

QUANTIFYING THE IMPACT OF ENVIRONMENTAL POLICY ON
ENGINEERING DESIGN DECISIONS

BY

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PREFACE

A note to the multidisciplinarian:

A colleague of mine, Bart Frischknecht, once referred to scholars of multidisciplinary studies as cave men and women, finding their own way in the wilderness, far away from the glitzy cities of established disciplines. But I prefer the analogy of the multidisciplinarian as a traveler between cities. The ideal multidisciplinarian is able to speak multiple languages, serving as an informed ambassador, contributing to issues that are valued by the classical disciplines in which they reside. Yes, some of their ways may seem strange to single-disciplinarians because they are influenced by multiple cultures, but they should be fluent in the methods and motivations of each of the disciplines they claim and able to clearly communicate their work and its value in the language of each discipline.

The need for ambassadors between disciplines is clear in issue areas such as the environment. Environmental concerns have a pesky tendency to ignore all of the nice and neat imaginary boundaries we have established, between jurisdictions, environmental media, and scholarly disciplines. Understanding and addressing formidable environmental matters such as climate change will require an integration of knowledge from the environmental sciences, economics, engineering, politics, and more. This dissertation contributes to a piece of this puzzle, establishing a methodology connecting economic analysis of policy with engineering modeling of the physical constraints and tradeoffs inherent in product design and production.

This work will attest to how close I have come to the ideal of a multidisciplinarian, as the reader may judge. But I certainly hope it will serve as a stepping-stone for future scholars to prove the worth of multidisciplinary studies and develop a code of rigor for this crucial work.

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CHAPTER 1: INTRODUCTION

“Technology, combined with improved design, can greatly aid the quest for sustainability. Indeed, the notion that technological choice is crucial for environmental improvement lies at the core of industrial ecology”
—Marian Chertow (2000)

The design of products is well recognized as a crucial component to achieve sustainable development (Anastas and Zimmerman 2003; Chertow 2000). Indeed, a majority of the environmental impact of a product is predetermined early on in the design stage (Hauschild et al. 1999; Borland and Wallace 2000). Potential opportunities to reduce environmental impacts through design have triggered a number of policy actions aimed at inducing environmentally preferred design changes. The Corporate Average Fuel Economy regulation and appliance standards in the United States and the Energy-Using Products directive in the E.U. aim to induce product design that minimizes energy use (Directive 2005/32/EC). The E.U.’s Waste Electrical and Electronic Equipment directive and Japan’s producer take-back requirements aim to encourage product designs that reduce waste streams from disposal (Directive 2002/96/EC; Ogushi and Kandlikar 2007). And, cap and trade policies implemented in the E.U. and proposed in the U.S. Congress create the incentive for capped firms to modify products to reduce emissions as well as sending a price signal to consumers, which raises demand for products with lower embodied emissions (Directive 2003/87/EC; H.R. 2454).

This expanding interest in policies targeting product design exposes the need for methods to support the development of these policies and industrial decision-making in response to these policies. Analysis tools are needed to evaluate the ability of these policies to effectively and efficiently induce desired design changes and reveal any additional positive or negative consequences. The impacts of a policy on design decisions are intrinsically connected to the interaction between the policy, consumer demand, engineering tradeoffs and constraints, and the economic structure of the industry.

Existing literature in economics and engineering design has developed methods to study these domains but an integration of these methods of the extent necessary to inform policy and industrial decision-making is still needed.

This dissertation presents an approach of integrating state-of-the-art models of consumer demand and engineering design to examine the relationship between environmental policy and product design. Climate change policies impacting the automotive industry will serve as the specific focus of the research although the methodology is directly applicable to other product categories. Specifically, the approach presented in this dissertation is appropriate to analyze industries that can be characterized as differentiated-product oligopolies in which policymakers are interested in increasing energy efficiency, and manufacturers make design decisions that affect energy efficiency and other product attributes that influence product demand. These characteristics encompass many industries that are relevant to policies targeting product design, such as light- and heavy-duty vehicles, household appliances, and certain consumer electronic industries.

A model of the U.S. automotive market is presented, representing consumer purchase decisions and firm design and pricing decisions for the full line of vehicles produced in a year. The methodology integrating engineering design models with economic analyses produces three contributions. First, the combined model allows for policy analysis of the full-scale automotive industry considering design options that may be profit-optimal in the presence of the policy even if the design options are not observable in current data. Second, the structure of engineering design decisions made throughout the product development process is used to address the difficulty of econometrically identifying demand parameters for design attributes. Third, cost parameters are estimated using engineering data when available and derived from the econometric demand model when engineering cost estimates are difficult to obtain.

The dissertation is organized as follows. Chapter 2 reviews state-of-the-art methods in engineering design, environmental and industrial-organization economics, and lifecycle assessment that form the foundation of the presented methodology. Chapter 3 describes the development of the engineering-design and econometric-demand models and synergies of combining these approaches. The approach of integrating these models

is then applied to three separate case studies. In Chapter 4, the combined model is used to evaluate a policy instrument in terms of its ability to incite the design changes targeted by the policy and its impact on firm profits. Chapter 5 uses the developed methodology to examine potential influences of a policy instrument on additional design changes that are not necessarily the target of the policy. Applications of the approach to lifecycle assessment are discussed in Chapter 6 with a demonstrational case study incorporating models of consumer demand, engineering design, and firm competition into a lifecycle analysis. A summary of this research and opportunities for future developments are discussed in Chapter 7.

CHAPTER 2: BACKGROUND

“If I have seen further it is only by standing on the shoulders of giants.”
—Isaac Newton

2.1 Economic Literature

A mature body of literature in economics focuses on modeling the impact of a change on the Nash equilibrium of a market, which specifies a set of decisions from which no individual firm has a profitable incentive to deviate (e.g., Fudenberg and Tirole 1993; Viscusi et al. 2005). This literature has developed well-known methods to estimate consumer preferences for differentiated products, a category that includes all designed-product industries, such as the automotive, consumer electronic, and appliance industries. While this research predominantly assumes that the designs of products are exogenously determined, increasing attention is being given to the product design decisions that producers make in addition to pricing decisions (e.g., Fan 2008; Sweeting 2007; Klier and Linn 2008; Knittel 2009; Seim 2006).

The standard theory of neoclassical economics for differentiated-product industries consists of firms maximizing profits with respect to the prices of their products given the prices that their competitors have chosen. The equilibrium of this system, called Bertrand equilibrium, is therefore defined as the prices for all products that simultaneously maximize profits for each firm with respect to their respective products' prices (Viscusi et al. 2005). Common assumptions of models in this literature specify that firms are rational; actions are chosen simultaneously (static equilibrium); and information is complete, meaning that each firm's payoff function is common knowledge among all firms (Gibbons 1992). A substantial body of research has studied modification of these assumptions (e.g., Fudenberg and Tirole 1993; Gibbons 1992), but this research will not be discussed here.

Typically, consumer demand is represented in this literature by a discrete choice utility model. In this model the utility, u_{ni} , or satisfaction consumer n receives from product i , is composed of an observed portion and an unobserved portion of utility: $u_{ni} = f(p_i, x_i, d_n, \theta_n) + \varepsilon_{ni}$. The observed portion of utility can generically be specified as a function of price, p_i , observed product attributes, x_i , consumer demographics, d_n , and parameters, θ_n , which the researcher estimates. The unobserved portion of utility, ε_{ni} , depends on unobserved product attributes and other unobserved data and is commonly assumed to be independently and identically distributed according to the Type 1 Extreme value distribution (e.g., Louviere 2003, Train 2003). This assumption allows the probability, P_{ni} , that consumer n will purchase product i out of the set of products \mathfrak{J} to be written in closed form:

$$P_{ni} = \frac{e^{f(p_i, x_i, d_n, \theta_n)}}{\sum_{j \in \mathfrak{J}} e^{f(p_j, x_j, d_n, \theta_n)}} \quad 2.1$$

In much of the applied economics literature that studies differentiated-product industries, the abilities of firms to change product designs is not considered or is largely underemphasized (e.g., Goldberg 1998; Jacobsen 2010; Nevo 2000). The majority of this work is concerned with firm pricing decisions in response to a policy intervention or change in the market, such as a merger, with all product designs considered fixed. This model formulation could be thought of as a representation of the short-run firm response (less than a year for many industries) but over longer time-spans, firms are able to adjust the designs of their products as well as the prices. Increasingly, researchers in the environmental economics and industrial organization have recognized the importance of accounting for firm decisions regarding product design, but many opportunities exist to advance the methods of modeling these decisions.

2.1.1 Environmental economics literature

In the environmental economics literature, significant interest has been given to studying the ability of policy instruments to induce technological change, but representations of technology are generally simplistic. A common approach of modeling endogenous technological change in this literature is to represent technology adoption as

an investment that leads to a reduction in production costs. For example, Jung et al. (1996) analyze policy instruments with respect to the ability to increase the supply of renewable electricity. In this study, firms pay some cost for the pollution they emit and the firm can choose to invest in a technology that reduces their pollution level. Fischer and Newell (2008) analyze the efficiency of policy instruments to encourage renewable energy diffusion, representing technology adoption as functions translating R&D investment and learning-by-doing experience to cost reductions for renewable energy.

These approaches model important mechanisms by which policy instruments influence design decisions but they ignore potential tradeoffs and constraints involved with these decisions. Extending these approaches to account for engineering constraints and tradeoffs associated with implementing specific technologies and design strategies may yield different results regarding the efficiency and effectiveness of environmental policy instruments. For example, higher efficiency dishwashers require longer cycle times (Consumer Reports 2010), which may deter consumers from purchasing them. A policy analysis that does not account for this tradeoff may undervalue the importance of providing additional incentives to consumers to purchase higher efficiency dishwashers. This dissertation presents an approach of explicitly accounting for relevant engineering tradeoffs and constraints in the analysis of policy instruments.

2.1.2 Industrial organization economics literature

As well as contributing to the environmental economics literature, this dissertation is relevant to industrial organization (IO) economics. The IO economics community has a long history of studying the structure of markets and the organization of firms. The decisions firms make regarding product design are an important aspect of firm competition and the structure of many differentiated-product industries. Much of the existing work modeling product design decisions has focused on relatively straightforward design processes that do not have constraints or tradeoffs with other product attributes (e.g., Seim 2006; Sweeting 2007; Fan 2008). The types of products that are relevant for design-targeting policies, such as automobiles and household appliances, present additional challenges because firm design decisions include many engineering constraints and tradeoffs that are necessary to consider. Recent research in this literature

is just beginning to develop methods to analyze these design decisions (e.g., Gramlich 2008; Klier and Linn 2008; Knittel 2009).

In order to estimate the longer run costs of the Corporate Average Fuel Economy (CAFE) regulation, Austin and Dinan (2005) and Kleit (2004) introduce an oligopolistic equilibrium model of CAFE where product design is not completely fixed, but instead firms adjust the fuel economy of their vehicles by implementing fuel-efficiency technologies. Changes in fuel economy enter the equilibrium model by assuming consumers treat the net-present value of a vehicle's lifetime fuel savings as a reduction in the vehicle's purchase price. All other vehicle attributes are considered exogenous. Unit production costs are modeled as increasing in response to fuel economy improvements according to technology cost curves. The only technologies included in the models are those that are assumed to increase fuel economy while having no effect on other vehicle attributes. The same strategy is incorporated in Jacobsen's (2010) study of CAFE.

While this approach advanced the state-of-the-art by incorporating technology decisions into an oligopolistic equilibrium using the standard Bertrand model where product prices change but all other aspects of the product are considered exogenous, the assumptions necessary to apply this method are not supported by consumer research. Incorporating decisions on fuel-saving technologies into the Bertrand model requires the assumption that consumers value fuel consumption as the net-present value of future fuel savings. However, Turrentine and Kurani (2007) present interviews of households across consumer-segment groups finding "no household that analyzed their fuel costs in a systematic way in their automobile purchases". These findings imply that consumers do not trade off net-present future fuel savings equally with purchase price and therefore consumer valuation of fuel economy should be estimated separately from purchase price.

Fischer (2010) develops a theoretical model of the automotive industry in which consumer valuation of fuel economy is not restricted to the net-present value of future fuel savings and is allowed to vary between consumers of different vehicle segments. She finds that an oligopoly of automotive firms over-provide fuel economy in vehicle segments in which consumer valuation of fuel economy is relatively high and under-provide fuel economy in segments in which consumer valuation is lower to encourage market segmentation. Similarly to Austin and Dinan, Fischer represents the ability of

firms to increase fuel economy as an increase in production costs and assumes all other vehicle attributes are exogenous and unaffected by changes to fuel economy.

This assumption that automakers will respond to fuel economy policies by implementing only design strategies that increase fuel economy and have no effect on other attributes is not justified. Many design options that increase fuel economy—for example, turbocharging, variable valve timing, and hybridization—will either increase or decrease acceleration performance.

Recognizing the importance of studying firm decisions that impact energy efficiency and other product attributes that trade off with efficiency, a few researchers have estimated the engineering tradeoffs between product attributes in the automotive industry. Knittel (2009) econometrically estimates the tradeoffs that automotive manufacturers face between the fuel economy, weight, and engine power of vehicles sold in the United States over the period of 1980–2006. He documents both movements along and shifts in the production possibility frontier (PPF) of these three vehicle attributes, representing the set of attribute combinations where no attribute can be improved without a loss in another attribute. Klier and Linn (2008) also econometrically model engineering tradeoffs between endogenous vehicle attributes on the supply side, coupling this model with a demand-side estimation to analyze the medium-run response to the CAFE regulation. The authors exploit an engine data set to estimate tradeoffs between endogenous attributes—including horsepower, fuel economy, and weight—using variation in observed attributes of vehicle models with the same engine program.

A notable challenge of econometrically estimating the engineering tradeoffs between product attributes is that the PPFs for a product are dependent on many product attributes, both observed and unobserved. Accounting for correlation between endogenous attributes and unobserved attributes, which are common in the automotive industry, is difficult. For example, the 2011 Chrysler 200 with a 2.4 L engine option has a combined fuel economy of 20.7 mpg and a 0-60 acceleration of 8.2 s, whereas the 3.6 L engine option has 19.2 mpg and 6.4 s. However, engine options are correlated with unobservable attributes; in addition to a larger engine, the 3.5 L option also has a 6-speed transmission instead of a 4-speed, a 160 amp alternator instead of 140 amps, and a suite of electronic accessories including heated seats, a tire-pressure monitor, a touch-screen

monitor, satellite radio, and an upgraded stereo system. The addition of these extra features affects fuel economy and typically increases demand, violating the *certeris paribus* assumption in counterfactuals. Moreover, many vehicle options have variations in design features that are even more difficult to obtain data on than the features listed above. For example, the coefficient of friction of engine components such as piston rings, material coatings, and lubricants impacts fuel economy, acceleration performance, and production costs but this information is rarely reported by manufacturers or available in even such detailed vehicle data sets as WARDs Automotive.

This dissertation contributes to this challenge by integrating an engineering model of product design to identify the tradeoffs between product attributes. Physics-based engineering simulations are used to construct the PPFs between fuel efficiency, acceleration performance, and production costs. This engineering-based approach confers two advantages. First, engineering tradeoffs between fuel economy and other product attributes can be identified without conflating changes in unobserved attributes that typically affect both fuel efficiency and consumer demand. Second, the engineering model can capture many combinations of product attributes that are not observed in the market to date, but are technologically feasible. This is important because these unobserved vehicle designs may be optimal under relevant policy regimes. In fact, manufacturers have stated that they will rely on further implementing advanced technologies in order to meet fuel economy standards in the future (Amend 2010).

In addition to the challenges of estimating the engineering tradeoffs between product attributes, a defining challenge of the IO economics literature relates to estimating consumer preference when endogenous variables are correlated with the unobserved portion of utility. If unaccounted for, this correlation produces biased estimates of consumer preferences. A common approach of addressing the correlation is to choose *instrumental variables*, which are correlated with the endogenous variables but are not correlated with unobserved utility (Wooldridge 2001). Following a two-stage least-squares procedure, first regressing the endogenous variables on the instrumental variables and then regressing the utility on the instrumented estimates of the endogenous variables, produces unbiased estimates of consumer preferences (Berry 1994).

In previous work, some researchers have used functions of non-price attributes of vehicles as instruments (e.g., Berry et al. 1995; Train and Winston 2007, Beresteanu and Li 2008, Petrin 2002). This choice of instruments is subject to the criticism that firms presumably choose these non-price attributes and prices simultaneously, and therefore the instruments are not independent of unobserved utility. This dissertation contributes to this research by using the well-documented structure of the automotive design process to identify vehicle attributes that are determined in earlier stages than the endogenous attributes of interest. The key identifying assumption is that powertrain architecture (e.g., hybrid), drive type (e.g., all-wheel-drive), and major vehicle dimensions are chosen earlier in the development process than detailed design variables in the powertrain that affect both fuel economy and acceleration performance. This assumption is supported by detailed descriptions of the automotive development process (Braess and Seiffert 2005; Sörenson 2006; Weber 2009).

2.2 Engineering literature

2.2.1 Decision-based Design literature

The engineering design literature has a long history of modeling the engineering tradeoffs and constraints inherent in product design and their relation to the objectives of a firm. While the discipline of engineering design originally was viewed as a problem-solving process aimed at minimizing costs subject to constraints of functional requirements, it has developed into a systems analysis of a decision-making process that aims to maximize the value of a designed product to a firm considering costs and consumer demand for design alternatives (Hazelrigg 1998; Lewis et al. 2006; Wassenaar and Chen 2003). This line of research provides a valuable foundation for integrating representations of consumer demand together with models of engineering tradeoffs and constraints necessary to understand the relationships between policy and product design decisions.

One goal of the decision-based design (DBD) paradigm is to combine models of demand, cost, and engineering performance of products into a comprehensive design optimization framework. A firm's ability to conduct forward-looking product planning scenarios in this context requires not only engineering models that link product

performance to design attributes but also customer decision models that appropriately link design attributes to product demand. The DBD literature has integrated such representations of customer decisions, especially applied to automotive design, by borrowing and adapting existing demand models from the social sciences (e.g., Besharati et al. 2006; Frischknecht and Papalambros 2008; Michalek et al. 2004; Shiau and Michalek 2009), estimating new versions (e.g., Kumar et al. 2007; Kumar et al. 2009; Shiau and Michalek 2009; Wassenaar et al. 2005), and exploring scenarios of uncertain demand (Besharati et al. 2006; Moon et al. 2010; Suh et al. 2007). Reviews of methods in this literature are available in Donndelinger et al. (2008), Frischknecht (2009), and Michalek (2005).

This literature has been formative to DBD research by coupling consumer utility models with design optimization but representations of both consumer demand and the economic structure of the industry are often simplified such that the analyses do not suitably represent the industries they aim to study. With respect to demand representations, this literature largely does not address the correlation between observed product attributes and unobserved product attributes, as described in Section 2.1. Without accounting for this issue, it is likely that the estimates of consumer utility parameters are biased.

For example, Kumar et al. (2007) estimate consumer utility coefficients for various vehicle product attributes, including price, interior dimensions, power, fuel economy, and interactions with these attributes and consumer demographics. The estimated coefficient on price of this model is positive, indicating that consumers prefer vehicles with higher prices. The authors identify that this unexpected sign is likely due to a correlation of price with premium attributes of vehicles, which are often difficult data to obtain, but do not attempt to correct the contamination of this parameter. As a result, this demand estimation is not appropriate for design studies or other counterfactual simulations because the relationship between consumer utility and price changes independent of other product attributes has not been identified. While this is an extreme example, where the sign of the estimated price coefficient is positive, similar contamination of demand parameters are likely to exist in many demand models estimated in this literature that use data of consumers' actual purchases (e.g., Kumar et al.

2006; Wassenaar and Chen 2003; Wassenaar et al. 2005). Properly designed stated-choice surveys (e.g., Luo et al. 2005; Orsborn et al. 2009; Reid et al. 2010) can avoid this issue but this approach relies on the assumption that consumer survey results represent actual purchasing behavior, which has been shown to not necessarily be the case (see for example, Kagal and Roth 1995; Slovic 1995).

With respect to representations of the economic structure of the industry, the DBD literature often uses simplified models where competitor decisions are not considered or only a subset of products in the industry are modeled. Li and Azarm (2000) and Jiao and Zhang (2005) represent a single firm's design decisions accounting for competing products but all competitor decisions are considered fixed. Williams et al. (2008) similarly consider all competitor decisions as fixed, but do account for the decisions of retailers that buy products from the manufacturer and sell them to the end consumer. Lewis and Mistree (1998) use economic approaches of equilibrium to model competing and cooperative decisions between engineering designers within the same firm but do not account for any strategic decision-making between firms.

A subset of DBD research has recognized the influence of economic structure of an industry, including relevant government regulations, on firms' optimal design decisions. Georgiopoulos et al. (2002) model the optimal product mix of a hypothetical automotive firm producing a passenger car and a light truck subject to the constraint of U.S. fuel economy standards, demonstrating the influence the regulation has on optimal design decisions. Kwak et al. (2007) develops a method to optimize the disassembly sequence of products to conform to the constraints of take-back requirements prevalent in Europe and Japan. And, Shiau and Michalek (2009) demonstrate that the economic structure of the market, namely whether manufacturers control prices directly or through a franchised or common retailer, affects optimal design decisions.

Conversely, Frischknecht (2009), Michalek (2004) and Shiau et al. (2009) examine the relationship between a firm's profit-optimal design decisions and the outcome of a policy objective, specifically reduced fuel consumption. Frischknecht (2009) demonstrates that efficiency frontier between greater firm profits and improved fuel efficiency often follows a concave tradeoff, and that the extent to which these

objectives are aligned (or opposed) depends on the technology considered, the extent of competition in the market, consumer preferences, and the regulatory environment.

Perhaps the most closely related research in the DBD literature to the contributions of this dissertation is presented in Michalek et al. (2004) and Shiau et al. (2009). In both studies, the authors investigate optimal vehicle powertrain designs and pricing decisions in response to specific policy measures and evaluate the policies with respect to the design responses. Michalek et al. (2004) determines the equilibrium of a hypothetical industry in which firms each produce a midsize vehicle model under multiple policy scenarios—including a minimum production constraint for diesel vehicles, a fine proportional to carbon dioxide emissions from produced vehicles, and an increase in the penalty for violating the fuel economy standard. Using the same hypothetical industry example, Shiau et al. (2009) evaluates the ability of U.S. fuel economy standards to induce design changes. The authors illustrate that if fuel economy standards are increased but the fines associated with violating the standards are not increased, then firms may have no incentive to improve the fuel economy of their vehicles. The results of these studies indicate that policy outcomes (e.g., realized reductions in CO₂ emissions) depend substantially on how they are linked to design decisions.

The research presented in this dissertation builds from the approach taken in existing DBD research (Frischknecht 2009; Michalek et al. 2004; Shiau et al. 2009), further developing the methods to inform policy analysis and industrial product planning. These developments comprise advancements on both the demand-side and supply-side of the system. The methodology presented in this dissertation includes estimation of a demand model using state-of-the-art econometric methods, and interfaces this model with the firm optimization problem. This addresses an issue with some DBD studies (e.g., Frischknecht and Papalambros 2008; Michalek et al. 2004; Shiau and Michalek 2007), which adopt demand models from previous literature that may not be valid for design optimization studies (Frischknecht et al. 2009). On the supply-side of the system, a full-scale model of the automotive industry is presented including all vehicle models and engine options from twenty brands (~500 products), which is substantially larger than the number of products studied in much of the DBD literature (2-25 products) (e.g.,

Georgiopoulos et al. 2002; Kumar et al. 2009; Michalek et al. 2004; Shiau and Michalek 2009; Wassenaar et al. 2005). Solutions to the firm optimization problem depend on both the types of products represented in the system and the extent to which product heterogeneity is captured. Consequently, the full-scale model should more closely represent the automotive industry.

2.2.2 Automotive engineering literature

In addition to contributing to the DBD engineering literature, this dissertation is relevant to a subset of engineering literature that focuses on the potential to improve vehicle fuel efficiency by implementing various technologies and, less frequently, compromising other aspects of vehicle performance. This literature can roughly be divided into two categories. The first category examines the potential for fuel efficiency improvements based on known technology advances (e.g., DeCicco et al. 2001; NHTSA 2008). The second category aims to predict future improvements in fuel efficiency by extrapolating historical trends (e.g., An and DeCicco 2007; Cheah et al. 2008; MacKenzie 2009).

The common approach used in this first category is defining discrete packages of technology options and determining the impact of these technology packages on fuel efficiency using engineering vehicle simulations. For example, DeCicco et al. (2001) determine the maximum feasible increases in fuel efficiency from 2010–2015 considering a number of technology packages, including low tire rolling resistance, increased aerodynamic efficiency, low-friction engines, lightweighting, and gasoline direct-injection engines. The authors find that average new-vehicle fuel economy can be increased to 36 mpg. Assuming that the costs of implementing these technology packages translates into vehicle prices by assuming markups are 1.8 times the manufacturing costs, results indicate that this improvement of fuel economy causes an increase of average vehicle prices by \$1,300.

NHTSA (2008) takes a similar approach, determining the maximum feasible increase in fuel efficiency by implementing technology packages into representative vehicles as well as considering the increases in fuel efficiency where the costs of the technologies equal the benefits in terms of fuel savings and reduced local emissions.

These results indicate that the maximum feasible increase in average new-vehicle fuel economy is 39.9 mpg for passenger cars and 31.3 mpg for light trucks, and the increase that equates costs and benefits is 38.8 mpg for passenger cars and 30.5 for light trucks. Using a markup factor of 1.5 times manufacturing costs, these results imply an increase in average new-vehicle prices of \$3,264 and \$2,785 for passenger cars and light trucks, respectively, to achieve the maximum feasible increase and \$2,367 and \$2,509, respectively, to achieve the equal costs and benefits increase.

This dissertation takes a similar approach of determining the impact of specific technologies on fuel efficiency and acceleration performance using engineering vehicle simulations. However, the methods presented in this dissertation do not aim to determine the maximum feasible improvement in fuel efficiency but rather the change in fuel efficiency and other vehicle attributes in response to policy instruments considering consumer preferences for vehicles and profit objectives of manufacturers. Furthermore, this research does not rely on the condition that vehicle production costs translate into vehicle prices through assumptions on markups; instead, manufacturers are modeled as setting prices as well as choices on technology options and vehicle attributes in order to maximize their profits.

A separate body of literature examines the impact of technology change on fuel efficiency and other aspects of vehicle performance by examining historical trends in the automotive industry instead of determining the impact of specific technology options. For example, An and DeCicco (2007) propose an indicator of technology change in the automotive industry, noting that the product of the sales-weighted average of vehicle size, specific power, and fuel economy—specifically, the ratio of horsepower to weight multiplied by interior volume and fuel economy—increased linearly over the period of 1977–2003. Using this indicator, called the Performance-Size-Fuel Economy Index (PSFI), the authors infer periods when technology gains were applied to improvements of fuel efficiency, improvements of size or acceleration performance, or some combination. Cheah et al. (2008) and MacKenzie (2009) use the same indicator to examine the potential to increase fuel efficiency by shifting the allocation of technology gains to reducing fuel consumption.

Cheah et al. (2008) define a measure of the allocation of technology gains towards fuel efficiency based on the PSFI indicator, called the Emphasis on Reduction of Fuel Consumption (ERFC). This measure represents the ratio between the realized fuel consumption reduction over a specified period and the potential fuel consumption reduction holding vehicle size and specific power constant, which is calculated based on sales-weighted average trends of the PSFI. The authors determine that between 1995 and 2006 the ERFC was 8% in the United States, 54% in Germany, and 83% in Italy. Additionally, the authors calculate that fuel consumption could be reduced 26% by 2035 if all technology gains were applied to fuel efficiency, and could be reduced 33% by also compromising acceleration performance such that the sales-weighted average time to accelerate from 0–60 mph increased by 5 s.

Similar to Cheah et al. (2008), MacKenzie (2009) uses the ERFC to determine the potential to increase fuel efficiency in the future but also couples the technology indicator with the willingness of consumers to pay for fuel efficiency and acceleration performance. Using the ERFC to represent the decision to implement technology and tradeoff fuel efficiency with acceleration performance, he models the impact of an increase in gasoline prices and the impact of CAFE standards on the sales-weighted average fuel economy and acceleration performance. This approach models the automotive industry as effectively a single decision-maker who adjusts the ERFC in response to these system changes. The automotive industry is assumed to make decisions on ERFC to maximize the value of the sales-weighted average vehicle attributes to consumers. Results of this approach indicate that a CAFE standard of 39 mpg on passenger cars in 2020 imposes a cost of \$200 per car in terms of consumer value compared to a 2005 baseline.

Similar to this literature, the research presented in this dissertation aims to identify the tradeoff between acceleration performance and fuel efficiency and examine the impact of CAFE standards on firm decisions regarding vehicle attributes and the resulting impact on firm profits and consumer welfare. However, the methods developed in this dissertation are distinctive from this literature. Tradeoffs between fuel efficiency and acceleration performance are identified at a vehicle level instead of relying on the average trend across the industry. This engineering model is coupled with a consumer

demand model that considers not only preferences for fuel efficiency and acceleration performance, but also vehicle price, size, segment, and additional vehicle attributes such as brand and luxury accessories. This approach enables modeling the design and pricing decisions of each automotive manufacturer in competition with each other with respect to the prices and attributes of their individual vehicles.

2.3 Lifecycle Assessment

Lifecycle assessment (LCA) is a method of conducting an inventory of the materials, energy, wastes, and emissions flows through the lifecycle of a product, process, or system and assessing the impact of these flows on the environment (SETAC 1993; ISO 1997). An LCA analysis consists of defining the boundaries of the relevant system; gathering data on environmental flows within the system, modeling system processes to calculate approximate input and output flows when data aren't available; evaluating the potential environmental impacts associated with the inventory data; and interpreting the results to inform decision-making. Over the past decade, practitioners in industry, academia, and government have used LCA as a means of understanding environmental impacts across lifecycle stages of products and environmental media (e.g., water, air) (Schmidt 2000). One common application of LCA is informing consumer choice among product alternatives to fulfill a particular need.

Many researchers have drawn attention to notable limitations of using existing LCA methods to inform policymaking, including challenges of setting suitable system boundaries, collecting appropriate inventory data, and verifying modeling assumptions (e.g., DeCicco 2010; Ross et al. 2002). One major limitation of commonly used LCA approaches for policy applications is the focus on individual products in isolation of the economic system in which they exist. Because many environmental policies consist of creating economic incentives for producers or consumers to reduce environmental impact, LCA analyses informing policymaking need to incorporate economic decision-making, and other crucial aspects such as engineering relationships that affect these decisions. This type of systems perspective is particularly important for product-targeting policies because the design decisions that producers make, which considerably impact

environmental outcomes, are governed by the economic structure of the industry, consumer demand, and engineering constraints and tradeoffs.

Some recent LCA analyses include consideration of certain economic factors such as demand elasticities (e.g., Ekvall and Andr e 2006; Sand en and Karlstr m 2007; Schmidt and Weidema 2008) but these studies are limited by considerably simplified assumptions. Most notably, they focus only on commodity products, which are uniform across all producers, and predominantly consider only the decision of whether to increase production of the product. Furthermore, economic parameters such as demand elasticities used in these studies are usually estimates adopted from existing literature without a substantive discussion on the assumptions associated with the estimation and in some cases (e.g., Ekvall and Andr e 2006), these parameters are derived purely from conjecture without a strong basis in econometrics. Development of these methods so that they are appropriate for informing policymaking will require an integration of state-of-the-art econometric approaches and increased transparency of any assumptions associated with parameter estimates. This dissertation contributes to these developments.

Addressing these concerns, policymakers—and in particular, the European Commission (EC)—recently called attention to the need to both broaden and deepen LCA approaches (Guin ee et al. 2010). With regard to broadening LCA, the EC appealed for methods to incorporate economic and social analyses into environmental LCA in order to implement sustainability assessments using a systems approach. With regard to deepening LCA, the EC proposed improving the rigor and suitability of LCA methods to analyze a more extensive set of product and process systems relevant for policymaking. This dissertation contributes to both the broadening and deepening of LCA methods in the context of designed-product systems. With respect to broadening LCA methods, linking lifecycle inventory data to the oligopolistic equilibrium approach described in Chapters 3-5 provides the means to analyze industry systems of designed products with respect to environmental impacts and economic indicators of producer and consumer welfare. With respect to deepening LCA methods, the presented methodology integrates state-of-the-art methods of demand and engineering design modeling to analyze the impact of policy on environmental emissions. While a complete LCA analysis using the developed model is not presented, Chapter 4 presents an analysis of fuel consumption and

greenhouse gas emissions using the developed model and Chapter 6 provides the blueprint for connecting the model or similar models to lifecycle inventory data.

The industrial ecology and LCA literature has distinguished two types of LCA methodologies: attributional LCA (aLCA), which describes the environmentally relevant flows to and from a lifecycle, and consequential LCA (cLCA), which describes how these flows may change in response to possible decisions (e.g., Finnvedan et al. 2009; Curran et al. 2005; Ekvall and Weidema 2004). cLCA extends the boundaries of an aLCA to include not only the flows of the product lifecycle of interest but also any flows of other products that are significantly affected. The system expansion approach of cLCA presents the structure necessary to study a number of indirect “ripple effects”, which have been identified as an important area of research in industrial ecology (Hertwich 2005). Ripple effects that are most commonly included in cLCA studies to date are the impact of increasing production of a product on the displacement of competing products.

Researchers in this literature have begun to implement cLCAs to study systems of commodities. For example, Schmidt and Weidema (2008) present a cLCA of the decision to increase vegetable oil production. The authors identify palm oil as the marginal source of vegetable oil and determine the products that are displaced from palm oil production—specifically that barley and soy meal are displaced by palm kernel meal, which is a co-product of palm oil. The increase in environmental flows resulting from the increase in palm oil production is compared to the decrease in environmental flows from displaced production of barley and soy meal. Using similar methods, Thomassen et al. (2008) studies the effects of an increase in milk production considering the secondary impacts of increased production of dairy-cow meat, which displaces beef-cow meat and pork products, and the increased production of the soy feedstock, which co-produces soybean oil that displaces palm oil. Schmidt (2008) conducts a cLCA of increased demand of wheat in Denmark, exploring various scenarios of increasing supply: increasing yield, land use, displacing other crops, increasing imports, or some combination.

A few researchers have demonstrated the capability of cLCA to encompass a much broader set of ripple effects than the displacement of other products by a co-product. For example, Sandén and Karlström (2007) point out that cLCA captures the propagation of a decision through cause-effect chains in the studied system, which may

include effects on the production of substitutes, demand for related products, technology costs, and changing preferences. The authors illustrate how ripple effects concerning technology adoption could be incorporated into cLCA, accounting for the effect of investing in a new technology—namely fuel cell buses—on the future cost of the technology and, consequently, the future demand for the technology. However, this study relies on very simplified assumptions of product demand, namely that once the marginal production cost of fuel cell buses reaches the cost of diesel buses, only fuel cell buses will be used.

Studies such as these have linked LCA with representations of supply and demand characterizing commodity industries, but further advancement of cLCA methods are needed to appropriately analyze differentiated products, such as light- and heavy-duty vehicles. Analyzing designed products requires extending the current cLCA approach to closely interact with models of consumer preferences for differentiated products and engineering models of product design, which are inherently coupled in differentiated-product systems. In the case of differentiated-product markets, such as automobiles and consumer electronics, demand depends on the product attributes and prices of all products that a consumer may consider purchasing. In these cases, the extent to which one particular product displaces competing products is often not known *a priori* and needs to be estimated for the particular study. Moreover, a change in the system—for example, a new policy intervention or a change in a competitor’s product—is likely to induce firms to adjust the prices and designs of their products, which can significantly affect upstream and downstream environmental flows from the system. Both the economic structure of the market and the design tradeoffs inherent in production are key determinants of these price and design responses and resulting environmental impacts. Understanding the cause-effect chains in such a system requires bridging methods from economics and engineering design together with lifecycle assessment.

This dissertation contributes to the cLCA literature by developing a methodology that bridges methods from economics and engineering design and demonstrating the integration of this methodology with lifecycle inventory data. Together, Chapters 3, 4, and 6 provide the blueprint for conducting LCA analyses from a systems perspective, considering economic decision-making of producers and consumers and the engineering

relationships that govern production options. Moreover, the research in this dissertation establishes methods of conducting LCA analyses using modeling approaches commonly used in economics, which are supported by a mature body of research establishing appropriate data collection, estimation procedures, and interpretation of results. For example, the methods presented consist of performing counterfactual simulations, which use observed data and a model of behavior to investigate the impact of a change (such as a new policy) on the system. The results of these simulations are appropriately interpreted as what would have happened in the past conditional on appropriate assumptions, and are not meant to be predictive. This approach follows similar principles as the fundamental best practices of LCA analysis (ISO 1997).

CHAPTER 3: MODEL DEVELOPMENT

"Design almost invariably involves compromise. Sometimes stated objectives may be in direct conflict with each other, as when motorists demand both good acceleration and low petrol consumption. Rarely can the designer simply optimize one requirement without suffering some losses elsewhere." —Bryan Lawson (1997)

"Getting to the heart of the reasons people purchase and use different products and services can open up new opportunities for resolving the environmental problems associated with them." —Ralph Horne, Tim Grant, and Karli Verghese (2009)

This chapter describes an empirically tractable approach to integrate engineering design models with economic analyses of industrial policies. The analysis begins by highlighting some relevant features of the automotive design process to both the engineering-design and demand-side models. Then, construction of the engineering design model is described, which represents the ability of firms to trade off fuel efficiency, acceleration performance, and production costs. Next, the development of the demand model is described. Finally, the demand model is used to estimate production costs that are not captured in the engineering design model.

3.1 Vehicle Development Process

The design response of an automotive manufacturer to government policies depends substantially on the structure of the vehicle development process. This process is a structured sequence of interrelated decisions, many of which constrain choices made at later stages (Sørensen 2006). The typical design process begins with concept development, followed by a system-level design that defines the geometric layout of the vehicle (including target vehicle dimensions), followed by detailed design of all subsystems (Sørensen 2006; Weber 2009).

For a newly designed vehicle model, the development process begins with a target catalog specifying the vehicle segment (e.g., compact), powertrain architecture (e.g.,

hybrid), variations (e.g., four-door sedan), major dimensions, transmission types (e.g., automatic, torque classes) and engine versions (Braess and Seiffert 2005; Weber 2009). For a redesigned model, the development process begins with the determination of any changes to major properties of the vehicle and specifications for subsystems, such as how many drivetrain configurations or engine options will be available. In both new design and redesign contexts, there are certain earlier design decisions that must be finalized before the detailed engineering design of vehicle subsystems can begin (Braess and Seiffert 2005; Sörenson 2006; Weber 2009).

Figure 3.1 provides a stylized representation of this development process. This figure is somewhat misleading insofar as it suggests that the design process proceeds in sequential, clearly defined stages. In fact, iteration loops and overlapping tasks often exist between the stages presented. This caveat notwithstanding, it is possible to identify a stage in current automotive development processes where vehicle segment, powertrain architecture (e.g., conventional gasoline, hybrid, diesel), and major dimensions are finalized but “tuning” of powertrain variables is still possible.

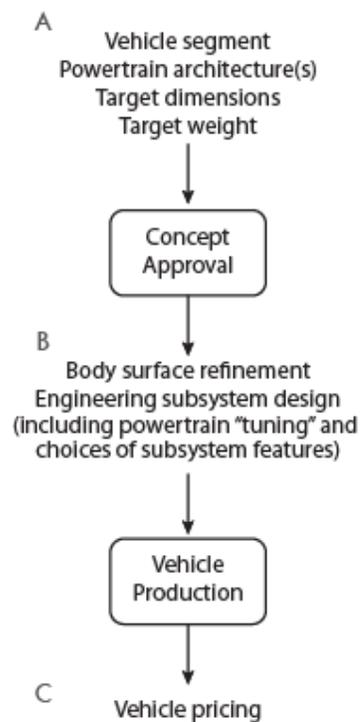


Figure 3.1 Simplified representation of an automotive development process. Stages of this process can be roughly be grouped into longer run (Stage A), medium-run (Stage B) and short-run (Stage C) design decisions

The structure of the automotive development process informs the demand- and supply-side models in two important ways. On the demand side, we use the variation in vehicle attributes determined in earlier stages of the design process (i.e., Stage A in Figure 3.1) to instrument for endogenous variables in our demand-side estimation, which are determined later in the design process (Stage B). On the supply side, we take as given the vehicle segment, powertrain architecture, and other vehicle dimensions that are determined in the earlier stages of the design process (Stage A). Conditional on these features and attributes, we model manufacturers' choice of fuel economy and acceleration performance (Stage B) and vehicle pricing strategies (Stage C). Ideally, the supply side would be modeled as a two-stage game to represent the sequence of choosing product attributes before prices (or prices with smaller adjustments of product attributes). However, given the scale of the model, solving the second-stage using traditional Newton-based methods is computationally infeasible and faster methods such as fixed-point calculations that account for the CAFE constraint have not yet been developed (Morrow 2008).

3.2 Engineering Design Model

Credible modeling of endogenous attribute selection in the design of technical products such as automobiles requires accurate representation of engineering and economic tradeoffs. We cannot directly observe all of the tradeoffs that firms make during different stages of the vehicle design process. We can, however, generate detailed engineering models of the tradeoffs that play an important role in determining vehicle fuel efficiency in medium-run design decisions.

Medium-run design tradeoffs are represented by iso-cost production possibility frontiers (PPFs) of fuel efficiency and acceleration performance. These frontiers, also called efficiency frontiers in the engineering literature, represent the combinations of fuel efficiency and acceleration performance where no attribute can be improved without incurring a loss in the other or by increasing production costs. The PPFs are constructed

by estimating a “surrogate model” using a flexible parametric regression on data generated from detailed vehicle simulations.¹

3.2.1 Medium-run design decisions affecting fuel efficiency

Our analysis of firms’ response to the CAFE regulations focuses on medium-run vehicle design decisions and short-run vehicle pricing decisions (Stage B and C in Figure 3.1). At this point in the vehicle development process, many major parameters of the vehicle have been determined including the segment of vehicle, key internal and external dimensions, and the powertrain architecture (e.g., conventional gasoline, hybrid, and diesel). The automotive manufacturer can still adjust fuel efficiency and acceleration performance at this point in the design process by “tuning” a number of variables in the powertrain (e.g., engine displacement and the final drive ratio) and including technology features (e.g., a high efficiency alternator). For example, consider a given vehicle design such as the Honda Accord. If Honda wants to increase the fuel efficiency of the Accord, it could decrease the displacement size of the engine, or it could simply change the programming in the powertrain electronic control unit to favor fuel efficiency over acceleration performance. Each of these adjustments to improve fuel efficiency will cause some loss in acceleration performance.

Another means of improving fuel efficiency at this stage in the design process involves incorporating various extra “technology features” to the vehicle design. Examples include high efficiency alternators, low resistance tires, and improved aerodynamic drag of the vehicle body (NHTSA 2008). Adding one or more of these features increases the cost of vehicle production. Depending on the specific technology features chosen, acceleration performance may increase, decrease, or remain the same. For example, cylinder deactivation of the engine can improve fuel efficiency by effectively decreasing the size of the engine but, because it only is active during coasting, it will not affect acceleration. Reducing aerodynamic drag of the vehicle body can improve both fuel efficiency and acceleration performance, whereas early shifting logic can improve fuel efficiency but will reduce acceleration performance. These technology

¹ The term “surrogate model” is commonly used in the engineering literature to denote a simplified model approximating a more complex model simulation, commonly done to reduce computation time and improve tractability.

features only affect demand through their influence on fuel efficiency and acceleration performance; they do not have intrinsic value to the consumer.

Although our goal is to identify the continuous iso-cost PPFs that define the relationship between fuel economy, acceleration performance, and production costs dependent on these medium-run design decisions, vehicle simulations and automotive data suggest that these PPFs are not in fact continuous. To illustrate this, again consider a given vehicle design such as the Honda Accord. The Accord could be described by its position on the two dimensional fuel-efficiency vs. acceleration-performance space. Honda can decrease the fuel consumption of the Accord without adding any additional technology features by trading off acceleration performance, which could be represented by the Accord moving along an “iso-technology curve” as in Figure 3.2. Considering that Honda could move along this curve in large increments by replacing the engine, smaller increments by decreasing the displacement size of the existing engine, or fine increments by adjusting the electronic control unit, approximating these possibilities as continuous is reasonable. However, incorporating technology features into the vehicle to increase fuel efficiency often causes discrete shifts in vehicle attributes. These discrete shifts of the iso-technology curves in the fuel-efficiency vs. acceleration-performance space cause discontinuities in the iso-cost PPFs as illustrated in Figure 3.2.

Ideally, we may like to model the discontinuities in the iso-cost PPFs caused by discrete technology options. However, because of the large number of discrete combinations of technology features, further described in Section 3.4, this is computationally infeasible. We address this challenge by approximating the effect of the technology features as a continuous variable. To do this, we first construct the iso-technology curves for each combination of technology features, and then order the technology-feature combinations by the position of their corresponding iso-technology curves. Finally, we approximate the technology features as continuous in the counterfactual simulations to construct the iso-cost PPFs.

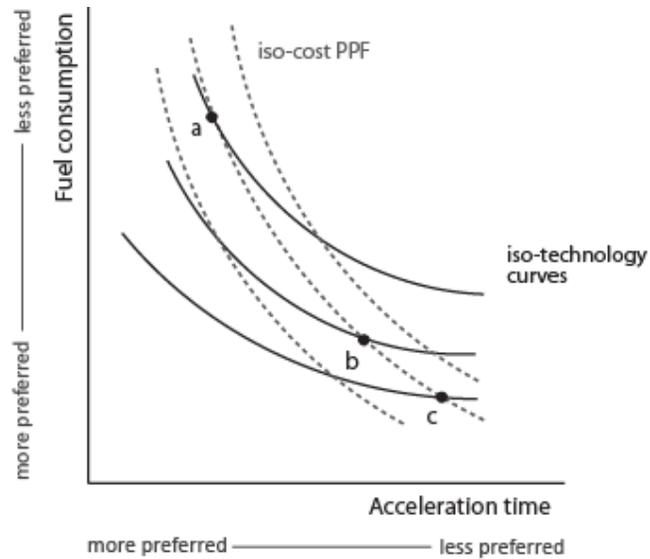


Figure 3.2 Iso-cost and iso-technology production possibility frontiers. Iso-cost PPFs are discontinuous (a to b to c) due to the discrete effect technology features have on possible attribute combinations

3.2.2 Vehicle simulations

We use detailed engineering simulations to construct the “baseline” iso-technology curves. This represents the engineering tradeoffs between fuel consumption and 0-60 mph acceleration time for a vehicle with no extra technology features. To determine the baseline iso-technology curves, we use the vehicle simulations software AVL Cruise to characterize the engineering tradeoffs between fuel efficiency and 0-60 mph acceleration time for each vehicle class, then construct a surrogate model of these tradeoffs. AVL Powertrain Engineering, Inc. (AVL) is an independent company, founded in 1948 and headquartered in Austria, specializing in the development of powertrain systems, simulation methods, and engine instrumentation and test systems. The vehicle simulation software Cruise, developed by AVL, is commonly used by automotive original equipment manufacturers to aid in powertrain development (Mayer 2008).

Cruise simulates vehicle-driving performance, fuel consumption, and emissions based on kinematic calculations. Specifically, Cruise models the physical dynamics that occur between subsystems in a vehicle, which translate inputs from a driver into motion of the vehicle. For example, as Figure 3.3 shows, the Engine module is physically connected to the modules making up the transmission, which include the Torque

Converter, Gear Box, Final Drive, and Differential modules. The Combustion Engine module calculates the fuel consumption, speed, and torque of the engine based on user inputs, such as fuel consumption maps, and input information from other vehicle subsystems, including the load on the acceleration pedal from the Cockpit (driver) module and the external temperature from the Vehicle module. It then transmits information about the torque and speed to the transmission modules.

The modular structure of Cruise allows researchers to simulate multiple vehicle architectures by customizing the subsystem modules (e.g., front or rear wheel drive, automatic or manual transmissions), and modifying various input parameters. For example, with the Vehicle module, a user can adjust the aerodynamic drag coefficient of the vehicle body and the curb weight of the vehicle.

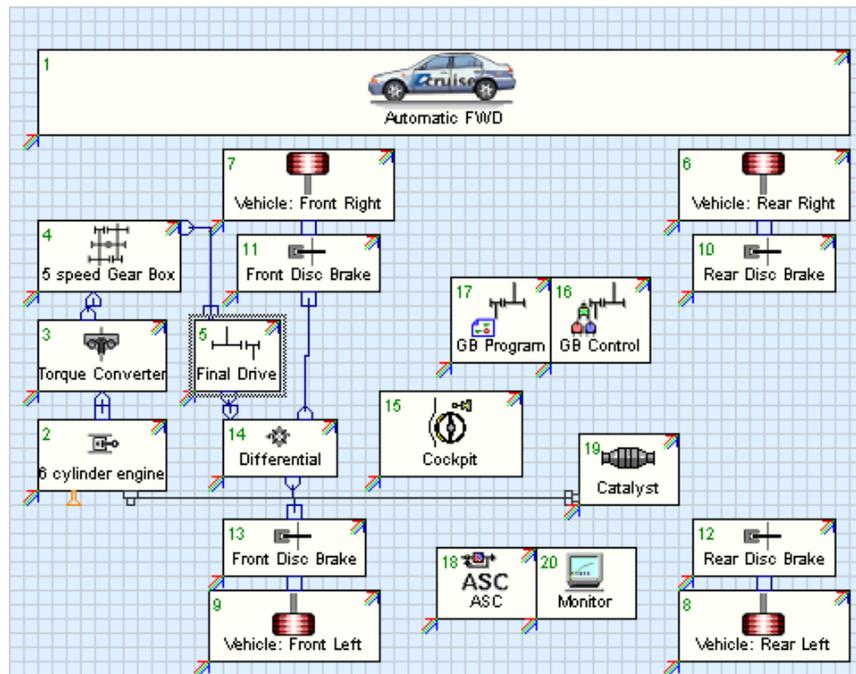


Figure 3.3 Screen shot of the AVL Cruise simulation interface

Using Cruise, a total of 29,575 vehicle simulations were conducted. Design input parameters were varied at small intervals so that we can observe the influence of each of these parameters and their interactions on attributes of interest (i.e. acceleration performance and fuel efficiency). The fuel efficiency of a vehicle design, dependent on input parameters, is determined in AVL Cruise by simulating the EPA's fuel-economy

test procedures. Acceleration performance is determined by simulating a shifting program of the vehicle from standstill to 60 mph. Table 3.1 summarizes the range of parameter values we consider in our analysis. These include the powertrain variables that can be changed in the medium run (i.e., engine displacement and final drive ratio) as well as longer run design attributes that are continuous (i.e., curb weight), which are used to more accurately construct the PPFs for a specific vehicle conditional on these longer run design attributes.

All other input parameters into the AVL Cruise simulations were determined from a representative base vehicle for each class.² Many of these parameters (e.g., front-wheel drive) are determined prior to the medium-run decisions we are interested in, but for some parameters (e.g., transmission gear ratios), it is possible that they could be modified in the same time period. In these cases, omitting these potential design options will only make our estimates of the costs of CAFE more conservative, representing an upper bound, because we are not accounting for design options that may be cost-effective.

Table 3.1 Ranges and intervals of vehicle simulation parameters

Vehicle Class	Base Vehicle	Displacement			Curbweight			Final Drive		
		Min	Max	Int.	Min	Max	Int.	Min	Max	Int.
2seater/Mini	Ford Mustang	1,000	8,200	400	1,900	4,300	800	1.0	6.0	0.4
Sub/Compact	Honda Civic	1,000	4,200	400	2,200	4,800	800	1.0	6.0	0.4
Midsize	Toyota Camry	1,000	4,200	400	2,400	4,800	800	1.0	6.0	0.4
Fullsize	Ford Taurus	1,600	6,800	400	3,200	5,400	400	1.0	6.0	0.4
SUV	Ford Explorer	2,000	8,400	400	3,200	8,000	800	1.0	6.0	0.4
Small pickup	Toyota Tacoma	1,600	8,400	400	2,800	5,200	800	1.0	6.0	0.4
Stand. pickup	Ford F150	2,000	8,400	400	3,200	6,600	400	1.0	6.0	0.4

Notes: This table lists the min, max, and interval of input parameters used in the “AVL Cruise” vehicle simulations. Engine Displacement is in cm³, Curbweight is in lb, and Final Drive is the final drive gear ratio. All other input parameters for the simulations (e.g., front-wheel drive) were taken using data for the “base vehicle”.

Our next step is to determine how the addition of one or more technology features affects the position of the iso-technology curve relative to the baseline. To accomplish this, we combine the AVL Cruise simulations and data from NHTSA (2008). We consider only a subset of the types of technology features identified by NHTSA in our

² The classes are based on EPA segment classifications, with some grouping of segments based on similar ranges of input design variables and similar predicted outputs from AVL Cruise.

analysis. The majority of technology features we omit from our analysis are only available in longer run planning stages, but some features are eliminated because of the challenges in simulating their effects (e.g., variable valve timing). Consistent with NHTSA, we omit the ability to lightweight vehicles by substituting vehicle components with lighter materials.³ Similar to excluding some design options, omitting these technology features will only make our estimated costs of CAFE more conservative.

Table 3.2 Technology costs and effects on fuel economy and 0-60 acceleration time

Technology	Two Seater			Compact			Midsize / Minivan			Fullsize		
	cost	% mpg	% acc	cost	% mpg	% acc	cost	% mpg	% acc	cost	% mpg	% acc
Low friction lubricants	3	0.5	0.3	3	0.5	4.1	3	0.5	0.6	3	0.5	0.6
Engine friction reduction	126	1	0.3	84	1	5.6	126	1	1.5	126	1	1.2
Aggressive shift logic	38	1	-0.2	38	1	-5.0	38	1	-0.2	38	1	-0.3
Early torque converter lockup	30	0.5	-	30	0.5	-	30	0.5	-	30	0.5	-
High efficiency alternator	145	1	0.3	145	1	5.6	145	1	1.5	145	1	1.2
Aerodynamic drag reduction	38	3	0.3	38	3	5.1	38	3	0.5	38	3	0.3
Low rolling resistance tires	6	1	0.1	6	1	2.5	6	1	0.2	6	1	0.1
Cylinder deactivation		n/a			n/a		203	4.5	-	203	4.5	-

Technology	SUV			Sm Pickup			Lrg Pickup / Van		
	cost	% mpg	% acc	cost	% mpg	% acc	cost	% mpg	% acc
Low friction lubricants	3	0.5	1.6	3	0.5	0.4	3	0.5	0.7
Engine friction reduction	126	1	3.1	126	1	0.7	168	1	1.5
Aggressive shift logic	38	1	0.0	38	1	-0.2	38	1	-2.8
Early torque converter lockup	30	0.5	-	30	0.5	-	30	0.5	-
High efficiency alternator	145	1	3.1	145	1	0.7	145	1	1.5
Aerodynamic drag reduction	38	3	1.4	38	2	0.5	38	2	0.4
Low rolling resistance tires	6	1	0.5	6	1	0.2	0	1	0.1
Cylinder deactivation	203	4.5	-	203	4.5	-	229	4.5	-

Notes: cost represents the unit production cost in \$/vehicle produced, % mpg is the percentage increase in combined highway-city fuel economy, and % acc is the percentage reduction in 0-60 mph acceleration time in seconds. Cost and fuel economy figures are taken from NHTSA (2008). The change in acceleration is calculated in the engineering vehicle simulation model, AVL Cruise.

NHTSA (2008) estimated the effect of each technology feature listed in Table 3.2 on fuel economy, in terms of the percentage improvement, based on values reported by automotive manufacturers, suppliers, and consultants. We use these estimates to determine how the baseline iso-technology curve changes with the addition of one or more technology features. To do this we also need to know the impact of each technology

³ NHTSA does not consider lightweighting in order to evaluate the ability of manufacturers to meet CAFE standards without reducing the weight of vehicles because of concerns that this will increase traffic safety risks. Chapter 5 discusses this concern in more detail.

feature on 0-60 acceleration time, which is not reported by NHTSA. We determine these impacts by simulating each technology feature in AVL Cruise to a level that matches the improvement in fuel economy reported by NHTSA. For example, NHTSA reports a 0.5% improvement in fuel economy from using “low friction lubricants” in compact vehicles. We simulate this impact by reducing the friction losses in the engine of our representative compact vehicle model until we observe fuel economy improving by 0.5% and then observe the percentage improvement of 0-60 acceleration time. When NHTSA provided a range of fuel economy improvement for a technology feature, the lower bound of this range is used, consistent with our other assumptions in creating a conservative engineering design model. The results of these simulations are reported in Table 3.2.

3.2.3 Costs of medium-run design decisions

In addition to representing the impact of medium-run design decisions on vehicle attribute performance, we also need to account for the effect of these decisions on production costs. We use two separate sources of data to estimate these costs, one describing costs dependent on the powertrain variables, which we use to determine costs along the baseline iso-technology curve, and another data set detailing production costs for each technology feature. The production costs of the baseline iso-technology curve—representing the costs dependent on choices of engine size and final drive ratio without any extra technology features—is taken from Michalek et al. (2004). The authors collected cost data from manufacturing, wholesale, and rebuilt engines of varying displacements. The additional production costs resulting from each technology feature is taken from NHTSA (2008), which are shown in Table 3.2. These cost data were estimated by NHTSA based on reported values from automotive manufacturers, suppliers, and consultants, and are currently used to perform cost-benefit analyses of the CAFE regulations.

We treat the costs of technology features and the costs of adjusting powertrain variables as additively separable. Engines are manufactured separately from other subsystems of the vehicle before assembly. The specific technology features we consider do not require changes in engine design or affect the assembly of the engine with other vehicle subsystems, consistent with our assumption that costs are additively separable,

with only two exceptions. Two technology features—engine friction reduction and cylinder deactivation—do affect the engine subsystem. Even in these cases, it is reasonable to approximate technology costs as additively separable from the baseline production cost of the engine. For example, engine friction can be reduced by using lubricants, the costs of which are independent of all medium-run decisions considered.⁴

3.2.4 Model of engineering tradeoffs and costs

Ideally, all of the detailed information about design tradeoffs that are captured by the AVL Cruise model would be incorporated directly into our model of supply-side design and pricing decisions. However, because of the computational time required to execute the vehicle simulations, and the large number of discrete combinations of technology features, this is computationally infeasible. Instead, we approximate these relationships with a surrogate model using a flexible parametric form.

Taking all possible combinations of technology features gives automotive firms, depending on the vehicle segment, 128–256 options to choose from for each vehicle. From this set, we consider only those combinations of features that are cost effective—meaning that there is no lower cost combination that could achieve the same or better level of acceleration performance and fuel efficiency. Although this reduces the set of technology feature combinations to between 20 and 76, depending on the vehicle segment, it is still computationally infeasible to model this number of choices per vehicle for each manufacturer in our counterfactual simulations, so further simplifications are necessary.

We approximate the discrete choices of technology features as a continuous variable, *tech*, ranging from zero (the baseline case) to the maximum number of cost-effective combinations of technology features for each vehicle class. Note that a particular value for *tech* maps to a specific combination of technology features (e.g., low resistance tires and a high efficiency alternator) and does not represent the number of

⁴ The case of cylinder deactivation poses a larger challenge for treating technology costs as additively separable from engine costs. Given large changes in engine displacement achieved by switching the engine architecture (e.g., replacing a V-8 engine with a V-6) would slightly reduce the costs of cylinder deactivation due to a smaller number of cylinders. However, even with this cost reduction, cylinder deactivation is the highest-cost technology feature considered and therefore would not significantly affect counterfactual results.

technology features. The set of cost-effective technology feature combinations is ordered by increasing fuel efficiency (decreasing fuel consumption) for the same acceleration performance, which is also increasing in cost. Therefore, a higher value of *tech* corresponds to a higher fuel efficiency and higher cost vehicle conditional on 0-60 acceleration time. The impact of the continuous approximation on the results is relatively small with the average gap between discrete features less than 1 mpg. Furthermore, we provide some evidence in Section 3.5 that the particular specification we use to estimate the relationships of the continuous *tech* variable to fuel consumption and cost preserves important properties of the discrete technology combinations.

We use the results of the engineering simulations together with data on the technology features and technology costs to estimate Equations 3.1 and 3.2, which together define the PPFs between vehicle fuel consumption, acceleration performance, and the portion of production costs dependent on design decisions, w_j . Several specifications for each equation were tested; the equations below performed the best under the Akaike Information Criterion.

$$eff_j = \kappa_{1s} + \kappa_{2s}e^{-acc_j} + \kappa_{3s}tech_j + \kappa_{4s}tech_j \cdot acc_j^2 + \kappa_{5s}wt_j + \kappa_{6s}wt_j \cdot acc_j + \varepsilon_j \quad 3.1$$

$$w_j = \sigma_{1s} + \sigma_{2s}e^{-acc_j} + \sigma_{3s}tech_j + \sigma_{4s}wt_j + \sigma_{5s}wt_j \cdot acc_j + v_j \quad 3.2$$

The subscript j in Equations 3.1 and 3.2 denotes the vehicle design in vehicle class s , where the specific design represents a combination of design parameters which were input into the vehicle simulations as described in Section 3.2.2.

The dependent variable in Equation 3.1 is the fuel efficiency of a vehicle, *eff*, in terms of gallons per 1,000 miles. The 0-60 acceleration time is denoted *acc*, *wt* is the curb weight of the vehicle, and *tech* is the scalar measure of technological features incorporated. Equation 4 models the portion of production costs that are dependent on the medium-run design decisions considered. This portion of production costs is a function of curb weight, acceleration time, and the continuous measure of technology features. The terms ε_j and v_j represent the error associated with approximating the calculations performed in the vehicle simulations with simplified relationships. Curb weight is included in Equations 3.1 and 3.2 although it is considered fixed in our analysis.

Including curb weight, and estimating the parameters for each vehicle class, conditions

the fuel consumption and cost relationships on vehicle parameters that are exogenous in the medium run and greatly improves estimation fit.

3.2.5 Model estimation

Parameters defining the tradeoffs between vehicle fuel efficiency, acceleration performance, and production costs are estimated using the data generated from the vehicle simulations described in Section 3.3. Estimated parameters for Equation 3.1, summarizing the relationship between vehicle attributes dependent on technology features and powertrain parameters for each vehicle class, are reported in Table 3.3. The estimated relationships fit the vehicle data in each class reasonably well ($R^2 > 0.89$) except for the two-seater class ($R^2 = 0.44$). However, the two-seater class comprises less than 1% of vehicle sales in MY2006 so the poorer fit of this class should not significantly affect counterfactual results.

All parameter estimates have expected signs. The negative sign on the variable representing technology features and positive sign on the interaction between the technology variable and acceleration indicate that implementing more fuel-efficient combinations of technology features reduces fuel consumption with decreasing returns, as illustrated in Section 3.5. The positive sign on the weight parameter and negative sign on the weight-acceleration interaction imply that the iso-technology curves in Figure 3.1 shift up and rotate clockwise with vehicle weight. This indicates that heavier vehicles will have worse fuel consumption given the same 0-60 mph acceleration time, as expected, but that this effect increases for vehicles with faster acceleration.

The estimates describing the relationship between production costs and choices of acceleration performance and technology implementation, described by Equation 3.2, are reported in Table 3.4. These estimates fit all vehicle classes reasonably well ($R^2 > 0.83$). As expected, these results indicate that production costs increase with the level of technology implementation and decrease with worse acceleration performance. The positive sign on the weight term and negative sign on the weight-acceleration interaction term indicate that incrementally improving acceleration is more costly in heavier vehicles and this effect is magnified for vehicles with relatively better acceleration performance. All parameter estimates in both equations are significant to the 90% level or better.

Table 3.3 Estimation results for fuel consumption in technology and design model

	Two seater		Compact		Midsize / Minivan		Fullsize	
	param	std. err.	param	std. err.	param	std. err.	param	std. err.
constant	20.8484 ***	0.9414	10.7920 ***	0.2158	11.5531 ***	0.5674	10.8515 ***	0.4034
exp(-acc _j)	89.6806 ***	31.1595	69.5244 ***	5.3977	733.71 ***	55.37	452.55 ***	23.78
tech _j	-0.2049 ***	0.0245	-0.2605 ***	0.0129	-0.0829 ***	0.0018	-0.0794 ***	0.0042
acc _j ² ?tech _j	0.0016 *	0.0005	0.0013 **	0.0003	0.0002 ***	2.3E-05	0.0002 ***	2.7E-05
wt _j	2.9159 ***	0.3667	12.9897 ***	0.3047	8.6680 ***	0.1119	8.3583 ***	0.1208
wt _j ?acc _j	0.0280	0.0476	-0.5593 ***	0.0456	-0.2954 ***	0.0223	-0.2539 ***	0.0079
R ²	0.443		0.941		0.896		0.976	
Obs.	4473		5117		3542		3542	

	SUVs		Small Pickup		Large Pickup / Van	
	param	std. err.	param	std. err.	param	std. err.
constant	14.0535 ***	0.4985	10.5032 ***	0.4049	10.5185 ***	0.4083
exp(-acc _j)	1329.85 ***	115.80	13387.53 ***	1836.19	2979.10 ***	411.24
tech _j	-0.1540 ***	0.0082	-0.0933 ***	0.0071	-0.0890 ***	0.0065
acc _j ² ?tech _j	0.0006 ***	0.0001	0.0003 **	0.0001	0.0003 **	0.0001
wt _j	9.0653 ***	0.1069	8.9932 ***	0.3207	8.6604 ***	0.2813
wt _j ?acc _j	-0.2934 ***	0.0148	-0.2224 ***	0.0295	-0.2225 ***	0.0299
R ²	0.965		0.952		0.952	
Obs.	16863		9450		9450	

*p<0.1, **p<0.05, ***p<0.01, all others p>0.1, standard errors are clustered by vehicle curb weight

Table 3.4 Estimation results for cost of technology and powertrain design

	Two seater		Compact		Midsize / Minivan		Fullsize	
	param	std. err.	param	std. err.	param	std. err.	param	std. err.
constant	0.3669 *	0.0865	0.7800 ***	0.0091	0.5540 ***	0.0355	0.4029 ***	0.0450
exp(-acc _j)	10.6686 *	2.2311	1.9716 ***	0.1631	24.3842 ***	1.3842	24.0527 ***	2.7273
tech _j	0.0175 ***	0.0001	0.0016 ***	0.0002	0.0054 ***	0.0001	0.0057 ***	3.0E-05
wt _j	0.2579 ***	0.0132	0.2250 ***	0.0051	0.1963 ***	0.0103	0.2339 ***	0.0052
wt _j ?acc _j	-0.0082 ***	0.0013	-0.0123 ***	0.0005	-0.0071 ***	0.0012	-0.0069 ***	0.0004
R ²	0.890		0.898		0.898		0.931	
Obs.	4473		5117		3542		3542	

	SUVs		Small Pickup		Large Pickup / Van	
	param	std. err.	param	std. err.	param	std. err.
constant	0.0200 **	0.1337	0.3025 *	0.0607	0.3025 *	0.0607
exp(-acc _j)	92.3965 ***	16.4768	719.579 *	162.643	160.560 *	36.291
tech _j	0.0038 ***	0.0003	0.0066 ***	0.0001	0.0066 ***	0.0001
wt _j	0.3470 ***	0.0143	0.2621 ***	0.0137	0.2538 ***	0.0117
wt _j ?acc _j	-0.0108 ***	0.0016	-0.0055 *	0.0014	-0.0055 *	0.0014
R ²	0.887		0.831		0.831	
Obs.	16863		9450		9450	

*p<0.1, **p<0.05, *** p<0.01, standard errors are clustered by vehicle curb weight

Taken together, the estimates of Equations 3.1 and 3.2 define the iso-cost PPFs conditional on longer run vehicle-design decisions. These results suggest that significant improvements in fuel efficiency are possible in the medium run but require either substantial tradeoffs with other aspects of vehicle performance or an increase in production costs. To illustrate this, Figure 3.4 plots the estimated iso-cost PPFs for selected vehicles, indicating that a 10% reduction in fuel consumption can be achieved in many vehicles without increasing production costs by reducing acceleration performance by 1 s or less.

On the other hand, fuel efficiency can be increased without affecting acceleration performance by implementing technology features, which instead raise production costs. Figure 3.6 in Section 3.3 plots the relationship between technology costs and fuel economy for select vehicle models. This figure illustrates that the required technology costs to incrementally increase fuel economy vary considerably between vehicles depending on the vehicle class and characteristics such as fuel economy and weight. For many vehicle models, the fuel economy can be increased by 1 mpg by implementing \$200 or less worth of technology features but these costs are substantially more for larger vehicles, up to \$600 for the heaviest vehicles.

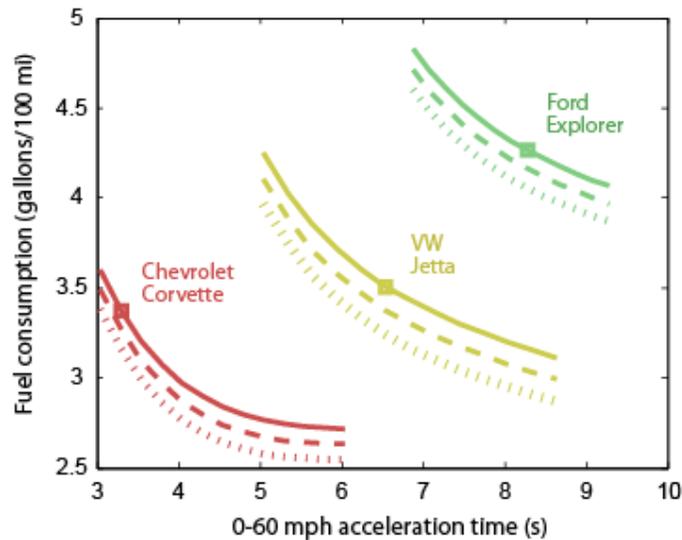


Figure 3.4 Estimated iso-cost production possibility frontiers for selected vehicles (■ current location, — baseline frontier, - - \$100 design changes, ··· \$200 design changes)

Validation tests were performed comparing the estimated model to observed vehicle data. Figure 3.5 plots observed and estimated fuel economy of non-hybrid gasoline vehicles from model-year 2006. Predicted fuel economy values fit the observed data with an R-squared value of 0.80. Additional validation tests comparing the estimated model with observed data and representations derived by MacKenzie (2009) are discussed in Section 3.6.

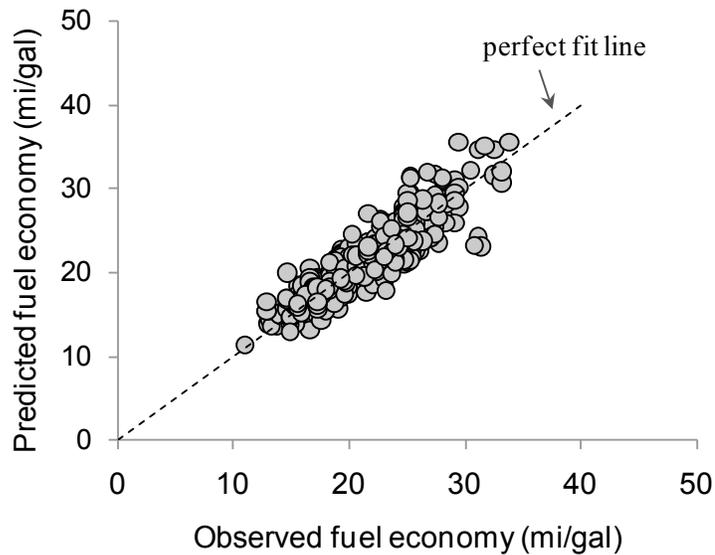


Figure 3.5 Comparison of compact-segment model to MY-2006 vehicle data

3.3 Demand Model

In this section, we introduce an econometric model of vehicle demand and a supply-side representation of decisions in response to CAFE. The specification and estimation of the demand-side model draws from the seminal work by Berry et al. (1995) and subsequent work by Train and Winston (2007) and others. The distinguishing feature of the demand estimation has to do with our choice of instruments, which is informed by our understanding of the vehicle design process as described in Section 3.1. Our model of the supply side departs significantly from much of the previous literature insofar as critical medium run design decisions are endogenous to the model.

3.3.1 Data summary

We employ a combination of household-level data conducted by Maritz Research and vehicle characteristic data available from Chrome Systems Inc. to construct our demand-side estimations. The Maritz Research U.S. New Vehicle Customer Study (NVCS) collects data monthly from households that purchased or leased new vehicles. This survey provides information on socio-demographic data, household characteristics, and the vehicle identification number (VIN) for the purchased vehicle. The survey also asks respondents to list up to three other vehicles considered during the purchase decision. Approximately one-third of respondents listed at least one considered vehicle. Because the survey oversamples households that purchase vehicles with low market shares, we take a choice-based sample from this data such that the shares of vehicles purchased by the sampled households matches the observed 2006 model-year market shares.

We supplement the survey data with information on vehicle characteristics using Chrome System Inc.'s New Vehicle Database and VINMatch tool. Vehicle alternatives are identified using the reported VIN, distinguishing vehicles by their make, model, and engine option, with a few modifications. We eliminate vehicles priced over \$100,000, which represent a small portion of market sales, and remove seven vehicle alternatives that were not chosen or considered by any survey respondent. We further reduce the data set by consolidating pickup truck and full-size van models with gross vehicle weight ratings over 8,000 lb to only two engine options each. Summary vehicle data are described in Table 3.5.

Table 3.5 Summary of Vehicle Characteristic Data

Attribute	Unit	Mean	Std. Dev	Min	Max
MSRP	<i>1,000 2006\$</i>	32.67	16.73	11.93	97.49
Fuel Economy	<i>mpg</i>	21.46	5.14	10.98	56.55
Horsepower	<i>hp</i>	241	78	65	520
Curb weight	<i>1,000 lb</i>	3.87	0.85	1.98	6.40
Footprint	<i>1,000 in²</i>	13.92	2.00	9.52	20.05
Make Grps.	38				
Obs.	473				

3.3.2 Mixed-logit consumer choice representation

Demand for new automobiles is modeled using a mixed-logit representation of consumer preferences. The indirect utility U_{nj} that consumer n derives from purchasing vehicle model j is defined as in Equation 3.3.

$$U_{nj} = V_{nj} + \epsilon_{nj} = \delta_j + \beta_n' \mathbf{x}_{nj} + \boldsymbol{\mu}' \mathbf{w}_{nj} + \epsilon_{nj} \quad 3.3$$

The model-specific fixed effect, δ_j , represents the portion of utility that is the same across all consumers; \mathbf{w}_{nj} are interactions between vehicle attributes and consumer characteristics that affect utility homogeneously across the population; \mathbf{x}_{nj} are vehicle attributes and attribute-demographic interactions that heterogeneously affect utility, entering the equation through draws, β_n , of normal distributions with standard deviations σ . Attributes in the vector \mathbf{w}_{nj} , which are assumed to have homogeneous effects in the utility specification, include the interaction between living in a rural area and the pickup truck segment, and interactions between children in the household and SUV and minivan segments. Attributes in the vector \mathbf{x}_{nj} , which have random effects in the utility specification, are the ratio of vehicle price to income; “gallons per mile”, gpm , or the inverse of fuel economy; the inverse of 0-60 acceleration time; and vehicle footprint. The disturbance term ϵ_{nj} is the unobserved utility that varies randomly across consumers.

Assuming that the disturbance term in Equation 3.3, ϵ_{nj} , is independent and identically distributed (iid) Type I extreme value, the probability that consumer n chooses vehicle i over all other vehicle choices $j \neq i$ or the outside option⁵ takes the form:

$$P_{in} = \frac{e^{V_{ni}}}{1 + \sum_j e^{V_{nj}}} \quad 3.4$$

where V_{nj} is the portion of utility of vehicle j for consumer n in Equation 3.3 excluding the error term. The predicted market share of vehicle i is $\sum_n P_{in}$.

The model specific fixed effects, δ_j , capture the average utility associated with the observed vehicle attributes denoted \mathbf{z}_j and unobserved attributes denoted ξ_j . Vehicle attributes in the vector \mathbf{z}_j include price, fuel consumption, the inverse of 0-60 acceleration

⁵ The utility of the outside option of not purchasing a new vehicle is assumed to be $U_{n0} = \delta_0 + \epsilon_{n0}$, where ϵ_{n0} is a draw from an extreme value Type 1 distribution, and δ_0 is normalized to zero.

time, vehicle footprint, and vehicle segment. The segments are based on the EPA's classes (e.g., minivans). The observable variables of primary interest (namely price, fuel consumption, and acceleration time) are likely to be correlated with unobserved attributes that are simultaneously determined and captured in the error term. Consequently, estimating Equation 3.4 directly will yield inconsistent parameter estimates. Following Berry (1994), we move this endogeneity problem out of the non-linear Equation 3.4 and into a linear regression framework. This allows us to address the endogeneity problem using the well developed two-stage least squares approach. More precisely, we define the model specific fixed effects to be a function of observed vehicle attributes, \mathbf{z}_j , including all endogenous attributes, and the average utility of unobserved attributes, ξ_j :

$$\delta_j = \boldsymbol{\alpha}'\mathbf{z}_j + \xi_j \quad 3.5$$

Berry (1994) shows that, given a set of values for $\boldsymbol{\mu}$ and $\boldsymbol{\sigma}$, a unique $\boldsymbol{\delta}$ exists such that predicted market shares match observed market shares. Given a set of exogenous attributes and instrumental variables for endogenous attributes, \mathbf{y} , the condition that $\mathbb{E}(y_j|\xi_j) = 0$ for all j is sufficient for the instrumental variable estimator of $\boldsymbol{\alpha}$ to be consistent and asymptotically normal conditional on $\boldsymbol{\mu}$ and $\boldsymbol{\sigma}$.

In related automotive studies (e.g., Berry et al. 1995; Train and Winston 2007), researchers use functions of non-price attributes as instruments, including vehicle dimensions, horsepower and fuel economy. This approach has been criticized because of two concerns: 1) firms presumably choose these non-price attributes simultaneously with prices and unobserved attributes, and 2) decisions regarding unobserved attributes may depend on previously determined non-price attributes, rendering them invalid as instruments.⁶ As Heckman and Leamer (2007) note, to obtain valid instruments in this context requires a model of the determinants of product attributes. Access to the engineering design literature provides a description of this model.

⁶ Berry et al. (1995), and Train and Winston (2007) both focused on short-run pricing decisions and therefore the assumption that many vehicle attributes are exogenous to their analysis is justified. However, anecdotal evidence suggests that automotive manufacturers routinely adjust the electronic control unit of vehicle engines, which affects fuel economy and acceleration performance, in the same time frame as setting suggested retail prices and thus fuel economy may not be exogenous to pricing decisions.

Availability of literature detailing the automotive development process allows us to limit the choice of instruments to only those attributes determined from longer run product-planning schedules than the endogenous variables, increasing the credibility of these instruments for medium-run analyses.⁷ Instruments are selected from attributes that can be considered fixed in the medium run as supported by evidence in Section 2.2: the moments of vehicle dimensions of same-manufacturer vehicles (din , $dsqin$) and different-manufacturer vehicles ($dout$, $dsqout$), powertrain architecture (i.e., hybrid, turbocharged, and diesel), and drive type (i.e., all wheel drive or 4-wheel drive).

Following Train and Winston (2007), the utility formulation is extended to include information about ranked choices when these data are available for a respondent. The ranking is specified as $V_{ni} > V_{nh_1} \dots V_{nh_m} > V_{nj}$ for all $j \neq i, h_1, \dots, h_m$ where i is the chosen vehicle; h_1 is the second ranked vehicle (the vehicle that would have been chosen if vehicle i was not available) and h_m is the m ranked vehicle. Therefore, the probability that respondent n purchased vehicle i and ranked vehicle h_1 through h_m is defined as:

$$L_{nih_1 \dots h_m} = \left(\frac{e^{V_{ni}}}{1 + \sum_j e^{V_{nj}}} \right) \left(\frac{e^{V_{nh_1}}}{\sum_{k \neq i} e^{V_{nk}}} \right) \dots \left(\frac{e^{V_{nh_m}}}{\sum_{l \neq i, h_1, \dots, h_{m-1}} e^{V_{nl}}} \right) \quad 3.6$$

The first two terms of this formulation correspond to the probability that the consumer purchased vehicle i , given all available vehicle models and the outside good, and the probability that they would have purchased vehicle h_1 if vehicle i and the outside good were not available.⁸ The outside good is excluded from the denominator of every term but the first because we do not observe whether the respondents would have chosen not to purchase a vehicle if their first choice was not available. When no ranking data are available for a respondent, the likelihood consists of only the first term in Equation 3.6.

Recently, significant concerns have been raised about the sensitivity of parameter estimates using similar random-coefficient discrete choice demand models (Knittel and

⁷ Literature detailing the automotive design process allows us to address the first criticism of instrument choice. A remaining assumption in our approach is that these longer run attributes do not affect choices of unobserved attributes in the medium run.

⁸ The outside good is removed from the ranked choice set (all but the first term in Eq. 7) because respondents indicated that they considered the ranked vehicles during their purchasing decision, but it is not clear if they would have chosen the 1st ranked vehicle, for instance, if the vehicle they purchased was not available or if they would instead have chosen to not purchase a new vehicle.

Metaxoglou 2008). We estimated the model using a series of randomly selected initial values to test the robustness of our estimates. Specifically, ten initial values were randomly selected from a uniform distribution from -15–15. Initial values outside of this range were also tested but these initial points often produced values of the log-likelihood that were near negative infinity, indicating a very poor fit to the model, which prevents the algorithm from solving the estimation problem.

Model estimation

Table 3.6 reports results from estimating Equation 3.6, which represent the heterogeneous demand parameters. Results of initial-value tests of these estimates are reported in Table 3.7. All ten initial values resulted in the same estimate solutions within 1e-4. Infinite-norms of the gradients for each solution were on the order of 1e-3 to 1e-4, and the Hessians at these solutions were all verified to be positive definite.

Table 3.6 Heterogeneous Demand Parameter Results

σ		
	<u>param</u>	<u>st. err.</u>
p	0.0366	0.0237
gpm	0.0215	0.0131
accinv	0.0335	0.0533
ftp	0.0390	0.0534
μ		
	<u>param</u>	<u>st. err.</u>
p/inc	-0.1721	0.0246
minivan-child	7.4388	0.5603
suv-child	0.9447	0.1468
truck-rural	1.8365	0.2422

Notes: The μ 's are the estimates of the demand parameters for attribute-demographic interactions in Equation 3.3, and the σ 's are the estimates of the standard deviations of the normally distributed random-variable parameters on vehicle attributes.

Table 3.7 Initial-value tests of heterogeneous demand parameter estimates

test	p	gpm	accinv	ftp	p/inc	minivan- child	suv- child	truck- rural	Log-Lik.	grad. norm
1	0.036643	0.021473	0.033539	0.039035	-0.172102	7.438812	0.944718	1.836548	7053.39256	0.0005
2	0.036643	0.021473	0.033540	0.039033	-0.172102	7.438795	0.944720	1.836550	7053.39256	0.0006
3	0.036643	0.021473	0.033539	0.039034	-0.172102	7.438796	0.944720	1.836558	7053.39256	0.0014
4	0.036643	0.021473	0.033539	0.039035	-0.172102	7.438812	0.944718	1.836548	7053.39256	0.0005
5	0.036643	0.021473	0.033539	0.039034	-0.172102	7.438774	0.944718	1.836565	7053.39257	0.0013
6	0.036643	0.021473	0.033540	0.039033	-0.172102	7.438796	0.944719	1.836554	7053.39256	0.0005
7	0.036644	0.021474	0.033538	0.039035	-0.172101	7.438782	0.944723	1.836571	7053.39256	0.0018
8	0.036643	0.021473	0.033539	0.039034	-0.172103	7.438800	0.944717	1.836572	7053.39256	0.0005
9	0.036643	0.021473	0.033539	0.039032	-0.172102	7.438778	0.944720	1.836556	7053.39256	0.0005
10	0.036643	0.021473	0.033539	0.039277	-0.172100	7.438800	0.944720	1.836600	7053.39257	0.0009

Notes: This table presents the initial value tests of the estimates presented in Table 3.6, representing the heterogeneous demand parameters. The value of the log-likelihood, and the infinity norm of the gradient is reported. Initial values were randomly selected from uniform distributions from -15.0–15.0.

All estimates have the expected signs. Recall that the σ parameters represent the standard deviations of the demand parameters in Equation 3.3 that are allowed to vary randomly in the population and assumed normally distributed. Only the standard deviation of the fuel consumption coefficient is found to be statistically significantly different from zero. Several of the parameters that capture the effects of interactions between vehicle attributes and consumer attributes are found to be statistically significant, including the ratio of price to income (p/inc), and the interactions between minivans and children, SUVs and children, and pickup trucks and living in a rural location.

Table 3.8 reports the second-stage IV estimates of the parameters in Equation 3.5. The estimates of the first-stage regressions of endogenous decisions (price, fuel consumption, and inverse 0-60 mph acceleration time) are presented in Table 3.9, with F-tests of 20.68, 19.62, and 21.38, respectively. The SUV indicator variable is positive and significant, implying that they are preferred more than sedans; and the minivan indicator is negative and significant, implying that they are preferred less than sedans. The parameter estimate for two-seater sports cars is negative and the parameter for pickup trucks is slightly positive, but neither is significant.

Table 3.8 Homogeneous demand parameter results

	α	
	<u>param</u>	<u>st. err.</u>
p	-0.4591	0.0998
gpm	-0.3677	0.1679
accinv	1.1262	0.3956
ftp	2.4541	0.7504
sport	-0.4654	0.3129
truck	0.0440	0.2412
suv	0.6669	0.2116
minivan	-5.1827	0.3032
constant	-8.0903	0.7262

Notes: This table presents the 2nd stage IV estimators of the demand parameters of vehicle attributes in Equation 3.5.

Table 3.9 First stage instrumental variable results

	<u>p</u>	<u>gpm</u>	<u>accinv</u>
din	0.0007	-0.0001	0.0005**
dout	0.1368***	-0.0216*	0.0448***
dsqin	-0.0054***	-0.0012**	0.0002
dsqout	-0.0468	0.0086	-0.0112
awd	0.7622***	0.4325***	0.0512
turbo	-0.1561	-0.1118	0.0896
diesel	0.6513	-0.9733***	-0.2685**
hybrid	0.0554	-1.6513***	-0.3875***
ftp	11.4430***	3.0836***	2.6178***
sport	2.885***	0.8498***	0.6702***
truck	-1.4788***	0.065436	-0.089059
suv	0.6541***	0.5843***	0.0843
minivan	-0.9603**	-0.4317***	-0.2751***
constant	-12.5413***	0.3783	-2.1626***

* p<0.1, **p<0.01, ***p<0.001

Notes: *din* and *dout* are the distances of vehicle dimensions (length x width x height) to the average dimensions of same and different manufacturers, respectively; *dsqin* and *dsqout* are these values squared. The remaining variables represent powertrain architectures— *turbo* (turbocharged), *hybrid*, *diesel*—and the type of drive—all wheel or four wheel drive, *awd*.

Based on these estimates, the average price elasticity is -1.9, (95% CI: -2.0, -1.8), and the sales-weighted average is -1.7, (95% CI: -1.8,-1.7). These estimates are somewhat lower than those found in previous studies, which range from -2.0 to -3.1 (Jacobsen 2010; Klier and Linn 2008; Train and Winston 2007; Goldberg 1998). Similar to other models of the automotive industry (Berry et al. 1995; Goldberg 1998; Beresteanu and Li 2008) we find that, in general, demand is more elastic for cheaper “economy” vehicles and less elastic for higher priced vehicles, although this relationship is not monotonic.

Using the demand-side estimates, we calculate the expected willingness-to-pay for an increase in fuel economy as illustrated in Figure 3.6. These results indicate that the willingness-to-pay for fuel economy varies substantially across vehicle models—both because the reduction in fuel consumption due to an increase in 1 mpg varies with the fuel economy of the vehicle and because the consumers that are likely to buy cheaper vehicles are less willing to pay for any improvements to vehicle attributes. However, the willingness-to-pay for fuel economy improvements in any given vehicle is generally lower than the technology costs associated with increasing fuel economy in that vehicle, and considerably less than the value of the associated (discounted) fuel savings over the vehicle’s lifetime.⁹ This discrepancy of willingness-to-pay for fuel economy with the net-present-value of fuel savings is well documented in other studies (Helfand and Wolverton 2009; Alcott and Wozny 2009).

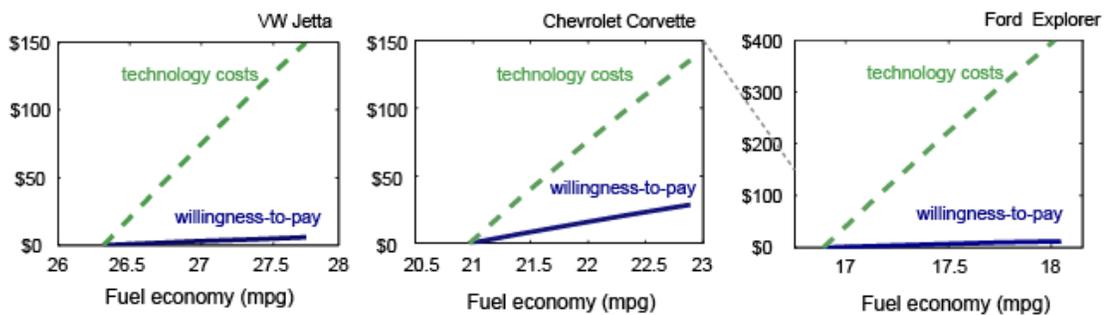


Figure 3.6 Select vehicles’ technology costs and willingness-to-pay to increase fuel economy

⁹ Back of the envelope calculations, assuming a discount rate of 4.5%, a vehicle lifespan of 13 years, constant gas prices at \$2.60 (the average in MY2006) and 14,000 annual vehicle miles traveled (the average in 2006 as reported by the Department of Transportation) give a net present value fuel savings of \$1,100 for increasing the fuel economy of a vehicle with 21 mpg by 1 mpg.

Our estimates imply that, in general, consumers' willingness-to-pay for a 1 mpg improvement in fuel economy is lower than their willingness-to-pay for an increase in acceleration performance that would correspond to a loss in fuel economy of 1 mpg. As expected, we find that the consumers who are more likely to purchase luxury vehicles or opt for the higher horsepower vehicle options are willing to pay more for acceleration performance relative to other consumers, and much less for fuel economy improvements.

3.3.3 Production costs

For all firms, the marginal cost of producing automobile j is represented as:

$$c_j = engcost_j + \omega_j \quad 3.7$$

The variable $engcost_j$ represents the portion of marginal cost dependent on the endogenous selection of attributes as described in Section 3.3. The remaining portion of marginal cost, ω_j , can be determined from the first order conditions of firms' profit maximization assuming that observed vehicle prices are in equilibrium. This procedure is standard in much of the IO economics literature, and we follow Jacobsen's (2010) process of determining these costs. Firms' profit maximization problems follow the standard Bertrand equilibrium but are also subject to the CAFE regulations. Similar to Jacobsen, we distinguish between American firms, who behave as though they are constrained to the CAFE standards, and European firms who often violate the CAFE standards and pay corresponding penalty fines. Asian firms are treated similarly to European firms but, because the Asian firms exceed the CAFE standards over the time period in the data, the constrained and unconstrained formulations are equivalent.

The optimization problem solved by a constrained firm is to maximize profit subject to meeting the CAFE standards ($stand_C$ and $stand_T$) for their fleet of cars, \mathfrak{S}_C , and their fleet of light trucks, \mathfrak{S}_T , as defined in Equation 3.8. In this equation, q_j and p_j are respectively the quantity sold and price of vehicle j , r_C is $1 - stand_C/mpg_j$ if $j \in \mathfrak{S}_C$ and zero otherwise; and similarly r_T is $1 - stand_T/mpg_j$ if $j \in \mathfrak{S}_T$ and zero otherwise.

$$\begin{aligned}
& \max_{p_j \forall j} \sum_j q_j(p_j) (p_j - c_j) \\
& \text{subject to: } \sum_{j \in \mathfrak{S}_C} q_j(p_j) r_{Cj} \geq 0 \\
& \sum_{j \in \mathfrak{S}_T} q_j(p_j) r_{Tj} \geq 0
\end{aligned} \tag{3.8}$$

For firms able to violate the CAFE standards, the profit maximization problem is given by:

$$\max_{p_j \forall j} \sum_j q_j(p_j) (p_j - c_j) - F_C - F_T \tag{3.9}$$

where F_C and F_T are the respective fines if the firm violates either the passenger car or light truck standard:

$$\begin{aligned}
F_C &= 55 \sum_{j \in \mathfrak{S}_{f,C}} q_j(p_j) \left(\text{stand}_C - \frac{\sum_{j \in \mathfrak{S}_{f,C}} q_j(p_j)}{\sum_{j \in \mathfrak{S}_{f,C}} q_j(p_j) / mpg_j} \right) \\
F_T &= 55 \sum_{j \in \mathfrak{S}_{f,T}} q_j(p_j) \left(\text{stand}_T - \frac{\sum_{j \in \mathfrak{S}_{f,T}} q_j(p_j)}{\sum_{j \in \mathfrak{S}_{f,T}} q_j(p_j) / mpg_j} \right)
\end{aligned} \tag{3.10}$$

Therefore, the first order conditions of these two optimization problems can be written in vector notation as in Equations 3.11 and 3.12:

$$\text{fine-paying: } \quad \mathbf{q}(\mathbf{p}) + \nabla_{\mathbf{p}} \mathbf{q}^T (\mathbf{p} - \mathbf{c}) - \nabla_{\mathbf{p}} F_C - \nabla_{\mathbf{p}} F_T = \mathbf{0} \tag{3.11}$$

$$\text{constrained: } \quad \mathbf{q}(\mathbf{p}) + \nabla_{\mathbf{p}} \mathbf{q}^T (\mathbf{p} - \mathbf{c} - \lambda_C \mathbf{r}_C - \lambda_T \mathbf{r}_T) = \mathbf{0} \tag{3.12}$$

Given data on vehicle sales and prices, and estimates of the cross-price elasticities, $\nabla_{\mathbf{p}} \mathbf{q}^T$, from the demand model, the vehicle costs for fine-paying firms can be directly determined from Equation 3.11. However because the Lagrange multipliers, λ_C and λ_T , are unknown and \mathbf{r}_C and \mathbf{r}_T depend on fuel economy, which is correlated with

marginal cost, we cannot directly solve for marginal cost for the firms constrained to the CAFE standard. The Lagrange multipliers, which are negative, represent the effect on firm profits of incrementally increasing the constraints in Equation 3.8 holding vehicle design fixed. If we assume that the Lagrange multipliers are zero then we would overestimate the marginal costs of vehicles with fuel economies below the standard and underestimate the costs of vehicles that exceed the standard.

Following Jacobsen (2010), we estimate these multipliers using the relationship of dealer markups to manufacturer markups. Specifically, there is evidence that dealer markups, b_j , for each vehicle j are a fixed percentage of manufacturer markups (Bresnahan and Reiss 1989):

$$\mathbf{b} = \gamma(\mathbf{p} - \mathbf{c} + \boldsymbol{\varepsilon}) \quad 3.13$$

Substituting in Eq. 3.12, we can relate dealer markups to the Lagrange multipliers:

$$\mathbf{b} = \gamma \left(-(\nabla_{\mathbf{p}} \mathbf{q}^T)^{-1} \mathbf{q} + \lambda_C \mathbf{r}_C + \lambda_T \mathbf{r}_T + \boldsymbol{\varepsilon}_j \right) \quad 3.14$$

Using data on dealer markups and parameters estimated in the demand model, we can obtain estimates for the Lagrange multipliers and then solve for the equilibrium vehicle costs for constrained firms from Equation 3.12. This estimation has the disadvantage of relying on the imposed form of the relationship between dealer and manufacturer markups. However, our interest in the estimates of λ_C and λ_T is limited to their role in controlling for the correlation of marginal vehicle costs with r_C and r_T . We conduct sensitivity analyses of marginal cost estimates to the estimates of λ_C and λ_T and find that this sensitivity is low.

3.4 Cost Estimation

Data on dealer transactions purchased from JD Power and Associates are used to estimate the Lagrange multipliers (i.e., λ_C and λ_T) in Equation 3.14. These data were collected from approximately 6,000 dealers from the proprietary Power Information Network data, aggregated to quarterly invoice costs and transaction prices for each vehicle model.

Table 3.10 shows the resulting estimates, which represent the effect of incrementally increasing the regulatory constraints in Equation 3.8 on domestic firm profits. Recall that these constraints are represented as a nonlinear function of the CAFE standards, and therefore these estimates do not directly correspond to an incremental increase in the CAFE standards. Using point estimates of λ_C and λ_T , we calculate the corresponding impact of incrementally increasing the passenger car and light truck standards of the unreformed CAFE regulation on firm profits, shown in Table 3.11. These profit losses, or shadow costs, of increasing the CAFE standards are in the range of those estimated by Anderson and Sallee (2009).

The estimates indicate that, for passenger cars, Chrysler faces a higher cost of compliance than Ford or GM. This result is intuitive given that in MY2006, Chrysler neither offered many small vehicles nor had any passenger cars with fuel economy higher than 26 mpg. For light trucks, the estimates indicate that Ford has the lowest cost of compliance and GM has the highest. This result can be explained by the fact that, while Ford produces fewer models of light trucks than GM, Ford produces a number of high-efficiency light trucks including the Escape Hybrid.

Table 3.10 Lagrange multiplier estimates

		I	II	III
Chrysler	λ_C	250.5	863.76***	861.06***
	λ_T	340.98**	355.70***	351.29***
Ford	λ_C	690.95**	733.56***	715.59***
	λ_T	520.84***	55.33	58.92
GM	λ_C	1042.98***	768.31***	760.75***
	λ_T	762.03***	739.42***	736.28***
Fixed Effects		None	Manufacturer and class	Manufacturer class, and quarter
Obs.		708	708	708
R ²		0.278	0.689	0.9973

legend: * p<.05; ** p<.01; *** p<.001

Notes: This table presents the impact on firm profits of incrementally increasing the constraints in Equation 3.8. Because the constraints are nonlinear functions of the CAFE standards, these values are not the shadow costs of the regulation, but the shadow costs can be derived from these estimates as shown in Table 9.

Table 3.11 Shadow costs estimates of unreformed CAFE regulation

		profit losses (millions)	losses per vehicle
Chrysler	passenger cars	\$19.849	\$41
	light trucks	\$30.654	\$19
Ford	passenger cars	\$27.905	\$31
	light trucks	\$5.649	\$4
GM	passenger cars	\$52.122	\$31
	light trucks	\$92.015	\$41

Notes: This table presents the impacts of incrementally increasing the unreformed CAFE standards on firm profits. These values were determined from point estimates of the third specification of the Lagrange multipliers presented in Table 10.

The sensitivity of production cost estimates to the estimates of λ_C and λ_T was assessed by increasing the value of these Lagrange multipliers for each firm by 10% and observing the change in production costs. Table 3.12 reports the results of these tests, indicating that the absolute value of changes in production costs are between less than \$0.01 to approximately \$63, with a mean absolute value change of \$1–\$4 depending on the firm. The maximum absolute change in these estimates due to increasing the Lagrange multipliers is less than 1%. We further tested the effect of completely ignoring the effect of the shadow costs of CAFE on production cost estimates, setting each value of λ_C and λ_T to zero. This test indicated that the absolute value changes in production costs are between less than \$0.01 and \$170, with a mean absolute value change of \$5.60. These results suggest that sensitivity of cost estimates to estimates of Lagrange multipliers are low and so we do not expect any errors in the Lagrange multiplier estimates to significantly affect any counterfactual results using this cost model.

Table 3.12 Sensitivity of production costs to estimates of Lagrange multipliers

	mean absolute change	min absolute change	max absolute change
Chrysler	\$1.05	< \$0.01	\$15.57
Ford	\$4.06	\$0.19	\$25.36
GM	\$3.98	< \$0.01	\$62.68

3.5 Appendix A: Modeling combinations of technology features

The specifications for Equations 3.1 and 3.2 were chosen after examining the relationship between the discrete technology feature combinations with cost and fuel economy. For example, Figure 3.7 plots production cost against the *tech* variable assigned to each cost-effective combination of technology features conditional on 0-60 mph acceleration time. Each point on the plot represents a potential vehicle design with a specified engine size, final drive ratio, and set of discrete technology features. The gaps between vehicle designs achieving the same acceleration time is an artifact of the ranges of input variables used in the AVL Cruise vehicle simulations. We would expect that as the intervals of these input variables approached zero, the gaps would disappear.

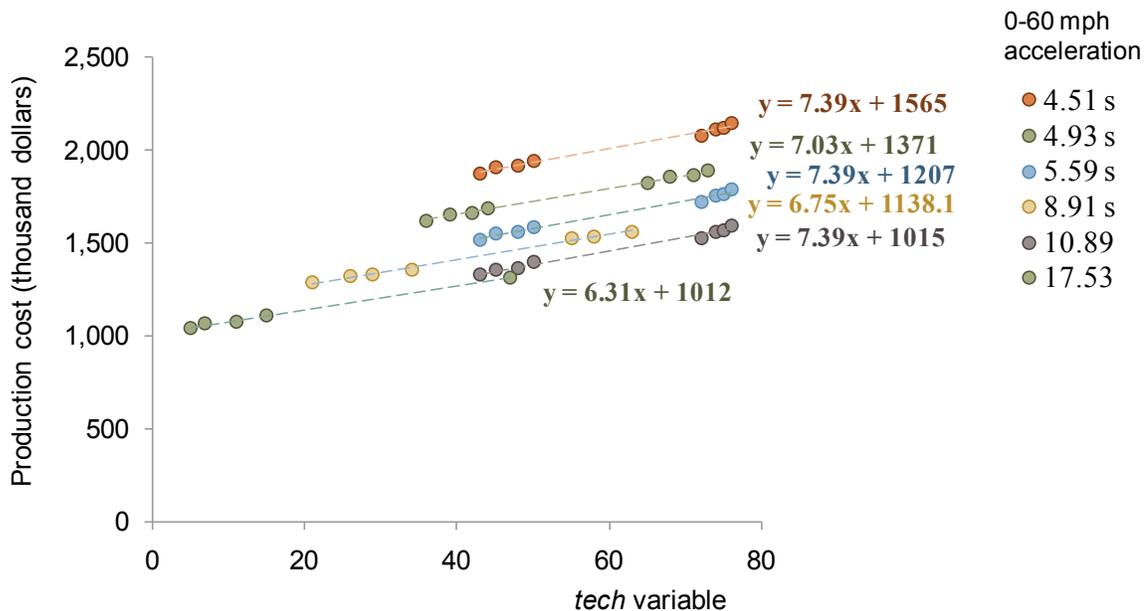


Figure 3.7 Relationship of ordered technology feature combinations to production cost conditional on 0-60 mph acceleration time

Figure 3.7 is generated for a specific vehicle segment (an SUV) and a specific curb weight (3,200 lb). Similar trends were found for other segments and other curb weights. The figure indicates that conditional on vehicle segment, curb weight, and 0-60 acceleration time, moving “up the line” of combinations of technology features increases cost linearly. It also indicates that the incremental change in cost of changing technology features is roughly constant across the various levels of acceleration performance. This

structure is preserved in the specification of Equation 3.3 where cost is linear in technology conditional on vehicle segment, curb weight, and acceleration time.

Figure 3.8 plots fuel consumption against combinations of technology features for the same vehicle segment (SUV) and curb weight (3,200 lb). This figure indicates that conditional on vehicle segment, curb weight, and 0-60 acceleration time, the set of combinations of technology features linearly decrease fuel consumption. However, unlike cost, the incremental change in cost of changing technology features varies across the various levels of 0-60 mph acceleration time. Figure 3.8 shows that the incremental decrease in fuel consumption from moving to a higher ordered combination of technology features becomes larger as acceleration time becomes faster, and the rate of this change increases as acceleration time gets faster. Similar trends were found for other segments and other curb weights. These properties are represented in the specification of Equation 3.1 by including a linear *tech* term as well as an interaction term multiplying *tech* by *acc* squared.

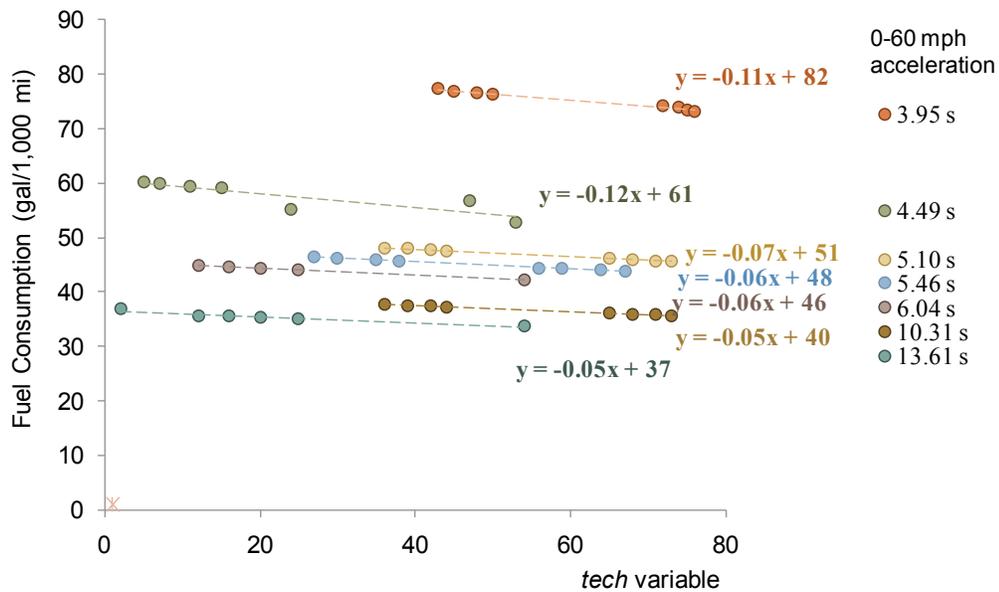


Figure 3.8 Relationship of ordered technology feature combinations to fuel consumption conditional on 0-60 mph acceleration time

3.6 Appendix B: Evaluation of Engineering Model

The engineering model describing the tradeoffs between acceleration performance and fuel efficiency was compared to observed data of MY2006 vehicles and similar models in the automotive engineering literature. Based on the work by An and DeCicco (2007), several studies have approximated the tradeoff between fuel efficiency and acceleration performance by noting that the product of vehicle power, interior size, and fuel economy has increased linearly over the period 1978–2008 (Cheah et al. 2008; MacKenzie 2009). Combining this trend with the relationship between vehicle power—specifically the ratio of peak horsepower to curbweight—with 0-60 mph acceleration time, these researchers can derive the implied tradeoff between acceleration performance and fuel consumption. Figure 3.9 and Figure 3.10 plot the predicted fuel economy using the model presented in this dissertation compared to the tradeoff derived from MacKenzie (2009) and observed attributes of MY2006 compact vehicles and midsize vehicles, respectively. MacKenzie’s (2009) derives the tradeoff for passenger cars only so his model results are not compared to light truck segments.

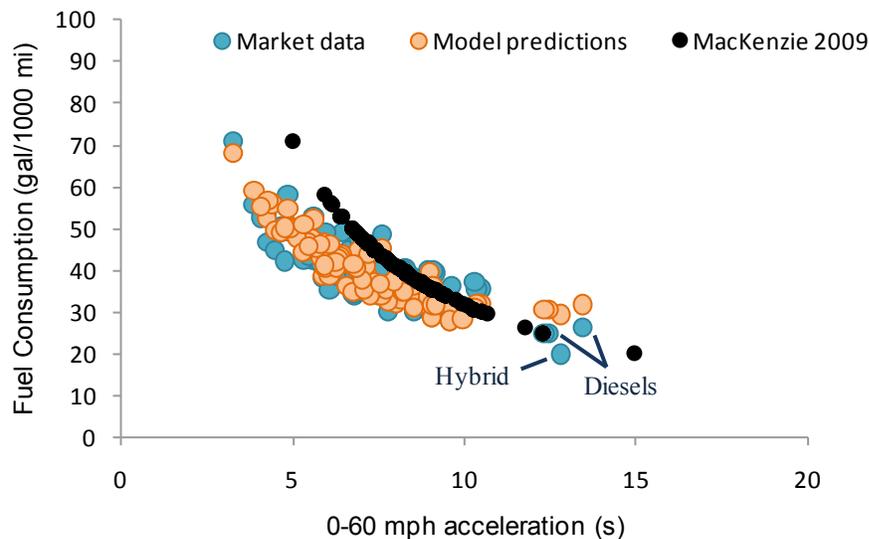


Figure 3.9 Comparison of compact vehicle engineering model predictions to observed MY2006 data and MacKenzie (2009) model results

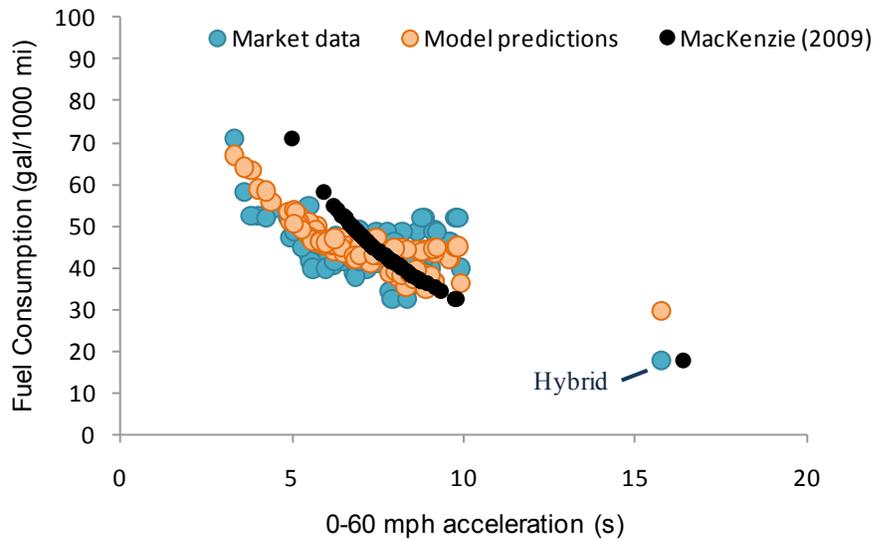


Figure 3.10 Comparison of midsize vehicle engineering model predictions to observed MY2006 data and MacKenzie (2009) model results

The figures illustrate that the engineering model presented in this chapter, which was based on engineering vehicle simulations, captures the basic tradeoff between fuel efficiency and acceleration performance observed in vehicle data. Furthermore, the model is able to represent this tradeoff more closely than the model derived by MacKenzie (2009). This improved fit is likely due to the more complex functional form of the relationship given by Equation 3.1, which conditions on vehicle curb weight and segment (i.e., compact, midsize, etc.). Many opportunities exist for future work to extend the approach used by Cheah et al. (2008) and MacKenzie (2009) to control for additional vehicle attributes to more accurately represent the tradeoff between acceleration performance and fuel efficiency, and even combine the approach of extrapolating historical technology change with the approach of representing attribute tradeoffs presented in this dissertation.

CHAPTER 4: EVALUATING FUEL ECONOMY STANDARDS USING AN ENGINEERING MODEL OF ENDOGENOUS PRODUCT DESIGN

“There exist limitless opportunities in every industry. Where there is an open mind, there will always be a frontier.” —Charles Kettering

Policies designed to incite product design changes to improve industrial environmental performance are increasing in scope and stringency. These policies can significantly influence engineering design decisions as firms reoptimize their products and processes to meet compliance requirements at minimum cost. This chapter integrates the models discussed in Chapter 3 to demonstrate an analysis of the impact of a policy on firms’ design and production decisions. As a case in point, a model is presented where automotive firms choose optimal medium-run compliance responses to the reformed Corporate Average Fuel Economy (CAFE) regulation.

4.1 Introduction

In order to reduce greenhouse-gas emissions, local-air pollutants, and dependence on foreign energy sources, energy-efficiency standards and incentives are being established for many durable goods. In 2007, Congress created efficiency standards for many household appliances, including dishwashers and furnaces; in 2009, the State of California adopted efficiency regulations for consumer products, such as battery chargers and televisions; and the Department of Energy just recently announced new efficiency standards for refrigerators and clothes washers. One especially noteworthy effort to reduce energy consumption, enacted first by Congress and then by the Obama administration, raises fuel efficiency standards for new automobiles to 35 mpg by 2017—representing a more than 30% reduction in fuel consumption per mile. How firms respond to these types of policies can have significant implications for how efficiently energy-intensity reductions are achieved and who bears the costs.

Firms can comply with energy-efficiency standards through a combination of modifying the relative prices of their products, for example by adjusting prices to shift demand toward their more-efficient products, and modifying the designs of their products to increase energy efficiency.¹⁰ In much of the economics literature that investigates industry response to regulatory intervention, the abilities of firms to change product designs is underemphasized (e.g., Goldberg 1998; Nevo 2000; Jacobsen 2010). However, energy-efficiency regulations are typically announced a number of years before they become mandatory, providing firms the opportunity to respond to these policies through product design changes. Recent work on the automotive industry indicates that engineering design decisions have played a significant role in determining fleet fuel-efficiency trends, including gains under CAFE (Knittel 2009; Klier and Linn 2008).

In order to analyze automotive firms' medium-run options to respond to the reformed Corporate Average Fuel Economy (CAFE) regulation, the models described in Chapter 3 are integrated into a partial equilibrium, static oligopoly model of the automotive industry. We use the partial-equilibrium model to simulate firms' responses to replacing the unreformed CAFE standards with the model-year (MY) 2014 reformed CAFE standards under multiple sets of assumptions. First, we account for the full complement of medium-run policy responses and then gradually restrict the ability of firms to exercise these responses, shutting down the ability to trade off vehicle attributes and then the ability to implement technology features.

4.2 Overview of CAFE

Since 1975, the CAFE policy has influenced automotive firms' decisions by setting a minimum standard for the average fuel economy of a manufacturer's fleet of vehicles sold in the United States. The principle motivation for Congress to create the CAFE regulation was to reduce dependence on oil consumption in the wake of the 1973-74 oil embargo. Since that time, interest in maintaining and strengthening the regulation

¹⁰ These strategies are analogous to Grossman and Krueger's (1995) concepts of composition, technique, and scale as a basis for understanding links between changes in economic conditions and emissions at the country-level. We note that this framework can also be used to characterize firm- or industry-level responses to regulations.

has been driven by concerns about global climate change as well as dependence on foreign oil.

The average fuel economy for each manufacturer is calculated as a sales-weighted harmonic mean fuel economy across the manufacturer’s fleet of vehicles in a particular class (i.e., passenger cars or light trucks). Using this particular formulation, a doubling of this average fuel economy corresponds with halving fuel consumption, assuming the same number of miles driven. In order to comply with the CAFE policy, this average must be greater than or equal to the CAFE standard, such that:

$$\frac{\sum_{j \in \mathfrak{S}_{f,c}} q_j(p_j)}{\sum_{j \in \mathfrak{S}_{f,c}} q_j(p_j)/mpg_j} \geq stand_c \quad 4.1$$

where q_j and mpg_j are the number of sales and fuel economy of vehicle j , and $stand_c$ is the fuel economy standard for vehicle j ’s class. If a firm violates this standard, they must pay a fine of \$5.50 per 0.1 mpg below the standard for each vehicle produced. Historically, there have been three categories of firm responses to the CAFE standard: all domestic manufacturers (GM, Ford, and Chrysler) have met the standard within an allowable deviation, certain Asian manufacturers (e.g., Toyota and Honda) have consistently exceeded the standard, and many European manufacturers have violated the standard and paid the fine (Jacobsen 2010).

The CAFE standards in place over the period 1975-2008 established a significantly lower standard for light trucks than for passenger cars. This distinction allowed minivans and SUVs, which composed a very small fraction of sales when the policy was introduced, to meet the lower light-truck standard despite their expanding role as a personal vehicle, giving rise to the so-called “SUV loophole”. In 2007, Congress passed the Energy Independence and Security Act (EISA), phasing out this disparity by setting a target standard for both vehicle classes of 35 mpg by MY2020, later moved up to MY2016 by President Obama’s administration.

In addition, Congress modified the design of the CAFE standard. The reformed CAFE establishes an individual fuel economy target, T_j , for each vehicle, based on

vehicle footprint such that vehicles with larger footprints have lower targets.¹¹ The fuel economy standard for firm f and vehicle class c is determined as a sales-weighted harmonic average of the fuel economy targets of the firm's vehicles in class c as defined in Equation 4.2

$$stand_{f,c} = \frac{\sum_{j \in \mathfrak{S}_{f,c}} q_j(p_j)}{\sum_{j \in \mathfrak{S}_{f,c}} q_j(p_j)/T_j} \quad 4.2$$

Unlike the unreformed CAFE standards, the reformed standards vary across manufacturers. This change has a number of important implications. With the unreformed CAFE, sales of any vehicle that had a higher fuel economy than its class standard (27.5 mpg for passenger cars and 21.6 mpg for light trucks in MY2006) helped a firm comply with the regulation, and any vehicle under the standard hindered a firm's ability to comply. Under the reformed CAFE, any vehicle that has a fuel economy higher than its individual footprint-based target will help a firm comply with the regulation. For example, a firm may prefer to produce a larger vehicle that can exceed its target versus a smaller vehicle that has higher fuel economy but does not exceed its target. Also, because domestic manufacturers tend to have larger vehicles than their competitors, the footprint-based standards allow domestic manufactures to meet a lower standard than European or Asian manufacturers. However, even though the footprint-based standards allow larger vehicles to meet lower standards, reformed CAFE overall imposes higher standards than the unreformed CAFE standards: the lowest standard for MY2014 is 1.5 mpg higher than the unreformed standard.

Both the unreformed and the reformed CAFE regulations provide some flexibility to meet the fuel economy standards. Specifically, both regulations allow firms to bank and borrow fuel economy credits. This allows a firm to meet the standard in a given year by applying any available banked credits earned from exceeding the standard in previous

¹¹ This decision was based on a National Association of Science report which raised concerns that the CAFE regulation encouraged production of smaller vehicles, and that smaller vehicles were more unsafe for the public (NRC 2002, 24; and dissent to this opinion, app. A). NHTSA responded to these concerns by defining the reformed CAFE standards as a function of the footprint (track width multiplied by wheelbase) of the vehicles in a manufacturer's fleet.

years or by borrowing credits, which will have to be repaid in future years. In addition to this, the reformed CAFE allows a trading program of credits within each firm, between the fuel economy and light truck standard, as well as among firms. Trading within each firm allows firms to have an average fuel economy for light trucks that is lower than the standard as long as this deficit is offset with a corresponding improvement of the average fuel economy of passenger cars over the standard, or vice versa. One limitation of this trading is that the average fuel economy of passenger cars of any firm must always meet a minimum standard, which is 32.4 mpg for MY2014.

While we do account for trading of fuel economy credits within firms in our model, we do not permit trading between firms or banking and borrowing credits. Therefore, our results should be interpreted as upper bounds on the producer surplus losses resulting from the regulation. This is consistent with our assumptions in the engineering design model, which is constructed to be a conservative representation of possible producer options to respond to the policy. For a discussion of banking and borrowing of fuel economy credits, interested readers should refer to Jacobsen (2010).

4.3 Industry Model

The automotive industry is modeled as an oligopoly of multiproduct firms that maximize the expected value of profits with respect to vehicle attributes and prices. Consistent with historical behavior, auto firms are characterized into two groups: those that operate at the CAFE standard (constrained), and those that can violate the standard and pay the corresponding fine. Similar to Jacobsen (2010) and Klier and Linn (2008), our counterfactual simulations account for heterogeneity in the compliance behavior of firms, distinguishing between firms that are constrained to meet the CAFE standards and those that can violate the standards and instead pay a fine.

Although both the unreformed and reformed CAFE regulations allow manufacturers to violate the standards and pay corresponding fines, which are proportional to the number of miles per gallon under the standard, there is evidence that domestic manufacturers should be treated as though they are constrained to the standards instead. First, domestic firms have historically always met the CAFE standards within allowable levels but have never significantly exceeded them (Jacobsen 2010). Second,

these firms have stated that they view CAFE as binding, believing that they would be liable for civil damages in stockholder suits were they to violate the standards (Kleit 1990). In contrast, many European firms, such as BMW and Audi, have chosen to violate the standards and pay the fines many times, so we do not model them as constrained in our simulations. It is difficult to know whether other foreign firms that have historically met the standards, such as Toyota and Honda, would choose to violate the higher reformed CAFE standards if it were more profitable. We model these firms as choosing whether to meet the standards based on the most profitable option and discuss the effect of this assumption on our simulation results.

In our counterfactual simulations, the domestic Big 3 manufacturers (Chrysler, Ford, and General Motors) are constrained to the standard following their historic behavior, and expected future behavior, of consistently meeting the CAFE standards within allowable banking and borrowing credits (Jacobsen 2010). The remaining firms are allowed to violate the standards if it is more profitable to pay the corresponding fines than to comply with the regulations.

The optimization problem solved by a constrained firm is to maximize profit subject to meeting the CAFE standards ($stand_C$ and $stand_T$) for their fleet of cars, \mathfrak{S}_C , and their fleet of light trucks, \mathfrak{S}_T . Rearranging Equation 4.1, this formulation can be written as:

$$\max_{acc_j, tech_j, p_j \forall j} \sum_j q_j(p_j) (p_j - c_j) \quad 4.3$$

$$\text{subject to: } \begin{aligned} \sum_{j \in \mathfrak{S}_C} q_j(p_j) r_{Cj} &\geq 0 \\ \sum_{j \in \mathfrak{S}_T} q_j(p_j) r_{Tj} &\geq 0 \end{aligned} \quad 4.4$$

where r_C is $1 - stand_C/mpg_j$ if $j \in \mathfrak{S}_C$ and zero otherwise; and similarly r_T is $1 - stand_T/mpg_j$ if $j \in \mathfrak{S}_T$ and zero otherwise.

For firms able to violate the CAFE penalty, the profit maximization problem is given by:

$$\max_{acc_j, tech_j, p_j \forall j} \sum_j q_j(p_j) (p_j - c_j) - F_C - F_T \quad 4.5$$

where F_C and F_T are the respective fines if the firm violates either the passenger car or light truck standard as defined in Equation 4.6.

$$\begin{aligned} F_C &= 55 \sum_{j \in \mathfrak{S}_{f,C}} q_j(p_j) \left(stand_C - \frac{\sum_{j \in \mathfrak{S}_{f,C}} q_j(p_j)}{\sum_{j \in \mathfrak{S}_{f,C}} q_j(p_j) / mpg_j} \right) \\ F_T &= 55 \sum_{j \in \mathfrak{S}_{f,T}} q_j(p_j) \left(stand_T - \frac{\sum_{j \in \mathfrak{S}_{f,T}} q_j(p_j)}{\sum_{j \in \mathfrak{S}_{f,T}} q_j(p_j) / mpg_j} \right) \end{aligned} \quad 4.6$$

Note that, for all types of firms, fuel consumption is determined through decisions on acceleration performance and technology features from Eq. 3 and therefore is not listed explicitly as a decision variable. We could instead have listed mpg and $tech$ as the decision variables and implicitly determined acceleration performance; this convention is arbitrary and does not affect the formulation.

4.4 Counterfactual Simulations

Using the estimated models of demand and engineering design from Chapter 3, we perform counterfactual experiments that simulate replacing the unreformed CAFE standards with the reformed CAFE standards that will be applied to the MY2014 fleet of vehicles. An underlying assumption of these, or any, counterfactuals is that the structure of decision-making is unaffected by the policy change. Because our supply model is constructed from physics-based simulations and we have no indication that demand would be directly impacted by the change in CAFE, this assumption is justifiable. One possible caveat, however, is that firms may have an incentive to allow adjustments of vehicle footprint later in the development process because the regulation allows manufacturers of larger vehicles to meet lower standards. This behavior is not captured here, but is explored in Chapter 5.

Twenty firms are represented in these simulations, producing a total of 473 vehicle models, described by Table 3.5. This represents all vehicle models and engine options in MY2006, which is a considerably larger scale than previous studies (e.g., Goldberg 1998; Jacobsen 2010). The choice of firms represented in these simulations is determined following the EPA's classification of manufacturers as listed on the MY2006 fuel-economy test data. For example, Saab is considered as part of GM but Land Rover is considered a separate firm from Ford.

Convergence of the counterfactual simulations to an equilibrium solution required between 12–38 cpu hours. At equilibrium, the infinity-norm of the gradient for each firm's profit maximization problem was $1e-5$ or less and the hessian was positive definite. We are not aware of any proofs of unique equilibrium that apply to this specific problem. Shiao and Michalek (2007) searched for possible multiple equilibria in the case where automotive firms choose prices and design variables for vehicle powertrains. This choice of powertrain variables is similar to the approach used in this dissertation but firms were restricted to producing only one vehicle each and the implementation of technology features was not considered. The authors could identify only one equilibrium in this case, which was determined using both the sequential method used in this dissertation and using an alternative solution algorithm that directly solves the first-order conditions for each firm and verifies second-order conditions. These results indicate that, at least with respect to vehicle prices and tradeoffs between acceleration performance and fuel efficiency, multiple equilibrium cannot be easily discovered. However, future research is needed to verify that multiple equilibria do not exist.

4.4.1 Counterfactual baseline

Because our endogenous attribute model is derived from engineering simulations and cost data, observed attributes are not necessarily restricted to be in equilibrium. We therefore perform simulations of the CAFE regulations that were applied to the MY2006 automotive market to serve as a baseline to compare counterfactual simulations. The simulation results are in Nash equilibrium with respect to firm decisions on 0-60 acceleration time, and technology implementation—which implicitly determines fuel economy—as well as price for each of their vehicles. Our results, shown in

Table 4.1, indicate that fuel economy and 0-60 acceleration time for MY2006 vehicles are very close to equilibrium.

Due to a lack of data on adoption of each technology feature, we cannot compare the results of adopted technology features to those in the MY2006 vehicles. But, the simulations results appear to match general information about technology. For instance, very few vehicles in MY2006 included cylinder deactivation, which is supported by the simulations.

Table 4.1 Comparison of observed attributes and baseline simulation

	Average Fuel economy (mpg)	Average 0-60 acceleration (s)	Average <i>tech</i>
Observed	21.5	7.11	-
Baseline Simulations	20.7	7.42	0.19

4.4.2 Reformed CAFE simulations

We simulate the effect of replacing the unreformed CAFE standards with the reformed standards under four sets of assumptions with increasing constraints. First, we account for the full set of medium-run responses in our model: technology implementation, tradeoffs between fuel efficiency and acceleration performance, pricing adjustments, and trading fuel economy credits between the passenger-car and light-truck standards within a firm. Second, we disallow within-firm trading. Third, we shut down the ability of firms to trade off acceleration performance with fuel efficiency, treating acceleration performance as exogenous. Fourth, we simulate short-run responses, only allowing for price adjustments.

Simulation results produce the partial-equilibrium price, marginal production cost, fuel economy, acceleration performance, and amount of technology implementation for every vehicle. Taken together, these simulation results can be used to calculate profits and consumer surplus. Point estimates of the effects of the reformed CAFE on producer and consumer surplus are shown in Table 4.2. Note that this welfare analysis does not account for any indirect benefits associated with reduced fuel consumption, such as reduction in environmental damages. All values are measured relative to a baseline of

partial equilibrium with respect to prices, acceleration performance, and technology implementation in the presence of the unreformed CAFE standards, described in Section 4.4.1.

Table 4.2 Impact of MY2014 CAFE on producer and consumer welfare

Change in Consumer Surplus				
	<i>Full Medium Run with within-firm Trading</i>	<i>Full Medium Run</i>	<i>Medium Run Without Tradeoffs</i>	<i>Short Run with within-firm Trading</i>
Total (billions)	-\$59	\$8	\$11	-\$113
Change in Producer Welfare				
	<i>Full Medium Run with within-firm Trading</i>	<i>Full Medium Run</i>	<i>Medium Run Without Tradeoffs</i>	<i>Short Run with within-firm Trading</i>
Total (billions)	-\$144	-\$142	-\$163	-\$182
Constrained firms	-\$17	-\$21	-\$44	-\$149 †
Fine-paying firms	-\$127	-\$121	-\$119	-\$33

Notes: This table reports point estimates of changes in producer and consumer surplus resulting from replacing the unreformed CAFE standards with the reformed CAFE standards. The Short-Run with within-firm Trading specification only allows firms to adjust the prices of their vehicles and trade fuel-economy credits between the passenger car and light truck standards; all vehicle designs are considered exogenous. The Medium-Run Without Tradeoffs specification accounts for price changes and the ability of firms to implement fuel-saving technologies but does not allow for any tradeoffs between fuel economy and acceleration performance. The Full Medium-Run specification accounts for price changes, technology implementation, and tradeoffs between fuel economy and acceleration performance. The Full Medium-Run with within-firm Trading specification further adds the ability of firms to trade fuel-economy credits between their passenger car and light truck standards.

† In the short run, neither Chrysler nor Ford could meet the reformed CAFE minimum requirement for passenger cars; Chrysler violated it by 4.2 mpg and Ford violated it by 4.0 mpg.

Results of the counterfactual simulations are shown in Table 4.2 using the four specifications of firm options to respond to the CAFE standards. These results highlight the importance of explicitly accounting not only for price responses but also for both technology implementation and tradeoffs between fuel efficiency and other vehicle attributes. Accounting for price changes and within-firm credit trading but ignoring any ability for firms to adjust vehicle designs results in profit losses of \$149 billion for firms constrained to the standards. Accounting for technology implementation and design tradeoffs in addition to these decision options lowers profit losses to \$17 billion. These simulations suggest that constrained firms use a combination of all decision options to increase fuel economy, but the majority of improvements are due to changes in product

design. In order to test the relative impact of design changes and price changes on fuel economy, we assign the prices from our pre-policy-change baseline to the counterfactual vehicle designs from the reformed CAFE simulations. We find that 62% of fuel economy improvements derive from changes to vehicle designs and 38% derive from price changes and credit trading.

4.4.3 Impact of firm heterogeneity on fuel economy

Results indicate that the domestic Big 3 manufacturers improve the fuel economy of their vehicle fleets by an average¹² of 4.3 mpg, compromising acceleration performance such that the average 0-60 acceleration time is 2.7 s slower. This result is consistent with Knittel's (2009) finding that meeting the reformed CAFE standards will require a non-trivial "downsizing" of vehicle performance attributes, such as acceleration, but is clearly attainable.

However, despite the rise in fuel economy by constrained firms, we find that for firms choosing to violate the standard and pay the fine, average fuel economy *decreases* in response to the regulation. This leads to a form of leakage, where efficiency improvements from complying firms are offset by reductions in fuel efficiency from non-compliant firms. This behavior, also noted by Jacobsen (2010), can be explained by the residual demand curve for lower fuel economy vehicles, which are larger or have better acceleration, shifting to the right in response to other firms producing higher fuel economy vehicles.

Simulations that account for design responses in addition to price and credit trading responses suggest that the extent of fuel-consumption leakage is large. Manufacturers that violate the standard offset the increase in fuel efficiency by compliant firms such that both the average fuel economy and acceleration performance across the market remain approximately the same—fuel economy increases by only 0.1 mpg and acceleration performance changes by less than 0.3 s. Results suggest that it is more profitable for even Toyota and Honda to violate the reformed CAFE standards and pay the corresponding fines due to the substantial increase in fuel economy required by constrained firms under the reformed CAFE standards.

¹² All fuel economy averages in this section are sales-weighted harmonic means; all other averages are sales-weighted arithmetic means.

Simulations that ignore design changes, only accounting for short-run responses, produce a much smaller leakage effect. In these simulations, foreign manufacturers only decrease fuel economy by an average of 0.3 mpg, resulting in an overall increase in average new-vehicle fuel economy by 2.3 mpg. Similar to the medium-run simulations, production of more fuel-efficient vehicles by compliant firms shifts the residual demand curve for less fuel-efficient vehicles to the right. But, because firms cannot adjust the fuel economy of their vehicle fleet as easily in the short run, the profit incentive for fine-paying firms to increase production of low-efficiency vehicles is much smaller than in medium-run simulations. These findings not only highlight the adverse consequences of non-compliance to the CAFE standards but also further underscore the importance of explicitly accounting for design responses to analyze the policy.

4.4.4 Impact of attribute tradeoffs on firm behavior and costs

In the third specification, shown in Table 4.2, we exclude the ability of firms to trade off acceleration performance with fuel economy, considering the determination of acceleration performance as exogenous. We do this to investigate the effect of ignoring the tradeoffs between these attributes on the resulting welfare estimations. Results suggest that the costs of the regulation to compliant firms, in terms of profits lost, are twice as large as when these tradeoffs are ignored. These results suggest that analyses of CAFE that do not account for tradeoffs between fuel economy and other vehicle attributes may substantially overestimate the costs of the regulation. Compared to the short-run specification, which treats all aspects of vehicle design as exogenous, costs to compliant firms are almost nine times lower in the specification that accounts for both attribute tradeoffs and technology implementation. Including within-firm credit trading further reduces these costs by 23%.

Contrasting the results of the “full medium run” and “medium-run without tradeoffs” specifications highlights the complex relationship between firm compliance strategies and production decisions. In the “medium-run without tradeoffs” specification, firms can only increase the fuel economy of their vehicles by implementing technology features, which increase vehicle production costs. Consequently, domestic firms (which are constrained to the standards) increase the prices of their vehicles. This behavior leads

to a 13% decrease in the market share of domestic firms. These firms also shift production substantially from passenger cars to light trucks, in order to take advantage of the lower fuel-economy standards for light trucks. As a result, the share of light trucks across the domestic firms' fleets increases by 25%.

This behavior does not occur in the simulations that account for tradeoffs between acceleration performance and fuel economy. In the "full medium run" specification, constrained firms choose to increase fuel economy primarily by compromising acceleration performance, which decreases marginal costs but also decreases consumer utility. As a result, these firms lower their vehicle prices considerably, by an average of \$1,300. This behavior leads to a much smaller loss in the market share of domestic firms (5.5%) and a much smaller shift to light truck production (4.5%). Including within-firm credit trading tempers these responses further: vehicle prices decrease by an average of \$750, the market share of domestic firms declines by only 4.2% and the shift to light trucks is less than 1%.

Comparing these results to other approaches in the literature, which project the impact of technology change on vehicle attributes by extrapolating past behavior (An and DeCicco 2007; Cheah et al. 2008; MacKenzie 2009), we find that results indicate that the reformed CAFE standards have the effect of inducing technology implementation of constrained firms equivalent to the expected technology change over a four-year period in the absence of the policy.¹³ Furthermore, using the metric created by Cheah et al. (2008) to quantify the allocation of technology used to improve fuel efficiency, called the Emphasis on Reducing Fuel Consumption (ERFC) index, we find that the reformed CAFE standards increase the ERFC to 112%. This value indicates that not only are all technology gains applied to improving fuel efficiency but that manufacturers trade off other aspects of vehicle performance, namely acceleration performance, to realize further improvements in fuel efficiency. This value of ERFC is slightly higher than the required level predicted by MacKenzie (2009), although his calculations were based solely on the passenger car fleet.

¹³ This comparison was calculated using the Power-Size-Fuel Economy Index created by An and DeCicco(2007). While this index uses interior volume, this data was not available in our data set, so instead we used exterior volume normalized to the scale of interior volume to approximate the index.

4.4.5 Implications for climate and fuel consumption policies

Our results suggest that the cost-effectiveness of the reformed CAFE, in terms of profit loss per reduction in fuel consumption, is significantly better than cost-effectiveness estimates of the unreformed CAFE (e.g., Goldberg 1998; Jacobsen 2010). For example, Goldberg (1998) estimated the costs of the CAFE standards in 1998 as approximately \$1,140 per short ton CO₂ reduced, or \$11.06 per gallon reduced. Assuming vehicles have a lifetime of 13 years and are driven 14,000 miles per year with a rebound effect of 10.3% (Small and Van Dender 2007), our counterfactual results indicate that compliant firms reduce fuel consumption of their vehicles by 14% at a cost of \$197 per short ton of CO₂ reduced, or \$1.91 per gallon reduced. Considering CAFE solely as climate policy, this estimate is notably larger than cost estimates for other potential climate policy instruments such as a comprehensive cap and trade system (e.g., Stavins 2008). However, the welfare benefits from reducing fuel consumption are not limited to only the benefit of reducing CO₂ emissions. Reduced local air pollution and dependency on foreign oil also contribute to welfare benefits from CAFE.¹⁴

Despite significant gains in fuel economy by compliant firms, our results underscore that the effectiveness of CAFE—in terms of both fuel consumption reductions and costs—is highly dependent on the behavior of Asian and European manufacturers. Given the current fine of \$55 per vehicle per mpg under the standard, our results indicate that it is more profitable for each of these firms (including Toyota and Honda) to violate the standard and pay the corresponding fines. Furthermore, we find that these firms have an incentive in the medium run to substantially decrease fuel economy such that the fuel consumption across all new vehicles is approximately the same. These results imply negligible reductions in CO₂ at exceptionally high costs.

It is important to emphasize that, unlike leakage problems that have been characterized elsewhere in the literature, the leakage we observe in our simulations can be readily mitigated through policy design—namely, by increasing the level of the fine. As Shiau et al. (2009) concluded, if it is desirable to encourage firms to meet a high fuel-

¹⁴ Estimates of the value of these welfare benefits are notably hard to obtain. For a rough comparison, estimates of welfare benefits from Parry et al. (2004) attributed to local air pollution and oil dependency sum to 22 cents per gallon of gasoline reduced. On the other hand, if the rebound effect leads to substantially higher driving during congested periods, CAFE may lead to welfare losses from increased traffic congestion.

economy standard, the fine for violating this standard must also be increased. These findings have direct implications for the recently announced greenhouse-gas emission standards for light-duty vehicles, which give the EPA the authority to set the penalties for noncompliance on a case-by-case basis. Ideally, the fines should be set equal to the marginal damages that would result from increasing fuel consumption above the level necessary to exactly meet the standard. Because fuel consumption is the inverse of fuel economy, this relationship varies with the standard and with the number of miles per gallon that a firm's average fuel economy is below the standard.

4.5 Conclusions

This study demonstrates the importance of accounting for design responses in the analysis of industrial policy impacts using a case study of medium-run firm responses to the reformed CAFE standards. In addition to accounting for fuel-saving technologies that firms can implement in response to CAFE but are unobserved in data, our model explicitly accounts for engineering tradeoffs between fuel efficiency and acceleration performance, which provide another mechanism for firms to adjust product designs to respond to energy-efficiency regulations.

We use this model to estimate the effects of the model-year 2014 CAFE regulation on producer and consumer surplus and fuel economy. Results indicate that the majority of fuel-efficiency improvements of compliant firms are from changes in product designs. Compliant firms also adjust product prices to shift demand to more efficient vehicles in response to fuel economy standards, but this has a smaller effect on fuel-efficiency improvements than design changes.

Results highlight the substantial sensitivity of profit losses and fuel efficiency gains to the product design strategies that firms use to comply with the regulation. When we ignore the potential for tradeoffs between acceleration performance and fuel economy, our results suggest that the profit losses of constrained firms are twice as high as when these tradeoffs are considered. When product designs are considered exogenous, the profit losses to constrained firms are over nine times greater. These results suggest that welfare analyses of CAFE or similar policy instruments that ignore the potential for changes in product design decisions could significantly overestimate the policy costs.

Furthermore, our results highlight the notable difficulty of significantly increasing fuel economy across the U.S. market of new vehicles when firms choose to violate the CAFE standards and instead pay a fine. Without consumer incentives for higher fuel economy, results indicate that increases in fuel efficiency from one set of firms could be almost entirely offset in the medium run by decreases in fuel efficiency from other firms. These results are sensitive to the assumption that Asian manufacturers will choose to violate the standard and pay the corresponding fines when it is more profitable, but underscore the large effect their behavior has on the outcomes of the CAFE standards.

A number of limitations to the current analysis exist and may affect these results. Sensitivity analyses are needed to test the robustness of our results to the assumptions used in our model and the standard errors on parameter estimates. Most notably, future work will include sensitivity tests to estimates of engine and technology-feature costs, the shadow costs of the unreformed standards, and the specification of our consumer utility function.

As data become available for the early years of the reformed CAFE standards, validation tests could be performed comparing the results of counterfactual simulations with observed trends in vehicle attributes. Comparing the simulated profit-optimal firm behavior with observed changes in fuel efficiency, acceleration performance and shifts in sales between passenger cars and light trucks will be valuable to examine how closely the presented model captures the predominant factors driving firm response to the reformed CAFE standards. Ideally, validation tests could be performed to compare simulation results with observed implementation of specific technology features and the extent to which firms rely on these technologies and tradeoffs with acceleration performance to increase fuel efficiency. However, data on all the technology features considered in this analysis are difficult, and in some cases impossible, to obtain. This lack of comprehensive data characterizing the design options that are available to automotive manufacturers presents a challenge for validating the detailed behavior simulated in the analysis but also underscores the value of such an approach that can capture design options through engineering modeling that cannot be captured through data alone.

CHAPTER 5: ANALYZING THE POTENTIAL FOR UNDESIRABLE DESIGN INCENTIVES FROM FOOTPRINT-BASED FUEL ECONOMY STANDARDS

“You don't have to change the course of the comet very much to miss the keyhole if you do it a number of years in advance [but] you don't want to nudge it until you know what the nudge is going to do.” —Clark Chapman (Than 2005)

Many policy interventions can induce product design responses other than the design changes targeted by the policy. The developed methodology discussed in Chapters 3 and 4 can be used to analyze the potential of these effects and their magnitudes. This chapter extends the methods presented in Chapter 3 to analyze potentially unfavorable incentives from the reformed Corporate Average Fuel Economy (CAFE) regulation. The regulation sets fuel economy standards based on the footprint (wheelbase by track width) of vehicles produced by a manufacturer each year. These footprint-based standards could create an incentive for manufacturers to increase the size of their vehicles in order to lower their fuel economy targets. An oligopolistic equilibrium model of the automotive market is presented where firms can respond to the CAFE regulation by modifying vehicle dimensions, implementing technology features that increase fuel economy, or compromising acceleration performance to increase fuel economy. The presence and magnitude of the incentive to increase vehicle size is determined for a range of simulated consumer demand parameters. Results suggest that firms have a significant incentive to respond to the footprint-based standards by increasing vehicle size except when consumer preference for vehicle size is low and preference for acceleration performance is high. Except for this case, simulation results indicate that average vehicle size increases by 1–13 sq. ft. depending on consumer preferences, undermining gains in fuel consumption reductions by 1–4 mpg.

5.1 Introduction

Passenger-car transportation accounts for 17% of U.S. greenhouse gas emissions and 40% of U.S. oil consumption. In order to reduce the effects of this consumption, the U.S. Congress has supported regulations on the fuel efficiency of new passenger vehicles in the form of the CAFE regulations. Although criticisms have been made regarding the efficiency and safety of these regulations, they have been credited with substantially restraining U.S. oil consumption (Greene 1998). Furthermore, the regulation is popular with the U.S. public, especially compared to alternative policies to reduce greenhouse gas emissions and oil consumption (Pew Center 2010). Despite this support for CAFE, the criticism that the policy may generate undesirable consequences for passenger safety appears to be unresolved and plays a substantial role in the current design of the regulation (NHTSA 2009).

Responding to concerns about CAFE's effects on vehicle size and weight, and the resulting impact on passenger safety, the National Academy of Sciences suggested that CAFE regulations could be improved by allowing the fuel economy standards to depend on key vehicle attributes (e.g., size, weight, or payload) (NRC 2002). Congress subsequently reformed CAFE so that the fuel economy standard for each automotive manufacturer's fleet of vehicles would be determined based on one or more vehicle attributes. The resulting standards are currently a function of the footprint of the vehicles in a manufacturer's fleet, allowing manufacturers that produce larger vehicles to meet lower fuel economy standards. This regulation design could potentially create an undesirable incentive for automotive manufacturers to increase the footprint of their vehicles and diminish the policy's goal of reduced fuel consumption.

Understanding the relationship between the CAFE standards and the potential incentive to increase vehicle size requires characterizing the tradeoffs between size, fuel economy and other vehicle attributes, production costs, and consumer demand. Multiple confounding factors in observed vehicle and consumer choice data present significant challenges to accurately estimating these relationships. As a result, the vast majority of analyses of CAFE and alternative fuel-economy incentives have assumed that vehicle attributes other than fuel economy cannot change (e.g., Goldberg 1998; Jacobsen 2010), and several assume that the production mix of vehicles also remains constant (e.g.,

Greene and Hopson 2003; Austin and Dinan 2005). In this analysis, we use physics-based simulations to characterize the engineering tradeoffs between vehicle size and other vehicle attributes, circumventing the challenges presented by confounding factors in observed vehicle data. Information on the design and manufacturing processes in automotive production allow us to approximate the relationship between vehicle size and production costs. Accurate estimation of consumer preference for vehicle size along with other vehicle attributes remains a challenge. Instead of attempting to estimate these parameters, we simulate multiple combinations of values for these preference parameters based on existing literature.

The potential for CAFE standards to encourage increases in the size of vehicles has implications for both fuel economy goals and traffic safety. With respect to fuel economy, we examine potential losses in fuel economy gains by determining the change in average fuel economy in simulations that allow firms to take advantage of lower fuel economy standards by increasing vehicle size and comparing this with fuel economy gains assuming vehicle size and sales remain unaffected. With respect to traffic safety, both the absolute measures of vehicle size (the dimensions of the vehicle) and the relative measures of vehicle size (spread of dimensions across vehicles) can impact safety risks (NRC 2002; Kahane 1997). This study does not attempt to predict any impact on traffic safety risks, but investigates the impact of footprint-based CAFE standards on both the absolute change in vehicle footprint and differences in vehicle footprint changes between passenger cars and light trucks. These results could prove useful in conjunction with ongoing research of the effects of vehicle size on traffic safety.

5.2 Background on Reformed CAFE

5.2.1 Motivation for attribute-based standards

As requested by Congress, the National Research Council (NRC) conducted a study in 2002 on the effectiveness and impacts of CAFE, including implications for vehicle safety. This study concluded that the reduction of vehicle weight and size that accompanied the early years of the CAFE program posed a significant risk to the safety of those vehicles' occupants and that, pending further investigation, the CAFE regulation should be modified so that no incentive exists to reduce vehicle size or weight (NRC

2002). The study also acknowledged the unresolved question of whether total traffic safety—including occupants of heavier vehicles, occupants of lighter vehicles, and pedestrians—would be better or worse if vehicle weight increased. Based on a 1997 report by NHTSA, the NRC report concluded that a uniform increase in vehicle weight for all vehicles would result in a reduction of traffic fatalities. Although the NRC report primarily focused on weight-based fuel economy standards, NHTSA established footprint-based standards noting that automotive manufacturers can more easily increase vehicle weight than vehicle footprint to take advantage of lower fuel economy targets.

Whereas in the unreformed CAFE, every manufacturer was required to meet the same fuel economy standards, one for passenger cars and one for light trucks, the reformed CAFE standards are calculated separately for each manufacturer as a function of the sizes of the vehicles it produces. Specifically, the regulation sets individual fuel economy targets for each vehicle based on the vehicle’s footprint, where larger vehicles have lower targets. A firm will comply with the passenger car standard if the sales-weighted average fuel economy of its fleet of passenger cars is equal to or greater than the sales-weighted average target set for these vehicles, and similarly for the light truck standard as in Equation 5.1.

$$Stand_c = \frac{\sum_{j \in \mathfrak{S}_{f,c}} q_j}{\sum_{j \in \mathfrak{S}_{f,c}} q_j / T_j} \quad 5.1$$

The variables q_j and T_j in this equation are respectively the sales and fuel economy target for vehicle j in vehicle class c (i.e., passenger cars or light trucks), where the set of vehicles in class c produced by firm f is denoted $\mathfrak{S}_{f,c}$. The MY2014 fuel economy targets for passenger cars and light trucks as a function of vehicle footprint are described by Equation 5.2 and illustrated in Figure 5.1.

$$\begin{aligned} \text{passenger cars: } T_j &= 1/\min\left(\max\left(5.308 \times 10^{-4} \times ftp_j + 4.498 \times 10^{-3}, \frac{1}{38.08}\right), \frac{1}{29.22}\right) \\ \text{light trucks: } T_j &= 1/\min\left(\max\left(4.546 \times 10^{-4} \times ftp_j + 1.331 \times 10^{-2}, \frac{1}{31.30}\right), \frac{1}{23.09}\right) \end{aligned} \quad 5.2$$

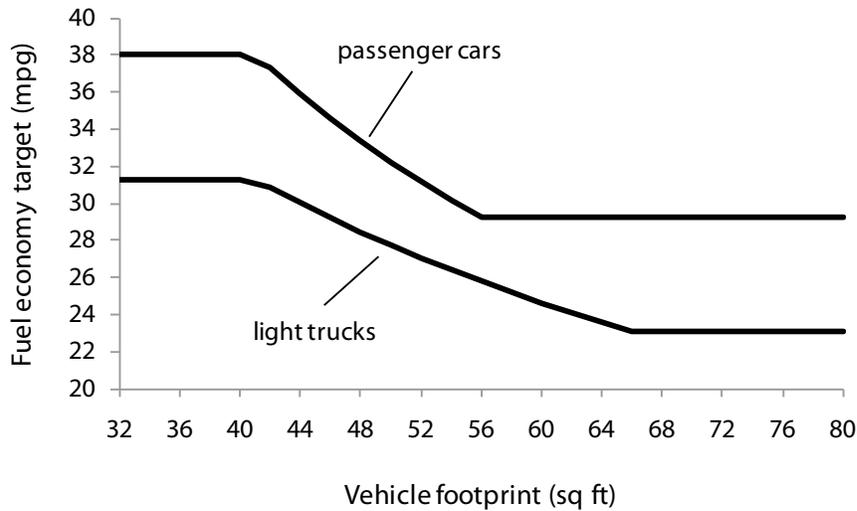


Figure 5.1 MY2014 footprint-based fuel economy targets as specified by CAFE

NHTSA chose these particular functions so that fuel economy targets decrease with vehicle footprint based on several concerns: 1) the attribute-based standards increase fuel savings compared to industry-wide average standards, 2) the standards should minimize the incentive for manufacturers to respond to CAFE such that traffic safety risk increases, and 3) regulatory burdens should be equally balanced among manufacturers (NHTSA 2009). However, no quantitative analysis was performed to assess what effect the chosen functions have on any incentives to increase or decrease vehicle size, and the resulting impact on average fuel economy. This study conducts such an analysis.

5.2.2 Safety criticisms of attribute-based standards

Despite the majority opinion of the NRC report that fuel economy standards have significant safety risks, many researchers have presented evidence that this connection is highly uncertain and potentially incorrect. Two authors of the NRC report dissented to the conclusion that increasing fuel economy has a negative impact on traffic safety (Greene and Keller 2002). This dissent focused on two main criticisms: 1) the fact that occupants in heavier vehicles are safer when they collide with lighter vehicles does not indicate that reducing weight of all vehicles will decrease traffic safety and 2) crash data contains many confounding factors that are not adequately addressed in many studies. Ahmad and Greene (2005) found no statistically significant relationship between fuel economy and traffic fatalities between 1967 and 2002. Anderson and Auffhammer (2011)

exposed an additional concern: assuming that consumers purchase vehicles considering only their own safety and not the safety of other vehicle occupants, the authors showed that the weight of vehicles on the road will be larger than is optimal considering total traffic safety. This study does not address the issue of traffic safety directly but investigates the impact of the footprint-based CAFE standards on vehicle size, which could be useful in future safety studies.

5.2.3 Discussion of potential undesirable incentives

In addition to criticisms of the link between improved fuel economy and increased safety risk, several researchers have suggested that footprint-based fuel economy standards could create the incentive to increase vehicle size, but a quantitative analysis of this incentive has not yet been performed. Norman (1994) recognized early on that attribute-based standards could be susceptible to unintended incentives for firms to design vehicles to be larger or heavier in order to qualify for a less stringent standard. He pointed out that, because these types of standards depend on the chosen attribute, they do not ensure that a given overall fuel economy will be achieved. Greene et al. (2005) pointed out that, depending on the costs and benefits of changing vehicle footprints, manufacturers may have an incentive to change the footprints of their vehicles and also noted that it was unfortunate that this incentive was not rigorously investigated by NHTSA before implementing the footprint-based CAFE.

Greene and Hopson (2003) considered the possibility of a weight-based standard creating the incentive to increase vehicle weight. They recognized that although manufacturers may be able to lower their required fuel economy standard by increasing vehicle weight, fuel economy also decreases with increased weight. The authors determined that increasing vehicle weight by 1% would reduce fuel economy performance by 0.6%. Assuming that increasing vehicle weight by 1% would reduce the CAFE requirement by 1%, the loss in fuel economy performance reduces the incentive to increase vehicle weight. Given a combined standard of 32.7 mpg by 2015, the authors find that the weight-based standard causes an average increase in weight of only 1% and a loss of fuel economy gains of 2.5%.

Although this analysis of weight-based standards illustrates some important tradeoffs necessary to understand the impacts of attribute-based standards, the results should not be generalized to footprint-based standards. Given an attribute-based CAFE standard, a profit-maximizing manufacturer will weigh various tradeoffs to determine whether modifying the key attribute (i.e., weight or footprint) is desirable. These tradeoffs include the cost of modifying the key attribute, the impact on fuel efficiency and other aspects of vehicle performance such as acceleration, and the resulting change in demand. All three of these types of tradeoffs may vary depending on whether the key attribute is vehicle weight or vehicle footprint. Consumers may prefer increased vehicle size more than increased vehicle weight, or vice versa; increasing the footprint of the vehicle may affect production costs differently than vehicle weight; and the degree to which fuel economy and acceleration performance are reduced from increasing vehicle footprint by 1% may be different than increasing vehicle weight by 1%.

This study investigates the effect of footprint-based fuel economy standards on any potential incentive to increase vehicle size considering consumer preferences, production costs, and engineering tradeoffs between vehicle footprint, fuel efficiency, and acceleration performance. The automotive market is represented using an oligopolistic equilibrium model in which engineering tradeoffs between vehicle attributes are derived from physics-based vehicle simulations. This certainly is not the only valid approach of analyzing footprint-based standards; indeed, we believe that multiple studies using both theoretical and empirical approaches are necessary to fully understand design incentives created by these standards.

5.3 Methodology

To investigate potentially undesirable incentives from the footprint-based CAFE standards, we consider the decisions that an automotive manufacturer may make in response to the regulation. If a manufacturer wishes to increase the footprint of a particular vehicle, the weight of a vehicle will increase to some extent. This will negatively impact both the fuel efficiency of the vehicle and the acceleration performance. These losses can be alleviated by incorporating various technology features (e.g., lower friction engine components or cylinder deactivation) at some additional cost.

Another option is to redesign the powertrain to improve fuel efficiency at some further cost of acceleration performance, or vice versa. A profit-maximizing manufacturer would balance these decisions based on how the resulting vehicle attributes affect vehicle sales (q), production costs (c), and the ability to meet the CAFE standard. This study is the first analysis of attribute-based standards to consider each of these tradeoffs.

These decisions can be formulated as an optimization problem where the manufacturer maximizes profits subject to the constraints of the CAFE regulation. The manufacturer can choose the footprint (ftp), acceleration performance (acc), level of technology features ($tech$), and price (p) of each vehicle in their fleet. The constraint of the CAFE regulation is a function of individual vehicle fuel economy targets (T), which depend on the footprint of the vehicle.

$$\begin{aligned}
 & \max_{ftp_j, acc_j, tech_j, p_j \forall j} \sum_j q_j(p_j, mpg_j, acc_j, tech_j, ftp_j) (p_j - c_j(acc_j, tech_j, ftp_j)) \\
 & \text{subject to} \quad \frac{\sum_{j \in \mathfrak{S}_{f,c}} q_j}{\sum_{j \in \mathfrak{S}_{f,c}} q_j / mpg_j} \geq \frac{\sum_{j \in \mathfrak{S}_{f,c}} q_j}{\sum_{j \in \mathfrak{S}_{f,c}} q_j / T_j} \quad 5.3 \\
 & \text{where} \quad mpg_j = f(acc_j, tech_j, ftp_j) \\
 & \quad \quad \quad T_j = g(ftp_j)
 \end{aligned}$$

Because fuel economy, acceleration performance, vehicle footprint, and the types of technology features incorporated into the vehicle are all related, the above formulation considers fuel economy as a function of the variables acc , ftp and $tech$, which the manufacturer chooses. This formulation choice is arbitrary and is equivalent to the manufacturer choosing vehicle footprint, fuel economy and acceleration performance with the $tech$ variable determined as a function of those attributes. The fuel economy target, T_j , is determined based on the formula prescribed by NHTSA as described by Equation 5.2.

Demand for a particular vehicle, q_j , in Equation 5.3 is dependent upon attributes of the vehicle j , but is also dependent on the attributes of other vehicles available to consumers. We account for this relationship by solving an oligopolistic equilibrium model where automotive manufacturers seek to maximize profits according to Equation

5.3. Similar representations of the automotive market as an oligopoly competing in prices and other vehicle production decisions are widespread throughout the literature because the market is characterized by differentiated products with high barriers to entry. The subsections below detail how each of the remaining functions in Equation 5.3 are derived and how the equilibrium model is formulated.

5.3.1 Tradeoffs between fuel economy, footprint, and acceleration performance

As discussed above, one effect of increasing vehicle footprint is reduced fuel economy and acceleration performance of the vehicle due to the increase in vehicle weight. We derive these relationships by first determining how vehicle weight changes with vehicle footprint and then using the model developed in Chapter 3 to characterize the relationship between vehicle weight, fuel economy, and 0-60 mph acceleration time. Approximately 42% of a vehicle's curbweight is attributable to components that are not affected by increases in external vehicle dimensions, such as the engine, transmission, seats, and wheels (Stodolski et al. 1995; Kelkar et al. 2001). An additional 9.5% of a vehicle's weight can be considered independent of footprint because the height of a vehicle is unaffected.¹⁵ Therefore, a 10% increase in a vehicle's footprint would result in approximately a 5% increase in curbweight.

The engineering model developed in Chapter 3 was used to represent the tradeoffs between vehicle weight, fuel economy, and acceleration performance for each of seven vehicle segments (e.g., midsize vehicles). Equation 3.1 and Table 3.3 summarize the estimated surrogate models used for each vehicle segment. Taken together with the relationship between vehicle footprint and vehicle weight, these surrogate models produce the function f in Equation 5.3, which determines the fuel economy of a vehicle dependent on the footprint, acceleration performance, and level of technology features implemented.

¹⁵ The body in white, interior less the seats, and window glass makes up 35% of vehicle curbweight (Stodolski et al. 1995; Kelkar et al. 2001). We assume that each of these components can be broken down into subcomponents that scale with one side of the vehicle body. Approximating a vehicle as a block with height h , length l , and width w , the surface area of the vehicle body is $2wl + 2wh + 2lh$. If the footprint increases by 1% the vehicle body's surface area increases by $2.02wl + 2\sqrt{1.01}wh + 2\sqrt{1.01}lh$. Using model-year 2006 vehicle dimensions, this represents a 0.73% increase in surface area. Therefore, we assume $(0.35)(0.27) = 9.5\%$ of a vehicle's curbweight depends on the vehicle's height but is independent of the vehicle's footprint.

This analysis does not consider the ability of manufacturers to lightweight their vehicles by replacing vehicle components with lighter materials. Data on the additional costs associated with incrementally lightweighting vehicle components and the resulting improvement in fuel efficiency and acceleration performance indicate that lightweighting is not as cost effective as the combinations of technology features considered in this analysis. Our results indicate that manufacturers do not implement the full extent of technology features considered in the vast majority of vehicles (87–99% of sales depending on demand parameters), implying that lightweighting is not cost effective for these vehicles. Therefore, we do not expect the omission of lightweighting to significantly affect results. Supposing the contrary, that lightweighting is actually a cost-effective option for firms to implement in response to the footprint-based standards, then firms would be able to increase the footprint of their vehicles with smaller losses in acceleration performance and fuel efficiency. Consequently, the extent to which firms have an incentive to increase the size of their vehicles would be, if anything, larger than the results presented in this study.

5.3.2 Tradeoffs between footprint and production costs

The automotive development process of a vehicle model begins with a target catalog specifying vehicle design features, including target vehicle dimensions, followed by detailed design of all vehicle subsystems and ending with vehicle production (Sörenson 2006; Weber 2009). The choice of target dimensions at the beginning of this process impacts the resulting production costs of each vehicle in the model line. Most notably, the material costs of the body panels, chassis, glass, driveshaft, axles, and certain interior components will increase with vehicle footprint. Production costs associated with manufacturing processes may also increase. The typical vehicle assembly process involves forming steel sheets into body panels using a series of stamping operations, assembling the panels using robotic arms, spot welding the panels together, and installing subsystem components (Braess and Seiffert 2005). The costs of these production processes may increase with the size of the vehicle footprint, for example if more energy is needed to lift heavier body panels or provide additional spot welds to assemble the larger panels. Labor costs may also increase if more time is needed to perform assembly

operations, for example if additional fasteners are necessary to attach larger subcomponents to the vehicle body.

As a conservative upper bound, we assume that increasing vehicle footprint will increase the incremental production costs according to a 1-to-1 relationship, such that a 1% change in vehicle footprint linearly increases incremental production costs by 1%. This implies that the costs of all components of a vehicle, and all manufacturing operations increase linearly and 1-to-1 with vehicle footprint. We expect that many of these costs increase at a smaller rate with vehicle footprint or are completely independent of footprint and so this assumption represents a substantially conservative estimate of the impact of vehicle footprint on production costs.

Because targets for vehicle dimensions are set early in the product development process and subsequent design of vehicle subsystems considers these dimensions, we do not expect fixed costs associated with vehicle design to increase with decisions on vehicle footprint. We also assume that fixed costs associated with manufacturing processes do not increase with decisions on vehicle footprint. One exception is that the dies used for body-panel stamping scale with footprint dimensions, and therefore the costs associated with the die material increase with footprint. However, the portion of die costs that depend on body panel area is small (Clark and Fujimoto 1991; McGee 1973) and so is not considered in this study.

As discussed above, increasing vehicle size will affect other vehicle attributes, including fuel economy and acceleration performance. Consequently, any incentive to increase vehicle size depends on consumer preferences for vehicle size and the vehicle attributes that trade off with size. For this analysis, we consider consumer preferences for vehicle size, fuel economy, and acceleration performance. Future work should consider to the extent possible any additional performance attributes that may be affected by increasing vehicle size, such as vehicle handling.

Consumer preferences are modeled as a discrete-choice utility model where consumer utility is a function of vehicle price, fuel efficiency, acceleration performance, and vehicle size:

$$U_{nj} = \alpha_1 p_j + \alpha_2 eff_j + \alpha_3 acc_j + \alpha_4 size_j + \xi_j + \epsilon_{nj} \quad 5.4$$

Vehicle price, p , in Equation 5.4 is measured in ten thousands of 2011 dollars. Fuel efficiency, eff , is measured in terms of the gallons of fuel needed to drive 100 miles. Vehicle size represents the length multiplied by the width of a vehicle in ten thousands of sq. in., and acceleration performance, acc , is the inverse of the time to accelerate from 0-60 mph in tenths of a second, which is approximately proportional to the ratio of horsepower to vehicle weight but also depends on transmission parameters other than horsepower. The ξ_j parameter represents the mean combined utility for all other vehicle attributes, and ϵ_{nj} is an error term specific to individual n and vehicle j .

Demand parameters as in Equation 5.4 are commonly estimated using vehicle purchase data. A notable challenge of estimating these parameters is that vehicle prices and observed attributes—including fuel consumption, acceleration performance, and size—are correlated with unobserved vehicle attributes that consumers value, such as exterior and interior styling. This correlation produces biased estimates of the demand parameters. Researchers commonly address this problem by conducting an instrumental variable regression to recover unbiased estimates of the parameters, relying on a set of instruments that are correlated with the observed attributes but are independent of unobserved attributes (Wooldridge 2001). However, the vast majority of these studies are only concerned with estimating the price parameter; identifying valid instruments for all the attributes listed in Equation 5.4 in addition to vehicle prices is difficult.¹⁶ Instead of attempting to solve this problem, we take a different approach, examining the potential incentive to increase vehicle size simulating many combinations of these parameters over ranges of plausible values.

Simulating combinations of demand parameters allows us to investigate the potential incentive to increase vehicle size over multiple scenarios of consumer preferences. This enumeration of demand parameter combinations presents a challenge with regard to computational costs. In order to tractably simulate combinations of the parameters in Equation 5.4, it is necessary to make a simplifying assumption that the α coefficients are common across all consumers, meaning that heterogeneous preferences are not accounted for in this model. Following customary assumptions of the logit model,

¹⁶ An instrumental variable regression for vehicle attributes was carried out by Klier and Linn (2008) who used a data set of vehicle engine platforms to construct instruments for vehicle price, weight, and power.

the ϵ_{nj} parameters are assumed independently and identically distributed across vehicles according to a Type 1 extreme value distribution. This assumption allows the expected value of sales of vehicle j to be written as in Equation 5.5.

$$\mathbb{E}(s_j) = N \frac{e^{V_j}}{e^{V_{og}} + \sum_{k \in \mathfrak{S}} e^{V_k}} \quad 5.5$$

$$V_j = \alpha_1 p_j + \alpha_2 eff_j + \alpha_3 acc_j + \alpha_4 size_j + \xi_j \quad 5.6$$

In Equation 5.5, N is the number of consumers; V_j is the observed portion of utility for vehicle j as described by Equation 5.6; \mathfrak{S} is the set of vehicles in the market including vehicle j ; and V_{og} is the observed utility of the outside good, representing the utility of not purchasing a new vehicle. By substituting Equation 5.6 into Equation 5.5, we can solve for ξ_j as in Equation 5.7. Consequently, given the sales of vehicle j (s_j); the number of consumers that did not purchase a new vehicle (s_{og}), and values of the α coefficients for price, fuel efficiency, acceleration performance, and size, the mean utility of all other vehicle attributes (ξ_j) can be inferred as:

$$\xi_j = \log\left(\frac{s_j}{N}\right) - \log\left(\frac{s_{og}}{N}\right) - (\alpha_1 p_j + \alpha_2 eff_j + \alpha_3 acc_j + \alpha_4 size_j) \quad 5.7$$

Plausible values for the α coefficients in the equations above were determined based on key properties of consumer demand for new automobiles estimated in the literature. Ranges for the price coefficient were based on estimated values for the average price-elasticity of demand, which range from -2.0 to -3.1 in the literature (Berry et al. 1995, Goldberg 1998, Jacobsen 2010, Klier and Linn 2008, Train and Winston 2007). Ranges of values for the remaining coefficients were informed based on the willingness of consumers to pay for improved fuel consumption, higher acceleration performance, and larger size as estimated from the literature. Estimated willingness to pay for an additional sq. ft. of size ranges from \$340-\$2,000, for an increase of 0.01 hp/lb ranges from \$160-\$5,500, and for a reduction in fuel consumption of 1 gal per 100 miles ranges from \$1100-\$9000 (Greene and Liu 1987; Goldberg 1998; Klier and Linn 2009). Helfand and Wolverton (2009) recently conducted a survey of consumer valuation for fuel economy and found that estimates for consumers willingness to pay for 1 mpg more of

fuel economy ranges from approximately \$200-\$600 in the literature. Using the vehicle data input into our simulations, the lower bound of \$200 per mpg implies a willingness to pay of \$800 for improved fuel efficiency of 1 fewer gal. per 100 miles, so this is used as the lower bound estimate of consumer preference for fuel efficiency in the simulations.

Table 5.1 reports the ranges of willingness-to-pay for vehicle attributes as estimated in the literature and the α coefficients that correspond to these ranges. Ideally, combinations of these parameters for the simulations would be determined by sampling from their joint distribution. However, existing literature has not produced estimates of this joint distribution or characterized correlations between these parameters. Consequently, combinations of these parameters were simulated without accounting for any potential correlations. Specifically, the parameter ranges were divided up into three levels for each parameter—representing the lower bound, midpoint, and upper bound for each parameter—and combinations of these parameter levels were used as simulation inputs. Because the parameters are considered independent, the range of the results of this study bound the results that would be produced using any correlation of input parameters.

Table 5.1 Ranges of demand parameters in literature and corresponding model coefficients

	<u>Range of mean elasticity</u>	<u>Coefficient range</u>
Price	2.0–3.1	0.65–1.00
	<u>Range of estimated willingness to pay</u>	<u>Coefficient range with price coefficient=1.00</u>
Footprint (sq. ft)	\$340–\$2,000	2.12–12.71
Acceleration performance (0.01 hp/lb)	\$160–\$5,500	0.06–2.07
Fuel efficiency (gal/100 mi)	\$800–\$9000	0.07–0.80

5.3.3 Equilibrium model

Producer decisions regarding vehicle prices and attributes are modeled as an oligopolistic equilibrium model where firms maximize profits with respect to the prices, acceleration performance, and levels of technology features of their vehicles. Twenty of the top automotive firms that sell vehicles in the United States are represented in the model. Vehicles are represented as all vehicle models and engine options produced by

these firms based on MY2006 data, totaling 473 for all firms. Firms are differentiated as to whether they are expected to meet the CAFE standards even if it is more profitable to violate them. The model allows BMW, Jaguar, Mercedes-Benz, Porsche, and VW to violate the standard and pay the appropriate penalties. The profit maximization of these firms takes the following form:

$$\max_{ftp_j, acc_j, tech_j, p_j \forall j} \sum_j q_j (p_j - c_j) - F_C - F_T$$

where $mpg_j = f(acc_j, tech_j, ftp_j)$

$$F_C = \left(\sum_{m \in \mathcal{C}_C} q_m \right) \left(\sum_{m \in \mathcal{C}_C} \frac{q_m}{T_m} - \sum_{m \in \mathcal{C}_C} \frac{q_m}{mpg_m} \right) \quad 5.8$$

$$F_T = \left(\sum_{n \in \mathcal{C}_T} q_n \right) \left(\sum_{n \in \mathcal{C}_T} \frac{q_n}{T_n} - \sum_{n \in \mathcal{C}_T} \frac{q_n}{mpg_n} \right)$$

F_C and F_T in Equation 5.8 are respectively the penalties for violating the fuel economy standard for passenger cars and light trucks. Fuel economy targets, T_m and T_n , for these vehicle classes are determined by Equation 5.2. All other firms are treated as constrained to the CAFE standards so that their profit maximization problems take the form of Equation 5.8. Fuel economy, mpg_j , is calculated from the model described in Section 3.2.

Firm decisions on vehicle footprint are constrained to a maximum of a 10% increase. This constraint is imposed to avoid extrapolation outside of the boundaries of data used to construct the engineering performance model and to account for any potential constraints of dramatically increasing vehicle size. Observations of vehicle footprint data from 1997–2010 indicate that firms have increased the footprint of redesigned vehicle models by 10% compared to the previous model design, supporting that any potential constraints on size are larger than 10%. Imposing this constraint on the model causes the results to represent a lower bound of the incentive to increase vehicle size.

5.4 Results and Discussion

Simulation results are presented in Table 5.2 for multiple combinations of consumer demand parameters. The values presented in this table represent the change in the sales-weighted average of vehicle footprint. Input demand parameters for these simulations represent combinations of consumer preference for vehicle size, acceleration performance, and fuel efficiency. For the results in this particular table, the price parameter was chosen such that the average price-elasticity of demand is -3.1 and demand parameters for acceleration performance and fuel efficiency are set at the same level (i.e., either both low, both high, or both at midpoints). The upper left corner of the table represents the lower bound of changes in vehicle footprint, where preferences for acceleration performance and fuel efficiency are high, price sensitivity is high, and preference for vehicle size is low. Table 5.3 displays the sensitivity of these results to independent variations of preference for acceleration performance and preference for fuel efficiency, and to variations of the price parameter. Future work will investigate the sensitivity of results to assumptions of production costs and vehicle weight.

Table 5.2 Results of change in vehicle size given combinations of demand parameters

		Preference for footprint			
		Low	Mid	High	
Preference for fuel efficiency	Preference for acceleration	High	-1.4 sq. ft.	+3.8 sq. ft.	+7.0 sq. ft.
		Mid	+1.5 sq. ft.	+7.5 sq. ft.	+9.2 sq. ft.
		Low	+2.1 sq. ft.	+9.6 sq. ft.	+13.4 sq. ft.

Table 5.3 Sensitivity of results to variations in consumer preference parameters

Price Sensitivity	Preference for fuel efficiency	Preference for acceleration	Preference for footprint	Average change in footprint
High	Mid	High	Mid	-1.0 sq. ft.
High	Mid	Mid	Mid	+7.5 sq. ft.
High	Mid	Low	Mid	+9.4 sq. ft.
High	High	Mid	Mid	+5.9 sq. ft.
High	Mid	Mid	Mid	+7.5 sq. ft.
High	Low	Mid	Mid	+9.2 sq. ft.
High	Mid	Mid	Mid	+7.5 sq. ft.
Mid	Mid	Mid	Mid	+10.5 sq. ft.
Low	Mid	Mid	Mid	+11.3 sq. ft.

Results indicate that there is an incentive to increase vehicle size in all simulations except the case where consumer preference for footprint is at the lower bound and preference for acceleration performance is at the upper bound. In those cases, firms have an incentive to shift production of their vehicles such that the average vehicle size decreases by 1.0–1.4 sq. ft. due to low consumer preference for vehicle size compared to acceleration performance. In all other simulations, firms have an incentive to increase the size of vehicles sold, both by increasing the footprint of vehicle models and by shifting production toward larger vehicles. The incentive ranges substantially depending on consumer preferences, from an average of 1.4–13.4 sq. ft. To put these results into context, average vehicle footprint increased 1 sq. ft. between 2008 and 2011.

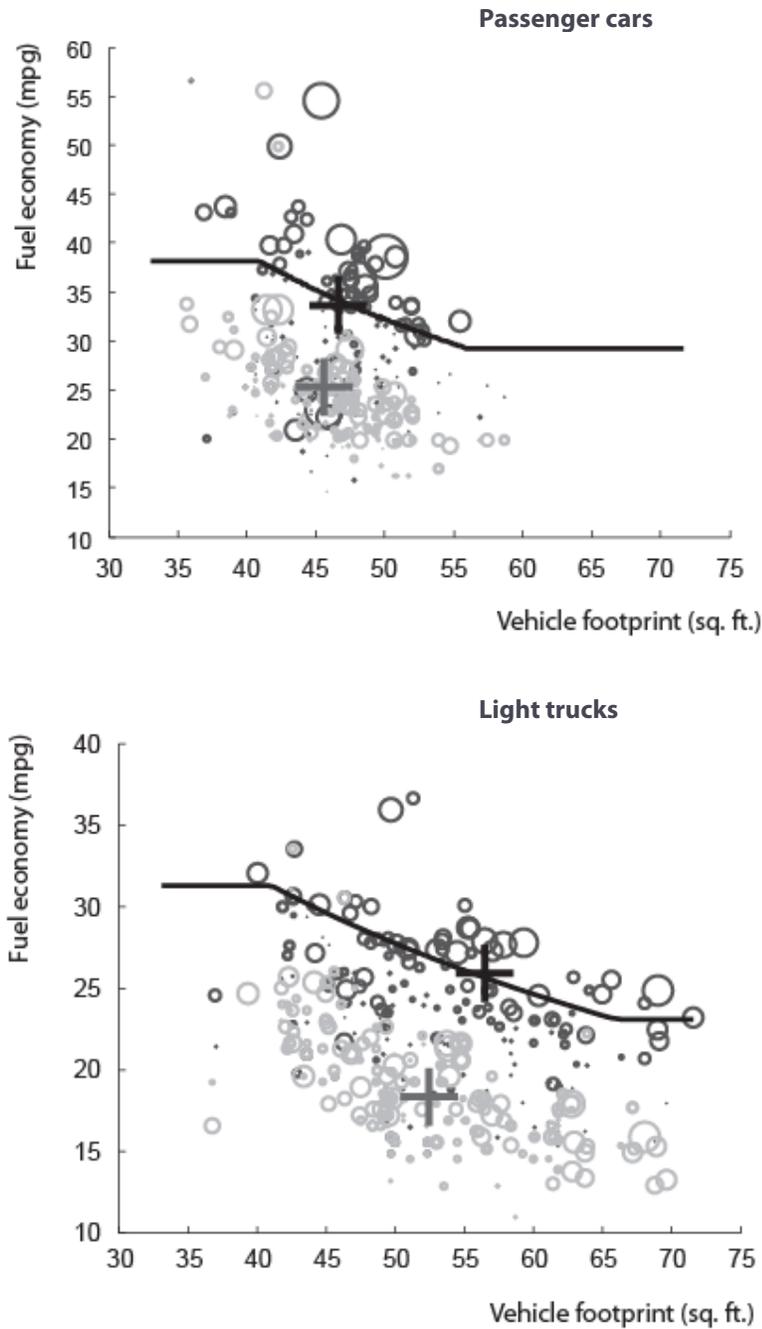
Between 7% and 33% of vehicle models and engine options are actively constrained by the 10% upper bound on the increase in vehicle footprint, with the larger percentage occurring in scenarios where consumer preference for footprint is high and preference for acceleration and fuel efficiency are low. This suggests that the increase in vehicle size for these scenarios would be even higher if this constraint was increased.

To test the impact of the incentive to increase vehicle size on fuel efficiency, we compare simulation results to the average fuel economy that the CAFE standards would require if vehicle footprint and vehicle sales remain unaffected. Specifically, the sales and vehicle footprint using MY2006 data was input into Equations 5.1 and 5.2 to determine these fuel economy standards. This is similar to the process NHTSA uses to predict future levels of fuel economy, except they use product development plans provided by automotive firms to extrapolate future vehicle attributes. Using vehicle data from MY2006, the required average fuel economy is 30.7 mpg. This is similar to NHTSA's estimated value of 31.5 mpg. Simulation results indicate that the combination of increases in vehicle size, and shifts in production to larger vehicles can reduce these fuel economy requirements. The resulting required fuel economy standards from the simulations are 1.4–3.9 mpg lower than if vehicle sales and size remained unaffected.

Simulation results also suggest a disparity in the incentive to increase vehicle size for light trucks and for passenger cars. Figure 5.2 illustrates the change in vehicle size and fuel economy from simulation results using midpoint values for consumer preference for fuel efficiency, acceleration performance, and vehicle size. Initial vehicle

data is displayed in gray with counterfactual simulation results in black. The sizes of the circles in the figure are proportional with vehicle sales.

Figure 5.2 Simulation results given midpoint consumer preferences. Sales-weighted harmonic mean vehicle attributes are represented as a cross (+). Initial data are in gray, with MY2014 CAFE counterfactual simulation results in black. Point size is proportional to vehicle sales.



The figure illustrates that both passenger cars and light trucks increase in size, but the increase in size for light trucks is much larger than for passenger cars. This behavior can be explained by the larger impact of the CAFE standard for light trucks on firm profits than the standard for passenger cars. Simulation results indicate that the shadow cost of CAFE, or the incremental profit loss given an incremental increase in the CAFE constraint, is 1.5–7.0 times larger for light trucks than passenger cars.¹⁷ Because the light truck standard causes larger profit losses than the passenger car standard, firms have a larger incentive to increase the sizes of light trucks to take advantage of lower fuel economy standards.

This difference in incentives between passenger cars and light trucks could create a second potential undesirable effect of the footprint-based standards. If the incentive to increase vehicle size is greater for light trucks than passenger cars, the regulation could cause further divergence in the sizes of vehicles in these classes. This divergence may negatively affect traffic safety because the risk of fatality in a two-vehicle crash increases if the difference in weight of the two vehicles is larger.

5.5 Summary and Recommendations

This study investigated the potential for footprint-based fuel economy standards to create an incentive to increase vehicle size. An oligopolistic equilibrium model was used to study automaker incentives. In this model, firms can adjust vehicle prices, tradeoff acceleration performance and fuel efficiency, implement fuel-saving technology features, and increase vehicle size. This model was solved using multiple combinations of demand parameters representing consumer preference for vehicle size, acceleration performance, and fuel efficiency.

Simulation results indicate that the incentive to increase vehicle size exists except in the case in which consumer preferences for vehicle size are low and preferences for acceleration performance are high. The average increase in vehicle size from all other simulations ranges from 1.4–13.4 sq ft. Results suggest that fuel economy standards can

¹⁷ These values were obtained from the Lagrange multipliers of the constraints in Equation 5.3. With regard to the unreformed CAFE standards, Anderson and Sallee (2009) also found that the ranges of estimated shadow costs of the standard for light trucks were larger than for passenger cars for Ford, GM, and Chrysler. Jacobsen (2010) found that the shadow cost for light trucks was larger than passenger cars for Ford, but that the shadow cost for passenger cars was lower than for light trucks for GM and Chrysler.

be substantially undermined by increases in vehicle size and shifts in production to larger vehicles. The required fuel economy standards from simulation results are 1.4–3.9 mpg lower than if vehicle size and production mix is assumed unaffected by the policy. Furthermore, results suggest that the incentive to increase vehicle size may be larger for light trucks than passenger cars. This could create a further divergence in vehicle size between these two classes, potentially leading to higher traffic safety risks.

The footprint-based CAFE standards can be modified to diminish or eliminate incentives to increase vehicle size, avoiding losses in fuel economy and a divergence of the sizes of passenger cars and light trucks. Flattening the slope of the function determining fuel economy targets based on vehicle footprint reduces the incentive to increase vehicle size (NHTSA 2009). This study illustrates that the incentive to increase vehicle size is considerably sensitive to the strength of consumer preferences for vehicle footprint relative to fuel economy and acceleration performance, indicating that the larger relative preferences are for vehicle footprint, the flatter the slope of fuel economy targets should be. Furthermore, results suggest that the slope of fuel economy targets for light trucks should be flattened to a further degree to avoid a divergence between the sizes of light trucks and passenger cars.

Further research is needed to understand the effects of footprint-based fuel economy standards and inform future policymaking. One area of research that has not been given enough attention in the discussion of attribute-based fuel economy standards is consideration of existing vehicles on the road. Fuel economy regulations only affect new vehicles but total traffic safety depends on the distribution of all vehicles on the road. Even if footprint-based standards induce an identical incentive to increase the footprints of all new vehicles so that the spread of new vehicle size remains the same, these larger vehicles will pose a greater risk to occupants of existing smaller vehicles.

Another area of research that should be investigated is whether fuel economy and safety goals can be effectively incorporated into one single regulation. The analysis presented in this study demonstrates that the incentive to increase vehicle size depends on a number of relationships including engineering tradeoffs between vehicle size and other vehicle attributes, consumer preferences for all of these attributes, production costs, and competition between automotive firms. Designing footprint-based fuel economy

standards such that manufacturers have no incentive to adjust the size of their vehicles is remarkably difficult considering that these factors may be different not just for light trucks and passenger cars but potentially for each individual vehicle model. Many economists emphasize that multiple market failures justify multiple policy instruments (e.g., Bennear and Stavins 2007; Goulder and Parry 2008). Likewise, two separate instruments may be better able to address policy concerns of fuel economy and traffic safety than existing footprint-based fuel economy standards.

CHAPTER 6: APPLICATIONS TO LIFECYCLE ASSESSMENT

“If humans set up systems that don’t share nature’s value system, we’re setting up the wrong incentives.” —James A. Edmonds, Pacific Northwest National Laboratory

To date, the cLCA literature has developed methods to analyze the effect of industrial decisions on environmentally relevant flows of energy and mass. However, further advancement is needed to incorporate the impacts of product or process design on these environmental flows, particularly when multiple firms compete for the product market. In these industries, consideration of firm design responses is beneficial because these design decisions predetermine many of the dominant sources of environmental emissions and resource consumption throughout the products’ lifecycles. This chapter presents a framework to capture market-driven design (MDD) responses into a cLCA analysis.

The chapter begins by illustrating the influence of design decisions on environmental impacts then reviewing existing cLCA studies with emphasis on opportunities to advance these methods to study designed-product systems. The concept of cLCA-MDD is then introduced and a case study is presented that demonstrates how design responses can be endogenously captured in a cLCA analysis. The case study is divided into two parts: first, incorporating endogenous design responses into a cLCA study analyzing the effects of an industrial design decision on greenhouse gas (GHG) emissions in a midsize vehicle market; and second, conducting a policy analysis using a cLCA-MDD approach, investigating the impacts of a policy decision on GHG emissions from midsize vehicles. Lifecycle inventory results using attributional LCA (aLCA), cLCA without MDD, and cLCA-MDD approaches are compared.

The case study illustrates that cLCA-MDD can capture multiple “ripple effects” resulting from an industrial decision (e.g., downsizing a vehicle’s engine) or a policy decision (e.g., raising gasoline taxes) and that these effects significantly influence results.

For this case study, endogenous MDD responses are incorporated by determining the equilibrium powertrain designs and prices of vehicles, as well as the resulting demand for vehicles and vehicle-miles-traveled, in response to the decision analyzed. A key challenge of the approach is appropriately managing and communicating uncertainties associated with the choice of economic parameters or models. We discuss sources of uncertainty in cLCA-MDD and demonstrate a presentation scheme to facilitate communication of result sensitivity to uncertainties from input parameters, models, and model structure.

6.1 Introduction

The design of products and manufacturing processes is well recognized as a crucial component to achieve sustainable development. Indeed, a majority of the environmental impact of a product is predetermined early in the design stage. This may not be the case for products such as wheat and cement, where production processes are largely the same across the industry and product variation is rare if not legally restricted. But, the majority of human impact on the environment is carried through products that are shaped by design. Automobiles, planes, household appliances and climate control, consumer electronics, and processed foods—which account for some of the largest environmental impacts in most impact categories (Tukker and Jansen 2006)—are all designed products with environmental impacts that are inherently connected to design decisions.

Recently, the European Commission identified the need to broaden LCA approaches to support sustainable assessment by taking a systems perspective and by developing methods to study wider set of applications, including those relevant for designed-product industries (Guinée et al. 2010). Consequential lifecycle assessment (cLCA) is a potential vehicle for this broadening of LCA but further advancement of cLCA methods are needed to accomplish this goal.

As opposed to the method of LCA formalized by the International Organization for Standardization (ISO), which characterizes environmental impacts of a particular product throughout its lifecycle, cLCA analyzes how the impacts of a product lifecycle and the surrounding system will change in response to a particular decision. A growing

body of cLCA literature has developed methods to incorporate cross-lifecycle effects in LCA studies (e.g., Ekvall and Andr e 2006; Sand en and Karlstr om 2007; Schmidt and Weidema 2008). However, there is a need to develop methods to incorporate product design decisions into cLCA when environmental flows are substantially dependent on product design. For example, the total environmental impact of redesigning the VW Touareg line so that the vehicles are smaller and more fuel efficient depends not only on the resulting changes in emissions from the redesigned Touareg’s lifecycle, but also on shifts in sales due to consumers substituting away from the redesigned Touareg to competing vehicles (because they prefer a larger vehicle) and any resulting incentives for manufacturers to change the size of these competing vehicles. Incorporating product design responses endogenously within cLCA can also make a valuable contribution to policy analysis. For instance, the effectiveness of carbon taxes, technology subsidies, and emission standards are all influenced by the changes to product designs that may result from the policy.

This research contributes to the development of cLCA by demonstrating a methodology that endogenously determines market-driven design responses to industrial and policy decisions. Specifically, we describe techniques to determine design responses in an LCA analysis using economic partial-equilibrium models. We then demonstrate the cLCA-MDD approach using a case study. In the first part of the case study, we analyze changes in lifecycle greenhouse gas (GHG) emissions associated with a midsize vehicle market in response to the decision to reduce the engine size of one vehicle model. For clarity, we refer to the product(s) that are the subject of the exogenous decision (the VW Touareg in the previous example) as the “protagonist product(s)”, so that they can be distinguished from competing products that are indirectly affected. In the second part of the case study, we conduct a policy analysis using cLCA-MDD techniques, analyzing the changes in lifecycle GHG emissions resulting from increasing gasoline taxes, accounting for equilibrium design responses of all firms in the mid-size vehicle market.

The case study is only meant to be illustrative of the cLCA-MDD methodology. To that end, it has many simplifications and should not be interpreted as a comprehensive characterization of GHG emissions resulting from the decisions analyzed. We note, however, that extension of the case study using more realistic submodels, such as those

presented in Chapter 3, is straightforward. Although we focus only on GHG emissions in the case study, the method is equally applicable to a complete inventory of emissions, wastes, and resource utilization.

Additionally, we discuss uncertainty in cLCA and present a scheme of communicating sensitivity of cLCA results to these uncertainties. The existing cLCA literature uses economic parameters such as elasticities and learning curves to incorporate cross-lifecycle flows (e.g., Ekvall and Andr e 2006; Sand en and Karlstr om 2007; Schmidt and Weidema 2008). Evaluating the sensitivity of results to such parameters is essential given that many of these parameters have large uncertainties. However, in practice, such uncertainty analyses are often not performed. In the case of cLCA-MDD, multiple economic models must be employed, including consumer demand and use functions dependent on product design and pricing, and cost models dependent on design. The need for these input models introduces uncertainty associated with the choice of the specific models and any uncertainty in model parameters. In the case study, this uncertainty is handled by conducting a sensitivity analysis under multiple combinations of available input parameters and models, and presenting these results side-by-side to allow for easy comparison.

The remainder of the chapter is structured as follows: Section 6.2 describes the development of cLCA-MDD methodology and its relationship to the existing computational framework for lifecycle inventory (LCI) analysis. Section 6.3 discusses uncertainties and the use of a decision unit in cLCA in addition to a functional unit. Section 6.4 describes Part 1 of the case study and presents results and Section 6.4.8 describes and presents results for Part 2. Section 6.5 offers a summary discussion of the value and practice of cLCA-MDD.

6.2 cLCA-MDD Modeling Approach

To endogenously incorporate market-driven design responses into LCA, we draw on customary economic concepts of Nash equilibrium based on profit maximization of firms and utility maximization of consumers (e.g., Samuelson 1983), similarly to the approach used in Chapters 4 and 5. A firm's profits depend not only on their own product design and pricing decisions, but also on their competitors' decisions. Consequently,

firms often have incentives to adjust the designs and prices of their products in response to a change in a competing product's design. We determine these design responses by using an oligopolistic partial-equilibrium model where each firm simultaneously maximizes their profits with respect to the prices and designs of their products. Using this approach, we can determine the equilibrium product designs in response to the decision of interest and changes to lifecycle flows resulting from these design adjustments.

In principle, other methods of incorporating design decisions could be used besides equilibrium modeling. For example, researchers have proposed that the consequences of economic behavior on LCA results be captured using agent based modeling (Axtell et al., 2001) and systems dynamics (Mihelcic et al., 2003). These approaches could indeed be incorporated into the cLCA-MDD methodology in place of an equilibrium model and consumer behavior models (e.g., for product demand and use). Given the added complexity of these models (e.g., Garcia 2005; Bouman et al. 2000), significant computational burdens would need to be overcome to adequately account for model and parameter uncertainty.

Let \mathbf{x}_i be a vector of all the design variables of the protagonist product(s), \mathbf{x}_{-i} be a (stacked) vector of all competing product design variables. Similarly, let \mathbf{c}_i and \mathbf{c}_{-i} respectively be vectors of the production costs of the protagonist products and competing products, \mathbf{y}_i and \mathbf{y}_{-i} respectively be vectors of the product attributes that influence demand of the protagonist products and competing products, and \mathbf{d}_i and \mathbf{d}_{-i} respectively be vectors of the demand of the protagonist products and competing products. Finally, let \mathbf{p} be a (stacked) vector of the prices of all products, including both protagonist and competing products. Throughout this chapter, we denote equilibrium variables with an asterisk (*).

Figure 6.1A represents a LCI where market-driven design decisions, product demand, and design-dependent use-phase behavior are factors that are left exogenous to the system boundaries. In this system, lifecycle material and energy flows are determined by scaling industrial process data to match exogenously determined demand. For instance, an automotive manufacturer estimating lifecycle emissions associated with selecting a specific engine for a vehicle via aLCI would typically assume a fixed number of units sold and fixed vehicle-miles-travelled (VMT), independent of the engine design. Uncertainty in these assumptions could be characterized with sensitivity analyses, but

dependent relationships between these parameters and the engine design would be ignored.

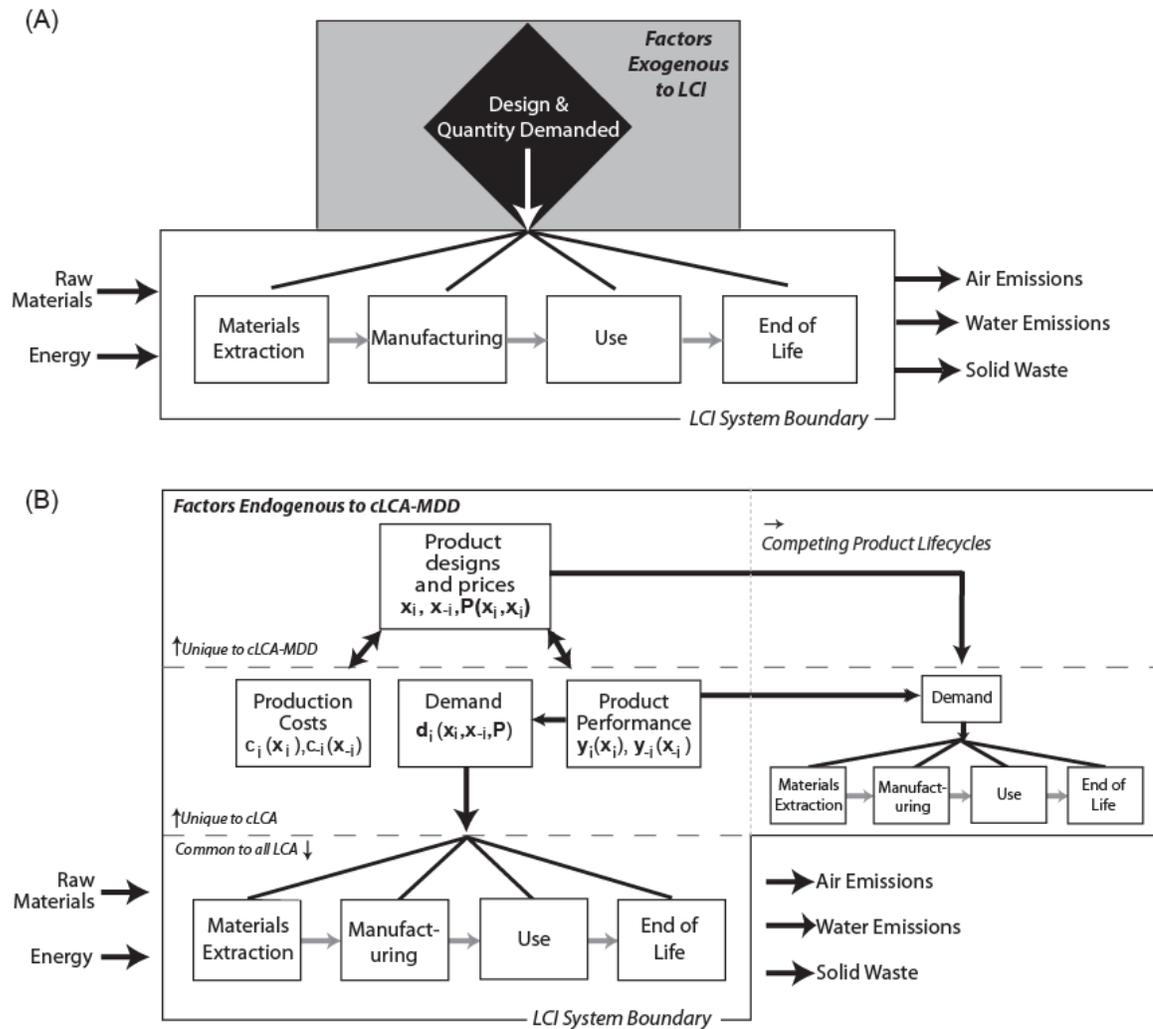


Figure 6.1 LCI system boundaries using an (A) aLCA approach, and (B) cLCA-MDD approach.

In the engine selection example, a cLCA-MDD analysis would determine the equilibrium horsepower for competing vehicles, $x_{-i}^*(x_i)$, and equilibrium prices for all vehicles, $p^*(x_i, x_{-i}^*(x_i))$, in response to a change in the protagonist vehicle's horsepower, x_i . These equilibrium decisions will depend on submodels characterizing vehicle demand as a function of the designs and prices of competing vehicles, and production costs as a function of vehicle design. The resulting demand and VMT (as well as associated

emissions) for the protagonist vehicle and its competitors can then be calculated given these equilibrium designs and prices.

The cLCA-MDD methodology can be used to analyze the lifecycle environmental impacts of a policy decision by endogenously accounting for design and price responses of relevant products in equilibrium. For example, if the policy decision were a carbon tax, changes to the equilibrium designs and prices of relevant products would be determined in response to the tax. The resulting demand and lifecycle flows could then be calculated based on these equilibrium decisions.

cLCA-MDD, unlike aLCA, requires a linkage between equilibrium models and LCI data. To explore this further, we build from the computational framework for ISO-based LCI that is well established in the literature (Heijungs 1994; Heijungs and Suh 2002; Suh and Huppel 2005; Hertwich 2005). In principle, it is also possible to incorporate the MDD approach within the EIO-LCA framework (e.g., by extending the approach in Takase et al. 2005) but this is left to future work.

Let A be a matrix (called the *process matrix* or *coefficients matrix*) defining the transformation of j inputs (e.g., raw materials and energy) and outputs (e.g., products and co-products) through k unit processes. Coefficients associated with the input of material or energy have negative values, whereas coefficients associated with the output of products have positive values. Let d be a vector of total quantity of products demanded, and s be a vector representing the scaling-up of unit processes needed to satisfy the product demand. Finally, let B be a l by k matrix (called the *emission factor matrix* or the *stressor matrix*) defining the amounts of l emissions and wastes associated with the k unit processes necessary to produce the product, and the vector v be a vector of length l defining the total emissions and wastes associated with the product.

The construct of LCI as a linear algebraic system of equations (e.g., Heijungs 1994) usually assumes that inventory parameters in the product system are defined by constant factors as shown in Equation 6.1. In Equation 6.1, d_i represents the total quantity of aluminum, steel, energy and generic machined parts required to produce the engine for a hypothetical vehicle model, with all other material inputs excluded for simplicity. Data collected indicate the inputs required to produce a single vehicle part, with the input of steel dependent on the vehicle's designed horsepower, x_l . In an aLCA analysis, both the

vehicle design variables, \mathbf{x} , and the demand vector for the unit process outputs, \mathbf{d} , are exogenously determined and may be varied in a sensitivity analysis.

$$\begin{array}{c}
 \mathbf{A} \\
 \text{Energy} \quad \text{Rolled Al} \quad \text{Rolled steel} \quad \text{Machine part} \\
 \begin{array}{l}
 \text{Energy (MJ)} \\
 \text{Aluminum (kg)} \\
 \text{Steel (kg)} \\
 \text{Machine part}
 \end{array}
 \begin{bmatrix}
 1 & -100 & -25 & -500 \\
 0 & 1 & 0 & -20 \\
 0 & 0 & 1 & -0.1x_1 \\
 0 & 0 & 0 & 1
 \end{bmatrix}
 \times \mathbf{s} = \begin{array}{c}
 \mathbf{d} \\
 \text{Product demand} \\
 \begin{bmatrix}
 0 \\
 0 \\
 0 \\
 100
 \end{bmatrix}
 \end{array}
 \end{array} \quad 6.1$$

The scaling vector, \mathbf{s} , can be calculated from Equation 6.2 as long as \mathbf{A} is invertible:

$$\mathbf{s} = \mathbf{A}^{-1}\mathbf{d} \quad 6.2$$

The manufacturing of products associated with matrix \mathbf{A} creates emissions to the environment, represented by the matrix \mathbf{B} . In our hypothetical example, represented in Equation 6.3, the first and last elements in \mathbf{B} indicate that production of one MJ of energy emits 200 g CO₂-equivalent (eq.) emissions, and the production of one machined part emits 50 g CO₂-eq. for every unit of horsepower). Given the scaling vector, \mathbf{s} , and an assumed horsepower (100), the cumulative lifecycle emissions, \mathbf{v} , associated with satisfying demand can be calculated with Equation 6.3:

$$\begin{array}{c}
 \mathbf{B} \\
 \text{Energy} \quad \text{Rolled Al} \quad \text{Rolled steel} \quad \text{Machine part} \\
 \text{Emissions intensity factors (kg CO}_2\text{-eq.)} \\
 \begin{bmatrix}
 200 & 10,000 & 2,000 & 50(100)
 \end{bmatrix}
 \times \mathbf{s} = \begin{array}{c}
 \mathbf{v} \\
 \text{Total emissions} \\
 77,500 \text{ kg}
 \end{array}
 \end{array} \quad 6.3$$

Two distinct extensions of the above formulation differentiate cLCA-MDD from aLCA. First, cLCA-MDD takes a systems analysis perspective, determining the environmental impacts not just of one product but also of competing products. In a cLCA-MDD analysis, \mathbf{d} is a stacked vector, containing entries for both the total demand of the protagonist product(s), \mathbf{d}_p , and the total demand of competing products, \mathbf{d}_c .

Similarly, \mathbf{A} is a stacked matrix defining all of the unit process inputs and outputs for the protagonist product(s) and all competing products, and \mathbf{B} is a stacked matrix determining the emission intensity factors associated with all of these processes. Second, cLCA-MDD determines the environmental impact of lifecycle flows dependent on endogenous changes to product design variables and demand as in Equation 6.5.

$$\mathbf{A}(\mathbf{x}_i)\mathbf{s}(\mathbf{x}_i, \mathbf{x}_{-i}^*(\mathbf{x}_i)) = \mathbf{d}(\mathbf{x}_i, \mathbf{x}_{-i}^*(\mathbf{x}_i), \mathbf{p}^*(\mathbf{x}_i, \mathbf{x}_{-i}^*(\mathbf{x}_i))) \quad 6.4$$

$$\mathbf{B}(\mathbf{x}_i)\mathbf{s}(\mathbf{x}_i, \mathbf{x}_{-i}^*(\mathbf{x}_i)) = \mathbf{v}(\mathbf{x}_i, \mathbf{x}_{-i}^*(\mathbf{x}_i)) \quad 6.5$$

The dependency of lifecycle flows on endogenous design responses allows cLCA-MDD to capture many direct and indirect “ripple effects”, as characterized by Hertwich (2005). For example, economists have recognized that automotive firms have an incentive to decrease the fuel efficiency of their vehicles in favor of larger size, in response to a decrease in size (and increase in fuel efficiency) of a competing vehicle (Jacobsen 2010). This indirect effect can be captured in cLCA-MDD, along with direct effects such as the classical energy-economics concept of rebound effects, where improvements in energy efficiency lead to increases in use that partially diminish reductions in energy consumption.

Equations 4 and 5 present at least two challenges for cLCA-MDD. The first is the parameterization of the process matrix $\mathbf{A}(\mathbf{x}_i)$ and the emission factor matrix $\mathbf{B}(\mathbf{x}_i)$ as functions of all relevant design variables. While this certainly is not trivial, similar data have been collected and analyzed in sensitivity analyses of design choices (e.g., Keoleian et al. 1998). The second issue is the need for models of consumer behavior (e.g., product demand and use functions) to determine $\mathbf{d}(\mathbf{x}_i, \mathbf{x}_{-i}^*(\mathbf{x}_i), \mathbf{p}^*(\mathbf{x}_i, \mathbf{x}_{-i}^*(\mathbf{x}_i)))$ and an equilibrium simulation to determine $\mathbf{x}_{-i}^*(\mathbf{x}_i)$. These issues increase data requirements and computational costs of cLCA-MDD.

Relevant consumer behavior submodels to determine \mathbf{d} in Equation 6.4 include consumer utility models of product demand (e.g., how consumer demand for a particular vehicle changes with the vehicle’s design and pricing) and use (e.g., how demand for VMT changes with vehicle horsepower). Determining equilibrium design responses, \mathbf{x}_{-i}^* , and prices, \mathbf{p}^* , also requires submodels of production costs, $\mathbf{c}(\mathbf{x})$, and product

performance (for example fuel economy as a function of engine horsepower), $y(x)$, in addition to a model of product demand. Given these models, one can determine equilibrium prices and competing product designs by simulating an oligopolistic-equilibrium model where firms maximize profits with respect to the design variables and prices of their product(s), given the prices and design variables of competing products. This process is outlined in detail and implemented in Michalek et al. (2004). We also refer the reader to other publication examples (e.g., Shiau and Michalek 2009; Frischknecht et al. 2009) as well as the methods in Chapters 3–5, which provide applications of oligopolistic equilibrium models to product design.

6.2.1 Functional and decision unit

Implementing cLCA-MDD requires the same goal definition and scoping stage as aLCA. Issues such as the purpose, scope, functional unit, and boundaries for the system must be considered. Unit processes must be defined and populated with the most representative data available, after a detailed and transparent analysis of the data. The complexity of accounting for flows through possibly hundreds of processes and managing the inventory of co-produced wastes (Heijungs and Suh 2002) must be rigorously addressed through model simplification and careful consideration of system boundaries and allocation methods.

During goal definition and scoping in cLCA, the authors have also found it necessary to clearly specify a *decision unit* along with a *functional unit*. For example, a decision unit for the VW Touareg example in the introduction could be “downsizing the VW Touareg model line by 10%”. In the same way that the functional unit is useful to help determine which lifecycle unit processes can be excluded from the analysis (e.g., on the basis of contribution to overall emissions or consumption), the decision unit helps the researcher justify the inclusion or exclusion of specific models and assumptions. In a cLCA, where impacts of a decision on the environment can cascade through countless indirect impacts on other products and consumer behavior, the significance of including a parameter or model to characterize these effects will usually not be evident from the functional unit alone without also specifying a decision unit.

6.3 LCA Uncertainties

Given perfectly accurate data and models of firm and consumer behavior, cLCA could reduce uncertainty compared to aLCA because the systematic relationships between input parameters are defined. However, even with sufficient validation of the individual input models and parameters, multiple models and parameters often exist and validation of the interaction of several submodels is very challenging and not generally possible (see Frischknecht et al. 2009 for a discussion of submodel evaluation). As a result, we would expect that cLCA adds significant uncertainties to those already present in LCA (see Ross et al. 2002 for a review). Considering the inventory stage, four categories of uncertainty that must be managed in both aLCI and cLCI are: 1) structural uncertainty, 2) model uncertainty, 3) parameter uncertainty, and 4) variable uncertainty. Below we define these four categories of uncertainty. We do not consider the uncertainties involved with translating LCI results to environmental impacts (see Lenzen 2006).

Structural uncertainty concerns the interconnections between models, embodying questions regarding the appropriateness of the overall modeling approach, and assumptions of how sub-models are interconnected. For instance, questions of structural uncertainty in cLCI could focus on what types of competing products are considered, what parameters are considered exogenous, and whether it is reasonable to assume that firms behave as though they are in partial-equilibrium. Structural uncertainty questions common to both cLCI and aLCI include the definition of the functional unit and the incorporation of unit processes inside and outside the system boundary, and have previously been addressed using computation-based, hybrid input-output LCI (Williams et al. 2009; Lenzen 2001).

Model uncertainty considers the appropriateness of the selected models to determine required outputs. The selection of a product performance model to convert design variables, x (e.g., horsepower) into consumer observable attributes, y (e.g., fuel economy) would be classified under model uncertainty, as would selection of models characterizing lifecycle flows in the absence of direct measurements.

Parameters are exogenous to the LCA study (e.g., elasticities) and often have uncertainties expressed by distributions, confidence intervals, or discrete values.

Variables are endogenous to the study and may also have uncertainty if they are generated by stochastic models (e.g., fuel economy dependent on random traffic conditions). Uncertainty associated with parameters and variables with known distributions can be treated using standard methods such as interval assessment, bootstrapping, and Monte Carlo analysis (Lloyd and Ries, 2008). Parameter uncertainty deriving from discrete values, however, presents additional challenges. For example, many different estimates of the elasticity of gasoline demand have been produced from the econometrics literature (Graham and Glaister 2002). This cross-study uncertainty cannot as easily be analyzed with distributional assumptions.

To address uncertainties associated with discrete parameters and models, we generate results under multiple combinations of selected submodels and parameters within models, referred to as *scenarios*. Structural uncertainty could similarly be handled under such a system but is not addressed in the case study. Uncertainty associated with input parameters with assumed or estimated distributions are captured with confidence intervals within each scenario, generated from bootstrap samples. Multiple scenarios can be arranged together in matrices, which we call *scenario landscapes*, to facilitate easy comparison. This presentation scheme complements uncertainty analysis discussed in Huijbregts et al. (2003). While the authors suggest assigning a probability of “faith” in models and discrete parameters to generate confidence intervals, we avoid this aggregation, instead illustrating result sensitivity to specific input parameters and models. This type of analysis can be used in cLCA to interpret the integrity of results over a range of scenario landscapes that are appropriate to the goals and scope of the analysis. We believe that this approach increases the transparency of system boundary decisions and overall study conclusions.

6.4 Case Study Part 1: Industrial decision

6.4.1 Goal and scope

This study investigates the change in lifecycle GHG emissions resulting from a decision to downsize the engine of a midsize vehicle by 25% (in terms of horsepower). Specifically, we evaluate the hypothesis that this level of engine downsizing will reduce lifecycle GHG emissions associated with the midsize vehicle market by at least 10%. The

scope of the study includes the effects of this decision on equilibrium design adjustments to competing vehicles, changes in demand for the protagonist and competing vehicles, and changes in VMT of these vehicles. Endogenous design variables considered include the horsepower and final drive ratio (the gear ratio between the transmission and wheels) of competing vehicles and the final drive ratio of the protagonist vehicle. The study includes the effects of these design variables and the protagonist vehicle's horsepower on production costs, fuel economy, 0-60 mph acceleration time and the mass of the vehicle body needed to support the engine. All other aspects of the vehicle are assumed fixed and equivalent to the midsize vehicle considered in Keoleian et al. (1998). Decisions on engine horsepower affect upstream material and manufacturing emissions, downstream end-of-life unit processes, and use-phase emissions associated with consumer demand for VMT based on the operating cost of the vehicle. The effect of changes to final drive ratios on lifecycle flows and production costs are negligible and so are not considered.

This study represents a type of analysis that a firm may wish to undertake if the firm is concerned about environmental impact of their industry and is considering potential design changes to reduce this impact. The analysis does not suggest that any firm is likely to downsize engine size, but simply investigates the impact of this decision on consumer and competing firm behavior and the resulting emissions to the environment.

A number of additional ripple effects are not considered in the boundary of this particular case study. For instance, decreases (increases) of vehicle prices in response to the decision analyzed may increase (decrease) the money consumers have available for other purchases. Consumption (or avoided consumption) of additional goods due to this change would have environmental consequences that are not considered. Macroeconomic effects such as the relationship of producer welfare to industrial investment, wages, or tax receipts are also not considered. Such economic shifts also lead to changes in consumption that are outside the boundaries of this case study. These effects could be included in a cLCA-MDD analysis and are already included in some large-scale policy analyses (EIA 2010).

The following subsections summarize the lifecycle unit processes and models employed in the case study. The descriptions are only meant to demonstrate how

submodels of product performance, demand, and use can be incorporated into cLCA. The results of the case study are not intended to accurately describe the affects of the decisions analyzed, but provide a useful demonstration of the cLCA-MDD approach.

6.4.2 Unit processes

The process and emission factor matrices are based on a generic vehicle LCI from the US Automotive Materials Partnership (Keoleian et al., 1998), which estimates the material and energy profile for a midsize vehicle with a gasoline engine (3 L, 140 hp). The baseline vehicle material inputs represent 90% of the body mass, 86.5% of the powertrain mass and 97% of the suspension mass; excluded components are not significantly impacted by the design decisions. To determine the relationship between horsepower and engine mass, we combine power-displacement data from Arnold et al. (2005) with the displacement-mass data from Messner (2007). The relationship between engine weight and the weight of the vehicle frame and body necessary to support the engine is accounted for with a weight-compounding factor of 0.5 from Lave et al. (2000). The study assumes that energy inputs for engine manufacture are independent of engine horsepower, and that energy used in body manufacture varies with body mass. A suspension system of constant size is also manufactured with materials and energy as modeled following Keoleian et al. (1998). Vehicles are assembled from the manufactured systems with additional inputs of materials (no other systems manufacturing is modeled) and energy. After production, the new vehicles are driven their useful life and then sent to a shredder, which recovers metals and sends non-metals to a landfill. Additional non-metal inputs and transportation between processing facilities is not included in the analysis.

6.4.3 Oligopolistic equilibrium model

We model the market for midsize vehicles as an oligopoly in partial equilibrium. Five producers are modeled, but the qualitative results of the case study do not change as a result of this assumption. Firms maximize profit with respect to the horsepower (between 100 and 210 hp), final drive ratio (between 0.2 and 1.3), and prices of their vehicles with demand and costs calculated dependent on these variables from submodels described below. The equilibrium is computed by sequentially optimizing each firm's

profits given fixed competitor vehicle designs and prices until convergence. Additional details can be found in Skerlos et al. (2005).

6.4.4 Vehicle performance model

The relationship between design variables and product performance attributes (fuel economy and acceleration performance) is taken from Michalek et al. (2004). This model approximates results from the vehicle simulation software, ADVISOR (AVL LIST GmbH, Austria). ADVISOR calculates a vehicle's fuel economy and 0-60 mph acceleration time based on input driving cycles, engine maps, and vehicle parameters, including the final drive ratio and scaling of the engine horsepower.

6.4.5 Product demand model

A logit model, based on the model estimated by Boyd and Mellman (1980), determines consumer demand for vehicles based on price and performance attributes. This model, while dated, provides the simplicity and convenience appropriate for demonstrating the cLCA-MDD approach in the case study. The model does not account for heterogeneity of consumer preferences. The possibility that consumers may not choose any of the product offerings is included, modeled as an "outside good". In this study, we assume the outside good is an old vehicle that has a fuel economy of 21.8 mpg, equivalent to the average on-road passenger vehicle in 1994 (EIA 1995, 2001).

6.4.6 Use demand model

Two econometric models are used to determine demand for VMT, one which predicts a lower sensitivity of VMT to the cost of fuel (Jones 1993), and one that predicts a higher sensitivity (Goldberg 1998). Demographic and transportation infrastructure variables that factor into these models were assigned constant average values using 1990's data to align with the input LCI data. Vehicle operating costs and purchase prices are determined from the equilibrium model. The lifetime of all vehicles is assumed as 15 years; the possibility that vehicles could be driven for fewer or more than 15 years is not modeled.

6.4.7 Comparison of aLCI, cLCI, and cLCI-MDD

In order to illustrate some of the differences of taking an aLCA, cLCA, or cLCA-MDD approach, we compare LCI results using the data and models used in this case study. Figure 6.2A shows lifecycle GHG emissions using an aLCI approach. The results assume that VMT for each vehicle is identical and independent of fuel economy, but subject to sensitivity analyses. The figure illustrates the results of varying both VMT (5,000 to 30,000 miles/vehicle-year) and engine horsepower (100, 140, and 200 hp). Results qualitatively match Keoleian et al. (1998) although values differ slightly because of the vehicle system boundary simplifications defined earlier. Figure 6.2B illustrates how the lifecycle CO₂-eq. emissions are broken down by lifecycle stage for the case where VMT per year is 11,200 miles and the selected engine is 140 hp.

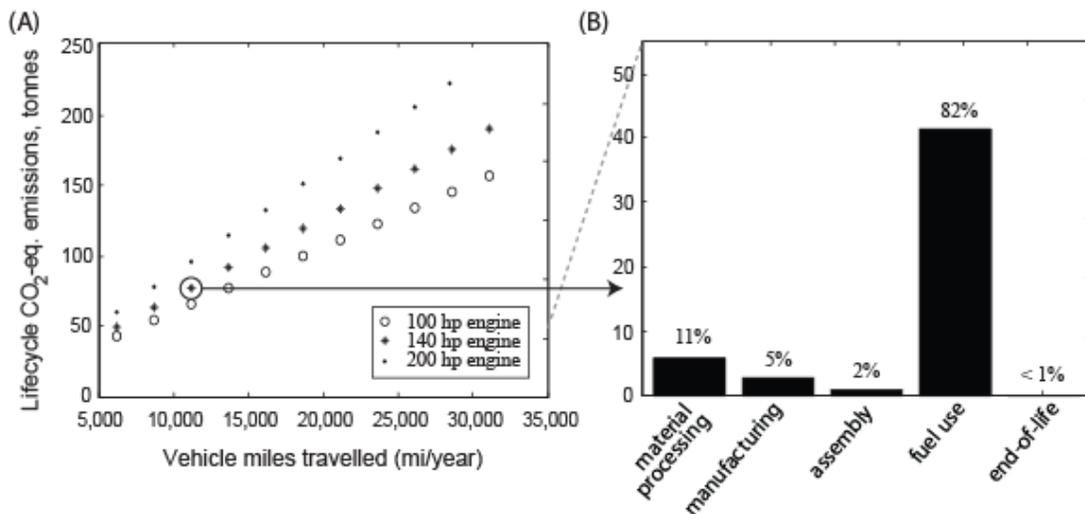


Figure 6.2 GHG emissions dependent on vehicle miles travelled using an aLCI approach. (A) Effect of varying VMT on lifecycle CO₂-eq. emissions using an aLCA approach, and (B) Emissions from the 140 hp vehicle with 11,200 VMT, broken down by lifecycle stage.

Figure 6.3A illustrates LCI results for the same vehicle model using a simple cLCA-approach, where VMT is calculated as a function of fuel price and impacts use-phase emissions. The horsepower of the vehicle's engine is assumed 140 hp. Figure 6.3B illustrates a cLCA-MDD approach, where both equilibrium design variables (horsepower and final drive ratio) and VMT are calculated based on fuel price. Here, emissions from all lifecycle stages are impacted by the design variable decisions in addition to use-phase emissions from VMT. The figures include evaluation of model uncertainty through the

comparison of VMT models by Jones (1993) and Goldberg (1998), and an assumed insensitivity of VMT to fuel price, representing a static assumption of VMT as is used in aLCA studies. Because both the demand and cost models in this simple example do not represent heterogeneity across firms, all firms have the same vehicle design variables in equilibrium in Figure 6.3B.

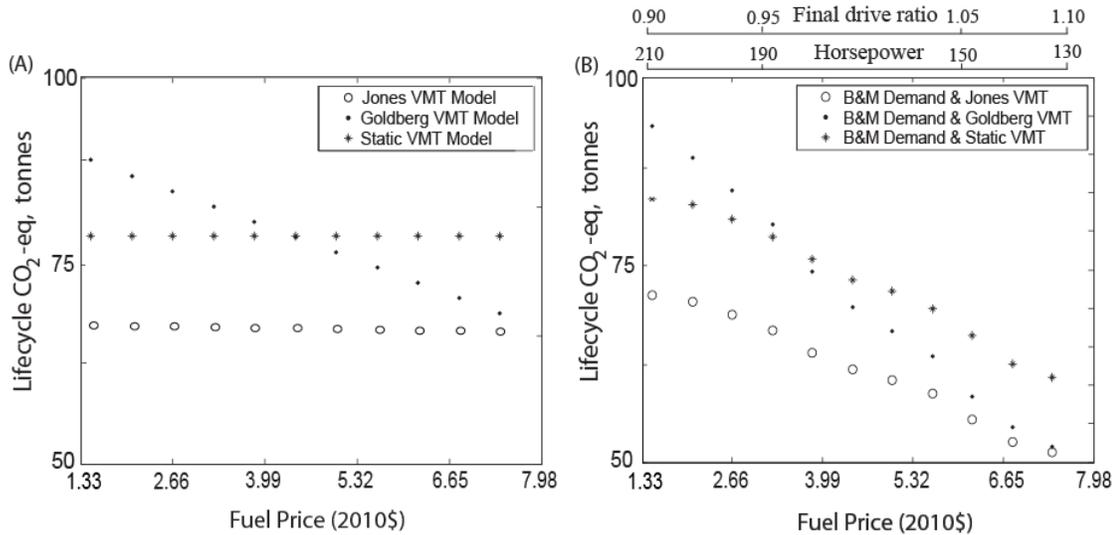


Figure 6.3 Comparison of lifecycle GHG emissions results as a function of fuel price. (A) Using a cLCA approach where vehicle design is fixed but VMT is a function of fuel price and (B) Using a cLCA-MDD approach where both VMT and equilibrium engine horsepower are dependent on fuel price.

Unlike the aLCA approach, shown in Figure 6.2, the cLCA-MDD approach accounts for the correlation of VMT and engine horsepower due to their mutual dependency on fuel prices. Contrasting Figure 6.3A with Figure 6.3B illustrates how endogenously determining design responses within an LCA can capture important ripple effects. The cLCA-MDD results suggest that lifetime GHG emissions are significantly lower at high gas prices than the cLCA without MDD. The cLCA-MDD results suggest that automotive manufacturers downsize their vehicles' engines in response to higher fuel prices and, even considering the rebound effect of VMT increasing due to better fuel economy, this downsizing decreases lifecycle GHG emissions.

6.4.8 Industrial decision results

The cLCA-MDD methodology was used to examine the changes in GHG emissions resulting from the decision to reduce the protagonist vehicle's horsepower. To

do this, we compared the lifecycle GHG emissions from a baseline case, where all firms choose the equilibrium design variables (as in Figure 6.3B), to a case where the protagonist vehicle horsepower is 25% lower than in equilibrium. The final drive ratio of the protagonist vehicle, equilibrium designs for competing vehicles, and all prices were determined in response to this decision. Figure 6.4 shows the results of this analysis using the Jones (1993) VMT model and assuming a fuel price of \$2.60. This figure illustrates that the cLCA-MDD approach captures a negative ripple effect: a reduction in horsepower of the protagonist vehicle causes residual demand for higher horsepower to increase, giving competing firms a profit incentive to increase the horsepower of their vehicles. Similar behavior is observed in Chapter 4 and in Jacobsen (2010). GHG emissions directly associated with a protagonist vehicle decrease by 11.4 tonnes CO₂-eq., but the redesign also induces an increase in lifecycle emissions of each competing vehicle by 3.3 tonnes CO₂-eq.

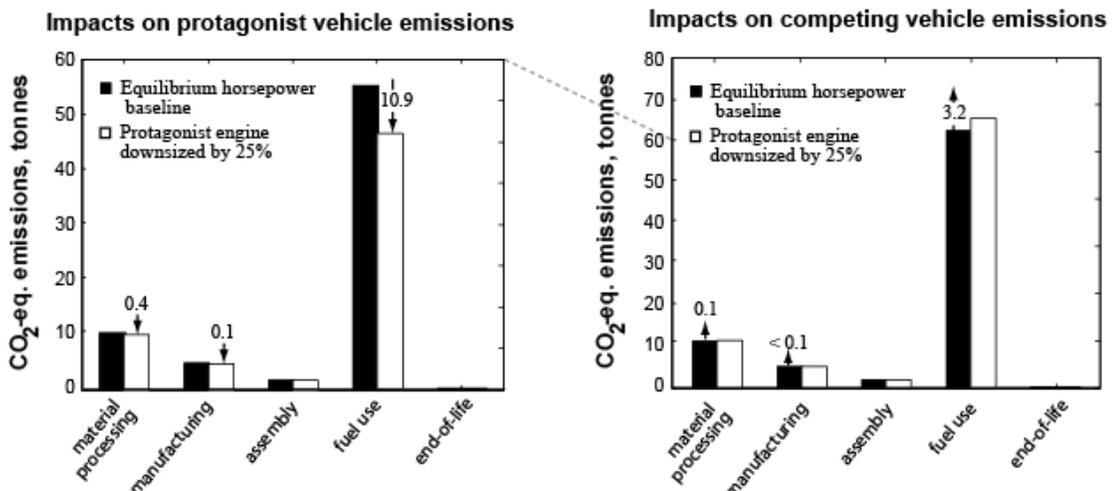


Figure 6.4 Changes in lifecycle GHG emissions resulting from the decision to downsize the protagonist vehicle's engine.

6.4.9 Sensitivity analysis under parameter and model uncertainty

We evaluate results, based on the hypothesis that a 25% reduction in the (equilibrium) horsepower of a mid-size vehicle can reduce the associated lifecycle GHG emissions by at least 10%, considering uncertainty in the fuel price and in the VMT model. Figure 6.5 illustrates a landscape of eight scenarios. The scenarios are created by

varying the baseline (pre-carbon-tax) gasoline price at four discrete levels from \$1.40 to \$5.00 and using two different VMT models (Jones 1993 and Goldberg 1998).

B&M Demand Jones VMT	-17.69% (-17.70,-16.49)	-16.25% (-16.41-14.08)	-11.58% (-16.61,-10.86)	-8.01% (-12.10,-7.97)
B&M Demand Goldberg VMT	-18.13% (-18.14,-16.96)	-16.85% (-16.99,-14.93)	-13.28% (-17.20,-12.69)	-11.06% (-13.85,-11.04)
	\$1.40	\$2.60	\$3.80	\$5.00
	Fuel Price (2010\$)			

Figure 6.5 GHG emission results evaluated over scenarios of fuel price parameter and VMT model.

Ninety-percent confidence intervals are shown in parentheses, calculated using 1,000 bootstrap samples of input demand-model parameters. Light shaded scenarios indicate that the hypothesis is supported, mid-shade regions, that it is not supported or rejected. Percentage reductions of GHG emissions are smaller for higher fuel prices because the 25% reduction of engine power from equilibrium is smaller.

6.5 Case Study Part 2: Policy decision

6.5.1 Goal and scope

This part of the case study investigates the lifecycle GHG emissions of the midsize vehicle market resulting from the decision to add a carbon tax on gasoline of \$25/tonne CO₂. Specifically, we determine lifecycle GHG emissions for the midsize vehicle market, modeled as in Section 6.4, with and without a carbon tax on gasoline of \$25/tonne CO₂. We evaluate the hypothesis that this level of a carbon tax on gasoline will reduce total lifecycle GHG emissions associated with the midsize vehicle market by at least 5% relative to a 1994 baseline when average gasoline prices were \$1.64 (adjusted to 2010 prices using the consumer price index). The scope of the study includes the effects of this decision on equilibrium design adjustments to all midsize vehicles and the VMT associated with these vehicles. Endogenous design variables considered are the

horsepower and final drive ratio of all midsize vehicles. The process and emission factor matrices and selected submodels are the same as in the first part of the case study.

This study illustrates the use of the cLCA-MDD approach to policy analysis. Advantages of this approach over an aLCA analysis include expanding the scope of the study to incorporate the economic system governing consumer and producer decisions that determine environmental impacts and explicitly incorporating engineering relationships that determine production options. However, many assumptions are made in this simplified analysis so that it should not be interpreted as a suitable policy analysis. In addition to the assumptions described in Section 6.4, an additional simplifying assumption is that, while this analysis models the impact of a carbon tax on gasoline, no changes of producer behavior due to increases in the price of materials, manufacturing processes, or other production factors resulting from the increase in gasoline price are considered.

6.5.2 Policy decision results

Incorporating endogenous design decisions in the analysis gives significantly larger estimates of lifetime GHG reductions from midsize vehicles due to the carbon tax. For example, using the Jones (1993) VMT model, and assuming pre-carbon-tax gasoline prices are \$2.60, results indicate that the carbon tax leads to a reduction of lifecycle emissions by 3.8% (90% CI: 1.38–5.03). The equilibrium horsepower of the midsize vehicles reduced from 210 hp in the baseline case to 200 hp with the carbon tax, and the equilibrium final drive ratio increased slightly. Ignoring these design changes, results indicate a reduction of only 0.50% (90% CI: 0.48–0.51) of lifecycle emissions in response to the tax.

6.5.3 Sensitivity Analysis under Parameter and Model Uncertainty

Similar to part 1 of the case study, we generate results over scenarios of the fuel price parameter and the VMT model, shown in Figure 6.6. The shade of the scenario indicates acceptance (light), rejection (dark), or neither (mid-shade) of the case-study hypothesis: a carbon tax of \$25/tonne CO₂ (\$0.08/gallon) can reduce total lifecycle GHG emissions of the mid-size vehicle market by at least 5% compared to a 1994 baseline where average gasoline prices were \$1.64.

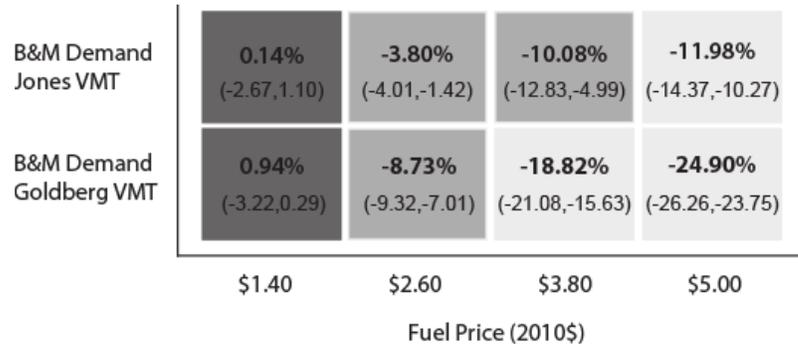


Figure 6.6 GHG emission results evaluated over scenarios of fuel price parameter and VMT model.

6.6 Summary and Conclusions

LCA analysis is currently used to inform decision-making in industry and government but appropriate application of LCA methods for this purpose is limited by the customary focus on a single product lifecycle without considering the systems in which these products exist. This research contributes to the LCA literature by presenting an approach to account for Market Driven Design responses in consequential LCA (cLCA-MDD). The cLCA-MDD approach takes a systems perspective, linking economic analyses of an industry and the engineering relationships that govern production decisions in the industry, to lifecycle inventory data. This chapter introduces the concept for a cLCA-MDD approach, demonstrates its feasibility, and illustrates its applicability with a simplified case study.

Development of cLCA methods so that they are appropriate for informing policymaking will require an integration of state-of-the-art econometric approaches and increased transparency of any assumptions associated with economic parameter estimates. Although this chapter presents only a demonstrational analysis with many simplifying assumptions, it provides the blueprint for connecting the state-of-the-art methods presented in Chapters 3 and 4 with lifecycle inventory data. This approach can contribute to LCA analysis by incorporating considerations of economic as well as environmental impacts.

The fundamental relationship between design decisions and environmental impacts is evident in industrial ecology: “technology, combined with improved design,

can greatly aid the quest for sustainability. Indeed, the notion that technological choice is crucial for environmental improvement lies at the core of industrial ecology” (Chertow 2000). Clearly, design decisions regarding the products and services we use have a close link with our impacts on the environment. Equally clearly, simply making available the technology or design options that can reduce environmental impacts is not sufficient. We also need to understand the various factors that facilitate or hinder their deployment and how these factors are influenced by industrial or policy decisions. The development of a lifecycle assessment approach that accounts for design decisions made in response to market forces is a step in this direction.

CHAPTER 7: SUMMARY AND FUTURE OPPORTUNITIES

*“One never notices what has been done; one can only see what remains to be done.”
—Marie Curie*

This dissertation presents an approach of integrating state-of-the-art models of consumer demand and engineering design to examine the relationship between environmental policy and product design. An oligopolistic equilibrium model was developed, capturing consumer purchase decisions and firm design and pricing decisions in a full-scale representation of the U.S. automotive industry. Application of this approach to policymaking was demonstrated through the analysis of specific policies that aim to increase fuel efficiency by inducing changes in vehicle design.

The unique contributions of this approach are evident in the integration of analysis methods from the industrial organization economics literature and the engineering design literature to the extent necessary to suitably represent the system by which environmental policies induce changes in product design, influenced by consumer preferences, engineering design relationships, and competition among firms. Specifically, the presented model is the first to simultaneously capture consumer preferences for the product attributes accounting for correlation of these attributes with unobserved product attributes *and* the engineering relationships among these attributes categorically independent of other changes to the product design, which were identified using engineering simulations. These conditions advance policy analysis by enabling a more accurate representation of both the engineering relationships and consumer preferences that govern firm response to design-targeting policies. In addition, this approach is the first to model the full-scale automotive industry, including all vehicle models and engine options produced in a year, which enables a more accurate representation of competition among products in the industry.

As discussed in Chapter 2, the developed methodology contributes to many distinct areas of research that span multiple disciplines. In industrial organization economics, researchers have struggled with both methods to identify the engineering relationships between product attributes and consumer preferences that are necessary to model firms' product design decisions. The presented methodology addresses these challenges by integrating engineering design models that explicitly represent engineering relationships between attributes together within economic analysis, and using information about the product development process to identify consumer preference parameters. In environmental economics, researchers have emphasized the importance of endogenously capturing changes in technology within their models but representations of technological change are often simplified, overlooking many tradeoffs that accompany choices of technology. The novel approach of representing design tradeoffs together with technology implementation, as described in Chapter 3, enables representations of many tradeoffs that firms consider along with choices on specific technologies.

This approach also contributes to both the decision-based design literature and the automotive literature in engineering by providing the means to model both technology implementation and design tradeoffs for industries with many products. In the automotive engineering literature, design tradeoffs and technology change are represented in aggregate by observing changes in average product attributes over time. In decision-based design, detailed models of design tradeoffs and technology options specific to individual products are often constructed based on engineering simulations, but representations of the scale of an industry are often compromised for this improved fidelity—firm design decisions are limited to only a few, often only one or two, products in these models. The presented methodology, as described in Chapter 3, contributes to these bodies of research by presenting a tractable method that more accurately represents both the heterogeneity and scale of product design options, enabling the modeling of approximately 500 products in an industry.

Finally, the methodology contributes to the lifecycle assessment literature. In this literature, researchers and policymakers have acknowledged the need to expand the scope and applicability of lifecycle analysis to a systems perspective, incorporating economic behavior as well as environmental impacts. The methods presented in this dissertation

enable such analyses by modeling the response of producers and consumers to specific policies or other changes to the industry system and demonstrating how this model can be connected with lifecycle inventory data. This approach contributes to the ability of lifecycle assessment to inform policymaking by allowing for analysis of changes in environmental impacts, producer profits, and consumer welfare of an industry system in response to policy options.

The developed methodology produces a number of advantages for policy analysis that would not be possible using solely an engineering-based or economics-based approach. First, incorporating engineering design relationships based on engineering simulations in the oligopolistic equilibrium model allows for analysis of the impacts of a policy on the automotive industry considering product design options that may be profit-optimal in the presence of the policy even if these design options are not observable in current data. Second, the structure of engineering design decisions made throughout the product development process is used to identify instrumental variables to estimate demand parameters for endogenous design attributes. Third, taking a hybrid engineering-economics approach to determine production costs allows a subset of cost parameters to be estimated using engineering data while the remaining parameters, for which engineering cost estimates are unavailable, can be derived using the econometric demand model.

The value of the developed methodology was demonstrated through three separate case studies. As presented in Chapter 4, the combined model was used to evaluate the U.S. CAFE regulation in terms of its ability to produce gains in fuel economy and its impact on firm profits. Results of this study illustrated that estimates of the cost effectiveness of CAFE are substantially sensitive to the design options considered, suggesting that policy analyses that ignore these design changes are considerably overestimating the costs of CAFE. This model was extended to include firm decisions on vehicle footprint to investigate the potential for footprint-based fuel economy standards to cause incentives for manufacturers to increase vehicles size, as presented in Chapter 5. These results indicate that footprint-based standards could encourage substantial increases in vehicle footprint that diminish gains in fuel economy. Finally, applications of the presented approach to lifecycle assessment were demonstrated using a simplified case

study incorporating models of consumer demand, engineering design, and firm competition into a lifecycle analysis.

The methodology was demonstrated by analyzing the automotive industry but the methods presented are directly applicable to many product categories that are relevant for environmental policy. The specific methods described in Chapter 3 and 4 can be directly applied to product categories in which policymakers are interested in improving energy efficiency, manufacturers make design decisions that impact energy efficiency and other product attributes, and the market is characterized as an oligopoly or monopoly. These characteristics encompass many important products including light- and heavy-duty vehicles, household appliances, and various consumer electronics.

For example, the U.S. Department of Energy recently established household efficiency standards that affect clothes washers and refrigerators. The refrigerator market can be characterized by an oligopoly with General Electric, Whirlpool, Amana, and Kenmore as some of the top manufacturers (Gupta and Kadiyali 2001). These manufacturers make design decisions that affect the energy efficiency of their products, including refrigerator capacity, motor efficiency, and features such as automatic defrosting, anti-condensation heaters, and through-the-door access. Both consumer preferences for these product attributes and the engineering tradeoffs among these design decisions could be represented using the methodology described in Chapter 3.

Given appropriate data on consumer purchases and engineering models representing product performance, the presented methods could be applied to not only refrigerators but also washing machines, dryers, dishwashers, air conditioners, and heaters. Consumer purchase data of household appliances is available through a variety of market-research firms (e.g., Bayus 1992; Gupta and Kadiyali 2001). Some researchers have estimated consumer utility models for household appliances (Dubin and McFadden 1984; Rapson 2008) that could potentially be further developed for an analysis similar to that presented in this dissertation.

Although the methodology presented provides the means to conduct analyses on household appliances, a few additional challenges exist. One challenge not addressed in this dissertation is that options to improve energy efficiency often include discrete decisions to remove various product features that consume additional energy, such as

automatic defrosting and through-the-door access in refrigerators, as well as choices to include technology features that improve energy efficiency. The presented methodology incorporates choices of energy-saving technology features, such as cylinder deactivation in vehicles, but incorporation of additional choices to remove energy-consuming features that increase consumer preference are not addressed.

Another example of future applications include analyzing energy efficiency decisions made by manufacturers of certain consumer electronics, including mobile phones, television sets, and computers. For example, energy-efficiency standards on computers may impact laptop manufacturer decisions on battery and charger choice, product features such as screen brightness, and design decisions affecting heat management. These decisions influence consumer preferences by affecting product attributes such as processor performance, battery lifetime and charging time, and laptop weight. The presented methodology enables an analysis that captures these relationships between energy efficiency policies, manufacturer design decisions, and consumer purchasing decisions.

In addition to these categories, the methodology could be more generally extended to include additional market structures and design incentives. One category of potential interest is industries where dominant environmental impacts occur in the manufacturing or disposal stages of a product's lifecycle. For example, as automotive manufacturers adopt more electric and hybrid-electric vehicles, policymakers may become increasingly concerned about energy use and emissions associated with the manufacturing and disposal of batteries. In this case, the methodology could be extended to analyze how policy instruments affect the equilibrium designs and sales of these vehicles and the resulting upstream and downstream environmental impacts, as illustrated in Figure 7.1. This extension could be accomplished by linking together models of manufacturer design decisions to the required manufacturing processes necessary to produce the product designs, and changes in consumer use and disposal dependent upon the product design. A simple case study demonstrating this extension was presented in Chapter 6 but many opportunities exist to develop this approach further using the methodology described in Chapters 3 and 4.

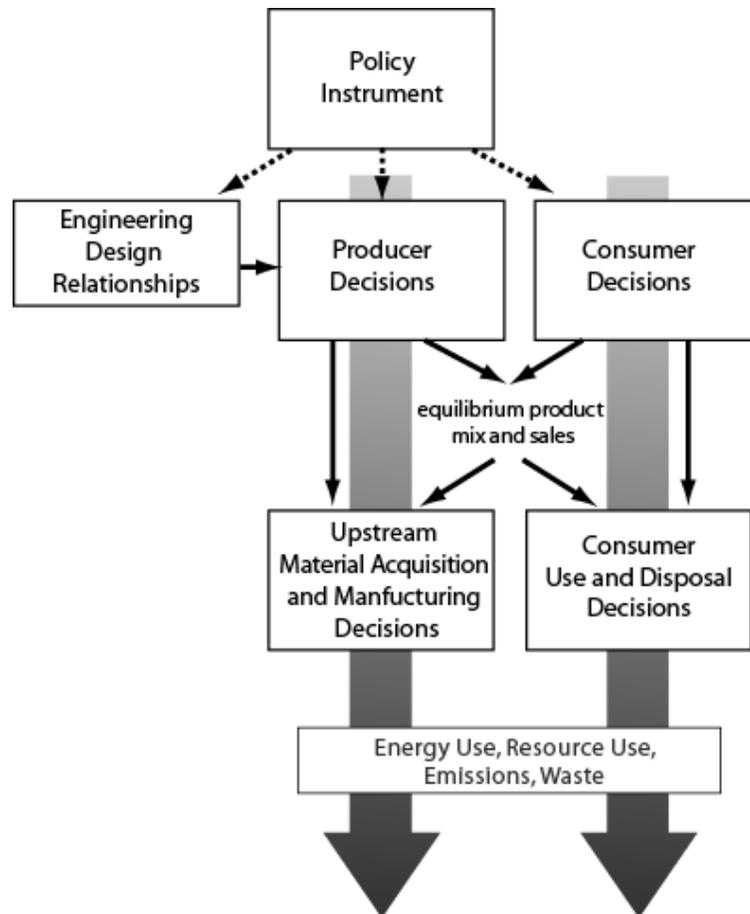


Figure 7.1 Diagram of extensions of methodology to incorporate upstream and downstream environmental impacts

While applications of the developed methodology are promising, a number of open questions remain for future work. First, further research is needed to address the choice of instrumental variables for endogenous product attributes in the demand model estimation. The methodology provided contributions to addressing this problem by using information on the structure of the product development process to choose instrumental variables that are fixed before the decisions governing endogenous product attributes. However, further work is needed to address the concern that decisions affecting unobserved product attributes may depend on these previously determined instrumental variables.

Second, the oligopolistic equilibrium model is solved by sequentially solving each firm's profit optimization problem until convergence. Further research is needed to investigate the robustness of results to the computational methods chosen and evaluate

the performance of these methods for the type of model presented in this dissertation. This research is complicated by the considerable computational times required to determine equilibrium solutions of a large-scale industry such as the U.S. automotive industry considering multiple design decisions in addition to pricing decisions for each product. Many opportunities exist to develop computational methods that can more quickly solve the regulation-constrained design and pricing equilibrium, such as fixed-point or complementary problem approaches (Morrow 2008). Further research could also pursue parallel computing as a means of reducing computational time, for example by solving each firm's profit maximization simultaneously in each iteration.

Finally, validation tests were not performed for every model in the presented approach. Validation of the engineering model was performed by comparing estimated fuel economy to observations in MY2006 data, but no validation was performed on the cost model because of the difficulty of obtaining relevant cost data. With regard to the demand model, tests were performed that provide supporting evidence that the estimated parameters represent the global optimum using the assumed specification of utility. But, further research is needed to examine the sensitivity of results to changes in this specification.

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