generic/ representative
Shiau & Michalek, 2009 [3]	Weight scales	4	Hypothetical
Besharati et al., 2006 [13]	Angle grinders	4	Hypothetical
Li & Azarm, 2000 [18]	Cordless screwdrivers	5	Hypothetical
Zhao & Thurston, 2013 [19]	Cell phones	5	Hypothetical
Wang et al., 2011 [20]	Laptops and smartphones	7	Hypothetical
Shiau et al., 2009 [15]	Midsize cars	10	Generic/ representative
Wassenaar et al., 2005 [16]	Midsize cars	12	Detailed (market subset)
Choi et al., 1990 [10]	Pain relievers	14	Detailed
Morrow et al., 2014 [11]	Cars	443	Detailed
Frischknecht et al., 2010 [6]	Cars	473	Detailed

Yip et al. [21] found that competitor product representation can substantially affect choice model predictions. Specifically, the study examined the practice of using product “composites”—a type of choice set alternative that represents a category or segment of products. For example, instead of a specific “elemental” product design variant such as a Ford Fiesta, the competing choice alternative may be a generic “compact car” or “sedan”, specified using a function (usually an average) of the attribute values of “elemental” product alternatives in that grouping. The study found that composite representation could significantly affect choice share predictions unless particular correction factors were applied to the model. Because competitor representation affects choice share prediction, it may affect optimal design conditional on choice share prediction.

Prior studies have characterized the implications of demand model assumptions for engineering design [6,7], including demand model functional form and specification [2,4,6,8,14,19,22], consumer and product heterogeneity [2,8,21,23], and market structure and competition [2,4,6]. We contribute to

[36] Full table in supplementary material.

this literature by characterizing the implications of competitor representation for optimal design. Specifically, we investigate conditions under which the optimal design is robust versus sensitive to variation in competitor representation. We pose a generic optimal design problem, derive first-order necessary conditions, and identify properties of the optimality conditions for several popular demand model specifications to determine in which cases the optimal design may depend on competitor representation. Then, in an automotive case study, we investigate the magnitude of this effect in one practical application and assess factors that affect the magnitude.

2. Influence of Competitors on Optimal Design

We examine the first-order conditions of the profit-maximizing design and pricing problem under different classes of discrete choice models to understand how competitors affect the optimal design solution. We first show that with logit and nested logit model representations of demand, the optimal design does not depend on any information about competitors—neither the number of alternatives, nor the values of their attributes. We then show how optimal design can be dependent on competitors when consumer preference parameters are heterogeneous in the cases of mixed logit and latent-class logit models.

Following a common formulation in the literature [1,13,14,24,25], we define a single-period profit-maximization problem where firm k seeks to maximize total profits π from its products $j \in J_k$ with respect to price p_j and a vector of product attributes $\mathbf{x}_j$ for each of its products $j \in J_k$:

$$\max \Pi = \sum_{j \in J_k} \left[\left(p_j - c_j \right) q_j \right] \tag{1}$$

w.r.t. $p_j, \mathbf{x}_j \; \forall j \in J_k$

where

$c_j = f_C(\mathbf{x}_j)$

$q_j = f_Q\left(p_j, \mathbf{x}_j \forall j \in J\right)$

where unit-cost c_j is a function of the attributes $\mathbf{x}$ of the product *j,* [37] and quantity demanded q_j is a function of the attributes $\mathbf{x}_j$ and price p_j of all products in the market $j \in J$. We exclude constraints for

[37] This formulation ignores fixed costs without loss of generality because adding a constant to the objective function will not change the design solution. It also ignores unit-costs that vary with volume or unit-costs that depend on attributes of other products.

simplicity, though these could be implemented with KKT conditions. Following common assumptions in the design for market systems literature, we assume that competing products of other firms are considered fixed and do not respond to the focal firm's decisions.[38] In this formulation, we also assume that the focal firm is attempting to decide the price and design variables for all of its products (i.e. all internal competitors)[39].

For this optimization problem, the first-order necessary condition with respect to price $\partial\Pi/\partial p = 0$ can be re-arranged into the following equation[40]:

$$p_j = c_j - \left(\frac{\partial q_j}{\partial p_j}\right)^{-1}\left(q_j + \sum_{j' \in J_k \setminus j}\left[\frac{\partial q_{j'}}{\partial p_j}\left(p_{j'} - c_{j'}\right)\right]\right) \quad \forall j \in J_k \qquad (2a)$$

where $J_k \setminus j$ refers to the set of internal competitors (i.e. all products of the focal firm except j).

For the specific case that the firm only has one product, Eq. (2a) becomes:

$$p_j = c_j - \left(\frac{\partial q_j}{\partial p_j}\right)^{-1} q_j \qquad (2b)$$

These equations state that at a solution, the price of product j is equal to the cost c_j plus a markup that depends on demand q_j and the sensitivity of demand to price $\frac{\partial q_j}{\partial p_j}$. This result has some expected properties: if the sensitivity of demand to price in a choice model were lowered toward zero, the optimal price solution would tend to infinity. If the sensitivity of demand to price were raised toward infinity, the difference between price and cost at the solution tends to zero. In the more general case of a firm with multiple products, the markup for product j depends also on the sensitivity of demand of its internal competitors to product j's price, and the markups of the internal competitors. For maximum profit, every product's price would be set to simultaneously satisfy each first-order condition. This condition for optimal price is well-known; we turn our attention on conditions for optimal design.

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[38] This is in contrast to the econometric literature and several recent engineering design studies [2,11,28], which determine the Nash equilibrium of competing firms. However, the formulation above where competitors are considered fixed is consistent with each firm's optimality conditions in equilibrium when there are no leading and following firms.

[39] We discuss cases with some fixed price and/or design variables in the supplementary material.

[40] Full derivations in supplementary material. We note a derivation that is similar but in terms of elasticities in Eq. (4) in Fischer (2010) [29].

By substituting the relationship in Eq. (2a) for price into the first-order necessary condition with respect to the product attributes, $\partial\Pi/\partial\mathbf{x}=0$, we obtain the following equation:[41]

$$\frac{\partial c_j}{\partial \mathbf{x}_j}=-\frac{\sum_{j'\in J}\left[\frac{\partial q_{j'}}{\partial \mathbf{x}_j}\left(p_{j'}-c_{j'}\right)\right]}{\sum_{j'\in J}\left[\frac{\partial q_{j'}}{\partial p_j}\left(p_{j'}-c_{j'}\right)\right]}\quad \forall j\in J_k \tag{3a}$$

which relates the marginal cost of a design change to an expression involving the marginal demand of design and price changes of each product in the market, weighted by their optimal markups. For the case where the firm has only one product,

$$\frac{\partial c_j}{\partial \mathbf{x}_j}=-\left(\frac{\partial q_j}{\partial p_j}\right)^{-1}\frac{\partial q_j}{\partial \mathbf{x}_j} \tag{3b}$$

which states that, at a solution, the marginal unit-cost of a design change[42] is equal to the population's aggregate marginal willingness-to-pay for the design change. Specifically, $-\left(\frac{\partial q_j}{\partial p_j}\right)^{-1}\frac{\partial q_j}{\partial \mathbf{x}_j}$ is the iso-demand price-equivalence of a design change – the price change required per unit change in the design attribute to maintain constant demand.[43] Willingness-to-pay is the term used in the choice literature for the iso-utility or iso-demand price equivalence of a design or feature change.[44,45] We refer to this as the population's aggregate willingness-to-pay for a design change (WTP) (iso-demand) to avoid confusion with WTP for individuals (where iso-utility and iso-demand are indistinguishable).

We note that the above equations (2-3) remain general to any demand model functional form for q. In the following sections, we examine the properties of these necessary conditions for several types of logit choice models that are used most frequently in the literature [1,8,24,26]. We begin with logit models that have homogeneous preference parameters (logit and nested logit) and then examine

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[41] This form of the FOC is equivalent to Eq. (6) in Fischer (2010) [29].

[42] Marginal unit-cost of a design change ($\partial c/\partial\mathbf{x}$) should not be confused with marginal cost of increasing production volume ($\partial C/\partial q$, where C is total cost). Unit-cost c is already "marginal" with respect to production volume– i.e.: the production cost per incremental unit ignoring fixed costs.

[43] For each value of $\mathbf{x}$, there is a corresponding value of p that produces demand q. To first order, setting $\partial q=\frac{\partial q}{\partial \mathbf{x}}\partial\mathbf{x}+\frac{\partial q}{\partial p}\partial p=0$ for iso-demand changes and solving for ∂p, we obtain $\partial p=-\left(\frac{\partial q}{\partial p}\right)^{-1}\left(\frac{\partial q}{\partial \mathbf{x}}\right)\partial\mathbf{x}$ or $\frac{\partial p}{\partial \mathbf{x}}=-\left(\frac{\partial q}{\partial p}\right)^{-1}\left(\frac{\partial q}{\partial \mathbf{x}}\right)$, which is the marginal change in price per marginal change in design needed to maintain constant demand (to first order).

[44] This concept is related to marginal rates of substitution, but it is applied to a population substituting design attributes of a product for price, rather than to an individual substituting one good or service for another.

[45] In the context of a population modeled with heterogeneous consumer preference parameters, the iso-utility framing does not apply (design changes would affect utility for different consumers differently).

logit models with heterogeneous preference parameters (random-coefficients i.e. latent-class and mixed logit).

2.1. Logit and Nested Logit (Homogeneous Preference Parameters)

In this section, we show that when logit and nested logit models are used with linear utility functions to represent demand, the optimal design solution is independent of competing products. Following derivations shown in Shiau and Michalek [15], and Besanko et al. [27], we derive the conditions for first-order optimality in the case of demand represented with a logit model and explicitly show that the optimality condition with respect to design does not depend on any information about competitors. We then extend these results to the case of nested logit and show that its optimality condition and design solutions are also independent of competitor representation.

Logit

Consider quantity demanded represented by a logit model:

$$q_j = m\frac{\exp(v_j)}{\sum_{j'\in J}\exp(v_{j'})} = m\frac{\exp(v_j)}{\exp(v_j)+\sum_{j'\in J_k\setminus j}\exp(v_{j'})+\theta_j}\ \forall j \in J \tag{4}$$

where m is the market size; v_j is the utility specification composed of consumer preference parameters and product j's price and attributes[46]; $J_k\setminus j$ is the set of internal competitors of product j (i.e. all products of the focal firm k, except j); $\theta_j = \sum_{j'\in J_{k'}}\exp(v_{j'})$ is a quantity equal to the sum of the exponential of utility of all products in the set $J_{k'}$, which is the set of product j's external competitors (i.e. all products of non-focal firms k').

By taking the partial derivatives of demand with respect to price *p* and attributes **x**, and substituting them into the first-order conditions in Eq. (2a) and (3a), we obtain Eq. (5a) and (6a)[47]:

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[46] At this point, we do not restrict utility to be linear or non-linear in price or attributes. However, we assume utility is homogenous i.e. no utility from product variables interacted with consumer group variables such as demographics.
[47] Full derivations available in the supplemental material.

$$p_j = c_j - \frac{1 + \sum_{j' \in J \setminus j} \left[-\frac{q_{j'}}{m} (p_{j'} - c_{j'}) \right]}{\frac{\partial v_j}{\partial p_j} \left(1 - \frac{q_j}{m} \right)} \quad \forall j \in \mathcal{J} \qquad (5a)$$

$$\frac{\partial c_j}{\partial \mathbf{x}_j} = -\left(\frac{\partial v_j}{\partial p_j} \right)^{-1} \frac{\partial v_j}{\partial \mathbf{x}_j} \qquad (6a)$$

Eq. (5a) says that the optimal price of product j is its cost plus an expression involving choice share of internal competitors and their markups that is inversely proportional to the choice share of all competitors $\left(1 - \frac{q_j}{m}\right)$ multiplied by the partial derivative of utility with respect to price. Because choice share is a function of competitor utility, the expression for the profit-maximizing price exhibits potential dependence on competitor representation.

Eq. (6a) says that at the optimal solution, the marginal cost of an attribute change is equal to the negative ratio of the sensitivity of utility to attribute change and the sensitivity of utility to price change. In the case where utility is specified to be linear in price, i.e. $\frac{\partial v_j}{\partial p_j} = \alpha$, we obtain Eq. (6b), an equation with expressions that do not depend on the optimal price.

$$\frac{\partial c_j}{\partial \mathbf{x}_j} = -\frac{1}{\alpha} \frac{\partial v_j}{\partial \mathbf{x}_j} \qquad (6b)$$

Eq. (6b) involves the cost function, which is a function of attribute variables **x** only and not other variables[48], and utility, which is also a function of attribute variables **x** only[49]. This means that Eq. (6b) implies the solution for the profit-maximizing attribute vector $\mathbf{x}^*$ that does not depend on the quantity θ involving competitor utility or variables p or q, which depend on θ. Therefore, the optimal design solution does not depend on the representation of competitors in this case[50],[51].

[48] This is not the case if unit-costs are modeled to vary with market share or sales volume, for example, if they are at a magnitude where economies of scale matter.

[49] Typically, a utility specification linear in attributes would yield $\frac{\partial v_j}{\partial \mathbf{x}_j} = \boldsymbol{\beta}$. We see that the conclusion drawn from Eq. (6b) applies even in the case of utility non-linear in attributes (where $\frac{\partial v_j}{\partial \mathbf{x}_j}$ may be a function of x) and/or cases where there are non-linear mappings between design variables and attributes.

[50] Assuming a unique solution exists in the feasible domain. There may be degenerate cases where there are no solutions or multiple solutions.

[51] This result holds for cases where not all internal competitors are being designed (i.e. fixed design for any internal competitor), as long as all prices are optimal. See supplemental information.

Nested Logit

In the case of nested logit, we also find the first-order optimality condition to be independent of competitor information. Generalizing Eq. (4) to a two-level nested logit specification:

$$q_j = \frac{1}{m} q_{j|l} q_l = m \left(\frac{\exp\left(\frac{v_j}{\lambda_l}\right)}{\exp\left(\frac{v_j}{\lambda_l}\right) + \phi_{J_l \setminus j}} \right) \left(\frac{\exp\left(\lambda_l \ln\left(\exp\left(\frac{v_j}{\lambda_l}\right) + \phi_{J_l \setminus j}\right)\right)}{\exp\left(\lambda_l \ln\left(\exp\left(\frac{v_j}{\lambda_l}\right) + \phi_{J_l \setminus j}\right)\right) + \phi_{J_{l'}}} \right) \tag{7}$$

where $\phi_{J_l \setminus j} = \sum_{j' \in \mathcal{J}_l \setminus j} \exp\left(\frac{v_{j'}}{\lambda_l}\right)$ and $\phi_{J_{l'}} = \sum_{l' \in L \setminus l} \sum_{j' \in \mathcal{J}_{l'}} \exp\left(\frac{v_j}{\lambda_{l'}}\right)$ are quantities equal to the sum of exponentiated utility of all of product *j*'s competitors within nest *l* and outside nest *l*, respectively; J_l is the choice set of alternatives within nest *l*; L is the set of all nests of products in the market; and λ_l is the nesting parameter for nest *l*. Eq. (7) reduces to Eq. (4) when $\lambda_l = 1\ \forall l \in L$.

By following the same procedure as above for obtaining Eq. (6a-b) for logit i.e. finding the partial derivatives of demand under nested logit and substituting them into the first-order condition with respect to design in Eq. (3a), we find that when using a two-level nested logit model to represent demand, the first-order optimality condition for design also reduces to Eq. (6a-b), which are functions of consumer preference parameters and not a function of variables such as $\phi_{J_l \setminus j}$ or $\phi_{J_{l'}}$, which would involve the utility from competitors of the same nest or of other nests.

2.2. Random-Coefficients Logit (Heterogeneous Preference Parameters)

In this section, we show that in the case of a logit demand model specified with random coefficients, such as latent-class logit or mixed logit, the optimality conditions do not, in general, establish design variables **x** independently of competitors, and competitor representation may affect the optimal design. For example, suppose consumers are directionally heterogeneous in their preference for attribute *x* (some prefer more while others prefer less). The optimal solution for attribute *x* for one firm may depend on whether competing firms are targeting consumers who prefer more of *x* or those who prefer less of *x*.

In a random coefficients logit model, preference parameters are modeled as distributions rather than point values. Using discrete distributions based on preferences of consumer groups indexed by i and of size m_i, such as in a latent-class logit model or a numerical approximation of a mixed logit model (sampling from continuous distributions), we have:

$$q_j = \frac{1}{N}\sum_{i}^{n} q_{ij}\ \forall j \in J \tag{8a}$$

$$q_{ij} = m_i \frac{\exp(v_{ij})}{\exp(v_{ij}) + \sum_{j' \in J_k \setminus j} \exp(v_{ij'}) + \theta_{ij\prime}} \forall i = \{1,2,\dots,n\}, j \in J \tag{8b}$$

where m_i is the size of consumer group i; q_{ij} is the quantity of product *j* demanded by consumer group i (size times choice share); v_{ij} is the utility of product j for consumer group i; $J_k \setminus j$ is the set of internal competitors of product *j* (i.e. all products of the focal firm except *j*); and $\theta_{ij\prime}$ is a quantity equal to the sum of exponentiated utilities for group i of product *j*'s external competitors. Again, by substituting in the partial derivatives of demand with respect to prices and attributes, the first-order optimality conditions from Eq. (2-3) become[52]:

$$p_j = c_j - \frac{q_j + \sum_{j' \in J_k \setminus j}\left\{\sum_i^n \left[-m_i \frac{\partial v_{ij}}{\partial p_j}\frac{q_{ij}}{m_i}\frac{q_{ij'}}{m_i}\right](p_{j'} - c_{j'})\right\}}{\sum_i^n \left[m_i \frac{\partial v_{ij}}{\partial p_j}\frac{q_{ij}}{m_i}\left(1 - \frac{q_{ij}}{m_i}\right)\right]} \quad \forall j \in J_k \tag{9a}$$

$$\frac{\partial c_j}{\partial \mathbf{x}_j} = -\frac{\sum_{j' \in J_k \setminus j}\left[\sum_i^n \left[-m_i \frac{\partial v_{ij}}{\partial \mathbf{x}_j}\frac{q_{ij}}{m_i}\frac{q_{ij\prime}}{m_i}\right](p_{j\prime} - c_{j\prime})\right]}{\sum_{j' \in J_k \setminus j}\left[\sum_i^n \left[-m_i \frac{\partial v_{ij}}{\partial p_j}\frac{q_{ij}}{m_i}\frac{q_{ij\prime}}{m_i}\right](p_{j\prime} - c_{j\prime})\right]} \quad \forall j \in J_k \tag{10a}$$

In the case of a firm pricing and designing only a single product (no internal competitors):

$$p_j = c_j - \frac{q_j}{\sum_i^n \left[m_i \frac{\partial v_{ij}}{\partial p_j}\frac{q_{ij}}{m_i}\left(1 - \frac{q_{ij}}{m_i}\right)\right]} \tag{9b}$$

$$\frac{\partial c_j}{\partial \mathbf{x}_j} = -\frac{\sum_i^n \left[m_i \frac{\partial v_{ij}}{\partial \mathbf{x}_j}\frac{q_{ij}}{m_i}\left(1 - \frac{q_{ij}}{m_i}\right)\right]}{\sum_i^n \left[m_i \frac{\partial v_{ij}}{\partial p_j}\frac{q_{ij}}{m_i}\left(1 - \frac{q_{ij}}{m_i}\right)\right]} \tag{10b}$$

Because mixed logit is generally implemented using a finite set of draws to approximate the distribution, these equations apply to the numerically calculated mixed logit case as well. For the case of $n = 1$, these first order conditions in Eq. (9-10) reduce to the logit result in Eq. (5-6). For $n > 1$, Eq. (10b) indicates that the marginal unit-cost of design change is equal to the ratio of the sum of

[52] Full derivations available in the supplemental material.

$\frac{\partial v_{ij}}{\partial \mathbf{x}_j}$ and $\frac{\partial v_{ij}}{\partial p_j}$ of each group, weighted by $\frac{q_{ij}}{m_i}\left(1 - \frac{q_{ij}}{m_i}\right)$. This right-hand side of Eq. (10b) is the population's aggregate marginal willingness-to-pay for that design change for a random coefficients logit model[53]. Notice that, for equal size consumer groups, the consumers that have choice probabilities closer to 0.5 (in the middle of the S-curve) have the greatest contributions to the summation because their marginal changes in demand in response to a design change are the most sensitive.

Unlike in the case of logit and nested logit, Eq. (10b) depends on the quantity demanded by each consumer group, q_{ij}. Because this demand depends on θ_{ij} as well as the optimal p_j (which depends on q_{ij} and thus θ_{ij}), the optimal design $\mathbf{x}_j$ is not generally independent of competitor representation.

We summarize these theoretical results in Table 2.

[53] We note a similar derivation in Wong [30], who describes this as "average MWTP under a hedonic model from the implicit price gradient." (Eq. 14 in [30]) This is not to be confused with what Wong defines as "average MTWP in a discrete choice model $MWTP = \int \frac{\beta_{ik}}{\beta_{ip}} dF_\beta$" (Eq. 13 in [30])

TABLE 2: First-order necessary conditions for optimal price and design for product *j* by firm *k*

		With respect to price	With respect to design
General to any demand model	Multiple products	$p_j = c_j - \left(\frac{\partial q_j}{\partial p_j}\right)^{-1} \left\{ q_j + \sum_{\not{j} \in \mathcal{J} \setminus j} \left[\frac{\partial q_{\not{j}}}{\partial p_j} (p_{\not{j}} - c_{\not{j}}) \right] \right\} \forall j \in \mathcal{J}_k$	$\frac{\partial c_j}{\partial \mathbf{x}_j} = -\frac{\sum_{\not{j} \in \mathcal{J}} \left[\frac{\partial q_{\not{j}}}{\partial \mathbf{x}_j} (p_{\not{j}} - c_{\not{j}}) \right]}{\sum_{\not{j} \in \mathcal{J}} \left[\frac{\partial q_{\not{j}}}{\partial p_j} (p_{\not{j}} - c_{\not{j}}) \right]} \quad \forall j \in \mathcal{J}_k$
	Single product	$p_j = c_j - \left(\frac{\partial q_j}{\partial p_j}\right)^{-1} q_j$	$\frac{\partial c_j}{\partial \mathbf{x}_j} = -\left(\frac{\partial q_j}{\partial p_j}\right)^{-1} \frac{\partial q_j}{\partial \mathbf{x}_j}$
Logit and nested logit[54]	Multiple products	$p_j = c_j - \frac{1 + \sum_{\not{j} \in \mathcal{J}_k \setminus j} \left[-\frac{q_{\not{j}}}{m} (p_{\not{j}} - c_{\not{j}}) \right]}{\frac{\partial v_j}{\partial p_j} \left(1 - \frac{q_j}{m}\right)}$ $\forall j \in \mathcal{J}_k$	$\frac{\partial c_j}{\partial \mathbf{x}_j} = -\left(\frac{\partial v_j}{\partial p_j}\right)^{-1} \frac{\partial v_j}{\partial \mathbf{x}_j}$ $\forall j \in \mathcal{J}_k$
	Single product	$p_j = c_j - \frac{1}{\frac{\partial v_j}{\partial p_j} \left(1 - \frac{q_j}{m}\right)}$	$\frac{\partial c_j}{\partial \mathbf{x}_j} = -\left(\frac{\partial v_j}{\partial p_j}\right)^{-1} \frac{\partial v_j}{\partial \mathbf{x}_j}$
	Multiple products, utility linear in price	$p_j = c_j - \frac{1 + \sum_{\not{j} \in \mathcal{J}_k \setminus j} \left[-\frac{q_{\not{j}}}{m} (p_{\not{j}} - c_{\not{j}}) \right]}{\alpha \left(1 - \frac{q_j}{m}\right)} \forall j \in \mathcal{J}_k$	$\frac{\partial c_j}{\partial \mathbf{x}_j} = -\frac{1}{\alpha} \frac{\partial v_j}{\partial \mathbf{x}_j}$ $\forall j \in \mathcal{J}_k$
Random coefficients logit	Multiple products	$p_j = c_j - \frac{q_j + \sum_{j' \in J_k \setminus j} \left[\sum_i^n \left[-m_i \frac{\partial v_{ij}}{\partial p_j} \frac{q_{ij}}{m_i} \frac{q_{ij'}}{m_i} \right] (p_{j'} - c_{j'}) \right]}{\sum_i^n \left[m_i \frac{\partial v_{ij}}{\partial p_j} \frac{q_{ij}}{m_i} \left(1 - \frac{q_{ij}}{m_i}\right) \right]}$ $\forall j \in J_k$	$\frac{\partial c_j}{\partial \mathbf{x}_j} = -\frac{\sum_{j' \in J_k \setminus j} \left[\sum_i^n \left[-m_i \frac{\partial v_{ij}}{\partial \mathbf{x}_j} \frac{q_{ij}}{m_i} \frac{q_{ij'}}{m_i} \right] (p_{j'} - c_{j'}) \right]}{\sum_{j' \in J_k \setminus j} \left[\sum_i^n \left[-m_i \frac{\partial v_{ij}}{\partial p_j} \frac{q_{ij}}{m_i} \frac{q_{ij'}}{m_i} \right] (p_{j'} - c_{j'}) \right]}$ $\forall j \in J_k$
	Single product	$p_j = c_j - \frac{q_j}{\sum_i^n \left[m_i \frac{\partial v_{ij}}{\partial p_j} \frac{q_{ij}}{m_i} \left(1 - \frac{q_{ij}}{m_i}\right) \right]}$	$\frac{\partial c_j}{\partial \mathbf{x}_j} = -\frac{\sum_i^n \left[m_i \frac{\partial v_{ij}}{\partial \mathbf{x}_j} \frac{q_{ij}}{m_i} \left(1 - \frac{q_{ij}}{m_i}\right) \right]}{\sum_i^n \left[m_i \frac{\partial v_{ij}}{\partial p_j} \frac{q_{ij}}{m_i} \left(1 - \frac{q_{ij}}{m_i}\right) \right]}$

[54] Eq. (6a) and (6b) hold for the case of demand represented by two-level nested logit.

Although the theoretical derivations show that when using a random-coefficients logit demand model, the optimal design may vary depending on competitor representation, it is unclear in general how large this effect may be in practical cases. We use a case study of the US automotive market to demonstrate and test the issue of competitor representation on optimal design.

3. Case study: Re-design of an Automobile

We construct a case study based on a model of the automotive market from the literature [28]. In this case study, we investigate whether and to what extent the optimal design of a single vehicle changes under heterogeneous consumer preferences for different fixed competitor representations. We adopt the model and data used in Whitefoot et al. [28], which was based on the 2006 US new car market, with some simplifying assumptions. We take as decision variables the vehicle's price p and acceleration x, measured as time to accelerate from 0 to 60 mph in seconds. Fuel consumption rate is calculated as a function of acceleration using their estimation of the Pareto frontier developed through simulation and design of experiments (equivalent to treating fuel consumption rate as a free variable and constraining the solution to lie on the Pareto frontier). In this model, cost decreases with increasing acceleration time (i.e. smaller engine displacement size), with diminishing returns, and is specified by Eq. (20-21):

$$c = 1000\gamma_1 + 1000\gamma_2 \exp\left(-\frac{x}{10}\right) + \gamma_3 w + \frac{\gamma_4 w x}{10} \tag{20}$$

$$\frac{\partial c}{\partial x} = -100\gamma_2 \exp\left(-\frac{x}{10}\right) + \frac{\gamma_4 w}{10} \tag{21}$$

where c is unit-cost in \$, x is acceleration time (0-60 mph) in seconds, w is weight in lbs, and the γ terms are parameters fit to engineering simulation results and cost data from [28]. For demand, we use a mixed logit specification and parameters from [28]. The consumer utility is specified by Eq. (22):

$$v_{ij} = \alpha_i p_j + \boldsymbol{\beta}_i^{\top} \mathbf{x}_j \tag{22}$$

where v is the consumer utility from observed attributes and $\mathbf{x}$ includes the attributes of fuel economy (inverse of fuel consumption rate), vehicle "footprint" area (length times width), and acceleration time. The $\boldsymbol{\beta}$ coefficients are specified as independently and normally distributed. Consumer demographic characteristics are ignored.

We hold all competitor products fixed in price and attributes (summarized by the θ parameter), and the firm solves the profit-maximization problem for price and acceleration time of the focal product, with other attributes fixed (fuel economy is specified as a function of acceleration, as described in [28]).

We first solve the problem using competitors represented as 470 elemental alternatives, and then we re-solve with competitors represented by 3 composite alternatives (one compact car, one midsize car, and one large car) intended to represent the 470 elemental alternatives. Each composite is specified by the weighted average price and attributes of their subsumed elemental alternatives – i.e.: the compact car composite's price is the average price of all compact cars, weighted by sales fraction. This type of composite using weighted averages is intuitive and has been used in the choice modeling literature[55] [21]. We use the *L-BFGS* algorithm implemented in the *R nloptr* package to solve the design optimization problem.

We first show the optimal solution in the base scenario with default parameterization. Then, we vary the heterogeneity in preferences in different scenarios. In a recent review of the automotive demand literature, Greene at al. [26] show that estimates of both mean and the standard deviation of consumer willingness-to-pay for vehicle attributes cover a wide range. We simulate a wide range of preference heterogeneity by applying a multiplier to the standard deviation of the normally distributed preferences found in Whitefoot et al. [28] from 0x to 10x, which is within the range found in Greene at al. [26]. For fuel economy, this represents a fixed $600/mpg at 0x, a heterogeneous distribution with a 90% interval from $472 to $728/mpg at 1x (the default parameter values), -$40 to $1240/mpg at 5x, and -$680 to $1880/mpg at 10x. Finally, we also test several cases of different cost functions, vehicle size classes, and the use of correction factors to specify composite utility, as discussed in Yip et al. [21], to assess their effect on the influence of competitor representation on optimal design solutions.

4. Case study results

Figure 1 shows the difference in the optimal decision variables when competitors are represented as 3 composite alternatives rather than 470 elemental alternatives under a range of consumer-preference heterogeneity multipliers. In the base scenario, shown in Fig. 1a, a compact car is redesigned. Using the default preference heterogeneity (1x), we find that competitor representation affects the optimal acceleration time by -0.03% and optimal price by 4.6%. When the heterogeneity is scaled down to 0x (no preference heterogeneity), the optimal acceleration time is identical regardless of the competitor

[55] In the surveyed optimal design literature, it is unclear what the attributes of hypothetical competitors are meant to represent. We do not find clearly stated rationale for attribute levels and values in the papers surveyed in Table 1 (see Table 1A for quotes). Other possible specifications include taking simple averages or sampling a subset of elemental alternatives, as discussed in the introduction discussing the literature in Table 1, or using composite correction factors and alternative-specific constants, which could lead to variation in results [21].

representation, as expected from our derivation in Section 2.1. With heterogeneity scaled up by 10x, competitor representation affects optimal acceleration time by -2.6%

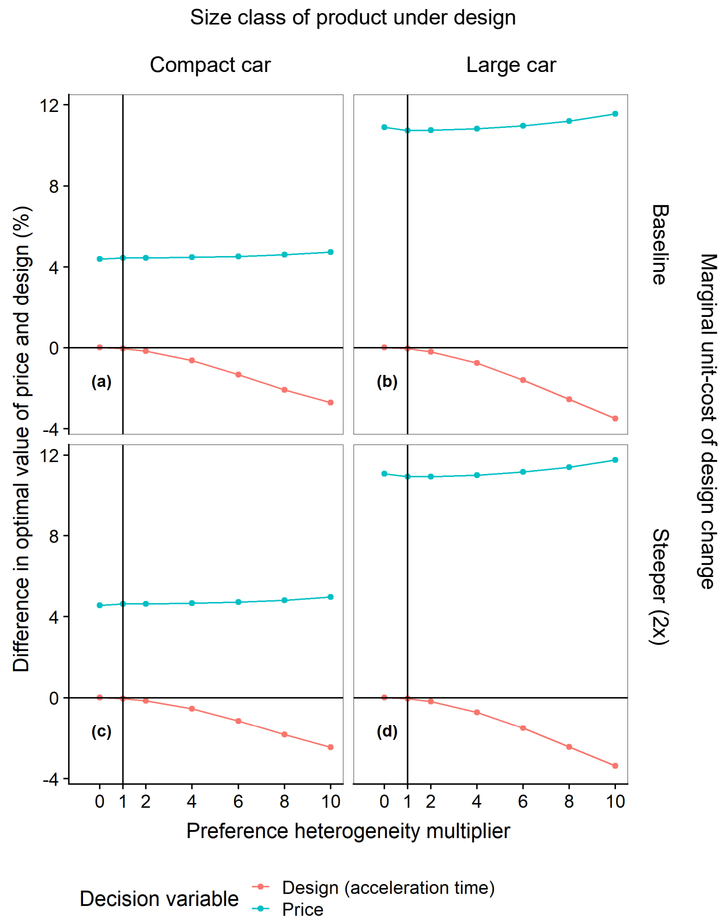

FIGURE 1: Differences in optimal values of price and design (acceleration time) when competitors are represented by elemental vs. composite alternatives

We repeat these tests for the case of re-designing a large car, which has different consumer utility parameters as estimated by Whitefoot et al. [28]. The optimal design results, in Fig. 1b, show larger differences than the case of the compact car. With a preference heterogeneity multiplier at 10x, competitor representation affected optimal acceleration time by -3.6%. In addition to the results shown in Fig. 1, we ran a series of cases varying the distributions and input parameter values across a wide range, including uniform and bimodal distributions. In most cases where parameter values were in a realistic range, the effect of competitor representation on optimal design is between 0% and -5%.

However, in some cases, we found that the optimal design changed up to 20%. Changes in optimal price were larger: typically between 5% and 15%, and in some cases as large as 30%.

In Fig. 1c and Fig. 1d, we assume a cost function with a steeper (2x) marginal unit-cost of design change, which affects the magnitude of the impact of competitor representation on optimal acceleration time slightly (-2.3% for small car and -3.4% for large car at 10x).

As shown in Section 2.2, the first-order optimality conditions stipulate that at an optimal solution, the marginal unit-cost of a design change is equal to the population's aggregate marginal WTP for a design change (Eq. 8). For the mixed logit case, the aggregate WTP is the ratio of the sum of coefficients $\boldsymbol{\beta}_i$ and α_i of each consumer (each draw from the distribution), weighted by $q_{ij}(1 - q_{ij}/m)$ (Eq. 19). To help explain how and why both the degree of preference heterogeneity and the curvature of the cost function influence the effect of competitor representation on optimal designs, we plot the marginal unit-cost of design change (MC for short, representing the left-hand side of Eq. 19) and the aggregate WTP for design change (WTP for short, representing the right-hand side of Eq. 19) in Fig. 2. Both of these values are negative because increasing acceleration time reduces both marginal unit-cost and willingness-to-pay.[56] We see that the optimal solutions for each simulated case lie at each intersection of the MC and WTP curves, where the marginal unit-cost change from increasing acceleration match the iso-demand price change, as expected.

The MC curve is independent of demand assumptions, consumer heterogeneity, or the representation of competitor products, because the marginal cost of production volume is independent of production volume in our formulation (Eq. 1). However, WTP is a function of demand and its parameters, and for latent-class logit and mixed logit models, this includes competitor products. As such, when competitors are represented by composites instead of elemental alternatives, the WTP curve shifts, changing the optimal solution. In this case study, the composite representation (solid lines; optima at circles) causes the WTP curve to shift to the left relative to the elemental representation (dashed lines; optima at crosses), and the magnitude of the shift increases with the degree of preference heterogeneity (shown by shades of gray of the pairs of WTP lines, shifting right as the preference heterogeneity multiplier goes from 0x to 10x).

[56] For lower values of acceleration time, the population's aggregate marginal WTP for increasing acceleration time is positive because in this model, fuel economy is also treated as a function of acceleration, following the Pareto frontier.

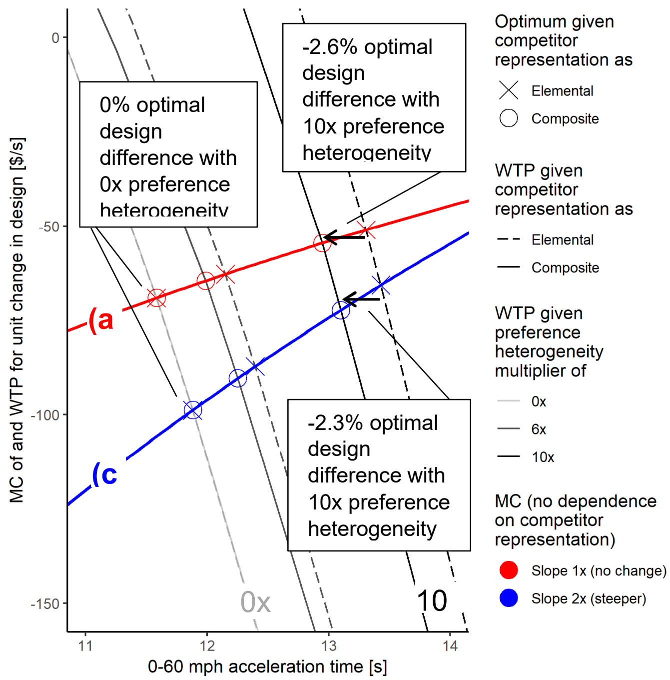

FIGURE 2: Marginal unit-cost of a design change (MC) and the population's aggregate marginal willingness-to-pay for a design change (WTP) as a function of the design variable (acceleration time) for the compact car redesign case

We also observe that a steeper MC curve (the blue line, noted by (c)) leads to a somewhat smaller effect of competitor representation on optimal design, corresponding to the result in Fig. 1c. We repeat this analysis for the large car case in Figure 3 and obtain similar findings. We summarize the numerical results in Table 3. We also visualize the optimal design result in Figure 4.

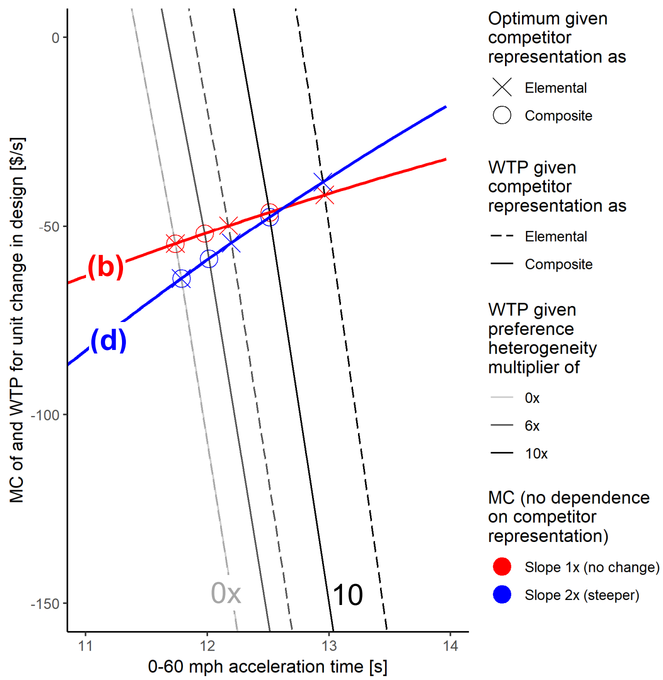

FIGURE 3: Marginal unit-cost of a design change (MC) and the population's aggregate marginal willingness-to-pay for a design change (WTP) as a function of the design variable (acceleration time) for the large car redesign case

TABLE 3: Summary of numerical results in case study - differences in optimal design variable due to composite representation (vs. elemental representation) of competitor products

		Difference in optimal design variable (acceleration time)	
Steepness of marginal cost (MC) curve	**Preference heterogeneity multiplier**	**Size class of product (car) under design**	
		Compact	**Large**
1x	0x	0 s 0%	0 s 0%
	1x	-0.004 s -0.03%	-0.005 s -0.04%
	10x	-0.36 s -2.6%	-0.45 s -3.6%
2x	0x	0 s 0%	0 s 0%
	1x	-0.005 s -0.04%	-0.005 s -0.04%
	10x	-0.33 s -2.3%	-0.44 s -3.4%

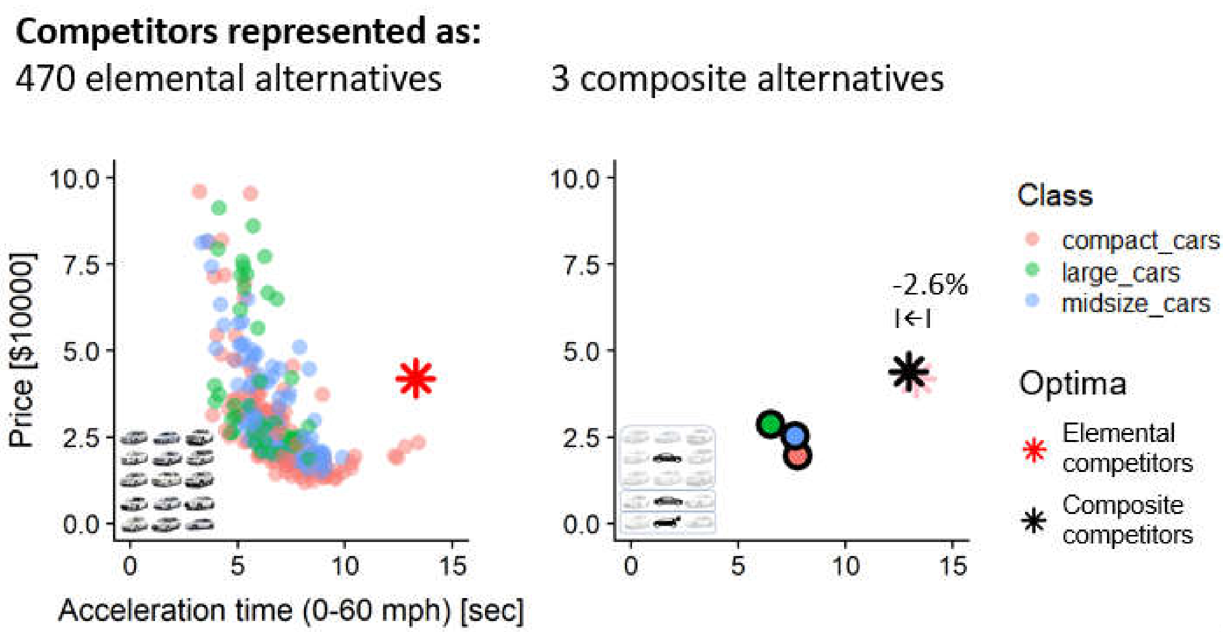

FIGURE 4: Summary of results from optimal engineering design case study

Finally, we find the optimal design while simulating composite competitors with utilities specified with full correction factors and we find a 0 s (0%) difference in the optimal design found from the benchmark model with 470 elemental alternatives for all marginal cost and preference heterogeneity cases. Given that Yip et al. [21] showed that full composite correction factors would generate choice share predictions for composite models that would match those from elemental models, we do expect that the optimal designs conditional on the choice model results would also match between composite and elemental model simulations. When adding only the size correction factor to the utility of composites (partial correction), the optimal design difference was larger in some cases and smaller in others.

The use of composite correction factors can affect the optimal design difference, as well as the computation of optimal design. Modelers using composites with correction factors may benefit from shorter computation times, particularly in more complex models that attempt to optimally price and design multiple vehicles and may in certain cases generate optimal design results that do not deviate from those from a corresponding elemental model. However, modelers may not have access to the precise information needed to compute the exact correction factors and the elemental model may itself be mis-specified and may not necessarily optimize design more accurately than the composite model.

5. Conclusion

We derive first-order optimality conditions for profit maximizing design and price and determine that competitor representation does not affect optimal design when demand is modeled using logit or nested logit models (homogeneous consumer preference parameters), but competitor representation may affect optimal design when demand is modeled using latent-class or mixed logit models (heterogeneous consumer preference parameters). Competitor representation may affect optimal price under all demand models. These findings hold for utility functions that are linear in price and cost functions where marginal unit-cost is independent of production volume.

In a case study of automotive design under mixed logit demand, we find that the optimal design (0-60 mph acceleration time) changes when competitors are modeled using a small set of composite alternatives to represent a larger set of vehicles available on the market. The magnitude of this effect depends on the specific form and parameters of the cost and consumer utility functions. In our case study, the magnitude of the change increases with preference heterogeneity and decreases with the steepness of the marginal unit-cost curve. By applying correction factors, one can obtain the optimal solution to the elemental competitor problem using a composite representation of competitors.

Acknowledgements

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Table Captions List

Figure Captions List

Supplemental Material and Appendices

A. Extended Table of Literature

TABLE 1A: EXTENDED VERSION OF TABLE 1 WITH EXAMPLES OF COMPETITOR REPRESENTATION IN THE DESIGN FOR MARKET SYSTEMS LITERATURE

Study (author, year)	Market	Number of competing alternatives	Type of competitor representation	Reasoning behind competitor representation
Shin & Ferguson, 2016 [14]	Cars	3	Hypothetical	No reason given
Shin & Ferguson, 2016 [14]	MP3 players	3	Hypothetical	No reason given
Kwak & Kim, 2012 [12]	Computers	3	Generic/ representative	“There are three competing products on the market (i.e., high-spec, mid-spec, and low-spec), and they differ from each other in terms of part specifications and selling price.”
Shiau & Michalek, 2009 [3]	Weight scales	4	Hypothetical	"Table 6 shows the specifications of four competing products C1, R2, S3, and T4 in the market, where each product has a unique combination of product characteristics."
Besharati et al., 2006 [13]	Angle grinders	4	Hypothetical	“We assume that in the market for this power tool, there are three competitive products.”
Li & Azarm, 2000 [18]	Cordless screwdrivers	5	Hypothetical	No reason given
Zhao & Thurston, 2013 [19]	Cell phones	5	Hypothetical	“a hypothetical market is assumed with five product competitors and their attributes as shown in Table 1. These data were collected from several real products in the current cell phone market.”
Wang et al., 2011 [20]	Laptops and smartphones	7	Hypothetical	No reason given
Shiau et al., 2009 [15]	Midsize cars	10	Generic/ representative	Computational reasons. Explanation: Case study: midsize vehicles, 10 generic domestic manufacturers competing in the market. “assuming each manufacturer has a single representative vehicle j in its fleet”. “We simulate 10 generic domestic manufacturers competing in the market”, with the “assumption of a single vehicle design per producer”
Wassenaar et al., 2005 [16]	Midsize cars	12	Detailed (market subset)	7 models, 12 trims, to represent the midsize segment. “Our implementation is subject to the assumption that customers only consider the 12 vehicle trims when purchasing a vehicle.”
Choi et al., 1990 [10]	Pain relievers	14	Detailed	14 existing brands. "small experimental preference data set on 14 over-the-counter analgesic pain relievers" "The reader should note that this example is not meant to be a thorough study of the market, but is simply meant to illustrate the properties of the proposed model and algorithms described in the paper."
Morrow et al., 2014 [11]	Cars	443	Detailed	"This model is not intended to be a high-fidelity model of vehicle design; our intended application of this model is a comparison of numerical methods in a large market."
Frischknecht et al., 2010 [6]	Cars	473	Detailed	No reason given

B. Extended Derivations

Given the profit-maximization problem defined in Eq. (1), and assuming analytic functions, we derive Eq. (2-3) by first writing out the first-order necessary conditions[57]:

$$\frac{\partial \pi}{\partial p_j} = q_j + \sum_{\jmath \in \mathcal{J}} \left[\frac{\partial q_\jmath}{\partial p_j} (p_\jmath - c_\jmath) \right] = 0 \quad \forall j \in \mathcal{J} \tag{S1}$$

$$\frac{\partial \pi}{\partial \mathbf{x}_j} = -q_j \frac{\partial c_j}{\partial \mathbf{x}_j} + \sum_{\jmath \in \mathcal{J}} \left[\frac{\partial q_\jmath}{\partial \mathbf{x}_j} (p_\jmath - c_\jmath) \right] = \mathbf{0} \quad \forall j \in \mathcal{J} \tag{S2}$$

Re-arranging to get Eq. (2-3) in the paper, reprinted here as (S3-S4):

$$p_j = c_j - \left(\frac{\partial q_j}{\partial p_j} \right)^{-1} \left(q_j + \sum_{\jmath \in \mathcal{J} \setminus j} \left[\frac{\partial q_\jmath}{\partial p_j} (p_\jmath - c_\jmath) \right] \right) \quad \forall j \in \mathcal{J} \tag{S3}$$

$$\frac{\partial c_j}{\partial \mathbf{x}_j} = -\left(\frac{\partial q_j}{\partial p_j} \right)^{-1} \frac{\partial q_j}{\partial \mathbf{x}_j} + q_j^{-1} \sum_{\jmath \in \mathcal{J} \setminus j} \left[\left(\frac{\partial q_\jmath}{\partial \mathbf{x}_j} - \frac{\partial q_\jmath}{\partial p_j} \left(\frac{\partial q_j}{\partial p_j} \right)^{-1} \frac{\partial q_j}{\partial \mathbf{x}_j} \right) (p_\jmath - c_\jmath) \right] \quad \forall j \in \mathcal{J} \tag{S4}$$

To obtain Eq. (3a), matching Eq. (6) in Fischer (2010), we first re-arrange Eqn. (S3):

$$p_j = c_j - \left(\frac{\partial q_j}{\partial p_j} \right)^{-1} \left(q_j + \sum_{\jmath \in \mathcal{J} \setminus j} \left[\frac{\partial q_\jmath}{\partial p_j} (p_\jmath - c_\jmath) \right] \right)$$

$$= -\left(\frac{\partial q_j}{\partial p_j} \right) (p_j - c_j) = \left(q_j + \sum_{\jmath \in \mathcal{J} \setminus j} \left[\frac{\partial q_\jmath}{\partial p_j} (p_\jmath - c_\jmath) \right] \right)$$

$$= -\left(\frac{\partial q_j}{\partial p_j} \right) (p_j - c_j) = q_j + \sum_{\jmath \in \mathcal{J}} \left[\frac{\partial q_\jmath}{\partial p_j} (p_\jmath - c_\jmath) \right] - \left(\frac{\partial q_j}{\partial p_j} \right) (p_j - c_j) \quad \forall j \in \mathcal{J}$$

$$q_j = -\sum_{\jmath \in \mathcal{J}} \left[\frac{\partial q_\jmath}{\partial p_j} (p_\jmath - c_\jmath) \right] \quad \forall j \in \mathcal{J} \tag{S5}$$

Then, we re-arrange Eqn. (S4):

$$\frac{\partial c_j}{\partial \mathbf{x}_j} = -\left(\frac{\partial q_j}{\partial p_j} \right)^{-1} \frac{\partial q_j}{\partial \mathbf{x}_j} + q_j^{-1} \sum_{\jmath \in \mathcal{J} \setminus j} \left[\left(\frac{\partial q_\jmath}{\partial \mathbf{x}_j} - \frac{\partial q_\jmath}{\partial p_j} \left(\frac{\partial q_j}{\partial p_j} \right)^{-1} \frac{\partial q_j}{\partial \mathbf{x}_j} \right) (p_\jmath - c_\jmath) \right] \quad \forall j \in \mathcal{J}$$

[57] We use matrix calculus notation here, where the partial derivative of a scalar with respect to a vector indicates a gradient, and gradients are row vectors.

$$= q_j^{-1}\left(-q_j\left(\frac{\partial q_j}{\partial p_j}\right)^{-1}\frac{\partial q_j}{\partial \mathbf{x}_j}+\sum_{\mathscr{j}\in\mathcal{J}}\left[\left(\frac{\partial q_{\mathscr{j}}}{\partial \mathbf{x}_j}-\frac{\partial q_{\mathscr{j}}}{\partial p_j}\left(\frac{\partial q_j}{\partial p_j}\right)^{-1}\frac{\partial q_j}{\partial \mathbf{x}_j}\right)(p_{\mathscr{j}}-c_{\mathscr{j}})\right]\right.$$
$$\left.-\left[\left(\frac{\partial q_j}{\partial \mathbf{x}_j}-\frac{\partial q_j}{\partial p_j}\left(\frac{\partial q_j}{\partial p_j}\right)^{-1}\frac{\partial q_j}{\partial \mathbf{x}_j}\right)(p_j-c_j)\right]\right)\quad \forall j\in\mathcal{J}$$

The last term in the parenthetical quantity is zero and can be dropped:

$$\frac{\partial c_j}{\partial \mathbf{x}_j}= q_j^{-1}\left(-q_j\left(\frac{\partial q_j}{\partial p_j}\right)^{-1}\frac{\partial q_j}{\partial \mathbf{x}_j}+\sum_{\mathscr{j}\in\mathcal{J}}\left[\left(\frac{\partial q_{\mathscr{j}}}{\partial \mathbf{x}_j}-\frac{\partial q_{\mathscr{j}}}{\partial p_j}\left(\frac{\partial q_j}{\partial p_j}\right)^{-1}\frac{\partial q_j}{\partial \mathbf{x}_j}\right)(p_{\mathscr{j}}-c_{\mathscr{j}})\right]\right)\quad \forall j\in\mathcal{J} \tag{S6}$$

Finally, we substitute Eqn. (S5) into Eqn. (S6):

$$\frac{\partial c_j}{\partial \mathbf{x}_j}= q_j^{-1}\left\{\sum_{\mathscr{j}\in\mathcal{J}}\left[\frac{\partial q_r}{\partial p_j}\left(\frac{\partial q_j}{\partial p_j}\right)^{-1}\frac{\partial q_j}{\partial \mathbf{x}_j}(p_r-c_r)\right]+\sum_{\mathscr{j}\in\mathcal{J}}\left[\left(\frac{\partial q_{\mathscr{j}}}{\partial \mathbf{x}_j}-\frac{\partial q_{\mathscr{j}}}{\partial p_j}\left(\frac{\partial q_j}{\partial p_j}\right)^{-1}\frac{\partial q_j}{\partial \mathbf{x}_j}\right)(p_{\mathscr{j}}-c_{\mathscr{j}})\right]\right\}$$

$$= q_j^{-1}\left(\sum_{\mathscr{j}\in\mathcal{J}}\left[\frac{\partial q_{\mathscr{j}}}{\partial \mathbf{x}_j}(p_{\mathscr{j}}-c_{\mathscr{j}})\right]\right)$$

$$= -\frac{\sum_{\mathscr{j}\in\mathcal{J}}\left[\dfrac{\partial q_{\mathscr{j}}}{\partial \mathbf{x}_j}(p_{\mathscr{j}}-c_{\mathscr{j}})\right]}{\sum_{\mathscr{j}\in\mathcal{J}}\left[\dfrac{\partial q_{\mathscr{j}}}{\partial p_j}(p_{\mathscr{j}}-c_{\mathscr{j}})\right]}\quad \forall j\in\mathcal{J} \tag{S7}$$

Eq. (S7) is reported in the main text as Eq. (3a).

Logit

Given Eq. (4) for quantity demanded represented by a logit model, we obtain Eq. (5-6) by taking the partial derivatives of quantity demanded with respect to prices and designs. We also make use of an expression for the summed choice share of all internal and external competitors (all except the focal product j)

$$\frac{\sum_{\mathscr{j}\in\mathcal{J}\setminus j}\exp(v_{\mathscr{j}})+\theta_{\mathcal{K}}}{\exp(v_j)+\sum_{\mathscr{j}\in\mathcal{J}\setminus j}\exp(v_{\mathscr{j}})+\theta_{\mathcal{K}}}=\frac{\sum_{\mathscr{j}\in\mathcal{J}\setminus j}q_{\mathscr{j}}+\sum_{\mathscr{k}\in\mathcal{K}}q_{\mathscr{k}}}{m}=1-\frac{q_j}{m} \tag{S8}$$

Partial derivatives

$$\frac{\partial q_j}{\partial p_j}=m\frac{\left[\dfrac{\partial v_j}{\partial p_j}\exp(v_j)*\left[\exp(v_j)+\sum_{\mathscr{j}\in\mathcal{J}\setminus j}\exp(v_{\mathscr{j}})+\theta_{\mathcal{K}}\right]-\exp(v_j)*\dfrac{\partial v_j}{\partial p_j}\left[\exp(v_j)\right]\right]}{\left(\exp(v_j)+\sum_{\mathscr{j}\in\mathcal{J}\setminus j}\exp(v_{\mathscr{j}})+\theta_{\mathcal{K}}\right)^2}$$

$$= m \frac{\frac{\partial v_j}{\partial p_j} \exp(v_j) \left(\sum_{\mathscr{j} \in \mathcal{J} \setminus j} \exp(v_{\mathscr{j}}) + \theta_{\mathcal{K}}\right)}{\left(\exp(v_j) + \sum_{\mathscr{j} \in \mathcal{J} \setminus j} \exp(v_{\mathscr{j}}) + \theta_{\mathcal{K}}\right)^2}$$

$$= m \frac{\partial v_j}{\partial p_j} \frac{q_j}{m} \left(1 - \frac{q_j}{m}\right) \quad \forall j \in \mathcal{J} \tag{S9}$$

and similarly,

$$\frac{\partial q_j}{\partial \mathbf{x}_j} = m \frac{\partial v_j}{\partial \mathbf{x}_j} \frac{q_j}{m} \left(1 - \frac{q_j}{m}\right) \quad \forall j \in \mathcal{J} \tag{S10}$$

The partial derivatives of demand for product j with respect to the design and price of internal competitors $\mathscr{j} \in \mathcal{J} \setminus j$ are:

$$\frac{\partial q_j}{\partial p_{\mathscr{j}}} = m \frac{\left[0 - \exp(v_j) * \frac{\partial v_{\mathscr{j}}}{\partial p_{\mathscr{j}}} \exp(v_{\mathscr{j}})\right]}{\left(\exp(v_j) + \sum_{\mathscr{j} \in \mathcal{J} \setminus j} \exp(v_{\mathscr{j}}) + \theta_{\mathcal{K}}\right)^2}$$

$$= -m \frac{\partial v_{\mathscr{j}}}{\partial p_{\mathscr{j}}} \frac{q_j}{m} \frac{q_{\mathscr{j}}}{m} \quad \forall j \in \mathcal{J}, \mathscr{j} \in \mathcal{J} \setminus j \tag{S11}$$

and similarly,

$$\frac{\partial q_j}{\partial \mathbf{x}_{\mathscr{j}}} = -m \frac{\partial v_{\mathscr{j}}}{\partial \mathbf{x}_{\mathscr{j}}} \frac{q_j}{m} \frac{q_{\mathscr{j}}}{m} \quad \forall j \in \mathcal{J}, \mathscr{j} \in \mathcal{J} \setminus j \tag{S12}$$

By symmetry, the partial derivatives of demand for each internal competitor $\mathscr{j} \in \mathcal{J} \setminus j$ with respect to the design and price of the focal product j are identical to the partial derivatives of demand for each focal product j with respect to each internal competitor $\mathscr{j} \in \mathcal{J} \setminus j$.

First-order optimality conditions

Substituting the partial derivatives (S9-S12) into the first-order optimality conditions (S3-S4) and further re-arrangement and simplification yields:

FOC with respect to price

$$p_j = c_j - \left(\frac{\partial q_j}{\partial p_j}\right)^{-1} \left(q_j + \sum_{\mathscr{j} \in \mathcal{J} \setminus j} \left[\frac{\partial q_{\mathscr{j}}}{\partial p_j} (p_{\mathscr{j}} - c_{\mathscr{j}})\right]\right)$$

$$= c_j - \frac{1 + \sum_{\mathscr{j} \in \mathcal{J} \setminus j} \left[-\frac{q_{\mathscr{j}}}{m} (p_{\mathscr{j}} - c_{\mathscr{j}})\right]}{\frac{\partial v_j}{\partial p_j} \left(1 - \frac{q_j}{m}\right)} \quad \forall j \in \mathcal{J} \tag{S13}$$

FOC with respect to design

$$\frac{\partial c_j}{\partial \mathbf{x}_j} = -\left(\frac{\partial q_j}{\partial p_j}\right)^{-1}\frac{\partial q_j}{\partial \mathbf{x}_j} + q_j^{-1}\left(\sum_{\not{j}\in\mathcal{J}\backslash j}\left[\left(\frac{\partial q_{\not{j}}}{\partial \mathbf{x}_j} - \frac{\partial q_{\not{j}}}{\partial p_j}\left(\frac{\partial q_j}{\partial p_j}\right)^{-1}\frac{\partial q_j}{\partial \mathbf{x}_j}\right)(p_{\not{j}} - c_{\not{j}})\right]\right) \quad \forall j \in \mathcal{J}$$

For all combinations of j and $\not{j}$,

$$\left(\frac{\partial q_{\not{j}}}{\partial \mathbf{x}_j} - \frac{\partial q_{\not{j}}}{\partial p_j}\left(\frac{\partial q_j}{\partial p_j}\right)^{-1}\frac{\partial q_j}{\partial \mathbf{x}_j}\right) = \left(-\frac{\frac{\partial v_j}{\partial \mathbf{x}_j} q_j q_{\not{j}}}{m} - \frac{-\frac{\frac{\partial v_j}{\partial p_j} q_j q_{\not{j}}}{m} * \frac{\partial v_j}{\partial \mathbf{x}_j} q_j\left(1 - \frac{q_j}{m}\right)}{\frac{\partial v_j}{\partial p_j} q_j\left(1 - \frac{q_j}{m}\right)}\right) = 0 \qquad \text{(S14)}$$

Substituting (S14) into (S4),

$$\frac{\partial c_j}{\partial \mathbf{x}_j} = -\left(\frac{\partial q_j}{\partial p_j}\right)^{-1}\frac{\partial q_j}{\partial \mathbf{x}_j} \quad \forall j \in \mathcal{J} \qquad \text{(S15)}$$

Substituting Eq.(S9-S10) into Eq.(S15):

$$\frac{\partial c_j}{\partial \mathbf{x}_j} = -\left(\frac{\partial v_j}{\partial p_j}\right)^{-1}\frac{\partial v_j}{\partial \mathbf{x}_j} \quad \forall j \in \mathcal{J} \qquad \text{(S16)}$$

We report Eq. (S13) (S15) (S16) as Eq. (5a) (3b) (6a) in the main text.

Random Coefficients Logit

Given Eq. (8) for quantity demanded represented by a random coefficients logit model, we obtain Eq. (9-10) by taking the partial derivatives of quantity demanded with respect to prices and designs.

Partial derivatives

Based on Eq. (S9) – (S14), we find the partial derivatives of quantity demanded with respect to prices and designs to be:

$$\frac{\partial q_j}{\partial p_j} = \sum_{i}^{n}\left[\frac{\partial v_{ij}}{\partial p_j}\frac{q_{ij}}{m_i}\left(1 - \frac{q_{ij}}{m_i}\right)\right] \ \forall j \in \mathcal{J} \qquad (S17)$$

$$\frac{\partial q_j}{\partial \mathbf{x}_j} = \sum_{i}^{n}\left[\frac{\partial v_{ij}}{\partial \mathbf{x}_j}\frac{q_{ij}}{m_i}\left(1 - \frac{q_{ij}}{m_i}\right)\right] \ \forall j \in \mathcal{J} \qquad (S18)$$

$$\frac{\partial q_j}{\partial p_{j'}} = \sum_{i}^{n} \left[\frac{\partial v_{ij}}{\partial p_{j'}} \frac{q_{ij}}{m_i} \frac{q_{ij'}}{m_i} \right] \quad \forall j \in \mathcal{J}, j' \in J_k \backslash j \tag{S19}$$

$$\frac{\partial q_j}{\partial \mathbf{x}_{j'}} = \sum_{i}^{n} \left[\frac{\partial v_{ij}}{\partial \mathbf{x}_{j'}} \frac{q_{ij}}{m_i} \frac{q_{ij'}}{m_i} \right] \quad \forall j \in \mathcal{J}, j' \in J_k \backslash j \tag{S20}$$

$$\frac{\partial q_{j'}}{\partial p_j} = \sum_{i}^{n} \left[\frac{\partial v_{ij'}}{\partial p_j} \frac{q_{ij'}}{m_i} \frac{q_{ij}}{m_i} \right] \quad \forall j \in \mathcal{J}, j' \in J_k \backslash j \tag{S21}$$

$$\frac{\partial q_{j'}}{\partial \mathbf{x}_j} = \sum_{i}^{n} \left[\frac{\partial v_{ij'}}{\partial \mathbf{x}_j} \frac{q_{ij'}}{m_i} \frac{q_{ij}}{m_i} \right] \quad \forall j \in \mathcal{J}, j' \in J_k \backslash j \tag{S22}$$

First-order optimality conditions

By substituting the partial derivatives specific to Random Coefficients Logit (S17-22) into Eqn. (S3-S4), we obtain FOC relationships:

FOC with respect to price

$$\begin{aligned} p_j &= c_j - \left(\frac{\partial q_j}{\partial p_j} \right)^{-1} \left(q_j + \sum_{\not{j} \in \mathcal{J} \backslash j} \left[\frac{\partial q_{\not{j}}}{\partial p_j} (p_{\not{j}} - c_{\not{j}}) \right] \right) \\ &= c_j - \frac{q_j + \sum_{\not{j} \in \mathcal{J} \backslash j} \left(\sum_i^n \left[-m_i \frac{\partial v_{ij}}{\partial p_j} \frac{q_{ij}}{m_i} \frac{q_{i\not{j}}}{m_i} \right] (p_{\not{j}} - c_{\not{j}}) \right)}{\sum_i^n \left[m_i \frac{\partial v_{ij}}{\partial p_j} \frac{q_{ij}}{m_i} \left(1 - \frac{q_{ij}}{m_i} \right) \right]} \quad \forall j \in \mathcal{J} \end{aligned} \tag{S23}$$

FOC with respect to design

$$\begin{aligned} \frac{\partial c_j}{\partial \mathbf{x}_j} &= - \frac{\sum_{\not{j} \in \mathcal{J}} \left[\frac{\partial q_{\not{j}}}{\partial \mathbf{x}_j} (p_{\not{j}} - c_{\not{j}}) \right]}{\sum_{\not{j} \in \mathcal{J}} \left[\frac{\partial q_{\not{j}}}{\partial p_j} (p_{\not{j}} - c_{\not{j}}) \right]} \\ &= - \frac{\sum_{\not{j} \in \mathcal{J}} \left[\sum_i^n \left[-m_i \frac{\partial v_{ij}}{\partial \mathbf{x}_j} \frac{q_{ij}}{m_i} \frac{q_{i\not{j}}}{m_i} \right] (p_{\not{j}} - c_{\not{j}}) \right]}{\sum_{\not{j} \in \mathcal{J}} \left[\sum_i^n \left[-m_i \frac{\partial v_{ij}}{\partial p_j} \frac{q_{ij}}{m_i} \frac{q_{i\not{j}}}{m_i} \right] (p_{\not{j}} - c_{\not{j}}) \right]} \quad \forall j \in \mathcal{J} \end{aligned} \tag{S24}$$

Eq. (S23-S24) are reported in the main text as Eq. (9-10).

Chapter 4: The dynamic costs and benefits of a technology-forcing policy nested in a broader performance standard: the case of ZEV and CAFE

This study was presented at several conferences, including at USAEE 2019[58], and is co-authored with Jeremy Michalek and Kate Whitefoot.

"I can make a model tie my shoe laces" - anonymous colleague, cited by Pindyck (2013)

Technology-specific policies may be less economically efficient than technology-neutral policies when addressing environmental externalities, but they may increase social welfare via longer-term dynamic effects resulting in technology-specific non-appropriable learning-by-doing spillover (Gillingham & Stock, 2018; Linn & McConnell, 2017). Additionally, complicating the cost-benefit analysis are interactions between technology-specific policies and technology-neutral policies, especially if they overlap in scope or jurisdiction (Goulder, Jacobsen, & Van Benthem, 2012; A. T. Jenn, Azevedo, & Michalek, 2016). I investigate the impact of these effects on the cost-benefit calculation of ZEV mandates. I do this by representing several of these effects explicitly and endogenously, building on models for consumer and firm behavior. Specifically, I model the updating of CAFE/GHG standard stringency based on induced technology cost reduction resulting from ZEV mandates. I characterize how this new policy interaction effect (ZEV dynamically influencing future CAFE) could change the cost-benefit calculation and analysis of the impact of technology-specific policies such as ZEV mandates.

1. Introduction

Many governments have implemented regulations to encourage the deployment of electric vehicles (EVs). The literature has found that many of these policies have cost society beyond what is justified by current environmental benefits and externality mitigation (Holland, Mansur, Muller, & Yates, 2016; Michalek et al., 2011; Weis, Michalek, & Jaramillo, 2016), though many regional and vehicle-specific factors can affect the relative environmental benefits of EVs (Yuksel, Tamayao, Hendrickson, Azevedo, & Michalek, 2016) and the US electric grid has changed quickly in recent years, reducing emissions associated with EV charging in the US (Holland, Mansur, Muller, & Yates, 2018).

A common argument to justify these policies that have been assessed as having low or negative near-term net benefits has been that EV technology-forcing policy can stimulate a technology transition for the future and generate long-term net benefits (D. L. Greene, Park, &

[58] Yip, A., Michalek, J., Whitefoot, K. (2019) THE DYNAMIC COSTS & BENEFITS OF TECHNOLOGY-FORCING POLICY NESTED IN A BROADER PERFORMANCE STANDARD: THE CASE OF ZEV & CAFE. USAEE 2019 conference proceedings.

Liu, 2014a). For example, when justifying bonus incentives for EVs and other alternative fuel vehicles in the 2017-2025 federal light-duty vehicle fleet standards, the Environmental Protection Agency (EPA) noted “EPA believes it is worthwhile to forego modest additional emissions reductions in the near term in order to lay the foundation for the potential for much larger ‘game-changing’ GHG emissions and oil reductions in the longer term.” (EPA, 2012; A. T. Jenn et al., 2016)

1.1. Dynamic effects

Gillingham and Stock (2018) discuss EVs as a case example of the importance of taking a perspective of “dynamic costs” as opposed to only considering static short-term costs. Several studies in the literature begin to tackle the complexity of dynamic costs and benefits while analyzing EV policies. Greene, Park, and Liu (2014b), in an analysis for the National Academies of Sciences, Engineering, and Medicine Transitions to Alternative Fuels and Vehicles study, simulated EV transition scenarios with dynamic effects, including learning-by-doing and consumer aversion reduction with adoption. Their simulations, using the LAVE-Trans model, demonstrated how the long-term benefits of an EV transition (including uncounted energy savings, GHG mitigation, air quality improvements, and changes in consumer and producer surplus) could dominate over the short-term costs of EV subsidies “by roughly an order of magnitude”. Liu and Lin (2017) include feedback loops in the MA3T model to represent dynamic effects accounting for “changes in non-technology factors as the market evolves” and they find large uncertainties in the future EV market. Sykes and Axsen (2017) modeled ZEV policies creating spillover effects associated with technological learning from EV adoption. These spillovers were found to justify regions implementing their own ZEV mandates to meet GHG targets. Linn and McConnell (2019) estimated the optimal innovation subsidy for EVs justified by learning-by-doing spillover, finding that spillover benefits appeared to be less than the current amount of government subsidies provided for EVs in the US. Adoption and investment in charging infrastructure in the short-term also generates spillovers in the form of positive externality benefits (and/or reduced costs) for future adopters. Fox, Jaccard, and Axsen (2017) demonstrated how capturing both dynamic effects on the supply (cost reductions from learning-by-doing) and demand side (neighbor effect and charging network) can lead to higher cost-effectiveness of technology-specific ZEV policy than if these dynamic factors are ignored.

While these studies innovatively simulate the long-term effects of several dynamic mechanisms, a limitation is that they analyze scenarios with policies tested one-at-a-time and implemented in isolation. For example, in Greene et al. (2014b) and Fox et al. (2017), the fuel economies of conventional and electric vehicles were projected separately and exogenously, which implicitly ignores how EV sales would contribute to and interact with existing fuel economy standards. This could lead to unaccounted lost progress in conventional vehicle fuel efficiency. When existing conventional technological options and policies are ignored or exogenously assumed to follow a static or fixed trend, the analysis can miss effects of policy interactions and pollution leakage, which could lead to underestimation of policy cost and/or reduce and negate some of the benefits of a technology or policy, and even some of the potential gains from dynamic effects.

1.2. Policy interaction and pollution leakage

Pollution leakage occurs when a policy has incomplete scope, jurisdiction, or geographic coverage, or a scope that overlaps with or is nested within a related policy's scope. For example, a state policy is typically nested geographically within federal policies. A policy may also be more stringent and/or more technology-specific than a related policy while addressing similar goals. Because these policies operate in markets, induced emissions reductions in one avenue "can simply make it less expensive for others to pollute," driving a "waterbed effect" (Fowlie, 2018).

The literature suggests that policy interaction and leakage can significantly erode a policy's environmental benefits and cost-effectiveness. Goulder et al. (2012) showed that nested GHG policy proposed by California could result in significant leakage, reducing the overall benefit of the policies. They analyzed three mechanisms of leakage: more stringent standard for new cars in certain states allows automakers to meet a less stringent standard for new cars in rest of US; more interest in used and existing cars, an effect exacerbated with nested policy coverage, reducing scrappage of existing stock of used cars; and technological spillover between regions, a "negative leakage effect" which counteracts regional leakage via development of technology available for deployment in both regions. They simulated the US car market to assess these "unintended consequences" and found the first two effects dominating the regional spillover effect. In another type of leakage, Jenn et al. (2016; 2019) showed that special accounting of alternative fuel vehicles (AFVs) in the CAFE standards and the combination of special accounting and ZEV mandates can amplify emission leakage into the rest of the non-AFV fleet under certain conditions. These analyses show that under fixed and binding environmental performance standards, nested policies that are more stringent can result in limited, redundant, or in some cases, negative environmental benefit. Table 4.1 shows a summary of various types of leakage in transportation energy and automotive policy.

Table 4.1: Types of leakage, their sources and sinks, and examples in transportation energy and automotive policy

Type of leakage	Pollution could leak to…	Examples	Literature
Geographical	other regions	Cars outside California/ZEV states	Goulder et al. (2012) Sykes & Axsen (2017)
Inter-sectoral	other parts of life cycle	Electric power, biofuel production Battery production	Yuksel et al. (2016) Tamayao et al. (2015)
Intra-sectoral	more VMT used cars existing cars	Rebound Deferred retirement Second car in household	Gillingham et al. (2016) Gruenspecht (1982) Archsmith et al. (2015)
Intra-fleet	larger cars light trucks	Less-regulated types of cars becoming more attractive and more polluting	Whitefoot & Skerlos (2012) Whitefoot et al. (2017)
Intra-fleet	non-EVs	Relaxed standard for non-EVs resulting from special accounting of EVs in CAFE and overlapping objectives	Jenn et al. (2016) Jenn et al. (2019)

1.3. Overall impact is unclear; new approach needed

Both dynamic effects and policy interaction effects can alter the estimated benefits and costs of technology-specific policy such as ZEV mandates. They are insufficiently considered in the literature on EVs and EV policy and it is unclear what their combined effect is on overall short- and long-run environmental outcomes and societal cost. In practice, when justifying policy intervention, policymakers and advocates have asserted the dominance of long-term benefits of dynamic cost reductions, but typically lack evidence on the magnitude and trajectory of the potential impact of actions today on future emissions reductions and net benefits, especially with consideration to the potentially counteracting effects of policy interaction.

Given the backdrop of fleet emission standards driving environmental outcomes, policies such as ZEV may produce potentially limited direct benefits due to leakage and policy interaction; however, they may generate indirect benefits via dynamic and spillover effects. Cost reductions due to technology-forcing policies could induce changes to the optimal future CAFE policy, leading to improved environmental outcomes and net societal benefit[59].

[59] Alternatively, EV cost reductions could cause future CAFE policy to cease to bind, which would be another way the benefits of technology-forcing policies may be realized. There may be scenarios and conditions where EVs and ZEV policy might cause CAFE overcompliance i.e. non-bindingness, leading to ZEV overtaking CAFE as the

Our approach explicitly models ZEV policy under the umbrella of CAFE/GHG standards. We allow the dynamic impacts of ZEV policy to be indirectly realized via the endogenous setting of CAFE standards. Several studies in the literature have attempted to model endogenous energy policy design by maximizing net societal benefit with respect to the stringency of the policy. van Benthem et al. (2008) estimated the optimal subsidy for solar photovoltaic installations by maximizing the net societal benefit from learning spillover. Beck et al. (2018) find the optimal subsidy for solar by maximizing societal welfare in a computable general equilibrium model. Linn and McConnell (2019) estimate the subsidy for electric vehicles where marginal societal benefit is equal to marginal cost of the subsidy (thus maximizing net societal benefit). This approach is also used to determine the optimal tax and subsidy for vehicles in Holland et al. (2016)[60] and is typical of models determining the optimal carbon tax. In contrast to this prior work, instead of simulating price-based policies (taxes and subsidies), we model existing “second-best” technology/sector-specific, performance/quantity-based policies (CAFE and ZEV standards/quotas), which can have more indirect and complex effects on the outcome and are more commonplace in real-world settings. We also note other work that study the impact of fleet standards on EV adoption (Carley, Zirogiannis, Siddiki, Duncan, & Graham, 2019; Fritz, Plötz, & Funke, 2019; Melton, Axsen, & Moawad, 2020; Ou et al., 2018; Sen, Noori, & Tatari, 2017; Zirogiannis, Duncan, Carley, Siddiki, & Graham, 2019); we build on this work and study a countervailing impact: the influence of EVs and EV policy on fleet standards.

2. Research Objectives

We investigate the following research questions:

- In the presence of policy interaction and leakage effects, can ZEV mandates reduce US light-duty fleet emissions dynamically by inducing increased stringency of future welfare-maximizing fleet standards (i.e. optimal CAFE)?
- Under what conditions do ZEV mandates increase social welfare?

3. Methods

3.1. Overview

We develop an integrated techno-economic model of the US new passenger car market, with three primary decision-making groups: consumers, firms, and government. Consumers determine demand by choosing among differentiated products (cars) according to random

governing driver of emissions reductions from light-duty transportation. This can be observed in the simulations by checking whether the optimal levels for CAFE are binding or not.

[60] under a limited scope of emissions sources

utility maximization. Automakers determine supply by deciding the prices and designs of their products to maximize profit in Nash equilibrium under policy constraints and oligopolistic competition. Finally, the federal government sets the stringency of fleet standards to maximize social welfare, given expectations of automaker and consumer responses (as a Stackelberg leader). Additional exogeneous factors, including ZEV mandates, can induce tightening of CAFE standards by changing the level of stringency that maximizes social welfare. We model this mechanism by simulating the dynamic effects of ZEV policy via cost reductions from technological experience and spillover. Policy interaction and leakage[61] effects are included as an inherent result of profit-maximizing firm behavior and incomplete/overlapping scope of regulations. The model is summarized in Figure 4.1.

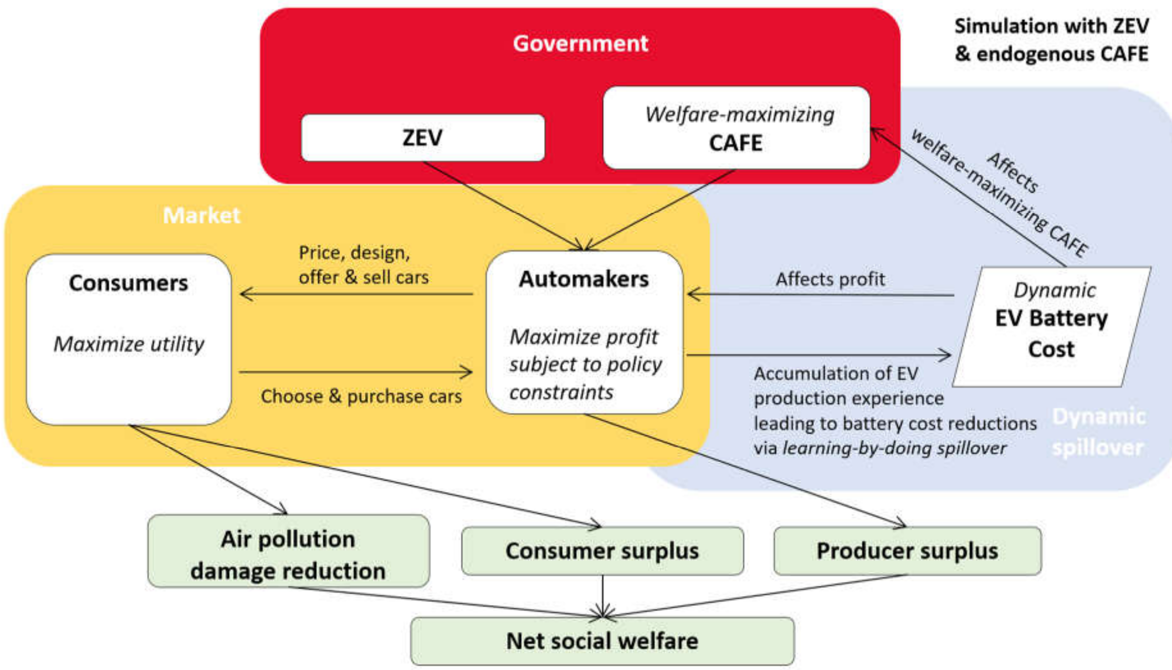

Figure 4.1: Model structure

3.2. Model of automotive market

We model firms and consumers making decisions that determine supply and demand of new passenger cars in the US[62]. We model oligopolist automakers maximizing the total net present value of expected profits from all their products over all time steps. The automakers do this by choosing their vehicle portfolios' prices and designs. Profit is modeled as a function of prices, costs, and sales based on demand of each vehicle variant, which is determined by a consumer

[61] In this study, we focus on representing intra-fleet leakages described in Table 4.1. Geographical and inter-sectoral leakage is not in the scope of this study, except for the partial consideration of life cycle impacts of electricity and fuels.

[62] For simplicity, we assume a single US market and ignore the regionality/jurisdictional aspect of ZEV embedded in CAFE

demand model. The automakers are subject to both ZEV and CAFE standards, which are modeled as constraints. The firm's optimization problem is represented by Eq. (1):

$$\text{maximize } \Pi_l = \sum_{t \in \mathcal{T}} \sum_{j \in \mathcal{J}_l} \{ q_{jt}(p_{jt} - c_{jt})(1 + r)^{-t} \} \tag{1}$$

w.r.t. $p_{jt},\ \mathbf{x}_{jt}\ \ \forall j, t$

subject to:

$$g_{lt}^{\text{CAFEGHG}} = s_t - \frac{\sum_{j \in \mathcal{J}_l} q_{jt} x_{jt}^{\text{GHG}}}{\sum_{j \in \mathcal{J}_l} q_{jt}} \leq 0$$

$$g_{lt}^{\text{ZEV}} = \frac{\sum_{j \in \mathcal{J}_l} q_{jt} x_{jt}^{\text{ZEV}}}{\sum_{j \in \mathcal{J}_l} q_{jt}} - z_t \leq 0$$

Indices	**Definitions**
$l \in \mathcal{L}$: firms $t \in \mathcal{T}$: time steps $j \in \mathcal{J}_l$: vehicle alternatives offered by firm l	Π_l: profit of firm l p_{jt}: price of product j in time t $\mathbf{x}_{jt}$: attributes of product j in time t x_{jt}^{GHG}: GHG rating of product j in time t r: discount rate considered by firms $q_{jt} = f_Q(p_{jt}, \mathbf{x}_{jt} \forall j)$: quantity of product j demanded and sold in time t $c_{jt} = f_C(\mathbf{x}_{jt})$: per-unit vehicle production cost of product j in time t g_{lt}^{CAFEGHG}: Corporate Average Fuel Economy / Greenhouse Gas (CAFE/GHG) constraint for firm l and in time step t g_{lt}^{ZEV}: ZEV quota constraint for firm l and in time step t s_t: CAFE/GHG standard in time step t z_t: ZEV quota in time step t

3.2.1. Consumer demand

We model the demand of new[63] passenger cars in the US with a discrete choice model with logit specification, informed by estimated parameters in the literature. This model predicts market shares based on consumer preferences and the prices and attributes of alternatives.

$$f_Q = \frac{1}{N} \sum_{i}^{N} m_i \frac{\exp(\alpha_i p_{jt} + \boldsymbol{\beta}_i \mathbf{x}_{jt})}{\sum_{l \in \mathcal{L}} \sum_{j \in \mathcal{J}_l} \exp(\alpha_i p_{jt} + \boldsymbol{\beta}_i \mathbf{x}_{jt})}$$

[63] Although the used car market is a source and sink of policy leakage as shown in Goulder et al. (2012), we do not plan to model the used car market explicitly. An outside good in the demand model could represent the choice of used cars (along with no-purchase), but we assume a fixed 17M market size for consumers purchasing new vehicles in the US annually.

Where α_i is the coefficient for price preference for consumer group i, $\boldsymbol{\beta}$ is the vector of coefficients for attribute preferences for consumer group i, $i = \{1, \ldots, N\}$ is the index for random draws representing consumers, and m_i is the market size of each consumer group.

This equation predicts the demand for a vehicle alternative based on the market size m and the choice share probability based on a random utility model with logit specification. The summation is a discrete approximation of a mixed logit model where α and $\boldsymbol{\beta}$ are continuously distributed preference parameters. The current implementation of the model draws only once (N=1) from point values for α and $\boldsymbol{\beta}$, which collapses the model into simple logit with homogeneous preferences.

We use stated preference (SP) estimates from Helveston et al. (2015), which were based on survey data collected from Amazon Mechanical Turk and the Pittsburgh Auto Show during 2012-13[64]. We caveat that consumers in that study had limited exposure and experience with EVs and that EV technology, offerings, and associated preferences (range anxiety, charging) may change going forward. We conduct sensitivity and scenario analysis on the willingness-to-pay (WTP) for EV parameter, discussed below in implementation.

3.2.2. Vehicle production cost

$$f_C = c^{\text{BASE}} + \begin{cases} f_{C^{\text{ENGINE}}}(\mathbf{x}_{jt}) \ \forall\ k = G \\ c^{\text{EVNONBAT}} + x_{jt}^{\text{EVBATSIZE}} * f_{C_t^{\text{BAT}}} \ \forall\ k = E \end{cases}$$

The vehicle production cost for gasoline and electric vehicles share a common base cost and differ in the remaining powertrain component costs, such as engine costs for gasoline vehicles, and battery and non-battery costs for electric vehicles.

3.2.3. Gasoline vehicle engine cost

We use equations derived by Whitefoot et al. (2017) based on engineering simulations and NHTSA cost estimates to define relationships between gasoline vehicle attributes and engine costs. Cost decreases with increasing acceleration time (i.e. smaller engine), with diminishing returns, and is specified by:

$$f_{C^{\text{ENGINE}}} = 1000\gamma_1 + 1000\gamma_2 \exp\left(-\frac{x^{\text{ACC}}}{10}\right) + \gamma_3 x^{\text{WT}} + \frac{\gamma_4 x^{\text{ACC}} x^{\text{WT}}}{10}$$

---

[64] Comparing the SP WTP estimates from Helveston et al. (2015) with revealed preference (RP) WTP estimates for acceleration time and fuel economy from Whitefoot et al. (2017), we find that the estimated WTP for acceleration time is 1-2x larger ($1200/sec improvement vs. $800/s) in the SP estimate compared to the approximate mean of the RP estimate, and the estimated WTP for fuel economy improvement is 2-3x larger (depending on the fuel economy level). For context, based on the estimates of WTP for fuel economy, I estimate the equivalent implied consumer discount rate to be in the order of 10% in Helveston et al. (2015) and 15-25% in Whitefoot et al. (2017).

where $f_{C^{\text{ENGINE}}}$ is unit-cost in \$ per unit, x^{ACC} is acceleration time (0-60 mph) in sec, x^{WT} is weight in lb, and the γ terms are parameters fit to engineering simulation results from Whitefoot et al. (2017).

3.2.4. EV battery cost reduction

We represent the impact of learning-by-doing via the industry-wide unit-cost (\$/kWh) reduction of EV battery packs from cumulative production experience. This is commonly modeled in the literature by a power-law learning curve (Matteson & Williams, 2015; Rubin, Azevedo, Jaramillo, & Yeh, 2015), which can be written as follows:

$$f_{C_t^{\text{BAT}}} = c_0^{\text{BAT}} * \left(\frac{Q_0 + \sum_{j\in\mathcal{J}}\{q_{j,\ t-1}^{\text{EV}} x_{j,t-1}^{\text{EVBATSIZE}}\}}{Q_0}\right)^{\log_2(1-\theta^{\text{LR}})}$$

This relationship is a model of technological cost reduction from the mechanisms of learning-by-doing, economies of scale, and R&D. The industry-wide EV battery production cost is modeled to fall as a function of cumulative production experience. The model is based on the power-law experience curve model, estimated on historical industry-wide EV battery price data (proxy for cost assuming fixed quality) correlated with cumulative EV battery production, a proxy for cumulative experience. The learning rate, θ^{LR}, represents the reduction in unit cost (\$/kWh) in an EV battery pack per doubling of cumulative production experience.

Many studies (Alberth, 2008; Ferioli, Schoots, & van der Zwaan, 2009; Gillingham, Newell, & Pizer, 2008; Nemet, 2006; Nordhaus, 2014; Pizer & Popp, 2008; Popp, 2019; Söderholm & Sundqvist, 2007; Taylor & Fujita, 2013) have discussed the suitability of using learning curves to represent technological change in energy-economic models. One key limitation is a lack of causality and identifiable mechanism when using industry-average price data correlated with a crude measure of industry-wide application-specific cumulative experience. The unit of analysis is often poorly defined, affecting data quality and specificity[65]. A firm's cost reductions may arise from learning-by-doing via a firm's own production experience, but are conflated by concurrent trends of economies of production scale (larger factories and production lines), economies of unit scale (larger battery packs), innovations in materials and product design that are independent of production, gains from R&D, and importantly, from non-appropriable spillover of direct and indirect competitor production experience and learning.

[65] Data for battery prices can vary significantly when there is ambiguity whether prices are at the cell- or pack-level, when prices do not reflect cost in an emerging market, and/or when battery chemistries, countries of production, or battery pack size differ, but the data do not specify and include values lumped together.

3.2.5. Spillover from dynamic and policy interaction effects

An additional complexity of modeling cost reductions from learning-by-doing is the appropriability and non-appropriability/spillover of learning-by-doing. Linn and McConnell (2019) and Muehlegger and Rapson (2019)(forthcoming) discuss the economic rationale for policies that address the market failure of non-appropriable learning spillover. Non-appropriable learning spillover occurs when firms learn and benefit from the production experience and investments of other firms. This is distinct from appropriable learning effects, which are within-firm cost reductions from investments and experience, where there are no discernable market failures. Linn and McConnell (2019) and Muehlegger and Rapson (forthcoming) identify several mechanisms: reverse-engineering of products, observing and adopting material selection, product design, production processes, and best practices, sharing of supply chains and inadvertent sharing of knowledge, and workforce transfers. Some of these mechanisms can be partially restricted by intellectual property protections, non-compete terms in employment contracts, or exclusivity clauses in supplier contracts.

We note that the literature on non-appropriable learning distinguished from appropriable learning is limited. A few studies have found that learning spillovers have been small in specific energy technology and automotive production contexts. Bollinger and Gillingham (2019) estimate the non-hardware costs of residential solar installations and estimate the appropriable and non-appropriable learning that occurred in the form of installation cost reductions in California residential solar installations 2002-2012. They find low amounts of non-appropriable learning spillover, compared to the learning that happens within firm and the cost reductions in the module and non-module/balance-of-system hardware costs.

In studies that simulate learning-by-doing using an industry-wide power-law learning curve, van Benthem et al. (2008) and Beck et al. (2018) observe the historic learning rate for solar PV and halve it to account for appropriability (and test other values in sensitivity analysis). Linn and McConnell (2019) apply 8% and 20% learning rates for EV batteries, based on Nykqvist and Nilsson (2015) and (Nykvist, Sprei, & Nilsson, 2019). They argue that their application should be considered as an “upper bound” on the cost reductions that are not fully captured by individual firms due to appropriability.

The present work attempts to simulate an optimistic case for the impact of learning-by-doing on the benefits of ZEV policy and therefore, a high level of non-appropriable learning-by-doing spillovers may be appropriate. However, assuming a correspondingly low level of appropriable learning may not represent the upperbound of the potential learning effect and incentive for firms to invest. Nevertheless, due to a lack of firm-specific data, the current version of the model ignores the appropriability of learning-by-doing and cost reductions and assumes industry-wide cost reductions come from the experience of all firms (complete spillover). All production experience from all firms is assumed to benefit the entire industry. This model represents large non-appropriable learning spillovers (as estimated from the industry-wide learning curve) and zero appropriable learning.

3.2.6. CAFE/GHG standard

In the US, the CAFE standard has been set jointly with GHG standards under a "National Program" since 2010. This study implements the GHG version of the standards, given the relative severity of the penalty for non-compliance of the GHG standard.

This standard forces the sales-weighted average GHG performance of the automaker's fleet of vehicles to be under the GHG standard s_t at each time step. The existing current US standards in place are footprint-based and the regulatory obligations are bankable, borrowable, and tradeable, but we use a simplified implementation where automakers comply with the standard with their own fleet in every time step. The existing standards also give special treatment to EVs and their emissions (Jenn et al., 2019), but we do not include these additional mechanisms. We account for consequential life-cycle emissions associated with gasoline and electricity consumed in the use phase (vehicle operation), including upstream fuel-cycle emissions, but exclude vehicle and battery production emissions and product end-of-life emissions. Details about the marginal emissions factors used to calculate the GHG emissions of vehicles can be found in the appendix.

3.2.7. ZEV quota

This constraint measures the proportion of an automaker's fleet of vehicles against the quota z_t at each time step. The existing current quotas in California and 9 other states offer a varied number of credits for zero-emissions-vehicles according to their type and performance such as range, but we use a simplified version with a single credit, extrapolated to the national level, and we ignore banking, borrowing, and trading.

3.2.8. Vehicle fuel economy

$$x_{jt}^{\mathrm{FE}} = \begin{cases} f^{\mathrm{FE}}(\mathbf{x}_{jt}) \ \forall\, k = G \\ x_{\mathrm{EV}}^{\mathrm{FE}} \ \forall\, k = E \end{cases}$$

Gasoline vehicle fuel economy are based on empirical relationships from Whitefoot et al. (2017) which were derived from engineering simulations using AVL Cruise. Fuel consumption is calculated as a function of acceleration using their estimation of the Pareto frontier developed through simulation and design of experiments (equivalent to treating fuel consumption as a free variable and constraining the solution to lie on the Pareto frontier).

3.3. Federal government, regulatory impact assessment, and policy setting

When setting future levels of the CAFE standards, the US EPA and NHTSA agencies conduct a cost-benefit analysis of the regulations, and in the past, this analysis has been used to set the regulatory stringency to the level that maximizes net societal benefit. During this process, the agencies consider the costs and effectiveness of fuel-saving technologies and factor this into the stringency of the regulations. We represent the effect that technology costs have on the stringency of the CAFE/GHG standards by modeling the standards as set at the level for which marginal costs equal marginal benefits. This allows the federal standards to be updated dynamically based on new information, particularly about newly realized cost reductions from ZEV-induced adoption of electrified technologies. We note that this is an oversimplification of the agencies regulatory process, and that the stringency of the standards is not always set at the level for which marginal costs equal marginal benefits. The cost-benefit analysis is one component of the rulemaking process; in practice, additional factors have also impacted the choice of the stringency level, including negotiating standards across the state and federal entities involved.

While we simplify the entire process into a strict cost-benefit calculation, we also enhance the complexity of the cost-benefit analysis compared to the EPA/NHTSA's analysis by including endogenous producer and consumer decision-making and allowing for impacts on producer and consumer surplus from changes in product prices and designs. This is in contrast to the EPA/NHTSA estimation of costs and benefits, which assumes vehicle demand remains fixed at an exogenously specified level despite price and design changes. Their methodology calculates technology costs and undervalued fuel savings[66] as the main impacts on producer and consumer surplus from new vehicles. In our modeling, technology costs and changes in fuel economy are part of the firm's and consumer's consideration and are reflected in changes in producer and consumer surplus. Our modeling currently assumes consumer valuation of fuel economy according to WTP results estimated by Helveston et al. (2015) and we do not count undervalued fuel savings towards social welfare. We also assume hidden costs of fuel-savings benefits are fully captured in the WTP (disutility) for EV estimated parameter from Helveston et al. (2015) and we vary this parameter in sensitivity analysis. Future work will include further sensitivity analysis on the WTP for fuel economy and consideration of uncounted/undervalued fuel savings as social welfare.

However, our implementation does not include a full multi-market model that includes impacts on VMT, rebound, and used cars, as recommended by Bento et al. (2019). This study attempts to isolate the effect of interest, which is the role of ZEV policy on short- and long-term environmental and net societal benefit. Although EVs may be driven more or could cause changes in the used car markets, these impacts are outside of the scope of this study.

3.4. Equilibrium Modeling Approach

We formulate the entire problem as a Stackelberg-type bi-level optimization problem. At the upper level, we model the federal government as a Stackelberg leader that anticipates the responses of automakers when it sets the CAFE/GHG standard $s_t \forall t$. At the lower level, firms fall into Nash equilibrium given the government-specified CAFE/GHG standard and an exogenously specified level of ZEV.

[66] "Undervalued fuel savings" assumes a degree of consumer myopia, as well as gasoline price perceptions and discount rates. Busse, Knittel, and Zettelmeyer (2013) find "little evidence of consumer myopia." See (Gillingham, Houde, & van Benthem, 2019; Leard, 2018; Xie & Lin, 2017) for further discussion.

At the upper level, the government seeks to maximize the net social welfare benefit of a policy scenario[67]:

$$\text{maximize}\,\psi = \psi^{\mathrm{PS}} + \psi^{\mathrm{CS}} - \psi^{\mathrm{ED}}$$

w.r.t. $s_t \forall t$

ψ^{PS}: producer surplus, measured in total firm profits.

ψ^{CS}: consumer surplus, measured by equivalent variation following Small and Rosen (1981). This is calculated as the sum of the expected value of the relative willingness-to-pay of each consumer's purchase less their prices. This can also be thought of as the total relative price-adjusted monetized utility of products purchased by consumers.

ψ^{ED}: environmental damages, measured in total monetized marginal damages from four major air pollutants (CO_2, NO_x, $PM_{2.5}$, SO_2) associated with the lifetime use of the products purchased by consumers. Full fuel-cycle emissions are included (well-to-wheels), but production and end-of-life-associated emissions (such as those from battery production) are currently excluded. Other environmental externalities such as other air pollutants, water pollution, and noise are not included.

s_t: CAFE/GHG standard for time t

The equations, assumptions, and data sources for calculating producer surplus, consumer surplus, and environmental damages are in Appendix A.

At the lower level, firms are modeled to be in Nash equilibrium, where each firm maximizes the total net present value of expected profits from all their products over all time steps according to Eq. (1). The firms decide the prices and attributes of their vehicle offerings.

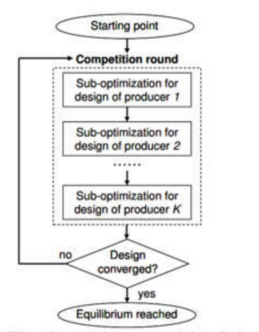

Figure 4.2: Sequential iterative approach to solving firm Nash Equilibrium problem, from (Shiau & Michalek, 2009)

[67] We ignore the no-policy baseline scenario's benefit and cost, because they are not affected by decision variables and they do not affect where the optimal solution lies. This means that the value of ψ cannot be interpreted with any real-world meaning.

We attempt to solve this bi-level optimization problem with several numerically-approximated-local-gradient-based and non-gradient-based optimization algorithms, where the Nash equilibrium between firms is solved via sequential iterations. Figure 2 illustrates the sequential approach as presented by (Shiau & Michalek, 2009). The profit maximization problem is solved individually for each firm l, while holding the pricing and design decisions of all other firms $p_{jt\setminus\mathcal{J}_l}$, $\mathrm{x}_{jt\setminus\mathcal{J}_l}$ fixed. This is done for each firm sequentially until all firms cannot achieve a better profit by moving unilaterally. This approach is easy to implement (analytical solutions do not need to be derived, constraints are supplied to the optimization algorithms as-is) but this approach can be computationally intensive.[68]

In theory, this type of Stackelberg bi-level optimization problem could be solved numerically by finding a solution for both the upper-level government problem and the lower-level firm equilibrium. However, because the lower level problem is solved computationally, this approach produces imprecise solutions due to numerical noise, which can mislead the optimization algorithm used to solve the upper level problem. To avoid this problem, we solve the upper-level government problem using an exhaustive grid search across values of the CAFE/GHG standard, and we observe the values when net social welfare benefits are maximized. The grid search for the results presented below was performed for CAFE/GHG standards ranging from 0-50 mpg, with more granular simulations where local optima were detected.

[68] An alternative approach is to find solutions that simultaneously satisfy each firm's KKT FOCs, which can be represented as constraints, thereby creating a Mathematical Problem with Complementary Constraints (MPCC). (Biswas & Hoyle, 2019) review the advantages and disadvantages of various methods for solving bi-level optimization problems. This approach may be considerably faster than sequential iterations. However, solutions may not be minima and require checking second-order sufficiency conditions or Nash equilibrium criteria, which could increase overall time to find an equilibrium depending on the nature of the problem and solution space. We expect that a carefully formulated FOC approach could solve for equilibrium much more quickly than the iterative approach, which would help run cases and scenarios faster and allow us to explore larger parameter spaces and in more dimensions. We leave this for future work.

4. Results and Discussion

4.1. Model implementation of policy scenarios and cases

In a simplified model implementation that demonstrates the key mechanisms driving how ZEV affects social welfare, we instantiate the model with 2 firms, each producing 1 vehicle design per fuel type (gasoline and electric), resulting in 2 products per firm and a total set of 4 vehicle alternatives in the market. The decision variables for the firms are $p_{jt} \forall j, t$, the vehicle price for all vehicles in all time steps, and $\mathbf{x}_{jt} \forall j \in \mathcal{J}^{\mathrm{GASOLINE}}, t$, a vector of vehicle attributes for gasoline vehicles in all time steps, consisting of the 0-60 mph acceleration time, and the tech parameter, representing the discrete number of fuel-saving technologies implemented in the vehicle design, based on physical simulations and estimated relationships in Whitefoot et al. (2017).

We include two time steps in the model, each representing a period of five years. In the first time step, we implement an exogenous ZEV quota at several levels that may bind. When binding, we expect the ZEV policy to force more EVs than the market would have without the policy. In the second time step, we simulate various levels of CAFE and find the scenario that produces the maximum net social welfare (via the grid search approach). To isolate the effect of ZEV in a prior time step on optimal CAFE in a future time step, we set the other policy to be non-binding[69] in the same time step i.e. non-binding CAFE in time step 1 and non-binding ZEV in time step 2. This is summarized in Table 4.2.

We note that these scenarios are a gross simplification of the real-world and foreseeable implementation of CAFE and ZEV[70]. The construction of these scenarios allows us to represent the counterfactual cases so we can see the isolated impact of ZEV in time step 1 on welfare and optimal CAFE in time step 2. However, these scenarios fail to represent the more complicated picture when both policies bind and interact—for example through geographic/jurisdictional and intra-fleet leakage. Future work will characterize where these non-binding levels are and what happens in scenarios where both policies bind and interact in both time steps.

Table 4.2: Policies in simulated scenarios

Time period, t	1	2
ZEV [% ZEV], z_t	$z_1 = \{0, 25, 50\}$	$z_2 = 0$ (non-binding)
CAFE [mpg], s_t	$s_1 = 0$ (non-binding)	$s_2 =$ level at which social welfare is maximized

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[69] This is equivalent to setting the other policy up to its binding level (the firms will respond with the same decisions and all model results will be the same).
[70] CAFE and ZEV requirements currently exist and likely bind in both current day and in the near future. They are also both likely to change slowly and/or increase in stringency rather than arbitrarily switch from binding to non-binding (high and binding ZEV requirements and then no ZEV requirements) or vice-versa (no CAFE and then binding CAFE) as we set up in the simulated scenarios.

In addition to simulating scenarios given different sets of policies, we consider and explore two key parameters, represented in two cases – optimistic and pessimistic EV cases. In the optimistic EV case, we assume low consumer disutility for EVs and low non-battery costs of EVs, whereas in the pessimistic EV case, we assume high values for both parameters. Finally, we vary the SCC given the high level of uncertainty in the value of GHG mitigation. Details of this can be in Table 4.3.

Table 4.3: Key non-policy parameters varied in simulated scenarios

Parameter	Description	Values in optimistic case	Values in pessimistic case	Description
$-\frac{\beta_{\mathrm{EV}}}{\alpha}$	Monetized consumer utility (WTP) associated with BEV relative to conventional vehicles	-$6000	-$12000	Based on Helveston et al. (2015), adjusted for EV range of 200 mi[71]
c^{NONBAT}	Costs of EV powertrain that are not affected by learning-by-doing	$1000	$4000	Based on Lutsey and Nicholas (ICCT) (2019), UBS (2017) teardown, and other projections (Hummel et al., 2017; Lutsey & Nicholas, 2019)[72]

[71] We vary the consumer disutility for EVs, the preference (or disutility) of the electric vehicle fuel type (all other attributes equal). Helveston et al. (2015) estimated a WTP of -$12000 for the "BEV150" (Battery Electric Vehicle with 150 mi range) fuel type compared to the conventional gasoline fuel type. Given significant changes in the EV market since 2012, the disutility and negative WTP for EVs based on EV range could very well be lower (improved knowledge in consumers, improved availability of charging infrastructure, overestimation by survey respondents) or higher (exhaustion of early adopters and technology enthusiasts, underestimation by survey respondents). We also test a value of -$6000 to account for the 200-300 mi electric range of typical modern EVs. This value is a linear extrapolation based on electric range.

The literature contains a wide range of estimates for WTP of electric vehicles and their range. Greene et al. (2018) review the literature for WTP for vehicle attributes and found a trimmed range of -$44k to +$31k and a mean of -$8k for EV (of an unspecified electric range). The trimmed range for WTP for range was -$20 to +$243 /mi, with a mean of $86/mi. Dimitopoulos et al. (2013) reviewed 33 SP studies and found a 95% confidence interval for the value of 1 mi in range: $29-104, mean of 66-75 (2005$). As discussed, Helveston et al. (2015) estimated a mean WTP of -$12k for EV150 (-$17k for EV75 and -$18k for EV100). We note problematic inconsistencies in definition of WTP for EV and range within and between studies that make values in the literature difficult to interpret and use.

The value of -$6k is a linear extrapolation of the WTP for an EV with 200 mi range. A rough estimate of the value of the additional 50 mi would be $3k, resulting in a -$9k disutility (WTP EV200 over gasoline). Caveats include: 1) Stated preference studies may not accurately reflect what people think when they consider a purchase. 2) Infrastructure, familiarity, and understanding of range affects valuation of range and range anxiety. 3) Value of range likely to be highly non-linear. High diminishing returns to increases in range as range is more than several multiples of a typical daily commute and/or approaches gasoline vehicle range.

[72] We vary the cost of producing the EV powertrain excluding the battery pack, which is meant to account for the electric motor, power electronics, charger, and other indirect/integration costs of EV manufacturing that are on top

θ^{SCC}	Social cost of carbon (SCC) [in $USD 2020 / metric ton of CO2]	$200	$50	Approximation of values from the Interagency Working Group on the Social cost of Greenhouse Gases (IWG) ((IWG), n.d.). SCC varies by year and discount rate and depends on projected future state of world, among many other assumptions. Revesz et al. (2017) suggest the use of $50/t (2020) as the "best estimate of the social cost of greenhouse gases." Ricke et al. (2018) find much higher SCC values and range (66% confidence intervals of $177-805/tCO2).

of the base cost of vehicle manufacturing. This parameter also includes credits for the gasoline fuel system and emissions controls systems that do not need to be installed in EVs. EV costs are highly uncertain and vary significantly in the literature. In this implementation, this parameter represents the cost gap between EVs and gasoline vehicles, excluding the production cost of the battery that benefits from learning-by-doing. We estimate values of $1000 and $4000 based on ICCT (2019) and UBS (2017) teardown study.

4.2. Results and Discussion

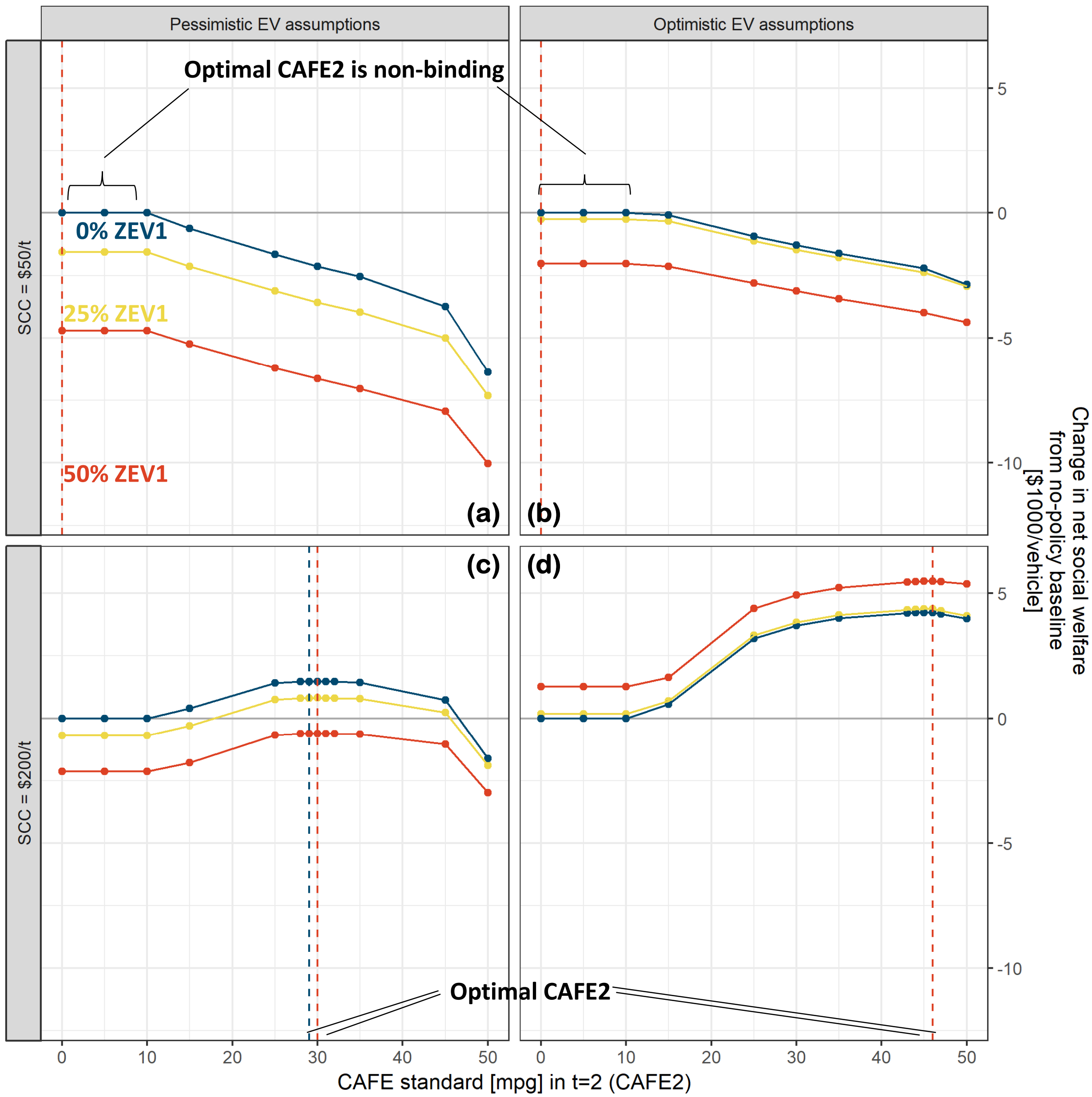

Figure 4.3: Change in net social welfare from the no-policy baseline (y-axis values) under three levels of ZEV requirements in time step 1 (ZEV1) (blue, yellow, and red), various levels of CAFE stringency in time step 2 (CAFE2) (x-axis), and four sets of model assumptions (rows and columns). Dotted lines show the CAFE level at which net social welfare is maximized. Change in net social welfare are relative to each scenario's no-policy baseline.

The effects of CAFE and ZEV on social welfare depend on model assumptions about EV costs and consumer preferences and the social cost of carbon (SCC). A binding CAFE policy increases net social welfare when assuming a SCC of $200/t (c,d) and decreases it when

assuming a SCC of $50/t (a, b). A binding ZEV policy increases net social welfare when assuming a SCC of $200/t and optimistic EV costs and consumer preferences (d), and decreases it in the other simulated scenarios (a,b,c).

Figure 4.3 shows how the net social welfare changes for three levels of ZEV requirements in time step 1 (ZEV1) and four sets of model assumptions. The dotted lines show the level of the CAFE standard for time step 2 (CAFE2) where net societal welfare is maximized given the level of ZEV1.

In cases with lower SCC (a, b), net societal benefit is at its maximum at fuel economy levels at or below the unregulated equilibrium for fuel economy (i.e. when CAFE2 does not bind as a policy constraint and does not affect decisions). Beyond that level, additional stringency in CAFE2 causes net social welfare to fall. This is consistent with recent literature on CAFE, showing that the estimated compliance costs of the policy has been equivalent to $50-300/t (Gillingham and Stock, 2018).

In the cases with higher SCC (c, d), there are values of CAFE that increase net social welfare. For the EV pessimistic case, we find that the social welfare optimal CAFE level in time step 2 is between 29-30 mpg depending on the value of ZEV in time step 1. For the EV optimistic case, we find that it is between 45-46 mpg. We find that a higher level of ZEV in time period 1 does indeed result in a higher optimal CAFE standard in time period 2 due to EV cost reductions from learning. The shifts in the optimal CAFE arising from higher ZEV standard are on the order of 1 mpg, as shown by the dotted lines shifting to the right in Figure 4.3. The change in net social benefit also is fairly flat in the region of the optimal CAFE, indicating that relatively small changes in net social welfare ($100/vehicle) within +/-10 mpg of the optimal value of CAFE. This result likely depends on the assumptions in the logit model and vehicle options represented in the simulations.

We note two phenomena of interest in case (d). A higher ZEV policy in the previous step raises the net societal benefit at the same CAFE level; and it also changes where net societal benefit is maximized (optimal CAFE in time step 2 increases when ZEV in the previous step is higher). Both of these effects contribute to increased net societal benefit induced by the ZEV policy (assuming CAFE is set according to net societal benefit maximization).

Whether the ZEV requirements increase net social welfare or not depends on factors including but not limited to consumer preferences for EVs and EV costs. We find that in three out of the four cases (a, b, and c in Figure 4.3), ZEV policy reduces net social welfare. In the case where the social cost of carbon is high ($200), consumer disutility for EVs is low, and EV non-battery costs are low (case d in Figure 4.3), ZEV policy in time step 1 increases net social welfare. To understand what drives the net change, we examine the breakdown in net social welfare changes in Figure 4.4 and scenario results in Table 4.4.

Table 4.4: Summary results[73] from cases and policy scenarios

Scenarios	**(a) P - 50**		**(b) O - 50**		**(c) P - 200**		**(d) O - 200**	
EV assumptions	Pessimistic		Optimistic		Pessimistic		Optimistic	
WTP_EV [$]	-12000		-6000		-12000		-6000	
Non-battery costs [$]	4000		1000		4000		1000	
SCC [$/tCO2]	50		50		200		200	
Outcomes given ZEV %								
ZEV [%] at t=1	0	50	0	50	0	50	0	50
EV sales share [%] in t=1	13	50	21	50	13	50	22	50
EV sales share [%] in t=2	15	17	26	28	28	31	47	48
Optimal and binding CAFE [mpg] at t=2	0-12	0-12	0-14	0-14	29	30	45	46
FE [mpg_e] in t=1	16	26	18	26	16	26	18	26
FE [mpg_e] in t=2	17	17	19	19	40	42	72	73

[73] Results so far rely on a homogeneous logit demand model specification and market scenario comprised only the compact car segment with two firms producing a total of four vehicle options as an illustrative case. Results are likely sensitive to these assumptions and specifications.

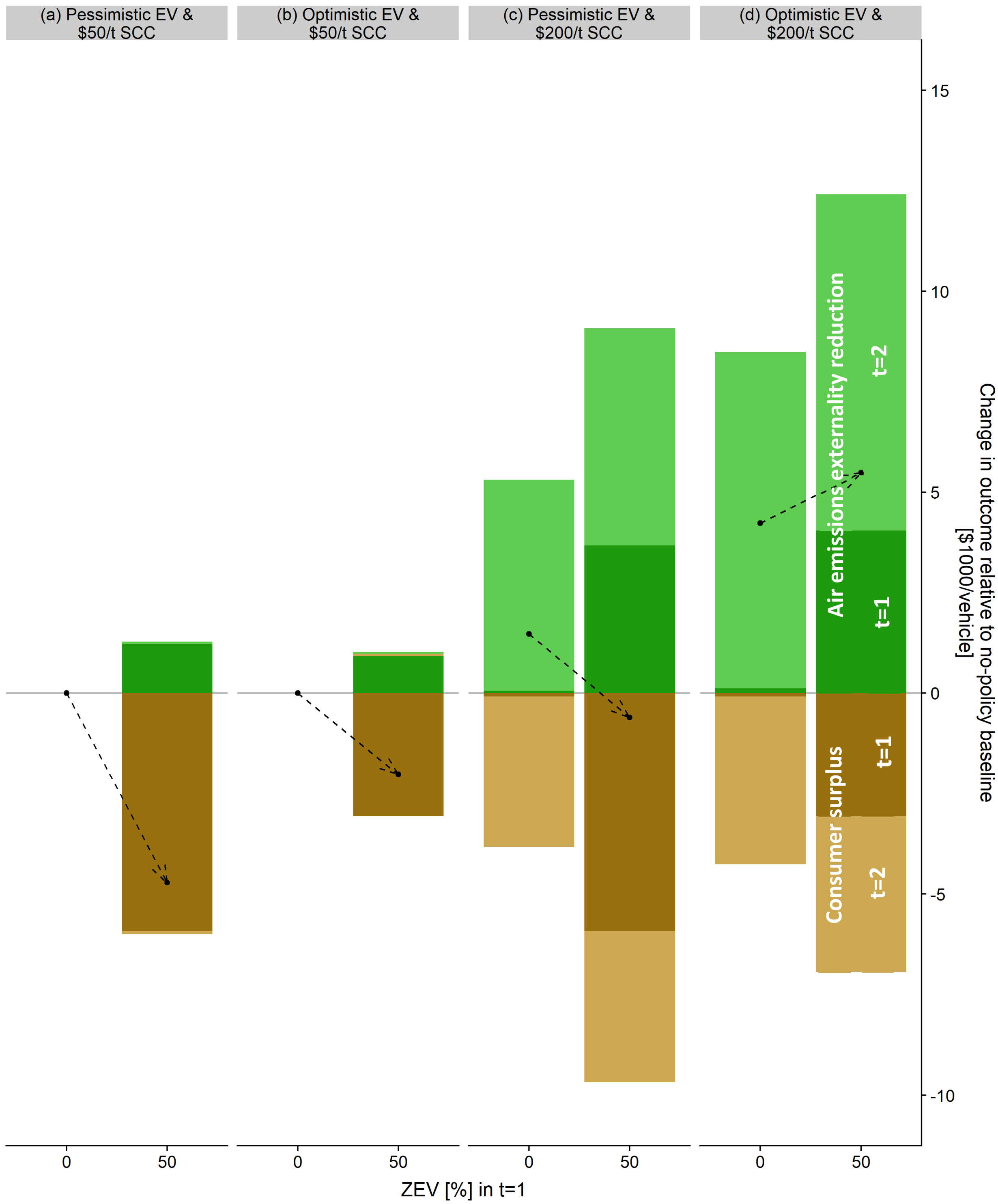

Figure 4.4: Societal outcomes under two levels of ZEV requirements in time step 1 (and their associated optimal levels of CAFE in time step 2) (pairs of bars) and four sets of model assumptions (columns). Dots represent net societal benefit in each scenario. All quantities are relative to baseline scenario outcomes. A third category of outcomes, producer surpluses, did

not change from the baseline in the cases and scenarios tested, and therefore do not show up as colored bars.

In (a) and (b), which use a $50/t SCC, the optimal CAFE2 is non-binding, so when ZEV1 is 0%, neither policy is binding and there are no changes in outcomes compared to the baseline no-policy case. ZEV quotas of 50% result in large reductions in consumer surplus and small increases in environmental benefit during the first time step (and no impact on the second time step because the optimal CAFE2 are still non-binding). As a result, ZEV causes drops in net social welfare.

In (c) and (d), which use a $200/t SCC, the optimal CAFE2 is binding. With ZEV of 0% at time period 1, the reduction of air emissions externalities from a binding optimal CAFE outweigh consumer surplus losses, resulting in a net benefit. ZEV quotas of 50% in time period 1 increase both environmental benefit (because valued damages are larger) and consumer surplus losses (because consumers prefer gasoline vehicles over EVs). In case (c), with pessimistic EV assumptions, ZEV decreases net social welfare due to large consumer utility losses outweighing reduction in pollution damages. In case (d), with optimistic EV assumptions, ZEV increases social welfare because consumer utility losses associated with EVs are smaller and are outweighed by their reduction in pollution damages.

The optimistic EV assumptions in (d) compared to (c) result in several nuanced impacts on the net social welfare of ZEV policy, which are worth unpacking. First, optimistic EV assumptions result in a large EV share in the baseline no-policy scenario. This reduces the change in benefits and costs attributable to a given ZEV policy since the counterfactual baseline would already include a large number of EV sales and associated benefits and costs. We see this in the results for a 25% ZEV quota are fairly close to the 0% quota (yellow and blue lines in Fig. 4.3 in (b) and (d)). This is because the model computes an EV market share of 21% (b) and 22% (d) in the no policy case, and therefore ZEV quotas below this level do not produce any change in social welfare in these cases and that the impact of a ZEV quota of 50% is being measured against a baseline no-policy scenario that already has a significant amount of EVs and their corresponding costs and benefits. Second, optimistic EV assumptions reduce consumer surplus losses associated with EV adoption. Third, optimistic EV assumptions may reduce the influence of cost reductions from learning-by-doing, reducing the policy-induced change in EV share. In case (d), we see the combined effect of the optimistic EV assumptions leads to smaller consumer surplus losses from CAFE (in time step 2) than in case (c), which comes from the higher level of EV cost reduction induced by the ZEV policy.

We find that when ZEV and optimal CAFE are binding, ZEV mandates result in increased optimal CAFE levels. We also find that ZEV mandates reduced social welfare in three simulated cases and increased social welfare in one case. This depends on whether environmental benefits of EVs outweigh reductions in consumer surplus and other effects and these depend on various inputs and assumptions. We summarize the key outcomes in Table 4.5.

Table 4.5: Key outcomes[74] from cases and policy scenarios

Scenarios	(a) P - 50	(b) O - 50	(c) P - 200	(d) O - 200
EV assumptions	Pessimistic	Optimistic	Pessimistic	Optimistic
WTP_EV [$]	-12000	-6000	-12000	-6000
Non-battery costs [$]	4000	1000	4000	1000
SCC [$/tCO2]	50	50	200	200
Key outcomes				
Is the optimal CAFE level binding at time period 2? [75]	No	No	Yes	Yes
Does ZEV result in a higher optimal CAFE in time period 2?	No	No	Yes	Yes
Does ZEV increase social welfare?	No	No	No	Yes

5. Conclusions

5.1. Key findings

CAFE and ZEV policy can have dynamic effects on consumer choice, firm decisions, and reduction in environmental damages. To understand their potential interaction and overall impact on social welfare, we simulate firms pricing and designing gasoline and electric vehicles under the two policies over two time steps representing five years each. We explicitly represent cost reductions from learning in EV battery pack production and account for policy-induced changes in producer surplus, consumer surplus, and use-phase air pollution damage reductions. We find that in the cases we tested, when assuming a lower social cost of carbon, the optimal CAFE level is non-binding, and ZEV mandates reduce social welfare. When assuming a higher social cost of carbon, the optimal CAFE level is binding, with higher ZEV mandates in the previous time period inducing higher optimal CAFE standards because of cost reductions from learning. In these cases, ZEV may either increase or decrease social welfare, depending on whether environmental benefits of EVs outweigh reductions in consumer surplus and other effects.

Our results suggest that the ZEV policy can cause the social-welfare-maximizing level of fuel economy standards to be tighter and can either reduce or improve social welfare. Whether ZEV standards and resulting increases in optimal CAFE standards increase net social welfare depends on assumptions including but not limited to the disutility and cost of electric vehicles, as well as environmental externality valuation.

[74] Results so far rely on a homogeneous logit demand model specification and market scenario comprised only the compact car segment with two firms producing a total of four vehicle options as an illustrative case. Results are likely sensitive to these assumptions and specifications.
[75] This is equivalent to "Can increasing CAFE2 beyond the binding level enhance welfare?"

5.2. Limitations and Future Work

Specific predictions about whether or not the optimal CAFE/GHG level is binding and whether ZEV mandates increase or decrease social welfare depend on many modeling assumptions beyond the EV disutility, cost, and SCC parameters explored in our results. We discuss each of these additional assumptions and their implications in turn.

Where possible, we assumed the optimistic level of parameter to show a potential upperbound impact of ZEV. However, there are many key model assumptions and parameters that are uncertain and remain to be tested for their impact on net social welfare from ZEV policy. Their impact can be complex due to their varied and heterogeneous impacts on the baseline no-policy scenario and on the two separate time steps. I discuss several categories of these:

5.2.1. Demand model uncertainties and heterogeneity

Based on the Greene et al. (2018) meta-study and Helveston et al. (2015) and Whitefoot et al. (2017), we note large variations, uncertainties, and heterogeneity in the consumer valuation of vehicle attributes, including but not limited to fuel economy, acceleration time, fuel type/EV, and EV range. We also note the potential for preferences to change over time, with experience, or with adoption and scale e.g. network externalities of charging infrastructure or consumer familiarity. Finally, we note the limited number and dimension of preferences for attributes currently represented (acceleration time and fuel economy).

In future work, we expect to capture a wider range of preferences and to simulate heterogeneous consumer groups and demand with simulated mixed logit. However, we will still face the same limitation noted in the discussion – multiple impacts result from optimism on EVs or certain preferences; conditions that are optimistic for EV adoption are not necessarily correlated or predictive of net social benefit. With simulation, we may hope to find some directional patterns within or between scenarios.

We also note that while stated preference estimates can sometimes be viewed as an upperbound for WTP due to survey takers having particular biases towards paying more than they actually would, this may not be the case for results of WTP for emerging technologies. Survey takers may either or both underestimate or overestimate how much they would actually consider attributes such as EV type and range. For example, depending on the survey sample, survey takers overall may be too enthusiastic and overlook EV/range disadvantages, and/or they may be overcautious about technology that they haven't previously considered or fully understood, given the unfamiliarity and limitations of the survey instrument and procedure.

In the longer-term future, it is possible for EVs to become widely accepted as alternatives to conventional vehicles without a disutility penalty (zero WTP_EV), for example, if extreme fast-charging technologies and ubiquitous infrastructure become available. Recent studies estimate WTP for charging, as well as social learning and neighbor effects of EV adoption (Edelenbosch, McCollum, Pettifor, Wilson, & Van Vuuren, 2018; D. L. Greene, Kontou, Borlaug, Brooker, & Muratori, 2020; Mau, Eyzaguirre, Jaccard, Collins-Dodd, & Tiedemann, 2008), which support the case of a changing disutility. When testing cases with lower EV disutility values such as zero, we find results with very high and up to 100% EV market share. This prevents ZEV policy from having any distinguishable impact on equilibrium solution results. We note that more work needs to be done to define the appropriate scope and applicability of simulations.

5.2.2. Supply model structure

In parallel with improving consumer representation with heterogeneous preferences, it may also improve model realism to represent the automakers and their products with more detail. The current representation of 2 firms and 2 products each (one gasoline and one electric vehicle) in one segment (compact cars) is crude and does not allow for consumer substitution between other vehicle fuel types, vehicle segments, or multiple firms in competition. We currently simulate a duopoly of 2 generic firms in Nash equilibrium, but would extend the number of automakers and products to be more realistic and to get appropriate price decisions and margins/markups more reflective of the real world.

One option for future work to address the product representation problem is the use of size and heterogeneity correction factors for composite vehicle alternatives to keep the model tractable while obtaining results consistent with a model with elemental choice alternatives.

The representation of technological progress of EV battery packs is a major limitation of this model. Hsieh et al. (2019) estimate a 2-stage battery learning model that separates material synthesis and battery production costs. This may help improve the cost reduction model, since the simple battery cost learning curve fails to distinguish between materials and materials synthesis costs, which are more incompressible than production, manufacturing, and assembly costs. The battery cost learning curve may therefore be overpredicting learning-by-doing cost reductions.

As noted, the current model is limited to using an industry-wide learning model with complete non-appropriable learning spillover. We expect EV battery-producing firms to learn (i.e. reduce battery production costs) at a faster rate based on their own production experience, but without appropriate data on firm-specific battery costs and production volumes, we do not have estimates on whether that is due to a higher learning rate or from being at an earlier stage of learning and building on much less cumulative experience, or if the exponential learning curve model is even a good model for appropriable within-firm learning-by-doing cost reductions.

While the current model attempts to represent appropriable and non-appropriable learning-by-doing, we note that economies of scale and R&D are also major drivers of cost reductions. These phenomena also have appropriable and non-appropriable portions, but we are not aware of appropriate data or models for this.

The cost and design of conventional gasoline vehicles are based on Whitefoot et al. (2017) and future work may involve adapting the work of recent work studying fuel economy technologies and compliance options, such as (A. Jenn, Hardman, et al., 2019) based on EPA OMEGA modeling inputs.

We assume a constant overall fleet size and do not include an outside good as a choice alternative. This was to avoid another source and sink of leakage, which would take the form of consumers buying the outside good generating uncertain impact on net social welfare.

5.2.3. Environmental damage calculation uncertainties

Environmental damages have uncertain and varied valuation in society – we vary the SCC in scenario analysis, but we could also vary the VSL assumption that is part of the monetized damages of pollution. Azevedo et al. (Deetjen & Azevedo, 2019; Donti, Kolter, & Azevedo, 2019) use $8.8 million (in 2010 dollars) for VSL, which is embedded in the damage estimates that are used in this study. The results in simulated scenarios have 10-30% of the environmental externality from conventional air pollution damages and the rest (majority) from climate-change-associated damages in the simulated cases assuming $50-200/t.

I use estimates of marginal emissions for the electric grid based on those used in EPA's own regulatory impact assessment for the CAFE/GHG rules for MY2022-2025 (detailed in the appendix). In an alternative case, I assumed 2018 marginal emissions for the electric grid, which are representative of short-run consequential emissions estimated from how the grid operates. However, these may not reflect potential longer-run changes to the grid, for example, if EV adoption induces power plant capacity expansion and particularly if this new generation causes changes in the merit order of power plants. Due to the near-medium term (next 2-10 years) scope of the current analysis, short-run marginal emissions factors are likely appropriate, though further and formal sensitivity analysis is necessary.

5.2.4. Scope of social welfare

We use the same 3% discount rate for firm and government calculations, but it is unclear whether the government would discount producer surplus at a social or private discount rate.

We currently do not count "uncounted energy savings" as a consumer benefit, as is done in the CAFE/GHG rulemaking (Bento et al., 2019). We ignore negative environmental and social externalities beyond air emissions, such as water pollution, noise pollution, or petroleum use reduction. All of these may increase the benefits of EVs but also of conventional fuel economy options.

Our scope of analysis is limited to impacts on the new light-duty vehicle market and we ignore other leakage pathways such as impacts from changes in VMT (rebound effect), the used car market and vehicle retirement (Gruenspecht effect), different usage of cars (second car in household, different driving patterns or habits), safety and related benefits and costs, or attractiveness of alternative transportation modes.

We ignore other policy details, such as compliance flexibilities, special accounting of EVs and EV emissions, attribute-differentiated standards, regional nature of ZEV, presence and interaction with other EV-related policies such as subsidies, incentives, and infrastructure.

5.2.5. Time and policy horizon

Computation limitations currently limit us to implementing two time steps representing a single year each. This means the model only accounts for the benefits and costs of products sold in each time step (5 years each) and their associated producer surplus, consumer surplus, and lifetime environmental damages. With only five years of ZEV and five years of CAFE after that, the criteria of increase in net social benefit may be too restrictive. To increase net social benefit, excess costs of ZEV1 must be paid off by the (lifetime) benefit of vehicles sold in the immediately following period. The benefits of ZEV may be undercounted and adding time steps that have associated impacts may allow for the accumulation of compound learning effects, which could be a large driver of cost reductions and ultimate net social benefit.

Instead of simulating more years with freely-decided variables and optimized decisions and policies, we attempted an alternative approach by representing longer time periods within time steps. This method only added an extrapolated amount of benefits and costs (assuming all variables, decisions, and policies were fixed within the entire time step). This approach is crude and only represents a rough attempt at counting more benefits of ZEV. Even though the discounted infinite series of years for time step 2 attempts to capture the maximum possible benefit in time step 2 (optimistic on ZEV impact), both constraints of no new learning and no new decisions keep the scenarios conservative. Unfortunately, the preliminary results from these side cases where I represented 10 years in time step 2 were not very meaningful or interpretable. ZEV1 of 50% became non-binding in the cases tested, resulting in no changes in outcomes. Further testing is warranted.

5.2.6. Other

Finally, inherently uncertain factors affecting the results include foreign markets and policies and gasoline prices, which are necessarily exogenous unless simulating globally or in general equilibrium, which is beyond the scope of this study.

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8. Supplementary Information

Appendix A: Fixed parameters, assumptions, and data sources

Table A1: Fixed Parameters

Parameter	Description	Base Value	Sensitivity Values	Notes / Basis
Fixed parameters				
r	Discount rate (firms and government)	3%		For simplicity and consistency, we discount producer surplus, consumer surplus, and environmental externalities with the same discount rate.
Parameters related to automotive products and attributes				
	size class, footprint, and weight of vehicle alternatives	Compact car class Footprint of 12135 sq in Curb weight of 2934 lb		2006 vehicle attribute data from Wards Automotive
m	Annual market size of light duty vehicles	17M		Total number of 2018 new vehicle registrations in the US (source: https://www.statista.com/statistics/269872/ largest-automobile-markets-worldwide-based-on-new-car-registrations/) Model instantiation assumes entire market is made of compact cars.
$x_{\mathrm{EV}}^{\mathrm{ACC}}$	EV acceleration 0-60 mph time	6.5 s		2018 Chevrolet Bolt
$x_{\mathrm{EV}}^{\mathrm{FE}}$	EV fuel economy	120 mpge		2018 Chevrolet Bolt
$x_{jt}^{\mathrm{EVBATSIZE}}$	EV battery pack size	60 kWh		2018 Chevrolet Bolt
γ, δ	Engine cost and fuel	Table S3 & S4 for		From Whitefoot et al. (2017)

	economy model coefficients	compact cars		
Parameters in demand model				
$\alpha, \boldsymbol{\beta}$	Demand model coefficients	From results of logit model (preference space)		From Helveston et al. (2015), except β_{EV}
i, N	Random-coefficients logit model parameters	1, 1		Model instantiation assumes homogenous consumer preferences of a single consumer group
Parameters in experience curve model				
θ^{LR}	Learning rate	0.2		Linn and McConnell (2019)
Q_0	Cumulative EV Li-ion battery production experience	300 GWh		Cumulative capacity of global Li-ion batteries produced for EVs 2010-2018, from BNEF, (Kittner, Lill, & Kammen, 2017; Schmidt, Hawkes, Gambhir, & Staffell, 2017)
c_0	EV Li-ion battery pack cost [$/kWh]	200		BNEF, for industry-wide battery cost.
Parameters used in calculating and monetizing environmental externalities				
	Annual miles traveled (for environmental benefit accounting) [mi/yr]	11200		NHTS reported household annual miles by age, averaged, from Transportation Energy DataBase https://tedb.ornl.gov/wp-content/uploads/2019/03/TEDB_37-2.pdf#page=214. Alternatively, more detailed schedule of annual mileage for cars and light trucks by age, estimated by EPA: https://tedb.ornl.gov/wp-content/uploads/2019/03/TEDB_37-2.pdf#page=91

	Multiplier for discounted lifetime of emissions	11.9		Based on assumed 15 year vehicle lifetime and r=3%. 11.9: multiplier for discounted (@ 3%) 15 yr lifetime of emissions (P/A, 3%, 15) https://www.me.utexas.edu/~me353/resources/flash/factor_calculator.html
$\theta^{CO2INTSTY-GV}$	CO2 intensity of gasoline vehicles [tCO2/gal gasoline]	0.0115		Based on well-to-wheels (full fuel cycle) emissions intensity from GREET. See appendix B for details.
$\theta^{CO2INTSTY-EV}$	CO2 intensity of electric vehicles [tCO2/gal gasoline equivalent]	0.0198		Based on marginal CO2 emissions estimate for 2030 used in EPA regulatory impact analysis. See appendix B for details.
$\theta^{APDI-GV}$	Air pollution damage intensity for gasoline vehicles [$2018/gal gasoline]	0.31		Estimated damages based on ANL GREET and NHTSA estimates of tailpipe emissions and US-average. See appendix B for details.
$\theta^{APDI-EV}$	Air pollution damage intensity for electric vehicles [$2018/gal gasoline equivalent]	0.78		Estimated damages based on US marginal power grid emissions in 2018 and monetized health and environmental impacts, from Azevedo et al. (2019). Assumes zero emissions from battery manufacturing. Assumes 10% transmission, distribution, and charging losses.

Appendix B: Net societal benefit calculation details and data sources

Δ producer surplus

Calculated from the total profits of all firms based on the sales of their products that are priced at prices different form their unit costs

$$\psi^{PS} = \sum_t \sum_l \{\pi_{lt}(1+r)^{-t}\}$$

$$\pi_{lt} = \sum_j \{q_{jt}\,(p_{jt} - c_{jt})\}\ [1000\$/car]$$

Δ consumer surplus

Calculated from the total relative monetized consumer utility of all products based on the consumers' expected relative willingness-to-pay for the products (relative value less price paid)

$$\psi^{CS} = \sum_t \sum_l \{\varphi_{lt}(1+r)^{-t}\}$$

$$\varphi_{lt} = \frac{1}{N}\sum_j \sum_i \left\{q_{ijt}\frac{v_{ijt}}{-\alpha_i}\right\}\ [1000\$/car]$$

$$v_{ijt} = \alpha_i p_{jt} + \boldsymbol{\beta}_i \mathbf{x}_{jt}$$

Δ environmental damages

Calculated from the total environmental damages of all products based on fuel consumption rates, pollution intensity (emissions factors of fuel and energy), and economic costs from environmental damages

$$\psi^{ED} = \sum_t \sum_l \{\rho_{lt}\,(1+r)^{-t}\}$$

Societal costs associated with lifetime CO2 and air pollution damages from firm l's car sales:

$$\rho_{lt} = \sum_j \frac{q_{jt}\ [sales]}{x_{jt}^{FE}\ \left[\frac{mi}{gal}\right]} / \sum_j q_{jt}\ [sales] * 11200\ \left[\frac{mi}{yr}\right] * 11.9\ [yrs - equivalent]$$
$$* \left(\theta^{CO2INTENSITY}\left[\frac{t\ CO_2}{gal\ gasoline\ equivalent}\right] * \theta^{SCC}\left[\frac{\$}{t\ CO_2}\right] + \theta^{APDI}\left[\frac{\$}{gal\ gasoline\ equivalent}\right]\right)$$

$$* \frac{1}{1000} \left[\frac{1000\$}{\$} \right]$$

CO2

For gasoline vehicles,

$$\theta^{CO2INTENSITY-GASOLINE} = (0.009268 + 0.00224) \left[\frac{tCO_2}{gal} \right] = 0.0115 \left[\frac{t\, CO_2}{gal\ gasoline} \right]$$

Full fuel cycle (well-to-wheels) emissions (9268 g/gal tailpipe, 2240 g/gal from gasoline well-to-pump fuel cycle (upstream, refining, transport) from ANL GREET 2018.

For electric vehicles,

$$\theta^{CO2INTENSITY-ELECTRIC} = 591 \left[kg \frac{CO_2}{MWh} \right] * 2.205 \left[\frac{lb\ CO_2}{kg} \right] * 33.7 \left[\frac{kWh}{gal} \right] * \frac{1}{1000} \left[\frac{MWh}{kWh} \right] * \frac{0.4536}{1000} \left[\frac{t\ CO_2}{lb\ CO_2} \right] * 1.10 = 0.0219 \left[\frac{t\ CO_2}{gal\ gasoline\ equivalent} \right]$$

Data sources for calculating electricity generation CO2 emissions intensity:

- Marginal CO2 emissions factor for average 2018 US electricity, from Electricity Marginal Factors Estimates website (Deetjen & Azevedo, 2019; Donti et al., 2019)(Azevedo et al., 2019): 591 kg/MWh (estimated for average US; does not include power plant life cycle emissions)
- Alternative assumption about electricity generation emissions rates, based on the 2016 EPA draft Technical Assessment Report for the Midterm Evaluation of Light-Duty Vehicle Greenhouse Gas Emission Standards and Corporate Average Fuel Economy Standards for Model Years 2022-2025: 0.534 g/Wh (time-invariant US-wide estimate based on EPA-assumed charging time profile and geographic weights where hybrid cars were sold 2006-2009 (EPA RIA of FRM, Ch 4.6); includes feedstock-related GHG emissions upstream of power plant)
  - This estimate results in total CO2 intensity of 0.0198 tCO2/gal gasoline equiv
- Assumes 10% transmission, distribution, and charging losses, and no battery end-of-life GHG emissions.
- Battery materials and manufacturing emissions are estimated to result in 0.06 - 0.1 tCO2/kWh of Li-NMC battery capacity (Dai, Kelly, Gaines, & Wang, 2019; Kelly, Dai, & Wang, 2019)(lower end: European battery manufacturing; higher end: Chinese battery manufacturing). 0.06-0.1 * 60 kWh pack = 3.6-6 tCO2 over lifetime. 11200 mi/yr / 120 mpge * 8 yrs = 747 lifetime e-gallons (assumes battery life of 8 yrs). This results in a mean estimate of 0.0065 (0.005-0.008) t/gal.

Air pollution

Combining estimates for emission factors from ("Argonne GREET Publication : Updated Emission Factors of Air Pollutants from Vehicle Operations in GREET Using MOVES," n.d.)Cai et al., 2013 (ANL 2013), ANL GREET (2018) ("Argonne GREET Publication : Summary of Expansions and Updates in GREET® 2019," n.d.), and NHTSA damage factors (NHTSA, 2012) and assuming 30 mpg for the 2018 car in ANL (2013), we obtain a value for well-to-wheels (WTW) air pollution damage intensity (APDI) for gasoline vehicles:

$$\theta^{APDI-GASOLINE} = 0.31 \left[\frac{\$}{gal\ gasoline}\right]$$

Data sources for gasoline emissions intensity and damages:

- Cai et al., 2013 (ANL) Updated Emissions Factors of Air Pollutants Vehicle Operations in GREET using MOVES, Table A2 lifetime mileage-weighted average [PTW] air pollutant emissions factors (g/mile) for gasoline passenger cars for model years 1990-2020
- ANL (2018) GREET model
- Table VIII-16, Economic Values Used for Benefits Computations, NHTSA (2012) FRIA for CAFE 2017-2025

For electricity-associated air emissions, we use marginal damage factors from Azevedo et al., 2019, for 2018 US-wide-average marginal damage factors for NOx, SO2, and PM2.5. We obtain a value for well-to-wheels (WTW) air pollution damage intensity (APDI) for electric vehicles:

$$\begin{aligned}\theta^{APDI-ELECTRIC} \\ &= \left(2.7\left[\frac{\$}{MWh}(NO_x)\right] + 5.8\left[\frac{\$}{MWh}(PM_{2.5})\right] + 9.9\left[\frac{\$}{MWh}(SO_2)\right]\right) \\ &* \frac{1}{1000}\left[\frac{MWh}{kWh}\right] * \ 33.7\left[\frac{kWh}{gal\ gasoline\ equivalent}\right] * 1.1 * 1.15 \\ &= 0.78\left[\frac{\$}{gal\ gasoline\ equivalent}\right]\end{aligned}$$

Data sources for electricity emissions damages:

- Electric grid air pollution emissions factors from Azevedo et al., 2019 (Deetjen & Azevedo, 2019; Donti et al., 2019), https://cedm.shinyapps.io/MarginalFactors/ (marginal damages from $PM_{2.5}$, NO_x, and SO_2 emissions for 2018, US-wide)
- Assumes 10% transmission, distribution, and charging losses, and no battery end-of-life emissions.
- 1.15 factor to bring \$2010 values to \$2018 values (based on GDP deflator)

For both gasoline and electric vehicles, we currently ignore criteria air contaminant emissions from manufacturing and battery production.

Chapter 5: Conclusions and contributions of this thesis

In this thesis, I explored and investigated consumer choice modeling, optimal engineering design, and technology-specific policy simulation in three studies. In the first study (Chapter 2), “On the Implications of Using Composite Vehicles in Choice Model Prediction,” I investigated the issues of choice set representation in choice modeling methodology. I derived composite correction factors for logit-class models that can help reconcile differences in modeling results in composite-level and elemental-level models. I then demonstrated cases where correction factors may be useful. This contributed to an improved understanding of how competitor representation affects choice predictions. In the second study (Chapter 3), “Implications of Competitor Representation on Optimal Engineering Design,” I investigated profit-maximizing engineering design models that integrate choice models for demand. Specifically, I studied how competitor representation can affect the trade-off between cost and benefit of design change. I derived a closed-form expression for the marginal cost and benefit relationship for the level of an attribute under optimal design assuming a latent-class or mixed logit (random-coefficients logit) demand model. I used this to characterize the impact of competitor representation in a case study of optimal automotive design. In the third study (Chapter 4), “The dynamic costs and benefits of a technology-forcing policy nested in a broader performance standard: the case of ZEV and CAFE,” I addressed the complexity of dynamic effects and nested policy interaction in automotive energy and environmental policy. I focus on two policies: Zero-Emission Vehicle (ZEV) mandates and Corporate Average Fuel Economy / Greenhouse Gas (CAFE/GHG) standards. I simulated consumer, producer, and government decisions in a model with explicit technological change, dynamic learning-by-doing spillover effects, policy interaction effects, and endogenous fleet standard setting via cost-benefit analysis. I demonstrated the potential impacts of ZEV mandates: potential net social benefit or net social cost, depending on key factors and parameters. I identified these key factors and quantified the trade-offs that may inform ZEV and CAFE/GHG fleet standard policy-making.

A few final words about research:

> *"Ce que l'on conçoit bien s'énonce clairement, // Et les mots pour le dire arrivent aisément." - Boileau-Despréaux (1674), believed to be the source of the saying "If you can't explain it simply, you don't understand it well enough"*
>
> *"Look forward"*
> *- Spot (2009)*