A Study of Optimal Automotive Materials Choice Given Market and Regulatory Uncertainty

by

Robert Joseph Cirincione, Jr.

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Signature of Author:____
Technology and Policy Program, Engineering Systems Division
May 9, 2008

Certified by:____
Richard Roth
Research Associate, Center for Technology, Policy, & Industrial Development
Thesis Supervisor

Certified by:____
Randolph E. Kirchain, Jr.
Assistant Professor of Materials Science & Engineering and Engineering Systems
Thesis Supervisor

Accepted by:____
Dava Newman
Professor of Aeronautics and Astronautics and Engineering Systems
Director, Technology and Policy Program

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ABSTRACT

This present thesis hypothesized that the increasing demand for fuel-efficient vehicles, recently updated Corporate Average Fuel Economy (CAFE) regulation, and volatile U.S. sales markets may foreshadow a shift in the competitiveness of lightweight alternative materials relative to incumbent steels. To test this hypothesis, a novel automotive materials selection methodology was developed which evaluates the net present value (NPV) of vehicle projects by incorporating five integrated models: (1) an ADVISOR-based vehicle performance model, (2) a market model that predicts expected annual sales, (3) a cost model that maps technology decisions and sales levels to fixed and variable costs, (4) a binomial lattice model of demand uncertainty, and (5) a regulatory model that mimics CAFE. The integrated model solves materials selection problems by optimization, using explicit simulation to find the set of materials choices for which the NPV of a vehicle project is maximized.

A case study was developed to illuminate the competitive dynamics between incumbent steel and lightweight composite materials in two vehicle subsystems (body-in-white, closure set) and three vehicle markets (small car, mid-size car, luxury car). The results suggest that the value of acceleration improvements due to a lightweight materials-enabled vehicle mass reduction is greater than the value of concurrent fuel economy improvements. When the value of acceleration improvements and fuel economy improvements are considered, the production volume at which it becomes economically efficient to switch from using composites to using steel shifts from the cost-competitive production volume to a higher one. The magnitude of this shift depends on the degree to which the car market values performance improvements and the rate at which composites become more costly than steel. Generally, more stringent CAFE policies were found to improve composite materials' competitiveness to a greater degree than the effects of demand uncertainty.

Thesis Supervisor: Randolph E. Kirchain, Jr.
Title: Assistant Professor of Materials Science & Engineering and Engineering Systems

TABLE OF CONTENTS

Table of Figures

Table of Tables

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Chapter 1: Introduction

Prevailing market forces and contemporary regulations have the potential to drastically alter the way passenger cars and trucks are made. Rising gasoline prices, increasing demand for environmental goods, and newly enacted federal fuel economy legislation foreshadow a shift in fleet characteristics. But the path is very uncertain. Volatile sales, entries from new competitors and new technologies, shrinking profit margins, and still unsettled issues such as CO_2 emissions regulation in the U.S. make automotive technology forecasting difficult. Yet the unpredictable nature of future industry dynamics itself may advantage novel technologies that are more adaptable to flexible projects, in contrast to incumbent technologies that excel when times are steady.

Certain classes of lightweight materials technologies suitable for automotive applications, including fiber reinforced composites, exhibit production economics that may make them attractive to firms that face an uncertain future. Essentially, the choice to manufacture components using composites as opposed to incumbent metals like steel entails a smaller initial capital investment and deferred tool costs that scale in proportion to production volume. (Composite fabrication equipment is generally less expensive than metal-forming equipment and most tools that shape composite parts are much less expensive, but also less durable than their expensive and long-lasting metal counterparts.) This means that while composite manufacturing usually cannot compete with steel’s excellent economies of scale at high production volumes, a composite-manufacturing firm stands to lose less on the downside than a steel-manufacturing firm does if demand falls or changing product needs necessitate re-tooling.

Moreover, automakers' material decisions are driven by the value that the technology can impart in the product, not just the cost of producing it. An automotive firm must balance the final manufacturing cost associated with production in a certain material against the material's potential to influence vehicle attributes like fuel economy and acceleration. For example, a lightweight composite component may be more expensive to manufacture than a conventional steel design, but the increased demand for a more efficient and faster car might make up for the production cost penalty. Alternatively, a vehicle designer could use the performance benefit from lightweight materials to increase the number of accessories and electronics while keeping acceleration or fuel economy constant. All things being equal, the best material choice is the best business choice: the one that generates the most value for the firm.

Automakers will be repeatedly turning to this value equation as they resolve strategies to address changing market trends and new fuel economy regulations. On the flip side, auto industry regulators need to be appraised of the state of the art in vehicle technologies and their economic implications in order to craft rules that are effective, technically feasible, but not extraordinarily burdensome.

This thesis lies at the intersection of these interests. It is a novel investigation of automotive materials economics that explicitly considers uncertainty in market demand and fuel economy regulation in order to shed light on a possible shift in materials competitiveness that may alter the automotive design paradigm.

1.1 Thesis Objectives

My primary goal with this work is to investigate the ways that market and regulatory uncertainty may advantage or disadvantage different classes of materials relative to each other and to other automotive technologies. To achieve that end, I have developed a methodology to evaluate the impact of those variables on the expected net present value of a vehicle fleet. While this methodology is a general approach that can be applied to many problem variations, the scope of this thesis is bounded by four critical decisions that more broadly inform technology strategy,

1. Materials choice for entire body-in-white
2. Materials choice for entire closure set
3. Engine power
4. Production capacity

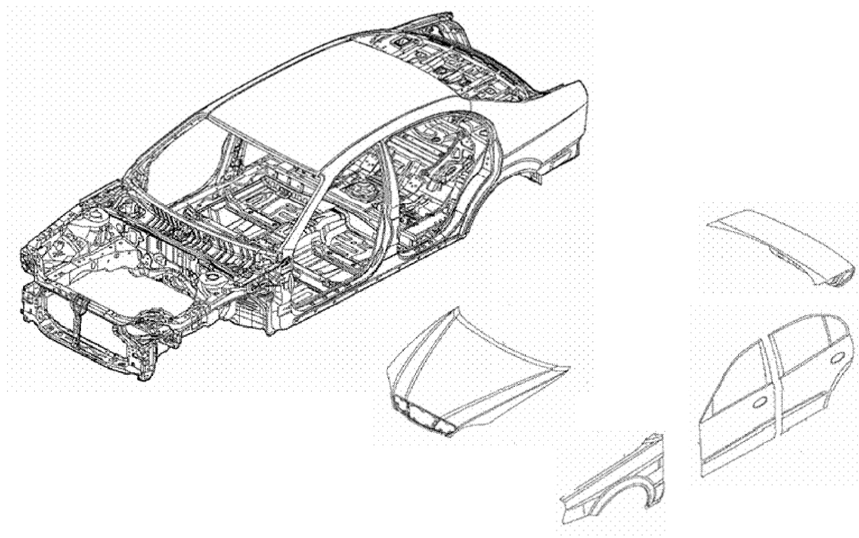
As the performance benefit and economic consequence of lightweighting just one part is often very small, the lightweighting options investigated in this thesis represent materials choices for large subsystems: the entire body and the entire closure set. By analyzing lightweighting effects on such a large scale, the analysis pushes the limits of current technology and documents the potential range of any uncertainty effects on an automaker's expected project value.

Furthermore, these parameters are broad enough to draw general conclusions about materials strategies in automotive applications, but still specific enough to offer insights into different variations on those approaches, such as options that involve a lesser degree of lightweighting (closures only or body only) combined with a more powerful engine, and vice versa. Above all, I intend to characterize the nature and degree of any effects that uncertainty has on the expected value of vehicle fleets with different technology strategies.

1.2 Relevant Automotive Industry Issues in Context

1.2.1 Historical materials use in the auto industry

In spite of the momentous transformations that the rise of the automobile enabled, the average car's composition has remained relatively stable over the years. Henry Ford's circa-1910 Model T was constructed in much the same way that modern cars are: using a stamped mild steel frame, stamped mild steel closure panels, and a cast iron engine block (Page 1917). Ford used wood for the body of the Model-T, but stamped steel soon replaced wood as the material of choice for car bodies and this conventional steel-iron construction became the standard formula for major automakers through the 1970's. Figure 1 illustrates the architecture of a typical modern steel car design in which the body and frame are designed as one subsystem (known as a unitized body, or unibody), and the closure panels (hood, doors, fender and decklid) are smaller subsystems that attach to the body.



Source: http://chevy.mrmax.dp.ua/EN/documents/Evanda/brm-v/3L_01.en.html. Accessed March 20, 2008.

Figure 1 Car body and closure panels

Materials use in automotive manufacturing has changed only slightly since 1970 at the vehicle level. In the past three decades, aluminum has made small gains each year at the expense of iron and steel, as Figure 2 and Table 1 illustrate. Although aluminum content has increased from 2% to 9% (on as mass basis) and plastic/composite use has increased from 4% to 8%, a typical modern passenger car is still basically a steel and iron machine.

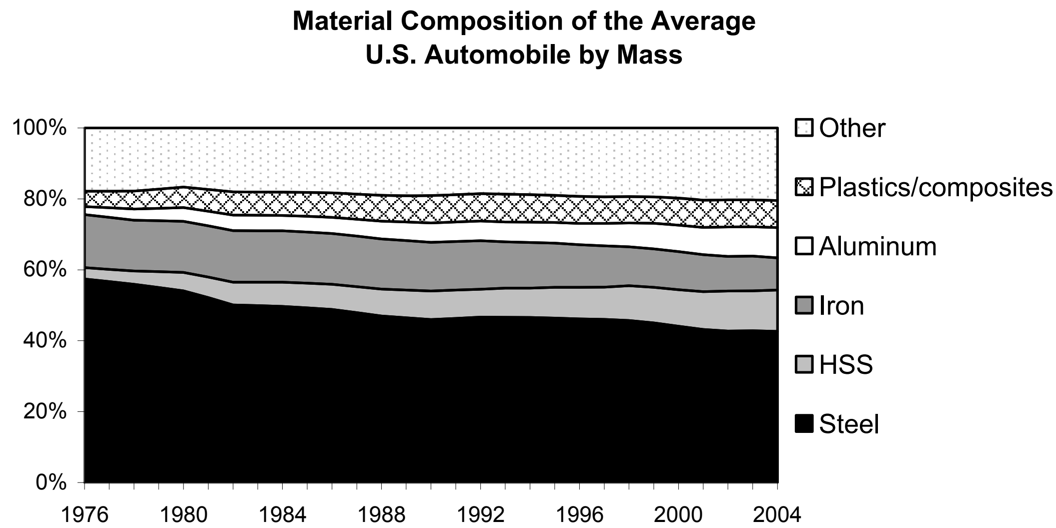


Figure 2 Material composition of the average U.S. automobile by mass

percent mass composition	***1976***	***1986***	***1996***	***2004***
Steel	57	49	46	43
High Strength Steel	3	7	9	12
Iron	15	14	12	9
Aluminum	2	5	6	9
Plastics/Composites	4	7	8	8
Other	18	18	19	20
Total	100	100	100	100

Table 1 Material composition of the average U.S. automobile by mass

Yet examining the applications where aluminum and composites have been able to achieve commercial success reveals ample opportunity for increased penetration by these lightweight alternatives. Aluminum has already achieved a significant share of powertrain and heat exchanger applications, including transmission cases, driveshafts, pistons, engine blocks, and cylinder heads.(Cole and Sherman 1995; Jackson 1997; Kelkar, Roth et al. 2001) But in order to achieve much greater penetration in overall automotive use, aluminum will have to be used more extensively in structural bodies and closures. (Kelkar, Roth et al. 2001) Some commercial use of aluminum in these areas has been successful, but it has yet to be widely adopted outside of low-volume sports and luxury cars (Audi A8 body) or special applications that place a premium on weight savings (Prius liftgate, Ford F-150 hood, among other vertically hinged panels).

Most of the plastics in vehicles are low-performance materials (Fuchs, Field et al. 2008), but several prominent uses of high-performance composites have been adopted in structural applications as well. For example, structural composites were first used in a mass-produced vehicle on the closure panels of the 1953 Corvette and have since been successful in the Pontiac Fiero (closure panels), early Saturn sedans (closure panels), and Ford trucks (pickup box). (Automotive Composites Alliance)

Still, a major impediment to greater adoption of aluminum and composites in the auto industry is the perceived expense that manufacturing with them entails. Industry discussions about materials alternatives such as aluminum or structural composites begin and end with cost (Corbett 2004; Diem 2005), so it’s essential to understand the production economics of different materials technologies before trying to characterize their commercial attractiveness.

1.2.2 Materials production economics

The three primary tasks required to produce a painted car or truck body are parts fabrication, body assembly, and paint. Materials choice affects each of these tasks in vital ways, because the decision to manufacture components out of a specific material entails capital investments in material-specific processing equipment that can vary widely by type, cost, and operation.

Parts Fabrication

Parts fabrication comprises the processes that form and shape materials into components which combine to make up body and closure subsystems. Fabrication in metal can be accomplished by several methods that use tools known as dies to shape different raw material forms. In stamping processes, metal sheets are “stamped” by dies in presses; in extrusion, metal billets are forced through a die; in casting, metal is poured into a die from a molten state or forced by pressure, vacuums and other means.

Common composite fabrication methods also employ machines and dies in analogous processes. For example, stamping-type composite processes include sheet molding compound (SMC), in which sheets of composite material are pressed between matched dies, and bulk molding compound (BMC), in which larger bulk composites are pressed. Casting-type composite processes include structural reaction injection molding (SRIM) and resin transfer molding (RTM), in which flowing composite resin is forced into a die. In each of these cases the required processing forces are smaller than in the analogous metal forming processes because the forces needed to shape composites or cause them to flow are less than the corresponding forces needed in steel forming.

Yet composite fabrication techniques that rely on flow processes generally require significantly longer forming times than steel forming methods, which means that composite fabrication can entail investing in multiple machine lines to assure sufficient operating capacity. Table 2 highlights some details of this capital cost factor, as well as other key dynamics that drive fixed and variable costs for parts production in steel stamping and two composite processes: SMC and SRIM. As the upper row indicates, the cost per machine for composite processes can be 1/10 the cost of a steel stamping machine, but composites require 20 to 40 times the processing time. Similarly, SRIM dies cost 1/20 that of steel stamping dies but wear out 5 times faster.

The information in the bottom three rows of the table affects variable costs. The ratio of raw material cost per mass and material strength per mass is a rough measure of how expensive the material cost of producing a comparable part will be. For example, SMC costs 100% as much as steel per kg but is also 30% stronger per kg, which implies the material costs to produce a functionally equivalent SMC part will be about 70% higher, everything else being equal. Finally, the last row lists overall reject rates, which is the average fraction of defective parts for the entire fabrication process. Higher reject rates (especially for SRIM) increase variable costs across the board, because for every good part produced a certain number of extra discarded parts must be produced as well

typical values to produce one part	***Steel Stamping***	***Sheet Molding Compound (SMC)***	***Structural Reaction Injection Molding (SRIM)***
Method	sheet pressing	sheet pressing	liquid molding
Fixed Cost Drivers			
Investment per Machine	$10.0M	$1.0M	$2.0M
Cycle Time	0.10 min	2.0 min	4.0 min
Investment per Die	$2.0M	$0.2M	$0.1M
Die Life	1.0M cycles	1.0M cycles	0.2M cycles
Variable Cost Drivers			
Raw Material Cost per kg	$1.0 /kg	$2.0 /kg	$2.5 /kg
Strength per kg	35.0	47.0	67.0
Raw Material Cost per kg /Strength per kg	0.03	0.04	0.04
Overall Reject Rate	0.5%	1%	25%

Table 2 Key cost parameters for metal and composite manufacturing methods

These back of the envelope figures indicate typical production-volume cost behavior similar to those shown in Figure 3. As the graph shows, steel exhibits excellent economies of scale at medium and high production volumes while composite manufacturing tends to have a relatively higher and flatter unit cost curve in the same volume range. Steel and composite fabrication generally has cost parity with steel stamping at low to medium production volumes, between 30,000 and 80,000 parts per year. Below these volumes composite fabrication is cost competitive with conventional steel stamping, which is one reason why successful composite applications tend to be low-volume vehicles such as the Corvette. (A premium for lightweighting in sports and luxury cars is another reason.)

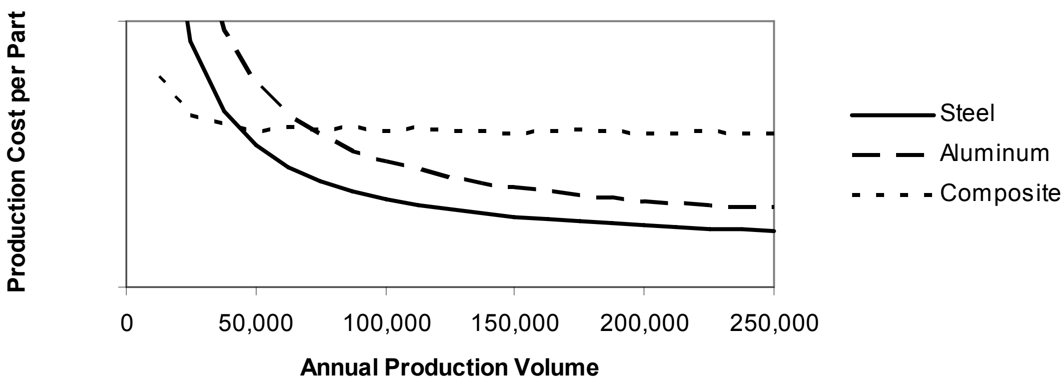


Figure 3 Typical cost - volume curves for parts fabrication

Figure 3 also depicts a typical cost-volume curve for parts fabrication using aluminum stamping. Aluminum stamping is more expensive than steel fabrication at every production volume due to higher material costs, higher reject rates, more expensive tooling costs, and slower cycle times. In aluminum stamping, for example, presses typically run 20% slower than steel stamping presses and 20% more parts are rejected.

Total die costs for aluminum stamping are commonly 20% more than steel. (The surfaces must be polished more than steel dies because aluminum scratches easily, and aluminum often requires more forming hits—thus more dies—to shape a part). Additionally, material costs for stamping a functionally-equivalent part in aluminum are higher because aluminum is three times as expensive as steel sheet per kg but only twice as strong per kg. In sum, aluminum stamping cost curves have the shape of steel stamping curves but are shifted up.

Body Assembly

After component parts are formed, they are assembled into subsystems by means of various joining methods. Steel and aluminum components are usually assembled with some mix of welding, rivets, adhesives, or hemming processes that fold together the edges of mated parts. Composite subsystems are usually assembled by some type of adhesive bonding process.

The assembly cost required for subsystems in different material classes is driven by the type of process used and the number of assembly operations required. Composite's ability to form complex shapes reduces the need for many of the supporting components found in steel subsystems and can sharply reduce the total number of parts—and thus assemblies, required. This parts-consolidation effect becomes greater as the complexity of the subsystem grows. For example, a composite door might be designed in four parts as opposed to six for a steel door (a difference of only two parts), whereas a full composite body-in-white could be designed in 25 parts as opposed to 150 to 200 parts for a steel or aluminum body. Although no fully-integrated composite vehicle bodies have been commercially produced, a previous study has demonstrated composite body designs that can reduce assembly costs by 60% at low volumes (~50,000 per year) and 30% at high volumes (>200,000 per year). (Fuchs, Field et al. 2008)

After the body has been assembled it is sent to the paint shop.

Paint

An automotive paint shop houses extremely complex and expensive robotic equipment under tight environmental controls. Although cost figures vary, typical paint shop investments are approximately \$300 - \$500 million for a fully equipped shop.(Automotive News 2007) The painting process usually relies on an electrically-activated paint that attaches easily to steel. Aluminum typically requires a special surface treatment in order to pass through the same process, while composites require at least a special surface treatment and in some cases an offline painting process which can impose color-match complications and additional costs.

After the body has been painted it is sent to general assembly where other sub-assemblies are attached. General assembly costs will be fairly consistent regardless of the material choice for body and closures so I will not go into detail here.

The finished vehicle is then ready for sale. While the manufacturing processes highlighted in the previous discussion influence an automaker's capital investments and operating cost factors, vehicle sales drive firm revenues—and vehicle sales are driven by consumer preferences. The next section covers the relationship between materials technologies and some key vehicle performance attributes that affect consumer preferences for new vehicles.

1.2.3 Vehicle lightweighting, performance, and consumer preferences

Car and truck buyers indicate preferences for vehicle performance attributes that materials choice may affect, like fuel economy and acceleration, but consumers are generally indifferent to the actual materials used. Fuel economy and acceleration improvements can both be achieved by reducing vehicle mass via materials-enabled lightweight designs, but the gains are usually small unless entire subsystems are lightweighted.

For example, a commonly used engineering rule of thumb holds that a 10% vehicle mass reduction results in a 5% fuel economy improvement. Applying this rule and an estimate that a 10% vehicle mass reduction results in a 10% 0-60 mph time improvement, Table 3 presents the fuel economy and acceleration improvements resulting from different lightweighting strategies for a hypothetical car with baseline mass of 1500 kg, fuel economy of 25.0 mpg, and 0-60 time of 8.00 seconds.

	Mass (kg)	***Mass Reduction (kg)***	***(%)***	***Fuel Economy (mpg)***	***0-60 mph (sec)***
Baseline Vehicle	1500	0	0	**25.0**	**8.00**
With…					
Lightweight Hood	1494	6.0	0.4	**25.1**	**7.97**
Lightweight Closure Set	1455	45.0	3.0	**25.4**	**7.76**
Lightweight Front End	1470	30.0	2.0	**25.3**	**7.84**
Lightweight Body	1420	80.0	5.3	**25.7**	**7.58**
Lightweight Body and Closure Set	1375	125.0	8.3	**26.0**	**7.33**

Table 3 Fuel economy and acceleration improvements for different degrees of lightweighting

As the table indicates, large performance improvements require radical lightweighting strategies (such as lightweighting the entire body and closure set). But in the highly competitive vehicle market, even a few tenths of a mpg improvement or a half second drop in 0-60 time made possible with less aggressive strategies could be the difference between a commercial success and a total flop. Determining the value of a lightweighting strategy ultimately requires understanding how consumers value fuel economy and acceleration.

The implied market consensus for the past decade was that American consumers valued fuel economy much less than they valued acceleration, as evidenced by the relative improvements of fuel economy and acceleration in the average U.S. car. According to work by Bandivadekar et al, changes in the average U.S. car from 1995 to 2006 reflect a mere 8% emphasis on reducing fuel consumption (ERFC) (Bandivadekar, Cheah et al. 2008), which the authors define as

$$\%ERFC = \frac{Actual\ fuel\ consumption\ realized}{FC\ reduction\ possible\ with\ constant\ size\ and\ performance}$$

Equation 1

The authors find that the technology gains which were realized in the average car during this period were used to improve other performance measures, including 0-60 time, which indicates a greater relative preference for acceleration as opposed to fuel economy, or the perception of such a consumer preference by automakers. Many studies have attempted to model the manifestation of these preferences in terms of demand elasticities of fuel economy and acceleration, but these backward-looking studies are not as useful to the work at hand because currently changing industry dynamics mean that it would be imprudent to rely on historical buying patterns to predict future trends.

Yet one past market trend is insightful, if only because it documents another driving force that can steer performance characteristics in the domestic vehicle fleet—the influence of government regulation. As Bandivadekar et al also find, ERFC was 90% for the decade from 1977 to 1987, which began three years after the Arab oil embargo, gasoline price spikes, and the enactment of fuel economy regulation in the U.S. Although the authors do not distinguish between gasoline price effects and regulatory effects, the result suggests that fuel economy regulation, in addition to market forces, can drive automakers' technology decisions. (Bandivadekar, Cheah et al. 2008)

1.2.4 Fuel economy and emissions regulation

Commercial vehicles sold in the U.S. are subject to three main areas of regulation: safety, emissions, and fuel economy. Although safety regulations affect automakers' materials choices, new fuel economy regulations and possible new emissions regulations have a greater potential to significantly alter materials-related technology decisions, so I will concentrate on these latter rules.

<u>Fuel Economy Regulation</u>

Fuel economy standards for new passenger cars sold in the U.S. were first enacted in 1975 and remained unchanged for decades until President Bush signed a December 2007 law that updated the original Corporate Average Fuel Economy (CAFE) legislation. The updated law requires automakers' new car and truck fleets sold in the U.S. to achieve

35 miles per gallon (mpg) by 2020, a 27% increase over the current 27.5 mpg car standard and a 58% increase over the current 22.1 mpg light truck standard. (Figure 4)

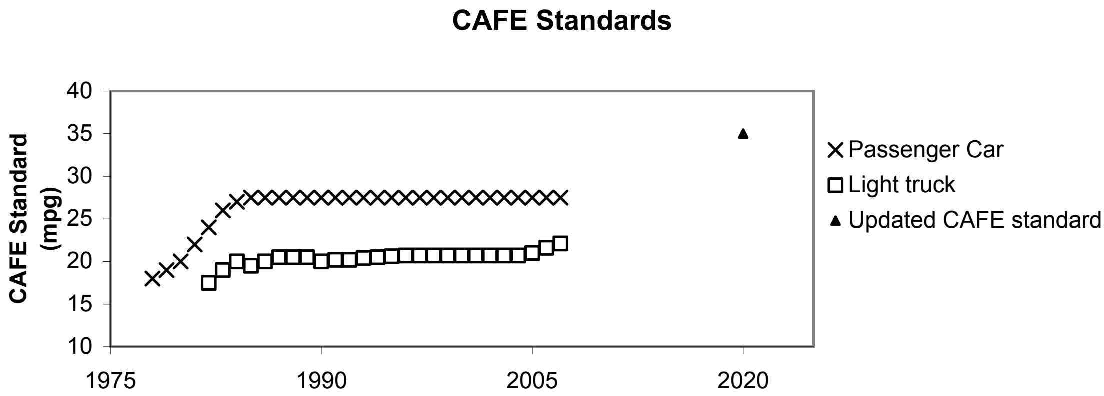


Figure 4 CAFE standards. Source: National Highway Safety Administration.

A congressional majority finally rallied around a CAFE update because of bipartisan support for the measure. Unease over the continuing Iraq war, rising gasoline prices, and a general weariness about the country's energy and economic security inspired conservatives to join with established liberal groups concerned with environmental issues in pushing for tighter fuel economy regulation. (Adair 2007) Concerns about energy security and economic stability in the wake of the Arab oil embargo motivated the 1975 CAFE law, so it should not have come as a surprise that the same mix of issues combined again to spur important legislation.

Although the new 35 mpg standard is less than environmentalists had lobbied for, it still represents a challenge for the auto industry—especially the Detroit automakers—which by the end of the 1990's had become heavily reliant on sales of inefficient SUV's and historically accustomed to unchanging fuel economy standards. (Bradsher 2002) As Figure 5 illustrates, the actual fuel economy of new cars and the actual fuel economy of new trucks remained fairly steady after CAFE regulation stagnated in 1985, and the average fuel economy of the combined fleet in fact dropped slightly because the sales fraction of more inefficient trucks increased dramatically.

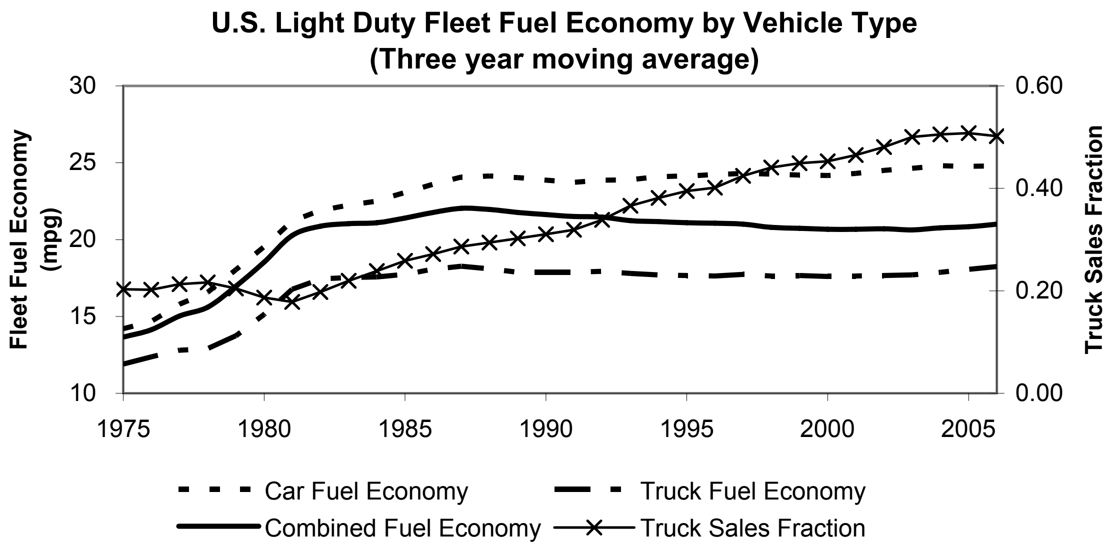


Figure 5 U.S. light duty fleet fuel economy by vehicle type. Source: EPA

Now that a new CAFE standard has been set and automakers have to consider new technologies and production strategies to meet it, the more interesting part of Figure 5 is the period from 1975 to 1985, which documents the fleet changes that occurred in the first decade after the first CAFE rules were issued. Investigating the details underlying these changes indicates that, if history is a guide, CAFE increases and vehicle weight reduction may go hand in hand. From 1975 to 1985, as CAFE took effect and the standard was progressively raised each year, a 20% weight reduction accompanied a 60% fuel economy increase. (Figure 6)

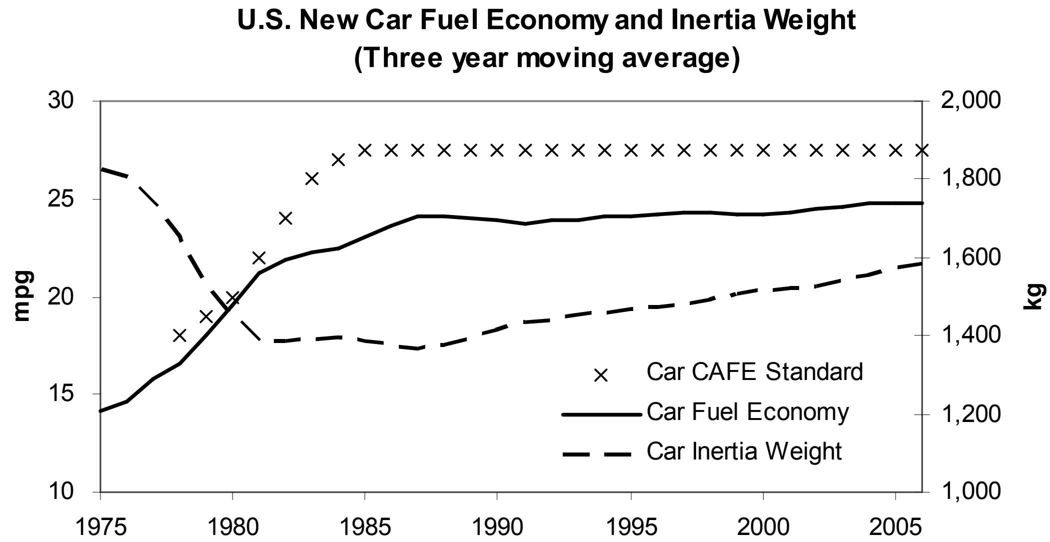


Figure 6 U.S. new car fuel economy and inertia weight (empty vehicle weight plus 135 kg). Source: EPA

Although the auto industry has just begun to consider the new CAFE standard, some insiders predict a reprise of the weight reduction trend seen after the original 1975 CAFE rules were issued. (Snavely 2007) Still others caution that higher cost and greater energy use in raw material production phases should preclude their use as a strategy to meet the new fuel economy standard. (Murphy 2008) In any event, increasing industry attention is being focused on lightweight materials as a possible means to achieve vehicle performance improvements that anticipate rising CAFE standards.

<u>Emissions Regulation</u>

Historically, regulation of motor vehicle emissions by the Environmental Protection Agency (EPA) under the Clean Air Act applied to emissions such as CO, NOx and particulate matter (PM) that cause visible pollution like smog and acid rain. These types of emissions can be controlled with “end-of-pipe” measures such as catalytic converters that treat engine exhaust before it is expelled into the environment.

But the recent Supreme Court decision *Massachusetts v. EPA* forces EPA to regulate CO2 from motor vehicles as well, which can only be controlled by reducing the amount of gasoline that a vehicle combusts, tantamount to controlling its fuel economy. (Eilperin 2007) However, EPA has not issued a vehicle CO2 rule yet and it is not clear how an EPA CO_2 rule would coexist with the congressional CAFE standard, whether it would be more or less stringent and in what respect. (Eilperin 2008) Moreover, the Clean Air Act contains a provision that allows California to set more stringent vehicle emissions standards than EPA levels due to its particularly acute pollution problems, so long as the state receives a waiver from the agency. EPA has granted every one of California’s waiver requests to set more stringent CO, NOx and PM, and other states have the option of adopting either the EPA emissions standard or the tighter California emissions standard. This progressive prod—known as the “California Effect,” has helped push emissions standards to stricter and stricter levels over the years in contrast to the usually stagnant CAFE. (Vogel 2000)

Yet even before EPA has issued its own CO_2 rule it has denied California’s first request to set its own CO_2 emissions standard under the Clean Air Act provision. (Clayton and Wood 2007) The outcome of this regulatory struggle will play out over the coming years and will only add to the uncertainty surrounding U.S. climate change policy, which might also include a cap-and-trade CO_2 emissions scheme or a carbon tax in the near future, with its own uncertain effects on vehicle markets and vehicle technology.

1.2.5 Demand uncertainty

Like the anticipation of an uncertain future regulatory action, the expectation of uncertain future annual sales levels can have profound effects on technology choice for an automaker, as the cost-competitiveness between technology substitutes is different at low-volume and high volume production. (See Figure 3) Moreover, annual sales levels can vary significantly during the five to seven year production life for vehicles, limiting a firm's ability to make accurate capacity, investment, and technology decisions up front.

Countless factors may affect annual sales volumes, from macroeconomic variables like interest rates and income levels to market competition and changing purchase preferences. From the perspective of an advanced product planner, the exact reason for sales volatility isn't as important as the degree of volatility itself.

Table 4 presents sales figures for three models, the Ford Focus, Infiniti G35, and Toyota Prius, over their first five full years of production. As the table shows, sales trends follow different patterns: the Ford Focus loses significant numbers each year, the Infiniti G35 fluctuates around a mean value, and the Toyota Prius sees dramatic growth. These trends are representative of the market as a whole—vehicles sales levels move in different directions and can fluctuate significantly from year to year.

I will investigate sales volatility in more depth later, but basic evidence of significant volatility in the U.S. vehicle market is sufficient to document this factor as a possible technology driver of interest.

vehicles sold in U.S. (full production year)	Year 1	Year 2	Year 3	Year 4	Year 5
Ford Focus	286,166	264,414	243,199	229,353	208,339
Infiniti G35	64,730	71,177	68,728	60,741	71,809
Toyota Prius	15,556	20,119	24,627	53,991	107,897

Table 4 Annual sales data for three model vehicles. Source: *Automotive News*

1.3 Relevant Materials Selection and Uncertainty Analysis Literature Review

1.3.1 Materials selection and competitiveness

The academic literature on materials selection presents several different methods and no consensus on the issue. Ashby proposes techniques that rely on plotting and ranking a constellation of function-specific performance indices. These "Ashby plots" are generated by analyzing the desired design function and determining which design aspect should be constrained, minimized, or maximized. For example, the material that maximizes $E^{1/2}/\rho$, where E is Young's modulus and ρ is density, will have the lowest mass for a beam of a desired stiffness. (Ashby, Brechet et al. 2004) This material index can be plotted against another, say, raw material cost, and the designer can then visualize the tradeoff between performance and material cost.

Rather than simply visualizing the choices on a material index plot, Ashby also proposes optimization methods to arrive at the best materials choice. These methods require quantifying the performance indices to be optimized and then determining tradeoff surfaces among multiple indices based on "exchange constants," which Ashby writes "measure the change in value for a unit change in a given performance metric, all others held constant." (Ashby 2000) (Ashby's exchange constants are also known as “shadow prices” in the optimization literature.) But calculating the appropriate exchange constants still requires determining an value function.

While Ashby offers some possible value functions that might make sense to a designer—such as cost minimization—he errs by substituting raw material cost for *final production cost*, which is the total cost a firm sees. More generally, he doesn’t develop a systematic method for determining the value function. Field, however, proposes using multi-attribute utility analysis to determine a value function in materials selection problems. (Field 1985) This method requires first surveying designers to establish their preference for design attributes and then constructing utility curves based on the responses. Field notes that a drawback to this approach is the effort required to conduct a proper survey and generate utility curves. Another limitation of this method, though, is that the utility function Field describes is derived without direct input from consumers. The true utility of the product—from the firm’s perspective—originates from its sales in the market, but these market preferences are only indirectly incorporated in the utility function by means of engineers’ preferences for product attributes that they believe to be aligned with consumers’ interests.

On a more practical level, Arnold surveys materials selection issues in automotive applications and concludes that a firm needs to make decisions based on risk and reward, especially when considering a lightweight materials alternative. After outlining materials production economics and the then-current state of manufacturing technology, he writes: “The best strategy for offsetting the risk and cost against the benefits of new technology is to apply it where current technology remains an acceptable alternative.” (Arnold 1993)

Several studies have applied materials selection methods and cost analysis to investigate the competitiveness of alternative materials in the auto industry. Field et al combine utility analysis with process-based cost modeling and other disciplines to hypothesize on market drivers for materials development in general, finding that economics, environment, and business dynamics will drive decision-making in the near future. (Field 2001) More specifically, Kelkar et al use process-based cost-modeling to understand the cost-competitiveness of aluminum bodies compared to steel and conclude that while most aluminum bodies are still more expensive than steel, opportunities exist to improve aluminum's competitive position. (Kelkar, Roth et al. 2001) Kelkar's analysis corrects Ashby's error by analyzing production cost as opposed to raw material cost, but Kelkar's analysis is still limited because it does not address the benefits of lightweighting, that is, the value imparted in products designed with lightweight materials.

Furthermore, Field et al elaborate on process-based cost modeling as a tool to perform cost estimation and understand cost drivers in automotive materials applications, but still ignore lightweighting benefits. (Field, Kirchain et al. 2007) In a similar vein, Fuchs et al employs process-based cost modeling extensively to project the costs of steel and composite bodies, finding that composite designs are cost-competitive with steel at production volumes less than 100,000 vehicles per year. (Fuchs, Field et al. 2008)

At a higher level, the National Academy of Sciences released a report on CAFE in 2002 which included an analysis of technologies that could potentially improve the fuel economy of the domestic fleet. This analysis considered lightweighting only in a general sense, as an emerging technology that could achieve a 3 to 4 percent improvement in fuel consumption at a retail cost of $210 to $350 per passenger car. (National Academy of Sciences 2002)

Less work has been published on the benefits of automotive lightweighting. Most published works have only considered fuel economy improvements (as opposed to acceleration and other performance gains as well), and have only analyzed the benefit in terms of the discounted fuel savings that improved fuel economy confers on the vehicle owner. These analyses do not make lightweight materials—or any fuel economy for that matter—appear very valuable. For example, Green shows that for most cars, even a 10 mpg fuel economy improvement is only worth about $100 in net value to the consumer (which he defines as the value of discounted fuel savings minus the increased cost of the car). (Green 1997)

1.3.2 Regulation effects and uncertainty analysis

Recent work by Michalek et al investigates the differing effects on automakers' technology strategy that various fuel economy regulation schemes (including CAFE, CO_2 tax, and diesel mandates) might have. Michalek found that in an oligopolistic market, firms will not produce smaller and more efficient engines without a regulatory standard. (Michalek, Papalambros et al. 2004) Yet Michalek's study only considered engine technologies, not materials technologies, and his analysis did not consider any uncertainty effects.

On the topic of uncertainty in business decisions, the finance literature abounds with methods for dealing with uncertainty. Some of the most relevant work to this thesis springs from the financial options and real options fields. For example, de Neufville et al describe spreadsheet simulation methods for calculating the improvement in net present value (NPV) of a construction project by explicitly considering demand uncertainty and options to expand. (Neufville, ASCE et al. 2005) De Neufville shows that typical NPV analyses err when they use expected values (such as the expected annual demand for a product) to model uncertain processes (like consumer demand over time). The critical flaw in this method is that it assumes that the expected value of the project over all scenarios is equal to the value of the expected scenario. This is almost never the case in real systems and business cases, where physical constraints and asymmetric returns demand a more explicit treatment.

Other real options work employs Black-Scholes or binomial lattice methods (Herath and Park 2002) to model uncertainty. Yet none of these works has yet been applied to automotive manufacturing with different materials technologies.

1.3.3 Gap Analysis

The automotive materials selection literature has presented methods that consider fundamental materials properties (Ashby, Brechet et al. 2004), production cost (Kelkar, Roth et al. 2001; Field, Kirchain et al. 2007; Fuchs, Field et al. 2008), and engineer-centric utility analysis, (Field 1985), but none have presented a treatment that fully evaluate the true costs and benefits of materials selection to the firm: final production cost *and* consumer-driven market value, and none have considered the effects of demand uncertainty or changing regulations on materials choice. On the other hand, the finance literature has presented methods that explicitly analyze business projects subject to uncertainties, though not with respect to the automotive materials selection problem.

Thus, the current opportunity for this thesis to contribute to the literature is to combine insights in techno-economic automotive materials selection together with a financial analysis of project value that explicitly models vehicle demand and regulatory uncertainty.

The analysis should distinguish between different materials technologies (not just lightweighting in general) and investigate how the ability to achieve lightweight designs and the varying capital intensity of different materials classes yields advantages or disadvantages under uncertain conditions similar to those observed in the actual vehicle market. Moreover, the value of materials choice should be based on fuel economy *and* acceleration benefits, and should take into account the utility of the end user, not just the preferences of the engineer-designer.

1.4 Thesis Problem and Research Questions

Automotive materials choice is a value proposition. The decision to manufacture vehicle components using a particular material entails a capital investment in the infrastructure to process and form parts and the ongoing variable costs associated with those operations. In turn, use of the material—especially lightweight materials—influences vehicle attributes like fuel economy and acceleration which determine market appeal and affect sales revenues. An automotive firm should evaluate materials alternatives just as it would other business opportunities, using net present value as an objective metric.

Yet future cash inflows and outflows from a vehicle project are highly uncertain. Demand varies from year to year, which means that sales revenues and production volumes are not steady either. Likewise, regulatory constraints may change over the life of a project.

Similar NPV analyses of complex systems like this usually present a deterministic treatment of salient uncertainties by studying their growth and variance and then picking expected (mean) values for use in the analysis. But these methods implicitly assume that the observation of expected values is equal to the expected value of all observations. That condition only holds for linear, symmetric systems, which is almost never the case in real systems.

In the case of a vehicle project, fixed plant capacity present a real upside limit to annual production and sales revenues when market demand rises. When demand falls, however, the amount of money an automaker can lose is only limited by the size of its investment. This asymmetry may alter the results of an NPV comparison between incumbent materials technologies such as steel which involve more capital-intense production methods than lightweight alternatives like composites. With the growing emphasis on reducing fuel use and increasing vehicle efficiency, a more sophisticated characterization of lightweight materials' competitiveness in automotive applications is timely and important.

In light of these issues, this thesis will investigate the following questions:

1. How can consumer preferences for fuel economy acceleration, in conjunction with demand uncertainty, be modeled to project the value of automotive materials choices?

2. Do market and/or regulatory uncertainty advantage composite materials relative to incumbent metals technologies in automotive applications? What is the nature of this advantage?

3. How can auto industry regulators make use of the above outcomes pertaining to lightweight materials' competitiveness to better inform fuel economy policy decisions which encompass the technological feasibility of new regulations?

Chapter 2: Methodology

This chapter presents the methods I employed to answer the questions posed by the previously stated thesis problem. The heart of my approach is a spreadsheet-based tool which calculates the expected net present value of a multi-vehicle fleet project over several time periods. The spreadsheet tool functions by linking several models that map initial technology and production decisions to final vehicle attributes, fixed and operating costs, sales revenues, and regulatory penalties. As a whole, this framework comprises an NPV optimization model. The following sections explain this framework and the underlying models in detail, and discuss how demand uncertainty and regulatory uncertainty are treated.

2.1 Modeling Framework

Figure 10 illustrates the overall framework that links initial decisions about vehicle technology, prices, and production capacities to models that determine intermediate results necessary to calculate an entire project NPV. This framework is explained in smaller pieces, beginning with the initial decision variables and working up to the final output.

The first task required is to specify what technology the modeled vehicles are to be outfitted with, and what prices they will sell at. In the work at hand, the technology decisions are limited to the materials choice for the body-in-white, the materials choice for the closures set, and engine power—but the general approach could be applied to any vehicle technology set. Next, a performance model maps the pertinent technical characteristics of the complete vehicle (mass and engine power in this case) to the salient on-road attributes that influence consumers' purchasing decisions, which are limited to fuel economy (mpg) and acceleration (0-60 time) in this study. A market model then takes the outputs of the performance model together with the price decision as inputs to predict what fraction of the new car or truck market the specified vehicles would garner. Given a market size, the expected annual sales in the first full year of production can then be calculated. These initial steps are outlined in Figure 7.

Note that the market model is only used to predict the expected sales level in the first year. In subsequent years, the price of the vehicle is held constant and demand variations are modeled by means of a demand uncertainty model, explained later.

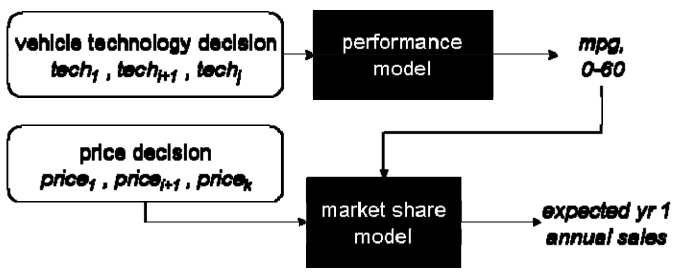


Figure 7 Performance model and market share model links

Once the expected annual sales level is year one is predicted by the market share model, a production capacity decision needs to be made. As the method is designed to be able to evaluate a fleet of different vehicles that might sell at different production volumes, I have defined the production capacity decision as a percentage of the expected annual demand in the first full year of production, rather than an absolute capacity. Thus, if the production capacity decision is 100%, a plant is modeled that can produce just as many vehicles as are expected to be sold. Capacity decisions over 100% imply extra capacity that can meet rising demand. Once this production capacity is determined, a model of production cost projects the required capital investments. These additional steps are added to the modeling illustration in Figure 8.

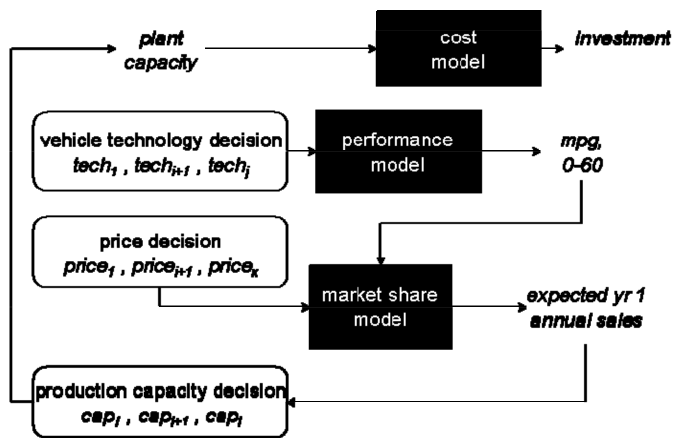


Figure 8 Performance model, market share model and cost model links

Next, I incorporated a multi-period demand uncertainty model to project the stochastic nature of vehicle sales from year to year. The uncertainty model takes the expected annual sales level in year one as a starting point and projects a sales probability distribution over the life of the project. The sales probability distribution is used to calculate a distribution of sales revenues and, with the cost model, a distribution of variable costs. These additional steps appear in Figure 9.

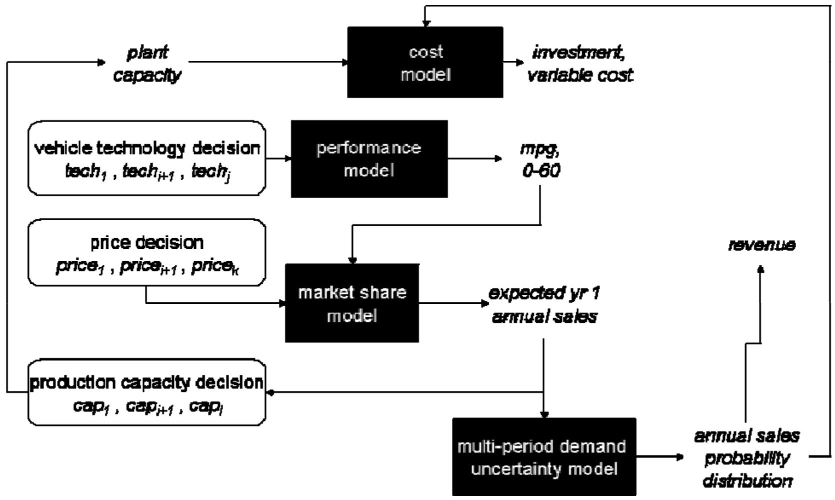


Figure 9 Performance model, market share model, cost model and demand uncertainty model links

Finally, I included a regulation policy model that determines compliance or noncompliance with a fuel economy policy that mimics CAFE. These calculations are based on the fuel economy of the modeled vehicles and their probabilistic sales levels, so the regulatory model calculates expected CAFE values and expected CAFE penalties.

After the expected CAFE penalties are assessed, all cash flows are known and the expected NPV of the vehicle fleet project can be calculated. This completes the modeling framework, as shown in Figure 10.

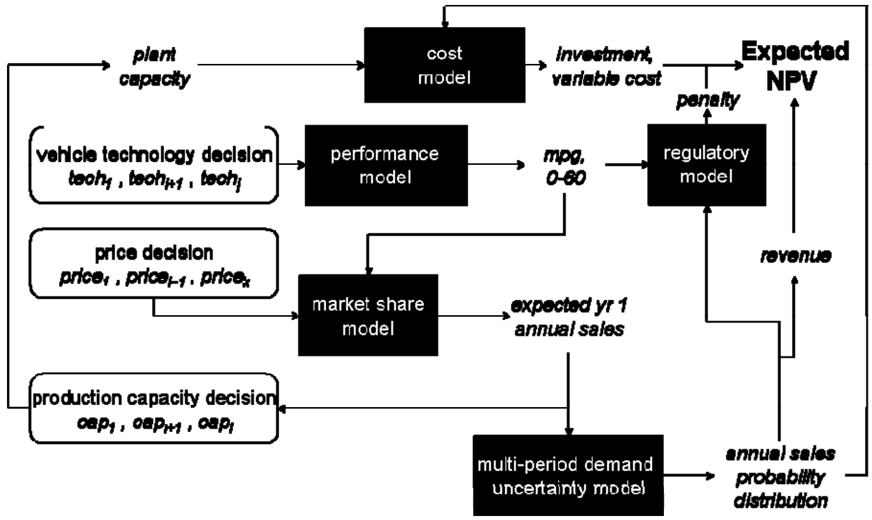


Figure 10 Entire modeling framework

2.1.1 Solution Method

Formally, the problem I am trying to solve by the above modeling framework is to find the set of vehicle price, technology, and production capacity decisions that maximize the expected net present value of the project:

$$x^* = \underset{x}{\operatorname{argmax}} \quad E[NPV(x)]$$

Equation 2

where x^* is the set of optimal price, technology, and capacity decisions. Generally,

$$x = [price \in [price_1 \ldots price_j], tech \in [tech_1 \ldots tech_k], cap \in [cap_1 \ldots cap_l]]$$

Equation 3

for j price decisions, k technology decisions, and l capacity decisions.

I chose to solve the problem by explicit simulation, that is, by running through an exhaustive set of all decision variable combinations of price, technology and production capacity.

Although the process becomes computationally intense as the number of decision variables increases, this method allows the user to easily track down and debug modeling problems or confusing outputs, which proved to be of great value during the early phases of this research. Other methods may be more suitable as the problem scales, but for a proof-of concept construction this basic simulation strategy was successful.

2.2 Model descriptions

In the interest of minimizing computation intensity, I reduced the underlying quantitative models to the key relationships that are being investigated in this thesis. In some cases this meant translating a complex cost model to just two numbers: variable and capital costs, and in other cases it meant converting a thousand-variable vehicle performance simulation model to a regression that can approximate fuel economy or acceleration using just mass and engine horsepower. The following sections describe these modeling activities.

2.2.1 Performance model

The performance model that I incorporated in the optimization model consists of a set of regression equations which approximate fuel economy and acceleration test results from ADVISOR vehicle simulator software, developed by the National Renewable Energy Laboratory of the U.S. Department of Energy and now available commercially from AVL List GmbH. (ADVISOR Downloaded February 2008) I chose ADVISOR over other vehicle simulators because of its flexibility, documentation (Markel, Brooker et al. 2002), and previous use in similar published works (Michalek, Papalambros et al. 2004).

ADVISOR models vehicle performance by means of a predominantly backward-facing simulation tool that runs in a MATLAB programming environment. When a user calls a test in ADVISOR, such as the standard EPA fuel economy test, ADVISOR sends a signal to the tires to attain a certain drive profile (speed changing with time), which propagates back through the rest of the vehicle systems (wheels, differential, transmission, engine, etc.). ADVISOR then calculates the required vehicle dynamics, fuel use, and emissions from the test.

Although ADVISOR allows a user to study the performance effects of altering vehicle systems in countless ways, I limited my investigation to simulations that varied (1) total vehicle mass, (2) maximum engine power, and (3) final drive ratio. The first two variables represent the design outcome of a set of materials and engine technology decisions, while the final drive variable represents the ability of vehicle designers to tune the powertrain in favor of either fuel economy or performance at no cost. (The final drive ratio is the ratio of the last gearset before the axle. A higher final drive ratio yields better acceleration but a lower ratio gives better fuel economy.) This powertrain tuning concept is illustrated in Figure 11, which plots the fuel economy – acceleration tradeoff for vehicles equipped with either a low power or high power engine. Furthermore, the effect of mass on vehicle performance is shown by plotting the performance curves for each engine when equipped in a light or heavy vehicle.

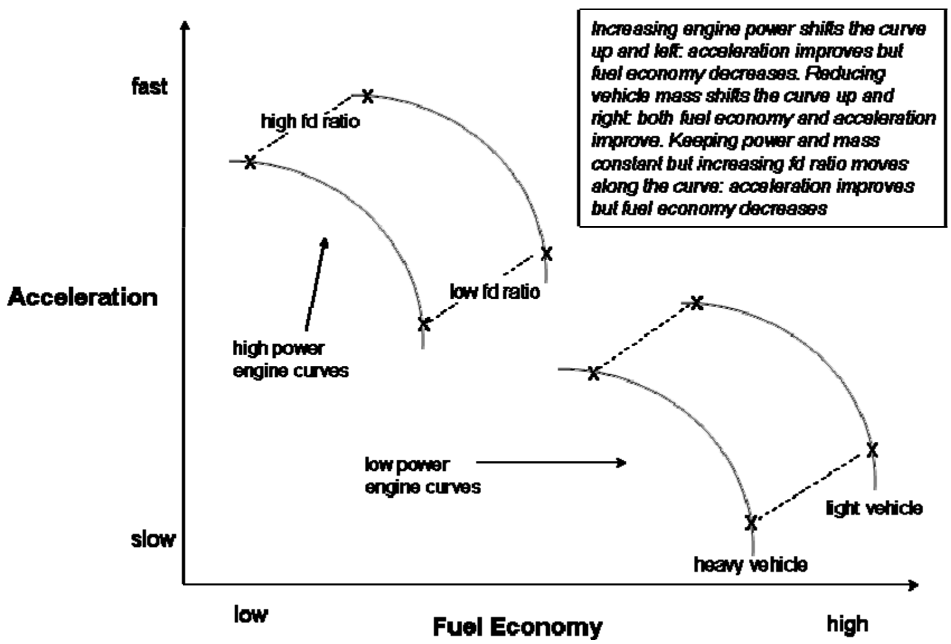


Figure 11 Powertrain tuning curves for a low power and high power engine

The pair of performance curves shown in Figure 11 plot the fuel economy – acceleration tradeoff for two engines (low power, high power) and two vehicle masses (light, heavy). As the figure indicates, without altering the transmission tuning (*fd ratio*) or engine, reducing vehicle mass improves fuel economy and acceleration concurrently—the performance curves shift up and to the right as the labels on the low power engine curves explain. However, increasing the final drive ratio alone improves acceleration but lowers fuel economy—the performance moves along a curve from *low fd ratio* to *high fd ratio*, as noted on the high power engine curves. Finally, switching from the low power engine to the high power engine while holding the other variables constant shifts the curve to the up and left—again increasing acceleration but reducing fuel economy.

The final drive ratio is just one powertrain variable that can be altered to move along the tuning lines, but I have used it as a substitute for all tuning options available. While this simplification doesn't capture the resolution of all powertrain tuning options available, it nonetheless provides a useful insight into the relevant fuel economy/acceleration tradeoff offered by the materials and engine options studied here.

To generate the performance curves that were implemented in the integrated NPV model I ran multiple ADVISOR simulations of fuel economy and acceleration tests on a standard passenger car model, holding the engine power constant while varying total mass and final drive ratio. I then performed statistical regressions on the results of the fuel economy and acceleration tests, which yielded a set of equations that constitute a "performance model" for a vehicle with a given engine power, predicting how its fuel economy and acceleration change over a range of total mass and tuning options. I then repeated this exercise with the same passenger car model but equipped with a more powerful engine to generate another set of performance curves. I assumed that these performance curves apply to all vehicles in the modeled fleet, implying that vehicle class-specific effects (such as aerodynamic drag) are small. The analytical form of these regression functions is described in more detail in chapter three because they are case study specific.

2.2.2 Market model

As described previously, the market model maps the fuel economy and acceleration outputs of the performance model, together with the price decision, to determine the expected market share in the first full year of production. In light of the importance of incorporating current market demand, I chose to base this model on work by Catarina Bjelkengren, who has developed a method for determining relationships between vehicle attributes and market share from data obtained from My Product Advisor, an online marketing tool operated by Market Insight Corporation and available at www.myproductadvisor.com. ("My Product Advisor") The following sections outline Bjelkengren's method and my application thereof, though the underlying approach is explained in more detail in her MIT master's thesis. (Bjelkengren 2008)

My Product Advisor gives product advice to potential car buyers and compiles market data for manufacturers by means of an online survey. The survey asks potential consumers a series of questions about their preference for brand, price, quality, performance, safety, etc., and matches the answers to current model vehicles. Market Insight Corporation then translates these stated preferences to relationships between vehicle attributes and market share. That is, given a vehicle with known attributes and price, Market Insight applies the stated preferences of survey respondents to predict the resulting market share. While certain systemic errors limit the precision of these absolute market share predictions, Market Insight Corporation advises producers to use their tool as a way to gauge the *relative* effects of different strategies. For example, instead of using My Product Advisor to estimate the total market share of a new vehicle, Market Insight advises automakers to test different attribute/price strategies against one another to see which offers the best relative market share change.

These differential relationships form the basis of the market model. The starting point is a reference vehicle (or multiple reference vehicles if a fleet is being modeled) of known fuel economy, acceleration, and price that is the same type of vehicle (small, mid-size, luxury, etc.) being modeled. By varying one attribute of the reference vehicle in the Market Insight website and recording how Market Insight predicts that market share should change, one can approximate the relationship for any vehicle of that type.

As the optimization model is simulating vehicle models with a particular combination of attributes, the market model predicts a delta market share for that particular vehicle relative to the reference vehicle of similar type. (Equation 4)

$$\Delta\, market\ share \quad = \quad market\ share_{modeled\ vehicle} \quad - \quad market\ share_{reference\ vehicle}$$

Equation 4

To calculate the delta market share, I divided it into three components: a delta market share due to a change in acceleration, a delta market share due to a change in fuel economy, and delta market share due to a change in price. Each of these relationships is based on a regression of Market Insight data for the reference vehicle, varying the pertinent variable and recording the resulting market share change. The total delta market share is the sum of each delta market share component. This method implicitly assumes that acceleration, fuel economy, and price each affect market share independently, which may not be entirely accurate. However, I assumed that this simplification was suitable for the work at hand, though future studies may wish to investigate its validity.

Finally, the delta market share of the modeled vehicle is added to the known market share of the reference vehicle and multiplied by the known market size to estimate the actual number of vehicles sold per year in the first year of production. (Equation 5)

$$annual\ sales_{year\,1} \quad = \quad (\Delta market\ share_{total} + market\ share_{reference}) \times market\ size_{reference}$$

Equation 5

These annual sales levels are used to compare different technology/price strategies in a relative sense just as Market Insight advises.

2.2.3 Cost model

After the expected annual sales level in year one is known, a production capacity decision (in terms of a percentage of this sales level) is made which determines plant size. The cost model then maps this production capacity decision to required capital investments. Later, the cost model also maps annual production volume levels to variable costs, following a determination of the distribution of annual demand in future years. These two functions circumscribe the requirements of the cost model in the spreadsheet tool, which are to: (1) provide capacity-dependent fixed costs and (2) provide volume-dependent variable costs, for the range of technology and capacity decisions considered.

Due to the limited requirements of the cost model, I constructed a simplified parametric model based largely on the results of more complicated Process-Based Cost Models (PBCM) of materials forming and assembly processes. The next section provides some background on the principles of PBCM, followed by details of the steps I used to construct the parametric cost model for each material class. The final part of this section presents the methods I employed to model the production cost of the engines and the remaining portions of the vehicle.

Process-Based Cost Modeling Background

Essentially, a Process-Based Cost Model translates the physical description of a product to its final production cost using detailed knowledge of the relevant manufacturing processes and operating conditions. The first step in the PBCM approach utilizes a process model that incorporates engineering relationships between the part description and the materials processing technology to determine the necessary processing requirements, such as cycle time and engineering scrap rates. Next, an operations model combines the processing conditions with the desired production scale to determine plant resource requirements, such as total annual machine time and total raw materials use. Finally, a financial model applies factor prices and accounting principles to the set of resource requirements outputted from the operations model in order to determine the production cost.

The Materials Systems Laboratory at MIT has developed PBCMs for many fabrication and assembly processes, which I was able to utilize for this thesis research. (Field, Kirchain et al. 2007)

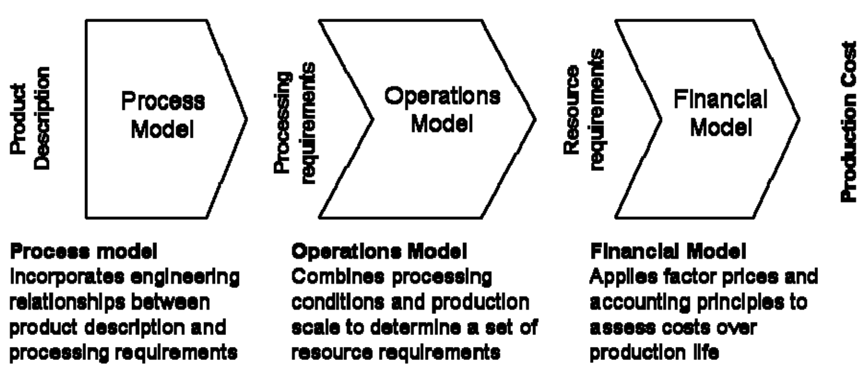


Figure 12 Process-Based Cost Model approach

The major elements of production cost can be organized by those that change with production volume (variable costs) and those are constant for any production volume (fixed costs). Typically, PBCM results categorize variable cost elements by material, labor, and energy; while fixed cost results are reported by equipment, tooling, building, overhead, and maintenance.

From Process-Based Cost Models to Simplified Parametric Models

Although Process-Based Cost Models can provide many detailed insights pertaining to cost drivers, this thesis is concerned with the cost of different technologies only in terms of (1) total production cost, and (2) capital cost intensity. These high-level goals imply that a relatively low-resolution parametric relationship can be used as a surrogate for a complicated PBCM without sacrificing explanatory usefulness, so long as the parametric model captures the basic relationships between production capacity and fixed costs and between production volume and variable costs indicated by the PBCM.

I constructed such a simplified parametric model using several different methods, explained below.

Material Systems Variable Costs

The variable cost components I considered for each material system are the cost of material, labor, and energy. Material cost accounts for the costs of all materials that are needed to make one good part, factoring in trim scraps, rejected parts, and required processing materials. Labor cost is the cost of direct workers; while energy cost includes all the energy required to form parts, join assemblies, and operate auxiliary machinery.

I modeled the total variable cost per unit as the sum of each variable cost component per unit (material, labor, energy), where the variable cost component per unit is the variable cost result from the respective Process-Based Cost Model. The total annual variable cost for all units' production is then given by the total variable cost per unit multiplied by the annual production volume.

To determine the variable cost component results to be used as the basis of these relationships, I first needed to model the closures and bodies-in-white (the two materials-specific applications being studied) in PBCMs of fabrication and assembly processes. In cases where the number of parts or assembly tasks was reasonably small, I explicitly modeled each part or task in a PBCM and then summed the cost components over all parts. The only production phase this method did not apply well for was the fabrication of the steel body-in-white, which has more than 200 parts. But for all other production activities (steel and composite closure set fabrication and assembly, composite body fabrication and assembly, steel body assembly), the variable cost components of the complete assembly—either the entire closure set or the entire body-in-white—are given by

$$material\ cost\ \ per\ unit_{activity} = \sum material\ cost\ \ per\ unit_{task}$$

Equation 6

$$labor\ cost\ \ per\ unit_{activity} = \sum labor\ cost\ \ per\ unit_{task}$$

Equation 7

$$energy\ cost\ \ per\ unit_{activity} = \sum energy\ cost\ \ per\ unit_{task}$$

Equation 8

where the subscripts are defined as:

activity: closure fabrication, closure assembly, body fabrication (except steel body), body assembly

task: individual part fabrication or individual joining operation

I performed this method for fabrication and assembly phases using PBCMs of the appropriate processes developed by the Materials Systems Laboratory. (More information on the fabrication and assembly models can be found in Erica Fuchs's master's thesis (for steel stamping, SRIM fabrication, and steel and composite assembly) (Fuchs 2003), and Paul Kang's master's thesis (for SMC fabrication) (Kang 1998). The method for constructing the simplified parametric variable cost model for all activities except steel body fabrication is then given by:

$$total\ annual\ variable\ cost_{parametric} = \sum cost\ \ per\ unit_{activity} \times annual\ \ production\ volume$$

Equation 9

where $cost\ per\ unit_{activity}$ is the material cost, labor cost, and energy cost per unit described above, for both the closure and body-in-white, in fabrication and assembly. Note that the equations presented in the current chapter are meant only to convey a generalized method for implementing a parametric cost model based on the results of

PBCMs. Specific cost figures for each material/design, for both fabrication and assembly phases, appear in the next chapter which presents details of the case study.

With respect to the steel body-in-white fabrication, I followed a cost modeling method presented by Erica Fuchs, which simplifies the task of modeling a multipart assembly by modeling groups of parts instead of each individual part. Fuchs's method, when applied to a body-in-white fabricated by steel stamping, calls for grouping parts according to the equipment they are processed with and the complexity of the part. (Fuchs 2003) Both of these criteria scale the capital investment required in fabrication. The equipment grouping determines the size of the unit capital investment (larger and faster presses are more expensive than smaller and slower presses), and the complexity level determines how many hits on the press the part will need to be formed. This grouping rubric is key to ensuring that the fixed costs of fabricating all part groups correctly scale with production capacity. (The relationships between fixed cost and production capacity will be addressed further in the next section.)

Once the parts have been organized by equipment and complexity, the average part mass for each group (*total mass/number of parts*) is then calculated and this mass—together with the material, press specification, and complexity level, is treated as representative design parameters for the group. The fabrication cost of each "average" part is then determined using the steel stamping PBCM. Once the fabrication cost of the average part is known, the fabrication cost for the entire part group is given by the product of this average fabrication cost and the total number of parts in the group:

$$cost\ per\ unit_{part\ group} = cost\ per\ unit_{average\ part} \times number\ of\ parts\ in\ group$$

Equation 10

The previous equation is evaluated for all variable cost components: material, labor, and energy cost per unit. The variable cost components of fabricating the entire steel body-in-white is then given by

$$material\ cost\ per\ unit_{body\ fab} = \sum material\ cost\ per\ unit_{part\ group}$$

Equation 11

$$labor\ cost\ per\ unit_{body\ fab} = \sum labor\ cost\ per\ unit_{part\ group}$$

Equation 12

$$energy\ cost\ per\ unit_{body\ fab} = \sum energy\ cost\ per\ unit_{part\ group}$$

Equation 13

for all part groups that comprise the steel body-in-white. The parametric model of total annual variable costs is then calculated as before, using the cost component results for body fabrication:

$$total\ annual\ variable\ cost_{parametric} = \sum cost\ per\ unit_{body\ fab} \times annual\ production\ volume$$

Equation 14

Material Systems Fixed Costs

The fixed cost components I considered are the cost of equipment, tooling, building, overhead, and maintenance. Equipment includes all primary processing equipment and auxiliary equipment, building space includes the requisite plant space such equipment takes up, overhead accounts for the time that supervisors, managers, and other indirect laborers expend on the project, and maintenance is the cost of maintaining and repairing the processing equipment. Of these, the first three are capital investments (usually one time investments), while overhead and maintenance are expenses that typically scale in relation to the size of the capital investments. That is, overhead and maintenance costs grow as the investments in equipment, tooling, and building grow.

Capital investments scale with production capacity in different ways depending on the type of production process being modeled, so I followed different fixed cost modeling methods according to the following descriptions.

Steel Stamping Fabrication Fixed Costs

The fixed cost of the tooling required to fabricate parts in steel stamping is modeled as a one time investment that does not change with production capacity because the tool is dedicated to the part (it is shape-specific and cannot be shared by other parts) and is durable enough to last millions of cycles, more than needed to produce vehicle components over a five year production life.

The fixed costs of equipment and building, however, generally scale linearly with production capacity because the same stamping equipment (and its building space) can be used to fabricate many parts, and parallel stamping lines can be brought on line as needed to satisfy desired annual capacity. As such, the *allocated* equipment and building investment of producing parts (the investment charged to the part of concern) is calculated by multiplying the one time capital investment by the fractional amount of time per year that parts fabrication entails. For example, if the production capacity is desired to accommodate a production volume of 200,000 parts per year and each part requires 0.5 minutes on the stamping line (slow for stamping, but used to illustrate the point), the process will require approximately 1,667 hours per year of stamping. If the maximum capacity of one stamping line is 1,500 hours per year, the fabrication process will be charged for 1,667/1,500 = 1.11 fractional units of the one time investments in equipment and building for an entire stamping line.

This fractional unit will increase as the time required for producing parts increases, which means that the allocated investments in equipment and building will increase at the rate that production capacity increases.

Therefore, to construct a parametric model, I first determined the allocated equipment and building investments for steel stamping fabrication at a production capacity of 100,000 APV using the steel stamping PBCM, and then multiplied this allocated investment by a capacity factor that represents how much larger or smaller the actual capacity is. For the steel closures each individual part was modeled in the PBCM, for the body-in-white, the part groups described previously were modeled.

At any capacity, the allocated building or equipment investment is thus given by

$$allocated\ investment_{parametric} = allocated\ investment_{at\ 100{,}000APV}\ x\ \left(\frac{APV}{100{,}000}\right)$$

Equation 15

where *allocated investment*$_{at\ 100{,}000APV}$ is the PBCM result for either equipment or building space at a capacity of 100,000 units per year, *APV* is the actual capacity being modeled in the parametric model, and *allocated investment*$_{parametric}$ is the allocated investment value used by the parametric model at the appropriate capacity.

With the tool investment, allocated equipment investment, and allocated building investment determined, all capital investments are known. The remaining fixed costs of overhead and maintenance are then calculated as a percentage of the total capital investment (tool + allocated equipment + allocated building).

Composite Fabrication Fixed Costs

The manner in which the capital investments required for composite fabrication scale with production capacity depends on the type of composite process being modeled. Sheet molding compound (SMC), as described earlier, is a sheet pressing process similar to steel stamping. Therefore, I judged that the capacity factor method for scaling the equipment and building investments involved in steel stamping fabrication outlined above is also appropriate to use as the method for scaling the equipment and building investments involved in SMC fabrication. Similarly, tool investments for SMC fabrication were modeled as one-time investments that are constant for any production volume, as was assumed for steel stamping. Overhead and maintenance were similarly calculated as a percentage of the total capital investment.

Structural reaction injection molding (SRIM), on the other hand, is a flow process quite different from sheet pressing processes. From a cost modeling perspective, the most important distinction is that SRIM tools have a much shorter useful life than steel stamping tools or SMC tools. In modeling the SRIM tool investment, therefore, I determined the unit tool investment required to produce one complete assembly (such as the body-in-white), and then established a period at which additional unit tool investments must be made, based on the useful life of the tools, the reject rates for the individual process steps involved in SRIM fabrication, and the cycle time. (If cycle time slows such than a parallel line is required, another tool set must be purchased.) The general form of the parametric model for SRIM tool investments is then

$$tool\ invest_{parametric} = unit\ tool\ investment_{SRIM\ body} \times \mathrm{roundup}\left(\frac{APV}{tool\ replacement\ period}\right)$$

Equation 16

where $unit\ tool\ investment_{SRIM\ body}$ is the tool investment required to produce one complete body, APV is the actual annual capacity, and $tool\ replacement\ period$ is the number of units of annual capacity before another unit tool investment must be made. This period will be shorter than the period implied by the useful life because of the effects of rejects and cycle time. Note that all SRIM tool investments were modeled as a single up-front purchase to simplify the parametric cost model. In reality, a firm manufacturing with SRIM would choose to defer the investments in additional tools until it needed them.

The two remaining capital investments required for SRIM fabrication: equipment and building, were calculated using the capacity factor method presented for steel stamping because the SRIM process is modeled as a parallel fabrication process. Finally, overhead and maintenance are calculated as a percentage of the total capital investment, as before.

Steel Assembly Fixed Costs

Unlike the fabrication processes, which are modeled in PBCMs as parallel processes, assembly processes are modeled in series. As a consequence, capital costs will generally not scale with production capacity in the manner described previously. The difference occurs for two main reasons: (1) at capacities with low production volumes, many assembly stations will be unutilized because cycle times are so long, limiting cost savings, and (2) at capacities with high production volumes, the fixed transportation times between stations puts a limit on cycle time reductions, again raising the capital cost compared to what could be possible if one extrapolated a linear cost projection from a lower production volume. The end result is a capital investment versus production volume curve that is generally shaped like that shown in Figure 13.

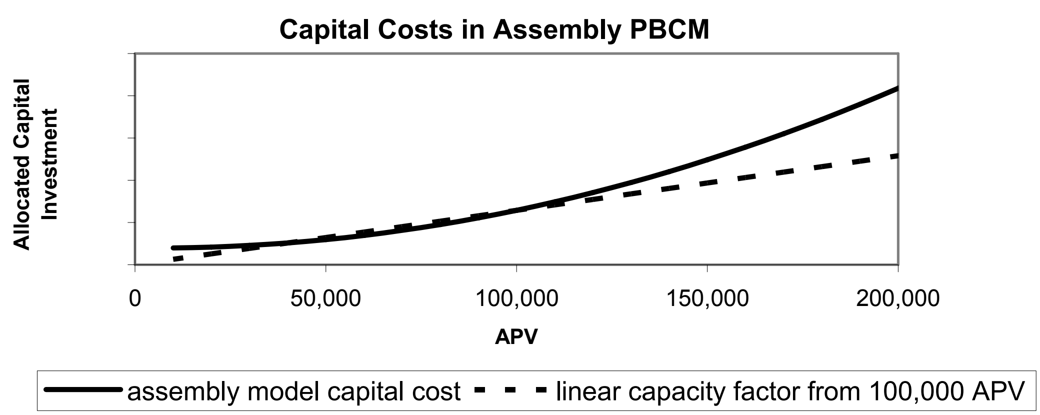


Figure 13 Assembly PBCM model capital investments

The graph plots both the capital investment predicted by the assembly PBCM and a linear extrapolation using the investment value at 100,000 APV scaled by a straight-line capacity factor. The first effect noted—higher assembly investments at low production volumes compared to the linear capacity factor extrapolation—is evident but much less pronounced than the effect at high production volumes, where the investments predicted by the assembly model are 50% to 100% greater than the linear extrapolation.

Constructing the parametric steel assembly fixed cost model for the spreadsheet tool thus required a different reduction strategy than the capacity factor used for the parametric steel fabrication fixed cost model. Instead, I determined regression equations which approximate the capital investments that the process-based assembly cost models predict, as a function of production capacity. The form of these regression equations are cast study-specific, and so appear in the next chapter.

Composite Assembly Fixed Costs

Composite assembly processes, for either SMC-type composites or SRIM type composites, are modeled in the same type of assembly model as is used for steel assembly, although the schedule of joining operations is different: steel assembly requires a variety of joining methods while composites are assumed to be joined by adhesive bonding only. Nevertheless, the manner in which capital investments required for composite assembly scale with capacity are controlled by the effects of serial processing, and therefore, the method for constructing a parametric model of composite assembly capital investments is the same as the method described above for steel (a regression of the results of the assembly PBCM).

Other Costs

Engine

I assumed that engines would be shared by many different vehicle models across an automaker's business, and so I considered them to be a marginal cost item for a new vehicle project. Without an available PBCM for engine manufacturing processes, I relied instead on a published regression of engine manufacturing cost as a function of maximum power (explained in detail in chapter three) to determine what this marginal cost should be.

Paint and Rest of the Vehicle

In the absence of either a PBCM or published functional relationships for paint shop costs I simply estimated the values based on news reports of paint shop investments by automakers and input from industry experts.

To estimate the cost of the rest of the vehicle, I compiled the previously determined costs and then added additional investments and variable costs until the expected profit margin of the vehicle at the reference market size was approximately 6% for the small car, 9% for the mid-size car, and 21% for the luxury car. These profit margins were estimated on the advice of industry experts.

2.2.4 Demand uncertainty model

After the cost model determines fixed costs as a function of production capacity, the future annual sales levels still need to be modeled in order to calculate operating costs and operating revenues over the life of the project. The demand uncertainty model, as identified in the modeling framework, accomplishes this by treating demand as a stochastic variable to project a probability distribution of future annual sales.

I chose to construct the demand uncertainty model by using a form of a binomial lattice, shown in Figure 14. A binomial lattice is similar to a traditional decision tree except that in a binomial lattice there are only two possible moves from every observation and the tree branches recombine.[1] That is, moving up in one period and down in the next arrives at the same observation as first moving down in one period and then up in the next. The probability of being at any observation is given by an associated value in a probability lattice (also shown in Figure 14), which recombines as well. The aggregate probability distribution of observations is then given by the dot product of the matrix of all observations in a given period and the probability matrix of those states.

[1] A detailed discussion of binomial lattices and their application to financial options can be found in Cox, J., S. Ross, et al. (1979). "Option pricing: a simplified approach." Journal of Financial Economics..

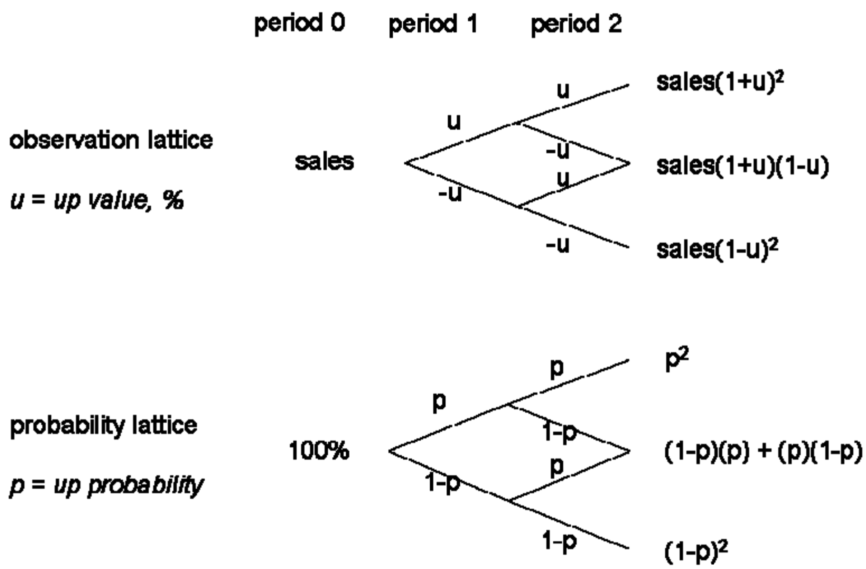


Figure 14 Binomial lattice model approach

The primary benefit of using a recombining lattice as opposed to a non-recombining tree is that the recombining lattice can significantly reduce the problem scale. For example, as the previous figure illustrates, the number of observations in any period *n* in a binomial lattice model is *n*+1. But if the lattice did not recombine, as in a traditional decision tree, the number of observations would grow at a rate of 2^n (assuming that there are only two ways that the observation can evolve from period to period). For *n*=5 these rates imply 6 states in a recombining binomial lattice and 32 states in a traditional tree, a sizeable difference. By *n*=10 the difference has become very large: 11 states in a binomial lattice and 1,024 states in a non-recombining tree. So as the number of periods grows, the binomial lattice becomes a much more attractive research tool in analytic models relative to the traditional decision tree.

The downside of using the binomial lattice, however, is that it assumes path independence—that the observation being studied will behave the same way if observations go up-down as when observations go down-up—and that the system remains unchanged. In the present problem, observations represent annual vehicle sales levels and the larger system includes an automaker's production infrastructure. Therefore, implementing a binomial lattice in this work assumes the system does not adapt to observations—that a firm does not add or reduce capacity based on the sales level its sees in a given year. This isn't perfectly true, as an automaker might install additional capacity after observing a period of high sales. However, I assumed that the errors introduced by this assumption are small relative to the computation benefit gained by using the recombining lattice, which makes it a suitable choice for this thesis.

<u>Contrast to Exponential Binomial Lattice Form</u>

As the previous figure illustrates, the observations in the binomial lattice I implemented evolve by moving up by a factor of *(1+u)* and down by a factor of *(1 –u).* This approach differs from the more common binomial lattice approach in which observations move up by *u* and down by *1/u*. The more common approach, familiar to the financial options field, uses the [*u, 1/u*] observation evolution because the u-values can be derived from an exponential growth function. For example, given a random variable *observation* that is known to grow exponentially at rate *r* for time step *t*, and with standard deviation σ, the expected value at any time *t* is given by

$$\mathrm{E}[observation_t] \quad = \quad observation_0 \times e^{rt}$$

Equation 17

And the corresponding *u* value for the representative binomial lattice is given by

$$u \quad = \quad e^{\sigma\sqrt{\Delta t}}$$

Equation 18 (Cox, Ross et al. 1979)

where Δt is the time step of the binomial lattice.

The problem with using such a lattice form in this thesis is that it retains some growth even when r is 0. Table 5 highlights this concern. On the left side of the table is a binomial lattice constructed using the modified form illustrated in Figure 14 with a starting value of 1.00, u = 0.162 and p = 0.5, modeling a random variable that has a 50% chance of increasing by 16.2% in each period and a 50% chance of decreasing by 16.2%. Over any number of periods the expected value of this variable in the lattice is still 1.00, so it does not exhibit any growth.

The right side of the table presents a binomial lattice constructed from an exponential growth function with r = 0 and a standard deviation of 15%, which yields a u value of 1.162 by Equation 18. Again, this random variable is defined as having an equal likelihood of being up or down in the next period (p = 0.5), but this time the expected value increases over the lattice evolution which implies some growth, contrary to the r = 0 rate from which the lattice is derived.

	Modified Binomial Lattice Form [1+u, 1-u]			Exponential Binomial Lattice Form [u, 1/u]		
	u = 0.162			*r = 0*	*σ = 15%*	*u = 1.162*
	p = 0.5			*p = 0.5*		
	Period 0	*Period 1*	*Period 2*	*Period 0*	*Period 1*	*Period 2*
	Observations			**Observations**		
	1.00	1.16	1.35	1.00	1.16	1.35
		0.84	0.97		0.86	1.00
			0.70			0.74
	Probabilities			**Probabilities**		
	100%	50%	25%	100%	50%	25%
		50%	50%		50%	50%
			25%			25%
EV	**1.00**	**1.00**	**1.00**	**1.00**	**1.01**	**1.02**

Table 5 Comparison of binomial lattice methods

I've chosen to use the modified form of the binomial lattice model in this work so that I can precisely characterize the growth (or no growth) of demand over time and be able to distinguish demand growth effects from demand uncertainty effects. However, this also means that I cannot specify the level of uncertainty (standard deviation) being modeled before hand, as is possible with the exponential form. Instead, the modified form requires picking a *u* value and then calculating an implied uncertainty in some future period by means of the resulting observation distribution.

2.2.5 Regulatory model

With the vehicle performance attributes known and the distribution of vehicle sales now characterized by the demand uncertainty model, the regulatory policy model can determine whether the firm's expected sales activities comply with a stated policy. For the current work I've defined the regulatory policy model to mimic a simplified version of CAFE, the U.S. fuel economy policy outlined in Chapter One.

The firm's CAFE value in this simplified policy model is defined as a sales weighted average of the fleet fuel economy,

$$firm\ CAFE \quad = \quad \frac{total\ \ firm\ sales}{\dfrac{sales_{vehicle\ A_i}}{mpg_{vehicle\ A_i}} + \dfrac{sales_{vehicle\ B}}{mpg_{vehicle\ B}} + \cdots \dfrac{sales_{vehicle\ N}}{mpg_{vehicle\ N}}}$$

Equation 19

for N vehicles. If the firm does not meet the CAFE standard set by the policy then it pays a penalty given by

$$firm\ \ penalty \quad = \quad \frac{CAFE\ standard - firm\ CAFE}{0.1\,mpg} \times total\ \ firm\ sales \times CAFE\ \ penalty$$

Equation 20

where *CAFE penalty* is the cost per vehicle per 0.1 mpg of noncompliance.

As this policy model imposes penalty costs that scale in proportion to sales levels and fuel economy attributes without asymmetric effects, there is no need to employ a complicated modeling method such as the binomial lattice to investigate uncertainty in policies. Instead, policy uncertainty (such as uncertainty in CAFE standards and uncertainty in CAFE penalties) is modeled by testing different scenarios (CAFE at several values, CAFE penalties at several values) and comparing the results.

2.2.6 NPV Calculation

Finally, all cash flows are accounted for in a net present value calculation, first to determine the NPV of each vehicle project and then for NPV of the entire fleet. As Table 6 shows, there are five main steps to the NPV calculation. First, the net revenue (*revenue – cost*) corresponding to each observation in the demand uncertainty lattice is multiplied by (1-*tax rate*) to determine the after tax cash flow for each observation. Next, the after tax cash flow lattice is multiplied by the probability lattice to calculate the expected after tax cash flow in each period. These expected cash flows are then discounted by some discount rate *r* and summed to give NPV.

	Period 0	***Period 1***	***Period 2…***
Step 1	(net revenue)*(1-tax)	(net revenue)*(1-tax) (net revenue)*(1-tax)	(net revenue)*(1-tax) (net revenue)*(1-tax) (net revenue)*(1-tax)
Step 2	p(observation)	p(observation) p(observation)	p(observation) p(observation) p(observation)
Step 3	[after tax CF] • [p(observation)]	[after tax CF] • [p(observation)]	[after tax CF] • [p(observation)]
Step 4	E[after tax CF]	E[after tax CF]/(1+r)	E[after tax CF]/$(1+r)^2$
Step 5	**NPV =** sum(all discounted after tax CF)		

Table 6 NPV calculation for one vehicle

The firm-wide NPV considering all vehicle projects is then given by

$$firm\ NPV \quad = \quad NPV\ A + NPV\ B + \cdots NPV\ N - firm\ penalty$$

Equation 21

for vehicles A through N.

Chapter 3: Case study

This chapter builds on the general modeling framework described in chapter two by defining a case study which investigates the previously stated research questions pertaining to the competitiveness of lightweight materials and engine technologies in automotive applications when demand and regulation policy are uncertain. An overview of the case study is provided first, followed by a description of how each model was tailored to the case.

3.1 Case Study Overview

In light of the thesis problem, I designed a general method to evaluate the NPV of vehicle fleet projects given a set of materials and engine technology decisions. While the method facilitates studying a host of materials and engine technologies, the goal of the case study is simply to demonstrate that the method is sound and can produce useful insights, thus the case study I designed has a more narrow scope. The materials options are thus limited to composites and mild steel, and the engine options are limited to a high power and low power version. I chose to investigate composites over aluminum and other light metals like high strength steel because the low capital-intensity of parts production in composites typically presents the starkest contrast to the high investment, low variable cost structure that characterizes steel stamping—which may improve composite's business case when demand is uncertain.

The engine options were limited to a low-powered gasoline engine or a more powerful gasoline engine. While other propulsion technologies such as diesels or hybrids could have been investigated, having one set of engine technologies separate from the materials choices provides enough resolution to demonstrate the general method. Furthermore, although the case can be reduced to isolate the choice between composite and steel—without considering additional engine options—the wider case definition including different engines allows more nuanced analyses that consider technology strategies such as conventional materials paired with powerful engines and lightweight (composite) materials paired with less powerful engines.

The materials options are thus defined for the case as

- *Body-in-White*: stamped mild steel or composite (based on SRIM/glass fiber design)
- *Closure set*: stamped mild steel or composite (based on a mixed SMC/RIM design)

And the engine options as

- *Engine*: 95 kW or 155kW spark-ignition (gasoline) internal combustion

The materials options were influenced by data availability. The closure set is based on an SMC/RIM (RIM stands for Reaction Injection Molding, which is equivalent to SRIM without reinforcement) design because SMC is currently being used in such applications and several industry experts were able to provide recommendations for the design parameters for a full SMC/RIM closure set. The composite body is based on an SRIM design because a previous MIT thesis investigated such a design in detail, including processing requirements and production costs (Fuchs 2003). Although other composite designs could have been chosen, these case study results should be broadly applicable to a class of automotive composites which has a similar production cost structure (high variable cost, low fixed cost).

The two engine options represent typical small (95 kW/127 hp) and mid-sized (155 kW/208 hp) gasoline engines that are equipped in passenger cars sold in the U.S.

A production capacity decision was also defined in the case study,

- *Production capacity:* 110% or 125% of expected year one sales

The production capacity decision introduces options for building a plant with an annual production capacity either 10% or 25% larger than the expected first year of sales. The choice between building in 10% extra capacity and 25% extra capacity will depend on the firm's technology-influenced cost structure, the profit margins on each vehicle, and the nature of demand uncertainty.

Each of these decisions: body material, closure material, engine, and production capacity was applied to three new vehicle projects, a small car, medium car, and luxury car. Table 7 provides an overview of the technology choices and associated system masses for each car. Note that the body-in-white and closure designs were developed for the mid-size car and then the masses were scaled by 85% to model a small car and 121% to model a luxury car, based on the relative curb weights of a representative small car, mid-size car, and luxury car. Furthermore, the mass which represents the rest of the vehicle was chosen such that the all steel, 95 kW engine small car mass approximates the mass of the small car (1275 kg), the all steel, 95 kW engine mid-size car approximates the mass of the mid-size car (1502 kg), and the all steel, 155 kW engine luxury car approximates the mass of the luxury car (1815 kg). These full vehicle combinations are denoted by bolded mass entries in the table.

	material	***Small Car***	***Mid-Size Car***	***Luxury Car***
		mass (kg)	mass (kg)	mass (kg)
Body-in-White				
Steel	stamped mild steel	220.5	259.4	313.9
Composite	SRIM, glass reinf.	142.2	167.3	202.5
Closure set				
Steel	stamped mild steel	106.1	124.8	151.0
Composite	SMC/RIM	67.4	79.3	96.0
Engine				
95 kW Engine	n/a	123.0	123.0	123.0
155 kW Engine	n/a	160.0	160.0	160.0
Rest of Vehicle	n/a	824.8	995.0	1190.1
Full Vehicle Combinations				
All Steel, 95 kW Engine		**1274.4**	**1502.2**	1778.0
All Steel, 155 kW Engine		1311.4	1539.2	**1815.0**
All Composite, 95 kW engine		1157.4	1364.6	1611.5
All Composite, 155 kW Engine		1194.4	1401.6	1648.5

Table 7 Case study vehicle options overview

As the table indicates, the composite body-in-white saves 35% mass compared to the steel design, while the composite closure set saves 36% compared to the steel version. These mass savings are aggressive, but both designs were devised with significant input from industry experts, as noted in the work of Erica Fuchs for the body (Fuchs 2003; Fuchs, Field et al. 2008), or directly by the current thesis for the closure set. Furthermore, note that the full-vehicle combinations with masses in bold *are not* fully equivalent to the reference vehicles because the engines are not the same as the engines in the reference cars. This implies that although the all steel-95 kW small car weighs the same as the reference small car, the fuel economy and acceleration of the all steel-95 kW modeled car will be different than the actual fuel economy and acceleration of the reference car because the modeled engine has a different power rating than the engine equipped in the vehicle used to model the reference.

Additionally, note that each vehicle is assumed to compete in a different market segment, and sales increases for each vehicle are assumed to occur without cannibalizing the rest of the fleet.   Prices were set at typical levels for each vehicle and held constant across all analyses to isolate the effects of technology choice on production cost and firm value.

As there are 16 different technology/production capacity combinations per vehicle (2 body x 2 closure x 2 engine x 2 capacity = 16 combinations) and three vehicles in the firm's fleet, the total number of possible fleet options for the firm is $16^3 = 4{,}096$.

The remaining sections of this chapter describe how each of the models in the spreadsheet tool was calibrated to the case study.

3.2 Model Calibration

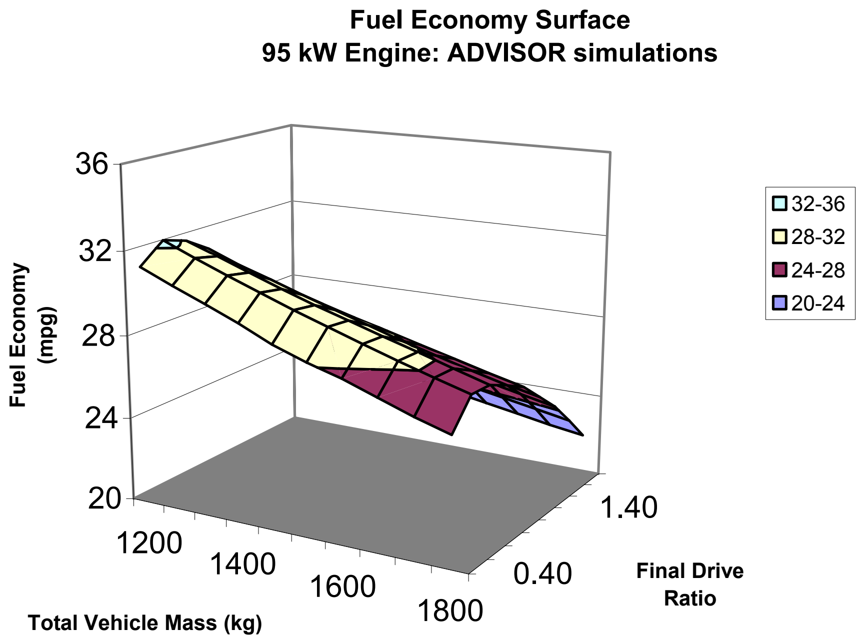
3.2.1 Performance Model

As described earlier, the performance model maps technology choice to vehicle fuel economy and acceleration. I accomplished this by first recording the results of ADVISOR test simulations (for fuel economy and acceleration) while varying total vehicle mass and final drive ratio; and then regressing the performance test results against mass and final drive ratio to establish vehicle performance curves for each engine choice over a range of transmission tuning options and vehicle masses. These performance curves *are not* an attempt to model any specific vehicle combinations in the fleet, such as the four full vehicle combinations presented in Table 7. Rather, they are generic relationships between engine power, vehicle mass, and transmission tuning which are applied to each car (small, mid-size, and luxury) in the fleet given *any* set of technology decisions for that car. Therefore, it was important to ensure that the range of ADVISOR test scenarios encompassed the possible range of engine power (95 kW and 155 kW) and the possible range of vehicle masses for all cars in the fleet (approximately 1200 kg to 1800 kg), but not necessarily the specific engine-mass combinations presented earlier.

All ADVISOR simulations were performed with the small car default model that is natively programmed in the software, using all default settings except those that were varied for this analysis: max engine horsepower, total vehicle mass, and final drive ratio. The two tests run in ADVISOR were the 0-60 mph acceleration test and the EPA Federal Test Procedure (FTP) test, which simulates the city driving cycle. Although a weighted average of the city fuel economy test and highway fuel economy test is actually used by regulators to determine CAFE compliance, city test results are affected by weight and engine power changes much the same way the highway test results are (and thus the same way that the weighted average results are). Therefore, using the city test results in this thesis as a proxy for the weighted average test results calculated for on-road vehicles imposes a more stringent fuel economy test in some sense but nevertheless captures the relationship between technology choice and fuel economy that is required for a meaningful analysis.

Figure 15 and Figure 16 graph the ADVISOR acceleration and fuel economy test results for the 95 kW and 155 kW engine, over a range of total vehicle mass from 1200 to

1800 kg and final drive ratios from 0.4 to 2.0. (The default final drive ratio in ADVISOR is 1.0.)



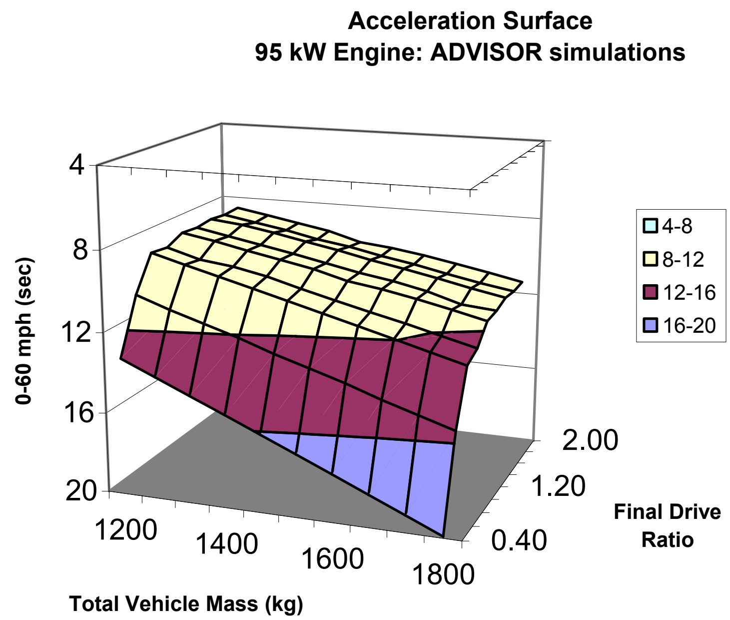
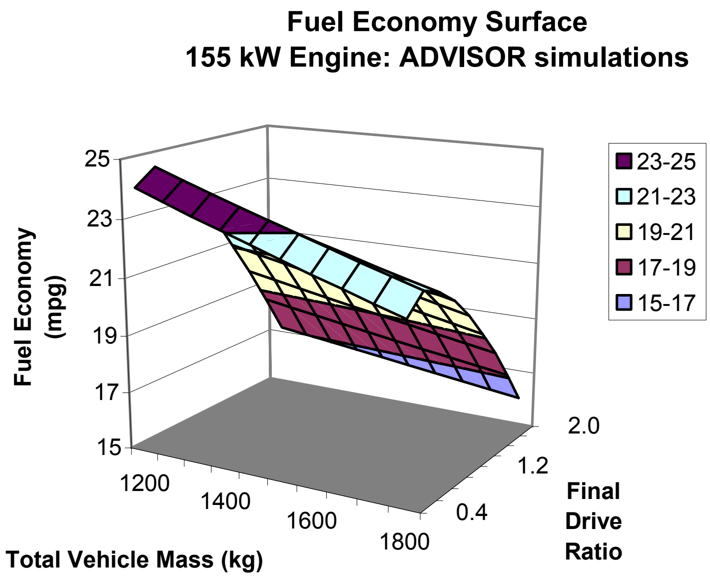


Figure 15 Fuel economy and acceleration surface for 95 kW engine



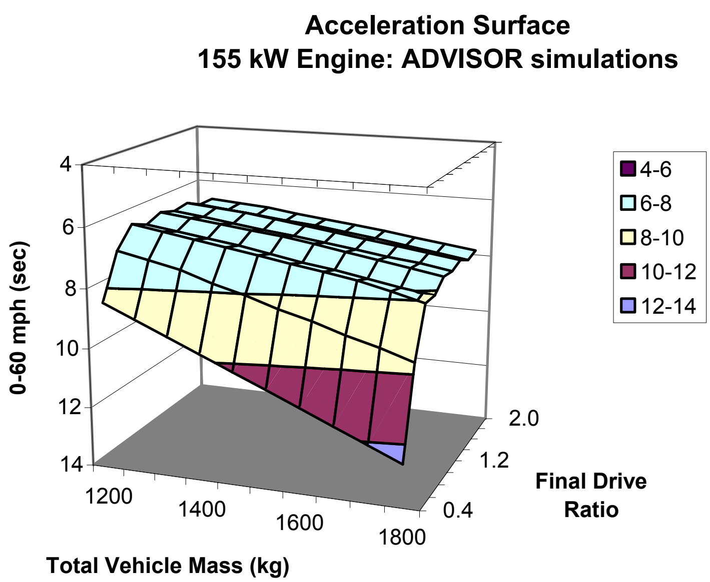


Figure 16 Fuel economy and acceleration surface for 155 kW engine

As the previous fuel economy and acceleration surface plots show, decreasing mass improves both parameters (lower 0-60 times correspond to improved acceleration). On the other hand, increasing the final drive ratio improves acceleration but lowers fuel economy. These two basic trends are the most relevant information to gather from the surface plots themselves. However, Figure 17 and Figure 18 translate this data to a single graph (for the 95 kW and 155 kW engine, respectively) to plot the more interesting tradeoff between fuel economy and acceleration at each tested vehicle mass. Each data point on the mass curves in Figure 17 and Figure 18 correspond to a different final drive ratio: 0.6, 0.8, and 1.2.

Only three points are plotted on each curve because they approximate the bounds of the efficient engine-tuning frontier for the given mass. As the plots show, tuning the final drive ratio higher than 1.2 will yield lower fuel economy and no more acceleration gains, while final drive ratios less than 0.6 will result in worse acceleration without fuel economy improvements. The useful tuning ratios, and thus the useful fuel economy-acceleration relationships, are found between these endpoints.

Note that the maximum convexity of each performance curve occurs close to a final drive ratio of 0.8 to 1.0 (the middle data point marker). This region of the curve balances fuel economy and acceleration best: shifts along the curve away from this region either dramatically reduce acceleration (to lower final drive ratios) or dramatically reduces fuel economy (to higher final drive ratios). But this doesn't imply that this region of the fuel economy-acceleration tradeoff curve is optimal for each car. If one performance measure is valued much more highly than the other, it may be best for the automaker to tune to either extreme, instead of the balancing middle.

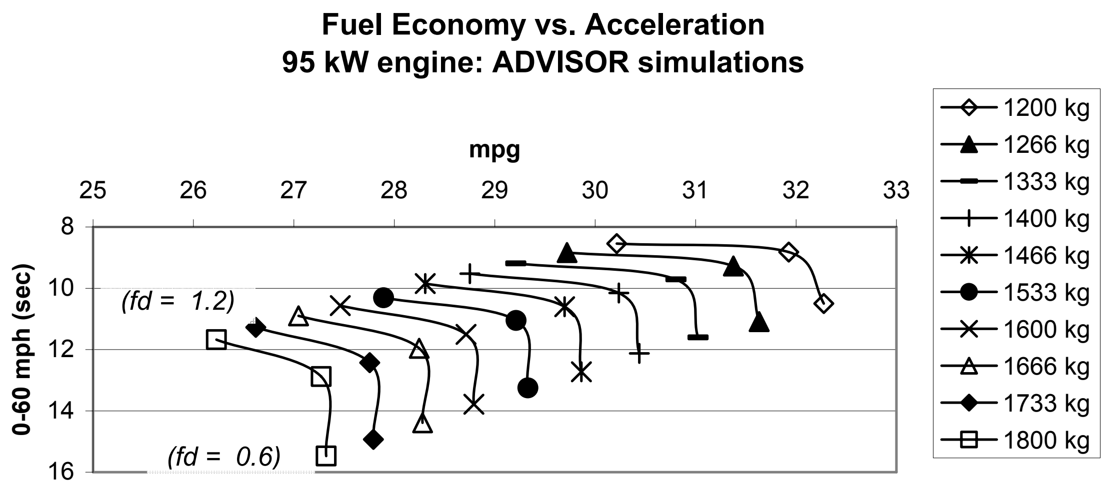


Figure 17 Fuel economy vs. acceleration for 95 kW engine

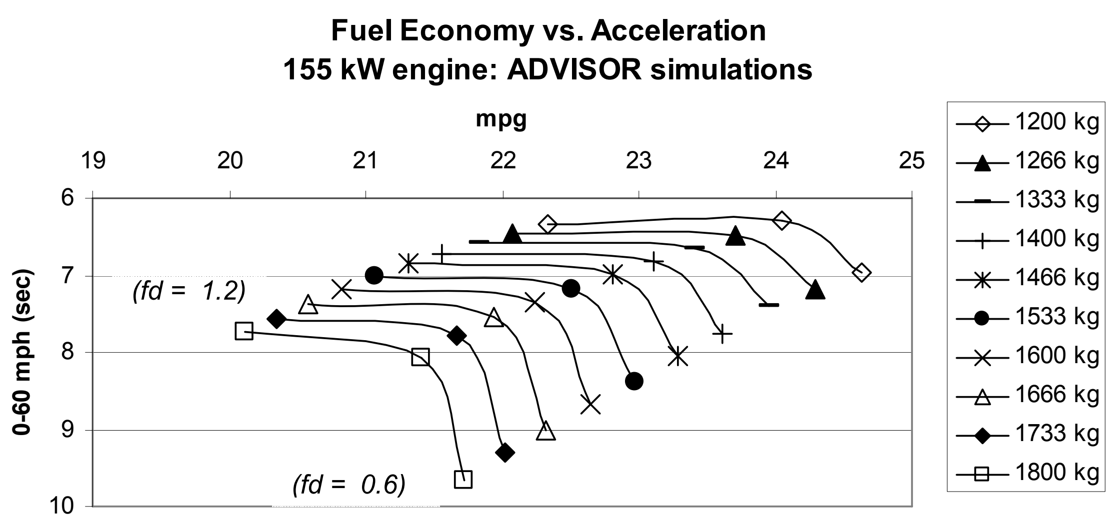


Figure 18 Fuel economy vs. acceleration for 155kW engine

The data sets which underlie the previous two graphs were then regressed using a log-log equation form to arrive at a pair of equations for each engine that predict fuel economy and acceleration as a function of vehicle mass and final drive ratio. The coefficients of these regressions are presented in Table 8 and, taken together, these four regression equations represent the implemented performance model used in the presnt thesis analysis.

ln variable = intercept+β_1(ln total vehicle mass)+ β_2*(ln final drive ratio)*				
	intercept	***β_1***	***β_2***	***adj. R^2***
95 kW engine				
ln mpg	**6.1487** (0.0961)	**-0.3824** (0.0132)	**-0.0785** (0.0060)	0.97
ln 0-60 (sec)	**-4.1315** (0.4050)	**0.8870** (0.0554)	**-0.3514** (0.0251)	0.94
155 kW engine				
ln mpg	**5.1675** (0.0905)	**-0.2855** (0.0124)	**-0.1286** (0.0056)	0.97
ln 0-60 (sec)	**-2.7094** (0.6392)	**0.6392** (0.0607)	**-0.2220** (0.0275)	0.86

Table 8 Performance model regression coefficients. (standard error)

In general, the regression statistics show a reasonably good fit to the data. The standard errors on all coefficients are small and the adjusted R^2 values are high (except for the 155 kW acceleration regression). To compare the results of these regression equations to the commonly used 10-5 rule (a 10% reduction in vehicle mass yields a 5% improvement in fuel economy), I held final drive ratio constant at 1.0 (the baseline value in ADVISOR), varied vehicle mass, and plotted the fuel economy and acceleration results as a percent change of an initial value. Figure 19 and Figure 20 present these results for the 95 kW engine.

As the figures show, the fuel economy-mass relationship predicted by the ADVISOR performance model regression is very close to the 10-5 rule of thumb, while the acceleration-mass relationship predicted by the ADVISOR regression is closer to a 10-10 rule: a 10% mass reduction leads to a 10% reduction in 0-60 time. This 10-10 relationship was also found by Catarina Bjelkengren doing related research in a contemporaneous MIT thesis. (Bjelkengren 2008) Although Bjelkengren's acceleration-mass relationship is the result of a proprietary performance model from a major automaker, the outcome is essentially the same.

The mass-performance relationships of the case study performance model are thus verified by a commonplace engineering rule of thumb (for fuel economy), and a colleague's independent research results (for acceleration).

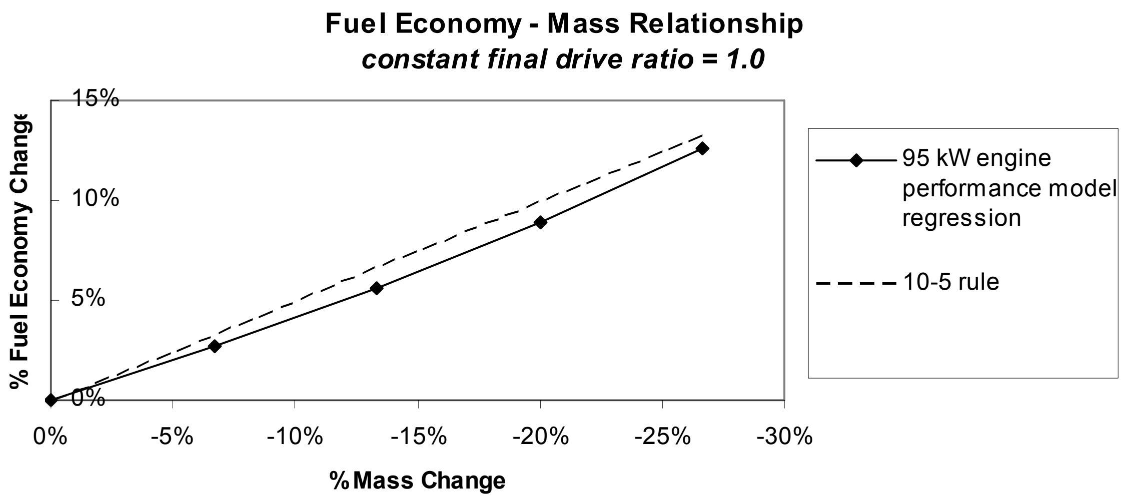


Figure 19 Fuel economy-mass relationship

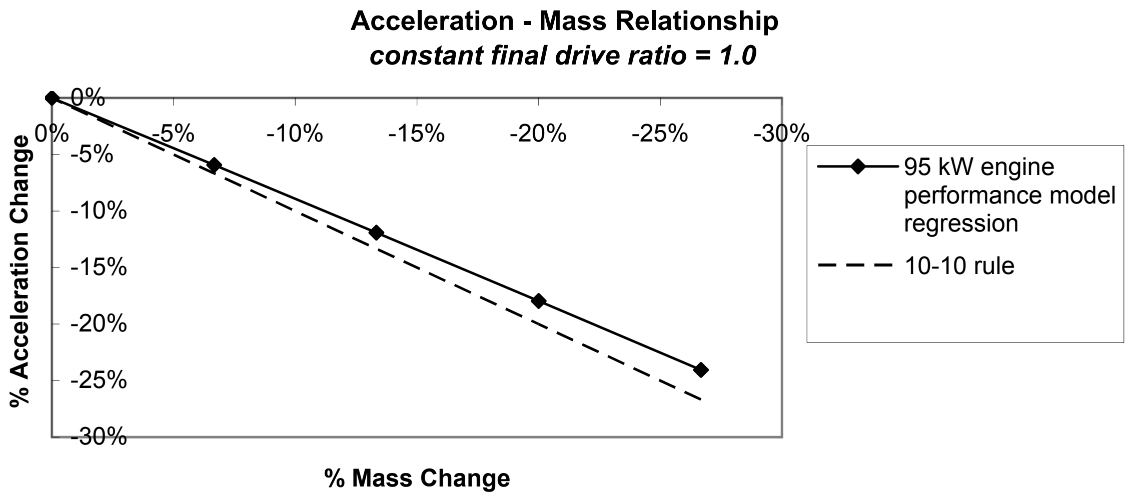


Figure 20 Acceleration-mass relationship

3.2.2 Market Share Model

The market share model, as described in chapter two, translates fuel economy and acceleration values to an expected market share in the first year of full production. The market share model works by measuring the difference between the fuel economy and acceleration of the modeled vehicle and the fuel economy and acceleration of a similar reference vehicle for which a market share is known. Given a relationship between the change in each performance measure and the change in market share for the reference vehicle, a total change in market share can be calculated for the modeled vehicle and then added (or subtracted) from the reference market share to determine the market share for the modeled vehicle. (Price is held constant in the case study at the reference value, so the change in market share due to a change in price is zero).

Table 9 presents the fuel economy, acceleration, price, and market share of each reference vehicle used in the case study market model. These values are based on numbers for actual vehicles gathered from the My Product Advisor database operated by Market Insight and reported by Bjelkengren. (Bjelkengren 2008) As mentioned earlier, Market Insight provides market share data for vehicles but not overall market size. Therefore, to determine the implied market size that the Market Insight market share numbers suggest, I compared the market share number to the known sales of these vehicles in 2006 and calculated the corresponding approximate market size. These implied market size approximations appear at the far right of the table.

The implied market sizes are simply a way of scaling the Market Insight market share numbers to actual sales levels. The fact that the implied market size numbers are the same or similar for each car does not mean that the cars compete in the same market; rather, a basic assumption of this model is that each vehicle competes in a separate market segment and cannot cannibalize sales from the other two vehicles.

	Fuel Economy (mpg)	*Acceleration 0-60 time (sec)*	*Price*	*Market Share*	*Actual 2006 Sales*	*Implied Market Size (approx.)*
	Market Insight data					
Small car	24.6	9.6	$15,992	0.514%	211,449	40m
Mid-size car	22.2	8.1	$20,769	0.534%	157,644	30m
Luxury car	18.7	7.0	$50,795	0.066%	25,676	40m

Table 9 Reference vehicles for market model

The market for each of these vehicles responds differently to variations in product attributes. To understand how the demand for these vehicles is affected by fuel economy and acceleration performance, Bjelkengren studied how the reported market share changed as the reference fuel economy and acceleration of each vehicle varied. The outcome of her work appears in Figure 21 and Figure 22, which plot the change in market share due to a change in fuel economy and acceleration, respectively, for each vehicle. As the graphs show, a one mpg increase in fuel economy results in the largest market share gain for the mid-size car, followed by the small car and then the luxury car. With respect to acceleration, the small car market share is most responsive to a one second 0-60 improvement, followed by the mid-size car market and then the luxury car market. (Bjelkengren 2008)

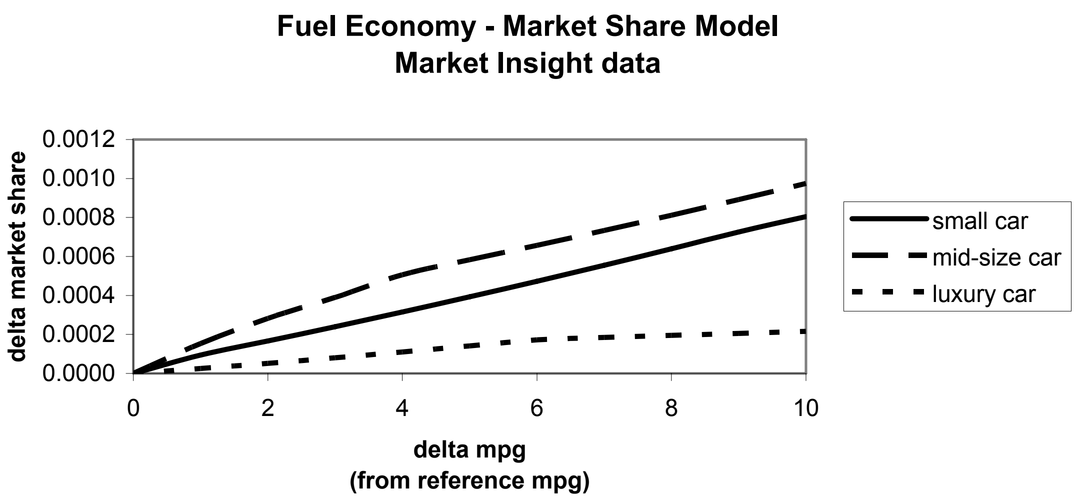


Figure 21 Fuel economy - market share model

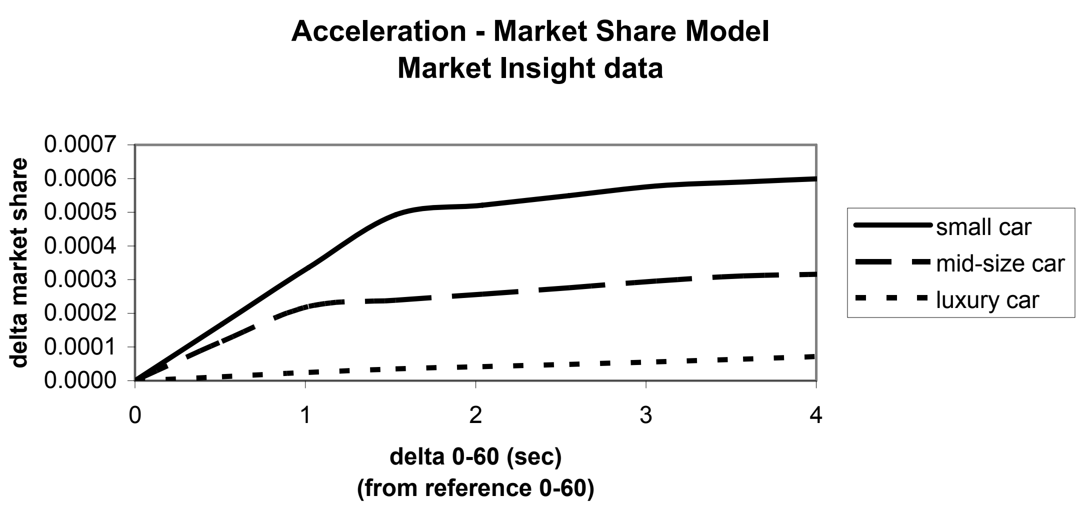


Figure 22 Acceleration - market share model

Bjelkengren then found regression equations which describe each market share – performance relationship. These equations appear below.

Small Car

$$\Delta\ market\ share_{mpg} \quad = \quad 7.85\times10^{-5}(\Delta mpg) + 1.81\times10^{-7}(\Delta mpg)^2$$

Equation 22

$$\Delta\ market\ share_{0-60} \quad = \quad 4.46\times10^{-4}(\Delta 0-60) - 1.14\times10^{-4}(\Delta 0-60)^2 + 9.86\times10^{-6}(\Delta 0-60)^3$$

Equation 23

Mid-size car

$$\Delta\ market\ share_{mpg} \quad = \quad 1.39\times10^{-4}(\Delta mpg) - 4.42\times10^{-6}(\Delta mpg)^2$$

Equation 24

$$\Delta\ market\ share_{0-60} \quad = \quad 3.77\times10^{-4}(\Delta 0-60) - 1.61\times10^{-4}(\Delta 0-60)^2 + 2.32\times10^{-5}(\Delta 0-60)^3$$

Equation 25

Luxury Car

$$\Delta\ market\ share_{mpg} \quad = \quad 3.31\times10^{-5}(\Delta mpg) - 1.10\times10^{-6}(\Delta mpg)^2$$

Equation 26

$$\Delta\ market\ share_{0-60} \quad = \quad 4.95\times10^{-5}(\Delta 0-60) - 1.52\times10^{-5}(\Delta 0-60)^2 + 3.16\times10^{-6}(\Delta 0-60)^3$$

Equation 27

Where Δmpg = (*model vehicle mpg - reference mpg)* and Δ*0-60* = (*reference 0-60 – model vehicle 0-60)*. The difference in sign accounts for the fact that improvements in fuel economy are positive, while improvements in 0-60 time are negative.

Once the market share changes due to fuel economy and acceleration are determined for each vehicle, they are summed according to the method outlined in Chapter Two to find the total market share change due to changes in performance (from the reference case). The expected annual sales in the first year of production is then given by

$$annual\ sales_{year\,1} \quad = \quad (\Delta market\ share_{total} + market\ share_{reference}) \times implied\ market\ size$$

Equation 28

3.2.3 Cost Model

With the expected annual sales level in year one now determined for each vehicle, the production capacity decision (either 110% or 125% of this value) scales the size of the required production plant. The cost model then maps the technology decision (steel or composites for the body and closures)[2] and plant scale to determine the required capital investments for each phase of production. The cost model must also be capable of calculating operating costs as a function of production volume (the number of cars actually produced in a given year, distinct from capacity), so this section will describe both fixed and variable cost calculations for each production process previously outlined. The section begins with a general overview of the cost modeling strategy for the case

[2] Recall that engine costs are treated as marginal cost items so they do not vary with production scale.

study, followed by case-specific cost details for the closures, the body-in-white, the engines, paint, and the rest of the vehicle.

Case study cost modeling strategy

As Chapter Two outlined, the parametric cost models constructed for the spreadsheet optimization tool in this thesis are derived (where possible) from the results of detailed process-based cost models of the underlying manufacturing methods. In the case of the steel stamped closure set, for example, all of the component parts are first modeled in a steel stamping PBCM and then the aggregate cost elements (allocated investment per unit of capacity and variable costs per unit produced) are used as the basis of a parametric cost model which can calculate annual fixed costs for a given capacity and variable costs for a given annual production volume. This transformation drastically simplifies the calculations that are performed while the spreadsheet tool simulates through all vehicle technology/capacity combinations to evaluate the total project cost of each option. Given that the solution method is computationally intense, this simplification improves solving time and increases the number of combinations that can be studied.

In performing the underlying PBCM cost studies, I made a further simplification by assuming that each car shares the same general closure set and body-in-white designs, which only vary by size. Therefore, instead of performing in-depth cost studies of each vehicle, I completed one detailed cost analysis for the mid-size car (in both steel and composites) and then scaled the cost results to approximate the costs of producing equivalent parts for the small car and the luxury car. (Although I assumed that engine costs and paint cost were constant across the vehicle fleet.) These costs were scaled using an engineering rule of thumb which holds that production costs for similar parts vary by the ratio of mass to the 0.6 power,

$$cost_{small\ car} \quad = \quad cost_{mid\text{-}size\ car} \times (\frac{mass_{small\ car}}{mass_{mid-size\ car}})^{0.6}$$

Equation 29

$$cost_{luxury\ car} \quad = \quad cost_{mid\text{-}size\ car} \times (\frac{mass_{luxury\ car}}{mass_{mid-size\ car}})^{0.6}$$

Equation 30

For

cost terms: material variable cost, labor variable cost, energy variable cost, tool investment, allocation equipment investment, allocated building investment

$mass_{small\ car}$ = 1274.4 kg

$mass_{mid\text{-}size\ car}$ = 1502.2 kg

$mass_{luxury\ car}$ = 1815.0 kg

The following sections present the details of the cost modeling analysis for the mid-size car.

Case study closures cost

Closures designs

Estimating the production cost for closure sets manufactured from both of the materials technologies being studied first required determining some general design parameters, such as part geometries, raw material inputs, and manufacturing processes to be used. In formulating these specifications for the steel and composite closure designs, I consulted several automotive industry experts with materials research, product design, and manufacturing/processing experience.

Table 10 presents the details of the two closure set designs, identifying the individual closures that were modeled. The closure sets consists of a hood, two front doors, two rear doors, two fenders, two quarterpanels, [3] and a decklid. For cost modeling purposes, only the hood, a generic door, a fender, and the decklid were explicitly modeled. All doors were assumed to be approximately of the same design, and the quarterpanel was assumed to be equivalent to the fender for mass and cost purposes. While all steel parts are stamped from mild steel, the composite closure set design consists of steel reinforced closures such as the door and un-reinforced RIM fenders and quarterpanels.

Closure	***Modeled Subassembly***	***Steel***	**Composite**	*Composite Structure*
		mass (kg)	*mass (kg)*	
Hood	hood	14.41	12.53	SMC/steel reinf.
Front R door	door	19.36	13.77	SMC/steel reinf.
Front L door	door	19.36	13.77	SMC/steel reinf.
Rear R door	door	19.36	13.77	SMC/steel reinf.
Rear L door	door	19.36	13.77	SMC/steel reinf.
R fender	fender	5.19	1.45	RIM
L fender	fender	5.19	1.45	RIM
Decklid	decklid	12.20	5.89	SMC/steel reinf.
R quarterpanel	fender	5.19	1.45	RIM
L quarterpanel	fender	5.19	1.45	RIM
Entire Closure Set		**124.80**	**79.30**	

Table 10 Closure set designs by individual closure

All parts in the steel design are joined by spot welding and hemming, while the composite closure set is assembled by adhesive bonding only. Table 11 provides an overview of the designs, assembly methods, raw material costs, and masses.

[3] Quarterpanels are usually considered part of the body-in-white, though they have been included in the closure set in this analysis.

	Steel Closure Set	*Composite Closure Set*
Primary material	mild steel	sheet molding compound
Manufacturing process	*steel stamping*	*SMC/RIM*
Raw material cost	*$1.00/kg*	*$2.40/kg / $2.65/kg*
Reinforcement material	n/a	mild steel
Assembly method	spot welding	adhesive bonding
Total mass (kg)	124.8	79.3

Table 11 Closure set design overview

Closure fabrication costs

To determine fabrication costs for the closures, I modeled all of the constituent parts in a process-based cost model of the steel stamping process and SMC process that were previously developed at the Materials Systems Laboratory according to the principles outlined in Chapter Two. More information on these process-based cost models can be found in Erica Fuchs's MIT master's thesis {Fuchs, 2003 #43} (for steel stamping and RIM) and Paul Kang's MIT master's thesis (for SMC). (Kang 1998)

Table 12 presents the process-based cost model results for the fabrication of the entire steel and composite closure sets, broken down by fixed costs and capital investments. This table is a list of PBCM results, but as discussed earlier, these cost component results comprise the foundation of the parametric cost model that the spreadsheet optimization tool utilizes to analyze each vehicle fleet/technology option.

fabrication costs	Steel Closure Set Fabrication	Composite Closure Set Fabrication
variable costs		
material	$215.25	$276.01
labor	$9.43	$24.36
energy	$2.99	$10.09
capital investments (fixed costs)		
allocated equipment investment at 100,000 APV	$16,700,000	$9,700,000
allocated building investment at 100,000 APV	$1,700,000	$4,200,000
tool investment	$24,900,000	$10,900,000*
**at 100,000 APV, varies by capacity factor*		

Table 12 Closure set parametric fabrication cost model

The top three entries in the table are the variable cost components that fabricating each closure set entails. The next two entries refer to the allocated investments in equipment and building space required to produce closures at a capacity of 100,000 units per year (or annual production volume, APV). These values are sensitive to production capacity because more plant resources (specifically, more equipment time) are devoted to closures as production capacity increases.

Recall that the use of the term “allocated” implies that these figures do not represent absolute investments, but rather the fraction of a machine or building investment that is devoted to the production of closures for this vehicle project. At production capacities other than 100,000 APV, the allocated investments are determined by multiplying the values in the table by a capacity factor as in Equation 15.

Furthermore, these one time investments (in machines or building space) are then annualized over the useful life of the item using a discount rate to account for the time value of money and the opportunity cost of investing capital in this project. The annual fixed cost will solve the equation

$$annual\ \ fixed\ cost = \frac{allocated\ investment \times r}{\left[1 - \frac{1}{(1+r)^{life}}\right]}$$

Equation 31

where *r* is the discount rate and *life* is the useful life of the capital item in years. In this thesis I assumed a 12% discount rate, a machine/equipment life of 10 years, and building life of 30 years.

The last entry in the table presents the total tool investment. Unlike the building and equipment investments, this investment is an absolute figure because tools are part-specific, so their useful production is dedicated to the part for which they were designed. Recall that the tool investment required for steel fabrication is assumed to be constant for any production capacity considered because steel tools are very durable (lasting millions of cycles) and are assumed to last the life of the project, while the some of the composite tools (for RIM closures) are less durable and must be replaced as production increases.

The combined SMC/RIM closure set design thus complicated the construction of a parametric model because the tooling costs of SMC fabrication and RIM fabrication vary with production capacity in different ways. As discussed earlier, SMC tool investments are assumed to be constant for any production volume (like steel stamping), but RIM tool investments must be made on a recurring schedule determined by a production volume period which is a function of tool life, reject rates, and cycle time. (This argument was actually made for SRIM, but the result holds for RIM as well.) Therefore, to model the capital cost behavior of the combined SMC/RIM closure set fabrication process, I analyzed the capital cost behavior of the mixed closure set predicted by the SRIM and RIM PBCMs across a range of production volumes and then determined the dominant trend. Based on the results of this examination, I determined that the composite closure set tool investment can be modeled in the parametric relationship as an investment that varies by the capacity factor method, which is indicated in the table.

Tool investments are annualized by Equation 31 as well, using a 12% discount rate and a product life of 5 years.

Recall that overhead and maintenance are each assumed to be a certain percentage of the total allocated capital investment (allocated equipment + allocated building + tool). For this analysis, I assumed that overhead is 35% of total capital investment and maintenance is 15% of total capital investment.

Figure 23 presents the total cost results for closure fabrication, using the cost elements presented above and adding overhead and maintenance fixed costs. The graph plots average cost as a function of production capacity, assuming that the plant is fully utilized, producing vehicles at 100% capacity for every capacity plotted.

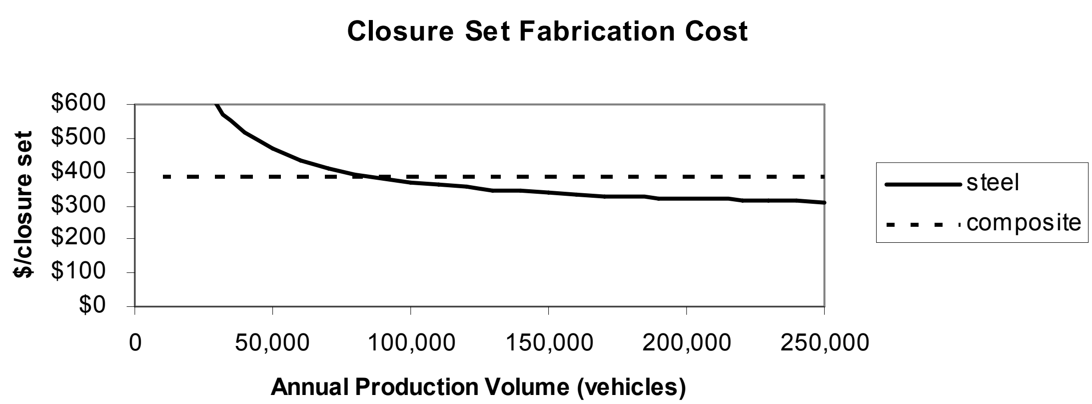


Figure 23 Closure set fabrication cost

As the graph shows, the modeled composite fabrication costs per closure set are constant at about $380 because the simplifying assumptions have treated all cost elements as capacity scaling (when fully utilized). This simplification ignores some small economies of scale that SMC and RIM fabrication undergo, but it should not significantly affect the results in this thesis. Steel, on the other hand, exhibits significant cost economies as production scale increases, due to the tool investment that can be spread over more units. The curves intersect at approximately 75,000 APV, above which steel fabrication is less expensive.

Closure assembly costs

The required assembly operations for the mid-size car steel and composite closure sets were modeled in a process-based assembly cost model that considers a range of joining methods including welding, mechanical fastening, and adhesive bonding operations. While the steel subassemblies were modeled as being joined by a combination of methods, the composite closures were assumed to be joined by adhesive bonding only.

Recall that the capital investments required for a series assembly process vary nonlinearly with capacity. As a consequence, I constructed regression equations which approximate the capital investments predicted by the assembly PBCM as a function of production volume (assuming fully utilized capacity). To generate the regression equations I modeled the steel and composite closure set assembly processes, recorded the required capital investments in tooling, equipment, and building space over a range of production volumes, and then regressed the predicted investments against production volume. These equations appear below, along with their associated R^2 values.

<u>Regression equations that approximate closure assembly PBCM capital investments:</u>

- Allocated equipment investment

$$equip\ invest_{steel\ closure\ assembly} = 8{,}000{,}000 - 22.2(APV) + 0.0002(APV)^2 \quad R^2 = 0.95$$

Equation 32

$$equip\ invest_{composite\ closure\ assembly} = 6{,}000{,}000 - 13.4(APV) + 0.0002(APV)^2 \quad R^2 = 0.97$$

Equation 33

- Allocated building investment

$$bld\ invest_{steel\ closure\ assembly} = 10{,}000{,}000 - 24.9(APV) + 0.0002(APV)^2 \quad R^2 = 0.93$$

Equation 34

$$bld\ invest_{composite\ closure\ assembly} = 5{,}000{,}000 - 14.7(APV) + 0.0001(APV)^2 \quad R^2 = 0.95$$

Equation 35

- Tool investment

$$tool\ invest_{steel\ closure\ assembly} = 10{,}000{,}000 - 10.2(APV) + 0.00007(APV)^2 \quad R^2 = 0.97$$

Equation 36

$$tool\ invest_{composite\ closure\ assembly} = 5{,}000{,}000 - 12.0(APV) + 0.0001(APV)^2 \quad R^2 = 0.94$$

Equation 37

where APV is the annual production volume capacity of the plant and all investments are in dollars.

To roughly compare these equations (and the underlying assembly processes), I have evaluated each equation at APV = 100,000 in Table 13, in addition to listing the variable cost components for each design. (I grouped material, labor, and energy together in one variable cost term for the assembly phase for simplicity.) Comparing Table 13 to Table 12 shows that the investment savings from producing in composites as opposed to steel are smaller in the assembly phase of production than they are in the fabrication phase.

assembly costs	***steel closure set assembly***	***composite closure set assembly***
variable costs	$14.00	$105.00
capital investments (fixed costs)		
allocated equipment investment at 100,000 APV	$7,800,000	$6,700,000
allocated building investment at 100,000 APV	$9,500,000	$4,500,000
tool investment at 100,000 APV	$9,700,000	$4,800,000

Table 13 Closure set parametric assembly cost model evaluated at 100,000 APV

Capital cost annualization and overhead/maintenance additions are carried out for assembly in the same manner as described above for fabrication. Figure 24 plots the resulting average cost curves. The composite cost curve still intersects the steel cost curve, but this time the crossover point is much lower, at approximately 40,000 APV (compared to the 75,000 APV observed in the fabrication cost curve comparison). This shift is due to the greater discrepancy in variable costs and higher capital investments required by composite assembly relative to steel assembly.

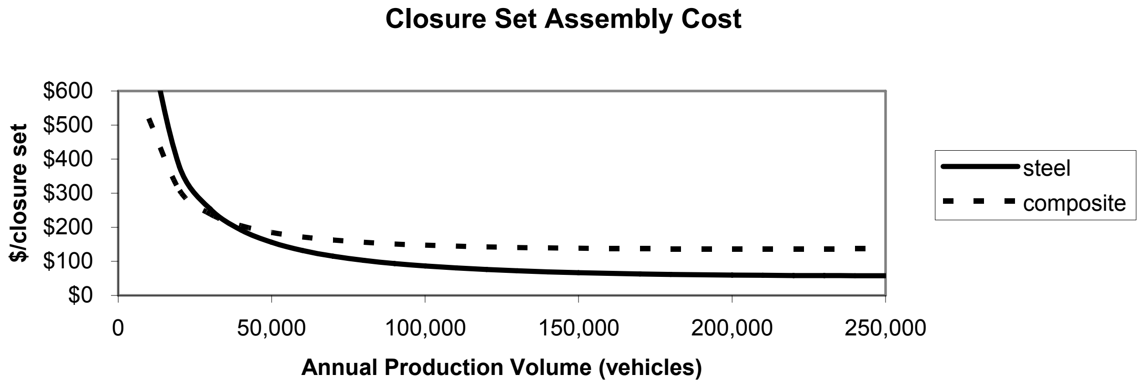


Figure 24 Closure set assembly cost

Closure set production cost

Figure 25 combines the fabrication and assembly costs, plotting average production cost for the mid-size car steel and composite closure designs modeled in this thesis. The crossover point is approximately 64,000 closure sets (or vehicles) per year, after which steel closure production is always less expensive. At high production volumes (more than 200,000 units per year), steel has a cost advantage of approximately $150 per closure set.

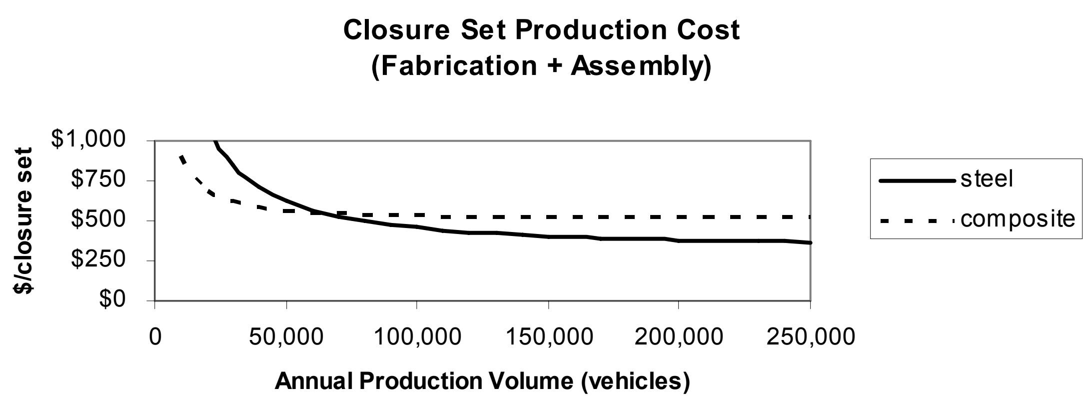


Figure 25 Closure set production cost

Body-in-white

Body-in-white designs

As described in the previous section on closure production costs, the first step in performing a production cost analysis requires determining the product design parameters. For the steel and composite bodies-in-white I used designs researched and published by Erica Fuchs. (Fuchs 2003; Fuchs, Field et al. 2008) However, this thesis studies cost issues at a broader level than Fuchs's work, so her detailed designs have been used as a guide that in some instances were slightly modified to reduce the cost modeling complexity without sacrificing essential information. This section describes those modifications and the resulting production costs.

Table 14 outlines the body-in-white designs. Although Fuch's steel body design used several different types of mild steels, all with yield strength below 210 MPa, I modeled the entire body from the same 140 MPa alloy. This simplification minimally changes cost results because the material properties (and thus the raw material cost and required forming forces) are so similar. The table also identifies the material system Fuchs used in her composite body design, an SRIM polyurethane reinforced with glass fiber.

The entire steel body is comprised of 111 components and 101 inserts that are joined by spot welding, while the composite body, by contrast, has only 25 parts and is joined by adhesive bonding. The composite body weighs 167.3 kg, a mass savings of 92 kg, or 35%, compared to the 259.4 kg steel body.

	Steel Body-in-White	*Composite Body-in-White*
Primary material	mild steel sheet	SRIM
Manufacturing process	*steel stamping*	*SRIM*
Raw material cost	*$1.00/kg*	*$2.65/kg*
Reinforcement material	N/A	glass fiber
Reinforcement material cost	*N/A*	*$2.50/kg*
Assembly method	spot welding	adhesive bonding
Number of parts	212	25
Total mass (kg)	259.4	167.3

Table 14 Body-in-white designs overviews

Body fabrication costs

While Fuchs presented total production cost values in her published work, she did not break out the variable cost and capital cost elements in a manner that easily translates to the parametric cost model needs of this thesis. Therefore, I modeled Fuchs's body designs in PBCMs in order to replicate her results and observe the needed cost components. In the case of the 25-component composite model, I directly modeled all parts in an SRIM PBCM, but for the 200+ part steel body I simplified the fabrication cost modeling task by following Fuchs's method of organizing parts into groups based on part complexity and processing equipment type, as outlined in Chapter Two.

The steel body part groups were organized according to the type of equipment each was assumed to be manufactured on: a progressive, tandem, or transfer press, and by the complexity of the part, which was assigned a complexity level of 1, 2, or 3. Both of these criteria scale the capital investment required in fabrication. The equipment grouping determines the size of the unit capital investment (progressive presses are the least expensive, followed by the investments for tandem and then transfer presses), and the complexity level determines how many hits the part will need to be formed. Parts with a complexity level of 1 need fewer hits than parts with complexity level 2, which need fewer hits than parts with complexity level 3. Table 15 provides an overview of all the part groups for the steel body.

Part Group [complexity]	*Total Mass (kg)*	*Number of Parts*
Progressive [1] *inserts*	10.6	94
Transfer [1] *inserts*	7.2	7
Progressive [1]	0.4	2
Progressive [2]	3.2	3
Progressive [3]	24.3	2
Tandem [1]	14.2	19
Tandem [2]	34.5	37
Tandem [3]	33.4	12
Transfer [1]	6.4	7
Transfer [2]	26.4	9
Transfer [3]	98.8	20
entire steel body-in-white	**259.4**	**212**

Table 15 Steel body-in-white part grouping

The average part mass for each group (*total mass/number of parts*) was then calculated and this mass, together with the material, press specification, and complexity level, were treated as representative design parameters for the group. The production cost of each "average" part was then determined using the same steel stamping PBCM as was used for steel closures.

Once the cost of producing the average part is known, the cost of the producing the entire part group is given by the product of this value and the number of parts in the group. The first data column in Table 16 presents the results of this cost modeling work for the steel body-in-white.

Although the fabrication cost of the composite body design was generally much easier to model than the steel design, determining the composite tool investment was slightly more complicated because the SRIM composite tool costs vary nonlinearly with production capacity. The SRIM tools have a useful life of approximately 250,000 cycles, but the slow cycle times and high reject rates of the SRIM process mean that the tools must be purchased at production capacity intervals much shorter than 50,000 APV (over five years of production 50,000 APV = 250,000 cycles). To model this effect properly, I analyzed the tool investment behavior predicted by the PBCM and then observed (1) the unit tool investment and (2) the effective tool replacement period. For the SRIM body the unit tool investment is approximately $10,000,000 and the effective replacement period is 20,000 APV. Thus,

$$tool\ invest_{composite\ body\ fab} = 10{,}000{,}000 \times \mathrm{roundup}(\frac{APV}{20{,}000})$$

Equation 38

This equation is evaluated at an APV of 100,000 in Table 16 and presented along with the remaining cost elements for composite body fabrication determined by the results of the SRIM PBCM.

fabrication costs	***Steel Body Fabrication***	***Composite Body Fabrication***
Variable Costs		
Material	$379.23	$731.84
Labor	$18.82	$346.98
Energy	$8.91	$36.04
Capital Investments (fixed costs)		
Allocated equipment investment at 100,000 APV	$56,100,000	$71,000,000
Allocated building investment at 100,000 APV	$5,700,000	$78,200,000
Tool investment	$41,800,000	$50,000,000*
**equation evaluated at 100,000 APV*		

Table 16 Body-in-white parametric fabrication cost model

Figure 26 plots the resulting average cost curves, using the above values as the basis for the parametric fabrication cost model. As the figure shows, composite fabrication costs are relatively steady at about $1,600 per body, due to the high variable costs and recurring tool investments, while steel costs fall dramatically until about 100,000 APV, at which point the fabrication cost per body is approximately $700. The cost crossover is at about 15,000 APV.

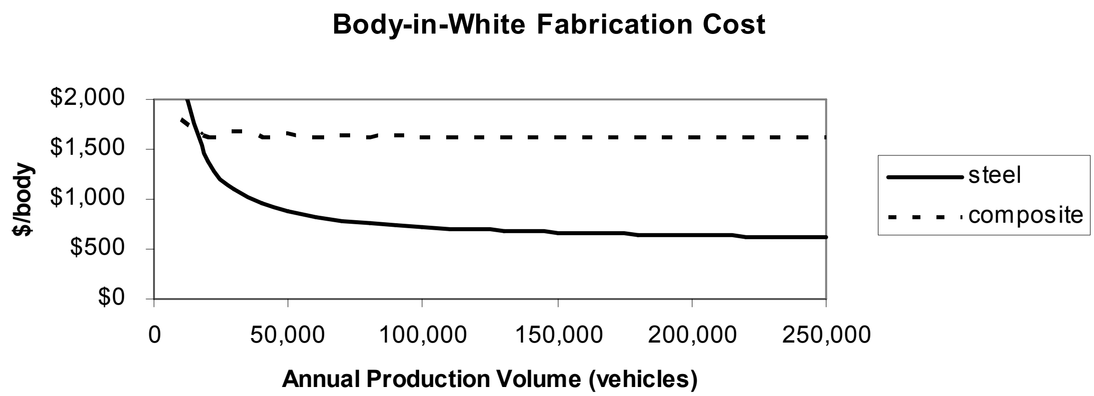


Figure 26 Body-in-white fabrication cost

Body assembly

Body assembly costs for the two designs were modeled in the same PBCMs that were used to model closure assembly. As was the case for the closures, determining capital investments for the assembly phase of body production required fitting the results of the assembly PBCM to a regression. Although the earlier method section explained why the capital investments required for assembly processes typically follow a nonlinear trend with respect to production capacity, I nonetheless implemented linear regressions for the body-in-white assembly process here. However, the R^2 values indicate that the linear form still provides a decent approximation.

Regression equations that approximate body assembly PBCM capital investments:

- Allocated equipment investment

$$equip\ invest_{steel\ body\ assembly} \quad = \quad 34{,}000{,}000 + 197(APV) \qquad R^2 = 0.96$$

Equation 39

$$equip\ invest_{composite\ body\ assembly} \quad = \quad 25{,}000{,}000 + 38(APV) \qquad R^2 = 0.88$$

Equation 40

- Allocated building investment

$$bld\ invest_{steel\ body\ assembly} \quad = \quad 48{,}000{,}000 + 138(APV) \qquad R^2 = 0.95$$

Equation 41

$$bld\ invest_{steel\ body\ assembly} \quad = \quad 34{,}000{,}000 + 196(APV) \qquad R^2 = 0.90$$

Equation 42

- Tool investment

$$tool\ invest_{steel\ body\ assembly} \quad = \quad 55{,}000{,}000 + 88(APV) \qquad R^2 = 0.97$$

Equation 43

$$tool\ invest_{composite\ body\ assembly} \quad = \quad 40{,}000{,}000 + 54(APV) \qquad R^2 = 0.90$$

Equation 44

where APV is annual production volume capacity and all investments are in dollars.

I have evaluated each equation at APV = 100,000 in Table 13, in addition to listing the variable cost components for each design.

assembly costs	Steel Body-in-White Assembly	Composite Body-in-White Assembly
Variable cost	$95.00	$33.80
Capital Investments (fixed costs)		
Allocated equipment investment at 100,000 APV	$53,700,000	$6,400,000
Allocated building investment at 100,000 APV	$61,600,000	$4,700,000
Tool investment at 100,000 APV	$63,300,000	$9,800,000

Table 17 Body-in-white parametric assembly cost model evaluated at 100,000 APV

Capital cost annualization and overhead/maintenance additions are carried out as before. Figure 27 plots the resulting average cost curves. As the figure illustrates, composite body assembly costs are a fraction of steel assembly costs, in large part due to parts consolidation (200+ parts for the steel body compared to 25 parts in the composite design) which significantly reduces the number of assembly steps required.

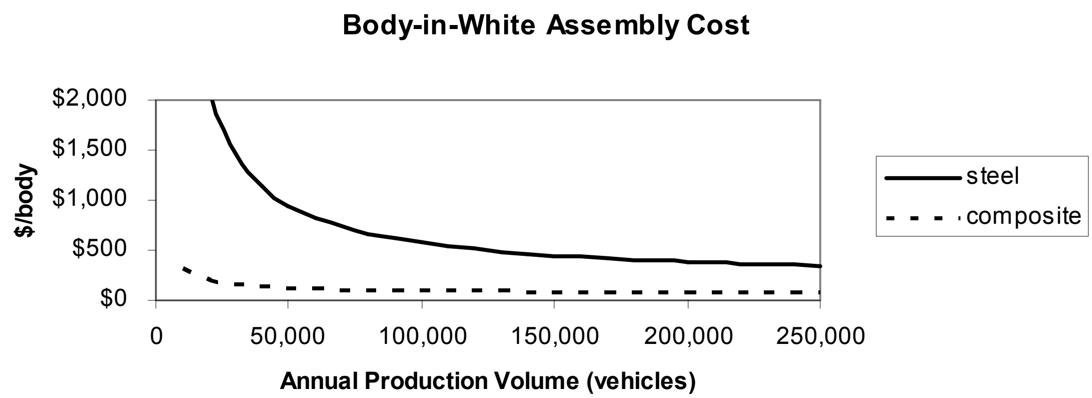


Figure 27 Body-in-white assembly cost

Adding fabrication costs to the assembly costs yields the total production cost for the body-in-white, plotted in Figure 28. The steel and composite curves behave much the same way that the closure set production cost curves do, although the steel body is even more cost-competitive than the steel closures are at high volumes. As the graph shows, the crossover point between the two body-in-white cost curves is approximately 54,000 APV (similar to the 64,000 APV point for the closures), but the composite body is approximately $700 more expensive than the steel body at high production volumes (compared to a $150 cost premium for the composite closures). In percentage terms, the composite body is approximately 72% more expensive than steel at high production volumes, while the composite closure set is approximately 40% more expensive than steel.

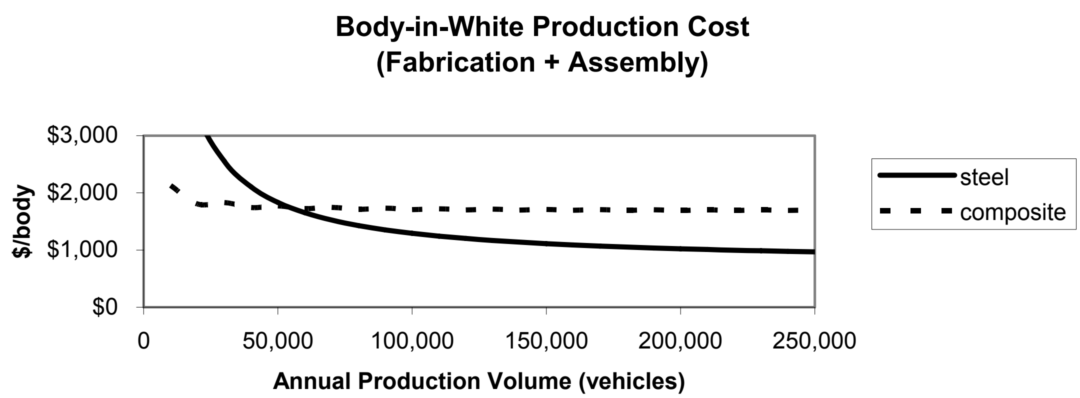


Figure 28 Body-in-white production cost

Material Systems Cost Summary

Table 12 summarizes the output of the parametric cost model for the closure sets and bodies-in-white at two production volumes, 50,000 APV and 150,000 APV, assuming that capacity is fully utilized, i.e., that plant capacity equals annual production volume. The table identifies variable costs, allocated equipment investments, allocated building investments, and tool investments for parts fabrication and assembly phases.

	Closure Set				Body-in-White			
APV	*50,000*		*150,000*		*50,000*		*150,000*	
	Steel	Comp.	Steel	Comp.	Steel	Comp.	Steel	Comp.
Fabrication								
Variable	$228	$310	$228	$310	$407	$1,115	$407	$1,115
All. Equip.	$8.4M	$4.8M	$25.1M	$14.5M	$28.0M	$35.5M	$84.1	$106.4
All. Bld.	$0.9M	$2.1M	$2.6M	$6.2M	$2.9M	$39.1M	$8.6	$117.4
Tool	$24.9M	$5.5M	$24.9M	$16.4M	$41.8M	$30.0M	$41.8	$80.0
Assembly								
Variable	$14	$105	$14	$105	$95	$34	$95	$34
All. Equip.	$7.4M	$8.5M	$9.2M	$5.8M	$43.9M	$4.4M	$63.6M	$8.2M
All. Bld.	$9.3M	$5.0M	$10.8M	$4.5M	$54.7M	$3.4M	$68.6M	$6.1M
Tool	$9.7M	$5.4M	$10.0M	$4.6M	$59.0M	$6.9M	$67.5M	$12.8M
Unit Cost	$625	$569	$403	$522	$1,834	$1,771	$1,112	$1,711

Table 18 Summary of parametric cost model output at 50,000 APV and 100,000 APV for closure set and body-in-white

Engine cost

The engines equipped in the modeled vehicles were assumed to be shared across many vehicle lines and their costs therefore were assumed to not be affected by individual vehicle production volume decisions. Engine costs were thus modeled as constant marginal costs regardless of vehicle production volume.

A relationship between engine power and cost for a spark ignition engine found by Michalek et al was used to determine the cost of each engine:

$$\textit{engine cost} \quad = \quad 670.51 + e^{0.0063 \times power}$$

Equation 45 (Michalek, Papalambros et al. 2004)

where *power* is the maximum power output of the engine in kW and the cost is in dollars. This equation is evaluated for a range of engine powers in Figure 29.

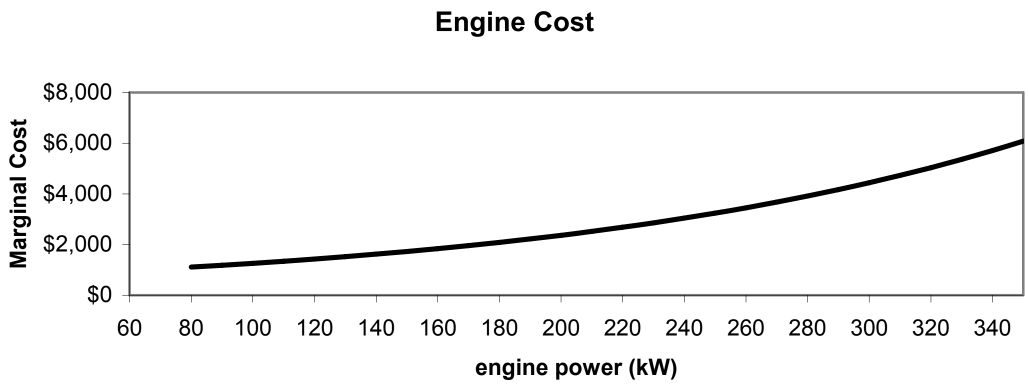


Figure 29 Engine cost vs. engine power

This relationship gives a cost of approximately $1,360 for the 95 kW engine and $1,700 for the 155 kW engine.

Paint cost

Paint costs were modeled as a one time investment and a variable cost. The one time investment was assumed to be $500 million, on the basis of industry-reported paint shop investments and expert opinions. Variable paint costs were assumed to be $500 per car for steel closure vehicles and $560 for composite closure vehicles, based on the input of industry experts. The paint cost premium was applied to composite closure vehicles because of the added difficulty that painting visible composite panels often entails. The one-time investment in paint shop costs were annualized according to Equation 31 using a 10-year amortization period.

It should be noted that the model charges the full $500 million paint shop investment to each car, though in realty several cars would be painted in the same shop, implying that the investment should be spread over several cars.

Additional costs

To account for the remaining investments and operating costs required to produce the rest of the car, additional cost items were added to the parametric cost model. These values were chosen such that the final profit margin on each vehicle (given the prices determined earlier) is approximately 3% to 10% for the small and mid-size car, and approximately 20% for the luxury car at baseline conditions (depending on the materials technology used for body and closures). The additional capital investment is treated as an equipment cost and annualized the same way as other equipment investments, using a 10 year amortization period.

additional production costs	***Small car***	***Mid-size car***	***Luxury car***
Variable Costs	$11,000	$14,000	$30,000
Capital Investments			
Equipment investment	$125,000,000	$125,000,000	$80,000,000

Table 19 Additional cost items

Total annual cost calculation

To translate all of the previous parametric cost elements into annual costs that can be integrated into an NPV analysis based on annual cash flows, the total annual cost in a given year (and for a given demand observation) needs to be calculated. Finding the total annual cost in turn requires finding the total variable cost per car, the total annual production volume, and the total annual fixed cost.

The total variable cost of producing each car is given by

$$\begin{aligned} var\ cost_{total} &= var\ cost_{fabrication} + var\ cost_{assembly} + engine\ cost + var\ cost_{paint} \\ &\quad + var\ cost_{additional} \end{aligned}$$

Equation 46

where the *var cost* terms are the sum of individual variable cost elements (material, labor, energy) for closures and bodies-in-white, the single variable cost term for the paint phases, and the single variable cost term for additional costs. The engine cost is modeled as a marginal cost item so it is also included in the variable cost summation.

The total annual fixed cost is given by

$$\begin{aligned} annual\ fixed\ cost_{total} &= annual\ fixed\ cost_{fabrication} + annual\ fixed\ cost_{assembly} \\ &\quad + annual\ fixed\ cost_{paint} + annual\ fixed\ cost_{additional} \end{aligned}$$

Equation 47

where the *annual fixed cost* terms are the sum of individual annual fixed cost items (equipment, building, tool, indirect labor, and maintenance) for closures and bodies-in-white, the single annual fixed cost term for the paint phases, and the single annual fixed cost term for additional costs.

Total annual cost for producing one car in year t for demand observation n is then

$$total\ annual\ cost_{t,n} = (var\ cost_{total} \times annual\ production\ volume_{t,n}) + annual\ fixed\ cost_{total}$$

Equation 48

where *annual production volume*$_{t,n}$ is the minimum of market demand (determined by the demand uncertainty model) or the production capacity of the plant in year t for demand observation n.

$$annual\ production\ volume_{t,n} = min(demand\ observation_{t,n}, annual\ production\ capacity)$$

Equation 49

To evaluate the previous equation under demand uncertainty and fully calculate total annual costs, the set of possible demand scenarios needs to be gathered from the demand uncertainty model. In the absence of demand uncertainty, though, the expected costs can be determined for the five-year project assuming that demand is constant for all years.

Table 20 thus summarizes all costs of producing the mid-size car at 50,000 APV and 150,000 APV without demand uncertainty. At each of these production volumes the variable cost, allocated equipment investment, allocated building investment and tool investment for producing an all-steel and an all-composite vehicle are given, excluding the marginal cost of the engine. The price is constant at $20,769, so the profit margin can be calculated with either the $1,360 95 kW engine or the $1,700 155 kW engine.

	Mid-size Car			
APV	*50,000*		*150,000*	
	All Steel	All Comp.	All Steel	All Comp.
Variable	$15,243	$16,070	$15,243	$16,070
All. Equip.	$712.7M	$675.6M	$807.0M	$762.7M
All. Bld.	$67.7M	$49.1M	$90.5M	$134.7M
Tool	$135.4M	$47.0M	$144.3M	$114.7M
Unit Cost				
w/ 95kW	$21,367	$21,248	$18,546	$19,224
w/ 155kW	$21,726	$21,607	$18,905	$19,583
Price	$20,769	$20,769	$20,769	$20,769
Profit Margin				
w/ 95 kW	-3%	-2%	11%	8%
w/ 155kW	-5%	-4%	9%	6%

Table 20 Mid-size car parametric cost model summary at 50,000 APV and 100,000 APV

As the table shows, the all-steel and the all-composite cars are unprofitable at 50,000 APV, though composites lose slightly less money per vehicle. At 150,000 APV, however, both cars are profitable but the steel car does better, earning a profit margin of 11% with the 95 kW engine (versus 8% for the composite car) and 9% with the 155 kW engine (versus 6% for the composite car).

3.2.4 Demand Uncertainty Model

To understand how demand for particular vehicles in the U.S. passenger car market varies over their sales life, I studied annual sales data for a group of similar cars over the first six years of their production. I chose to analyze sales data for subcompact and compact cars (as classified by the EPA) because the large number of vehicles in these categories increased the data sample size compared to that of other car market segments. However, I restricted my analysis to vehicles that maintained the same body and closure style over this six-year period, to control for the fact that automakers often make re-tooling investments in fresh exteriors over the production life of otherwise unaltered vehicles, which can cause endogenous demand shifts.

Annual U.S. sales data for the first six full years of production (or less for some newer model vehicles) was obtained from *Automotive News* for the following eight cars: Chrysler PT Cruiser, Ford Focus, Acura TSX, Kia Rio, Pontiac G6, Infinity G35, Chevrolet Cobalt, and Hyundai Tiburon. The annual sales level for each year was then normalized by the sales in the first full year of production, identified as *production year 0*. For example, as Table 21 indicates, the Ford Focus entered the U.S. market some time during 1999, so 2000 is *production year 0* and all subsequent annual sales levels are normalized by the sales in 2000. In the case of the Ford Focus, sales dropped steadily each year and were only 65% of their initial level five years later.

	Year	***U.S. Sales***	***Production Year***	***Normalized Sales***
Ford Focus	1999	55,846		
	2000	286,166	0	1.000
	2001	264,414	1	0.924
	2002	243,199	2	0.850
	2003	229,353	3	0.801
	2004	208,339	4	0.728
	2005	184,825	5	0.646

Table 21 Annual sales normalization for Ford Focus

Figure 30 plots the normalized sales data for all eight cars. The trends illustrate that some cars' sales behave like the Focus, while others inch up each year, and still others oscillate around their initial sales level. The overall sales trend of the entire market appears to exhibit zero growth with some volatility from year to year.

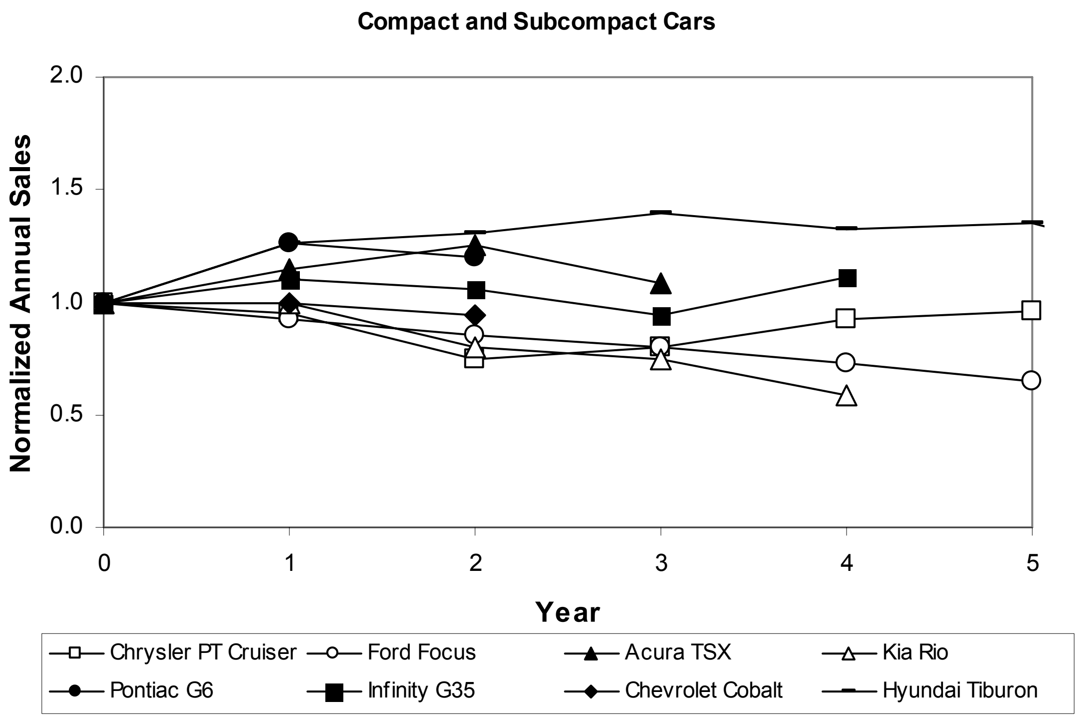


Figure 30 Normalized annual sales for eight cars

To model this pattern of demand uncertainty, I experimented with different *u* values in the binomial lattice presented in chapter two (with [1+u/1-u] evolution) and compared the resulting spread of demand observations predicted by the lattice to the actual spread of normalized annual vehicle sales. Figure 31 and Figure 32 present the results of this matching exercise, comparing the lattice outcome with $u = 0.08$ and $p = 0.5$ (simulating no growth) to the normalized sales data. For reference, note that the implied standard deviation of the demand observations in year 5 is 18%.

By visual inspection, the calibrated binomial lattice model appears to fairly well characterize the observed demand uncertainty in the compact and subcompact market.

Although more sophisticated means of gauging the goodness of fit between the observed sales data and the binomial lattice outcome were investigated, such as attempting to regress the sales data using time-series cross-sectional statistics methods, ultimately a visual inspection was judged to be suitably precise given the scope of the project and the purpose of the case study.

These lattice values are thus used to simulate demand uncertainty for each car modeled in this thesis, given the assumption that each car market segment exhibits similar demand trends.[4] Note that the starting sales level at year 0 is the expected annual sales predicted by the market share model. Annual sales profiles in a subsequent year are determined by multiplying the initial sales level by the set of demand observations for that year. The probability of each state is then determined by the associated probability lattice (generated according to the method illustrated in chapter two with $p = 0.5$), resulting in the PDF illustrated by Figure 33, which provides a visual representation of sales trends.[5]

A "no uncertainty" condition is simulated when the binomial lattice is calibrated with $u = 0.0$ and $p = 0.5$

[4] A useful area of further research might study patterns of demand uncertainty in different market segments and comment on the assumption made here that demand in each market behaves similarly

[5] The binomial lattice only generates a discrete PDF for the individual demand observations, but a continuous approximation was graphed in the figure to make the trends over time easier to see.

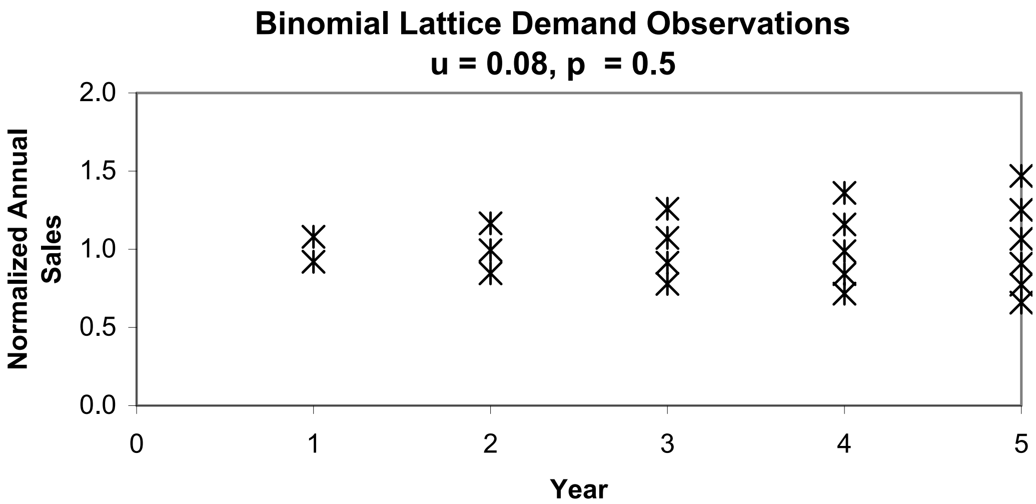


Figure 31 Binomial lattice observations, u = 1.08, p = 0.5

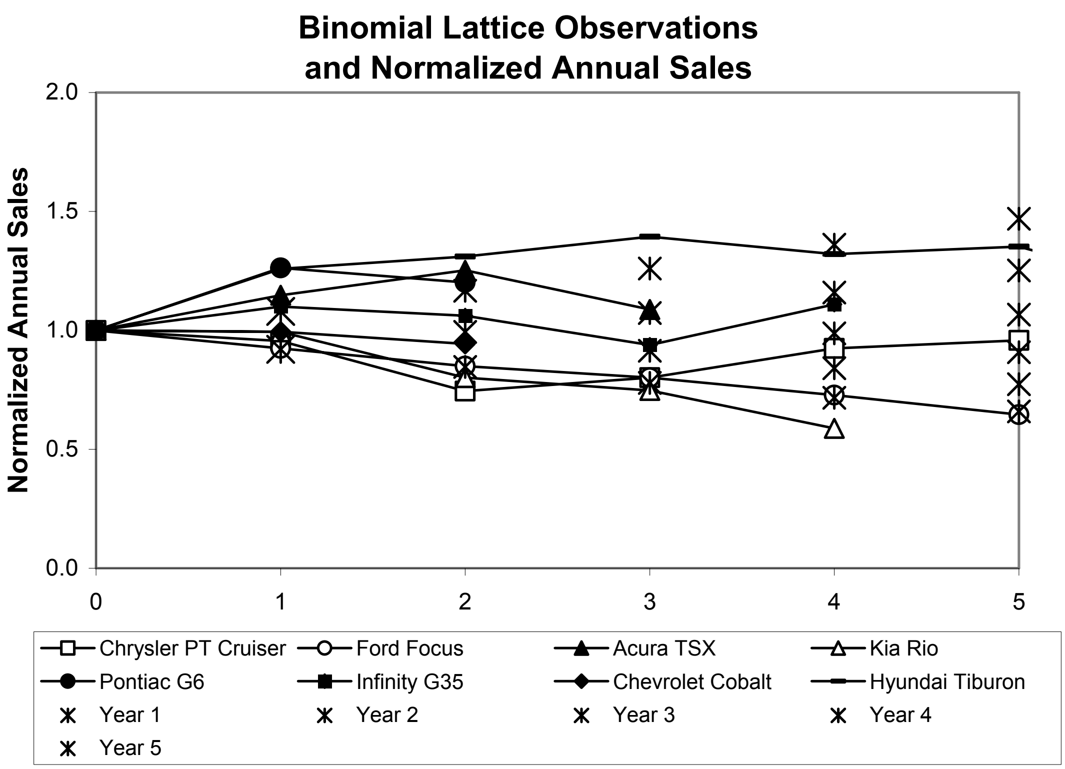


Figure 32 Binomial lattice observations and normalized annual sales data

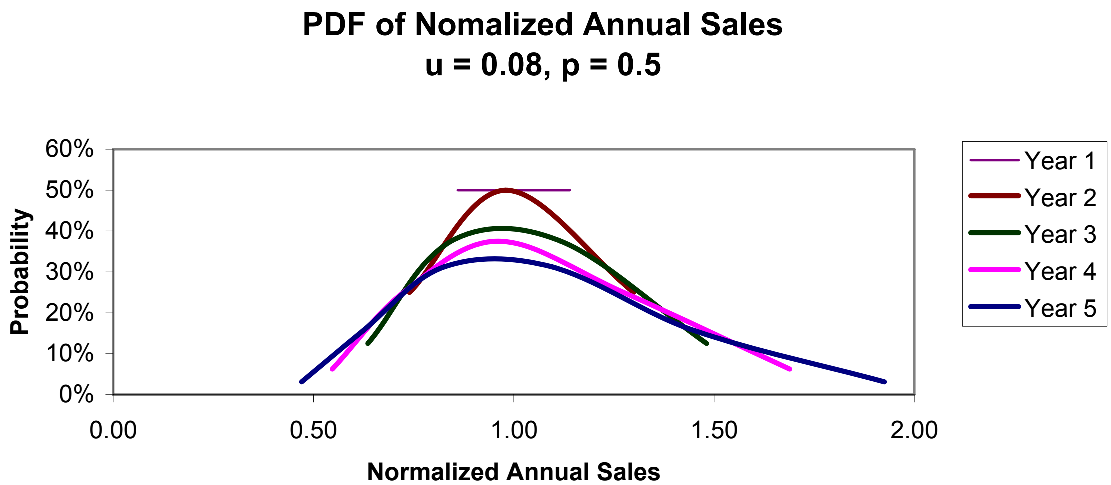


Figure 33 PDF of normalized annual sales with uncertainty

3.2.5 Regulatory Model

Depending on the fuel economy of the fleet and the number of vehicles sold in a given year, the regulation policy model determines compliance with or assesses penalties due to a simplified CAFE policy defined in Equation 19 and Equation 20 (page 69). Table 22 presents the range of policy scenarios considered in the analysis: a CAFE standard at 27.5 mpg (baseline) and 35 mpg, and penalties at \$5.50 (baseline), \$15.00, and \$50.00. The CAFE standards were chosen because they correspond to the current level and the 2020 upgrade, while the CAFE penalties were chosen to simulate the current level, a moderate upgrade, and a very aggressive increase.

CAFE standard (mpg)	***CAFE penalty ($/0.01 mpg infraction per car)***
(baseline) 27.5	*(baseline)* 5.50
35.0	15.00
	50.00

Table 22 CAFE policy scenarios

As CAFE is a sales-weighted fuel economy standard and sales vary according to the outcomes of the demand uncertainty model, both the fleet CAFE value and any applicable CAFE penalty are treated as stochastic variables. Determining the present value of the expected CAFE penalty requires a multi-step process outlined in Table 23.

First, the annual sales of each car in the fleet at each demand observation are determined. Next, the fleet CAFE and firm CAFE penalty are determined for each demand state, applying Equation 19 and Equation 20. Knowing the probability of being in each state, the expected CAFE penalty for each year is determined. These expected CAFE penalties are then discounted by a discount rate (12%) and summed, to give the present value of the expected CAFE penalties over the life of the project.

		Period 0	Period 1	Period 2…
Step 1	**small car** mpg	sales volume	sales volume sales volume	sales volume sales volume sales volume
	mid-size car mpg	sales volume	sales volume sales volume	sales volume sales volume sales volume
	luxury car mpg	sales volume	sales volume sales volume	sales volume sales volume sales volume
Step 2		CAFE penalty	CAFE penalty CAFE penalty	CAFE penalty CAFE penalty CAFE penalty
Step 3		p(observation)	p(observation) p(observation)	p(observation) p(observation) p(observation)
Step 4		E[CAFE penalty]	E[penalty]	E[penalty]
Step 5		E[penalty]/(1+r)	E[penalty]/(1+r)	E[penalty]/$(1+r)^2$
Step 6	**PV(E[penalty]) =**	sum(all discounted expected CAFE penalties)		

Table 23 Expected firm CAFE penalty calculation

3.2.6 NPV Calculation

The only values that still need to be determined in order to calculate the expected NPV of each of the cars as outlined in Table 6 (page 70) are the after tax cash flows, which requires first determining the net revenue and effective tax rate. For a given year *t* and demand observation *n*, net revenue is given by

$$net\ revenue_{t,n} \quad = \quad (price \times annual\ production\ volume_{t,n}) - total\ annual\ cost_{t,n}$$

Equation 50

where *price* is the price of each car identified earlier in Chapter Two. The after tax cash flow is then

$$after\ tax\ CF_{t,n} \quad = \quad net\ revenue_{t,n} \times (1 - tax)$$

where *tax* is the effective tax rate for the firm, assumed to be 34%.[6]

After all the expected after tax cash flows for five years have been found by multiplying the array of after tax cash flows by the array of associated demand probabilities (per Table 6), the expected cash flows are discounted at 12% and summed to give the expected NPV for the car project.

The total NPV for the fleet is then the sum of all individual car project NPVs and the present value of the expected CAFE penalty:

$$E[NPV_{fleet}] \quad = \quad E[NPV_{small\ car}] + E[NPV_{mid\text{-}size\ car}] + E[NPV_{luxury\ car}] - PV(E[CAFE\ \ penalty])$$

Equation 51

[6] This is a simplistic view of tax that affects all car projects equally. However, the functionality to consider tax was included in the model so that more sophisticated treatments which consider the tax benefits of capital asset depreciation (among others) can be added later.

Chapter 4: Case Study Results and Analysis

This chapter presents the results of the case study outlined previously: a three vehicle fleet (small car, mid-size car, luxury car), optimized by net present value of cash flows over five years of production with respect to four decisions for each vehicle (materials choice for body-in-white, materials choice for closures, engine size, and production capacity). The first section discusses optimal fleet decisions and the ways that materials choice influences both project NPV and the production volume at which it becomes economically efficient to transition from manufacturing with composites to manufacturing with steel (known as the competitive crossover). These initial analyses are performed in market environments with and without uncertainty, holding the baseline CAFE scenario constant. The second section studies the effect of alternative CAFE scenarios on optimal fleet decisions, in the absence of demand uncertainty. Finally, a summary of competitive crossovers is presented at the end of the section.

4.1 Baseline CAFE scenario

The baseline CAFE scenario corresponds to the current CAFE standard (27.5 mpg) and the current CAFE penalty ($5.50 per 0.1 mpg infraction per car), both calculated according to the simplified CAFE model detailed in chapter three.

4.1.1 Optimal Fleet Choice at Reference Market Size

Table 24 presents the optimal fleet under the baseline CAFE scenario and no demand uncertainty, at the reference market size (using the implied market size figures for each car presented earlier in Table 9, on page 85). Note also that while the functionality to investigate different powertrain tunings was built into the optimization model, all case study scenarios were analyzed holding the final drive variable constant at 1.0 (the default value).

optimal fleet	Reference Market Size No Demand Uncertainty Baseline CAFE		
	Small Car	**Mid-size Car**	**Luxury Car**
Decision Variables			
Body-in-White	steel	steel	**composite**
Closures	steel	steel	**composite**
Engine	95 kW	95 kW	**155 kW**
Capacity (% of expected year 1 sales)	110%	110%	110%
Performance and Market Model Predictions			
Fuel Economy (mpg)	30.4	28.6	21.1
Acceleration (0-60 sec)	9.1	10.6	7.6
Expected Year 1 Sales	231,132	172,469	28,284
Regulatory Model and NPV Results			
Fleet CAFE (mpg)		**28.8**	
PV(CAFE penalty)		**$0.0**	
Fleet E[NPV]		**$2.5b**	

Table 24 Optimal fleet with no uncertainty, baseline CAFE

As the table indicates, the optimal fleet under these circumstances includes a small car with a steel body, steel closures and small engine, a mid-size car with a steel body, steel closures and small engine, and a luxury car with both composite body, composite closures, and large engine. All three cars are produced in plants with annual production capacities of 110% of their expected first full year of sales. The fleet CAFE is

28.8 mpg (above the 27.5 mpg standard, so no CAFE penalty is applied) and the expected NPV of the entire project is $2.5 billion (considering cash flows from all five years).

Before investigating the specific factors that are driving the materials and engine choices, first consider the production capacity decisions. Without any demand uncertainty, the expected demand in the first year is 100% likely and constant over the life of the project because there is assumed to be no market growth. Given that demand is perfectly known and unvarying, there is no benefit to building a plant with excess capacity. By this logic, the best production capacity decision for each car should be 100% of the expected annual year one sales, but 100% is not a choice as the optimization problem is currently framed. Instead, the available production capacity choices are 110% or 125% of expected year one sales, so each car project has been driven to the smaller of the two.[7] The stated result thus doesn't present the optimal solution considering all alternatives, but rather the best choice given the available options in the framed problem. This caveat applies to all results presented here.

Turning to the materials results, the most straightforward to explain are those for the luxury car, which is being sold at an annual production volume of 28,284. At this low production volume, composites enjoy a production cost advantage compared to steel. Furthermore, the lightweighting effects afforded by using composites—in terms of improved fuel economy and improved acceleration—only add to this value. Therefore, steel is totally dominated in this case.

[7] 100% capacity was not included as an option in the no demand uncertainty scenarios in the interest of keeping the production capacity options the same for the scenarios with and without uncertainty. As will be shown later, the production capacity decision can alter the competitive crossover between steel and composites.

At the high production volume of the small car (231,132), and the volume of the mid-size car (172,469), however, steel is much more attractive. At these volumes the average cost of producing the composite body-in-white is approximately $700 more than the steel body and the average production cost of the composite closures is approximately $150 more than steel. In order to choose composites over steel in either of these applications, the marginal production cost penalty of using composites should be less than the marginal benefit of improved fuel economy and improved acceleration that they provide.

In the modeling framework at hand, this benefit derives from two sources: (1) from the increased market share that the firm sees when it improves the performance (fuel economy and acceleration) of a modeled vehicle relative to the market-reference car, and (2) from the reduced or eliminated CAFE penalties that may result from improved fleet fuel economy. The value of the second benefit may be quite significant if the use of composites eliminates CAFE penalties entirely by raising fleet CAFE from just under the standard to just above it. Even if composites cannot *eliminate* CAFE penalties, though, they may still have some value in *reducing* penalties by raising a sub-standard fleet fuel economy to a higher, but still sub-standard level.

Engine choice is influenced by a related tradeoff. Without CAFE, the engine decision balances the higher cost of the large engine and its better acceleration but worse fuel economy against the lower cost of the small engine and its worse acceleration but better fuel economy. With CAFE, however, there might be an additional benefit to using the smaller engine—the possibility of eliminating or reducing CAFE penalties by improving fuel economy (albeit at the expense of acceleration, unlike the case of composites). This could possibly be the reason for the 95 kW engine in the small and mid-size car. As this thought exercise demonstrates, understanding the firm's cost-benefit calculation given all technology combinations and the resulting fleet CAFE/CAFE penalties is exhausting work—hence the use of an optimization model.

But by setting the CAFE standard to 0 mpg and re-running the optimization we can compare the new results to the baseline case and see if the 27.5 mpg CAFE policy is indeed constraining the problem. As it turns out, performing this experiment yields the same optimal fleet decisions as before, so the policy is in fact not constraining. (The results table is identical to Table 24 so it has not been reproduced.)

Since CAFE is not constraining, the technology decisions are being driven by the performance-derived value which the firm sees through market share gains when fuel economy or acceleration improve. While the market model that is implemented in the spreadsheet optimization tool utilizes several relationships that calculate this market share gain directly, these performance-market share relationships can be translated into performance-*value* relationships by (1) observing the shift in the market share curves due to a change performance and then (2) altering the price to reset the resulting market share back to the reference market share. The price that negates the market share gain is equivalent to the consumer's willingness to pay for that performance improvement. Essentially, this method observes two points on the shifted demand curve, as illustrated in Figure 34.

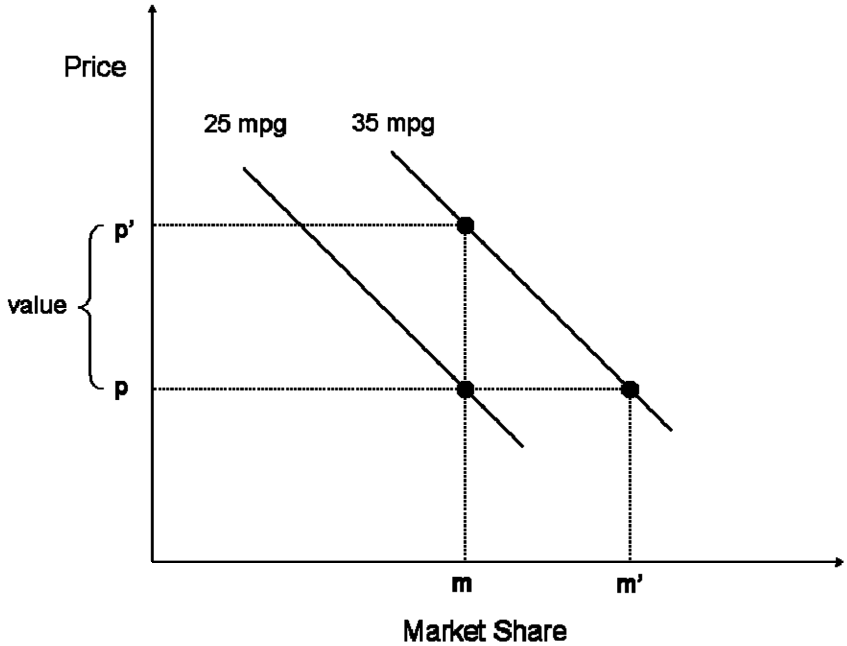


Figure 34 Method of determining value to due a performance shift

The first step in the process begins at the lower left point. This point represents the market share *m* that a car with 25 mpg fuel economy and price *p* garners. When the fuel economy of the car is improved to 35 mpg at the same price, the market share increases from *m* to *m'*. If the price of that car is then increased to price *p'*, (using a relationship between price and market share), the market share is reset to the level of the 25 mpg car. The difference between *p* and *p'* represents consumers' willingness to pay for a 10 mpg fuel economy improvement.

Bjelkengren devised and employed such a method for each car using the performance-market share relationships previously identified in this thesis in conjunction with a price-market share relationship that she also observed from the Market Insight data. More information on this method, including the price-market relationships, can be found in Bjelkengren's master's thesis (Bjelkengren 2008).

The resulting performance-value relationships are illustrated in graphical form below, first in absolute measures (mpg vs. dollars, seconds vs. dollars), and then as percent fuel economy improvement vs. dollar value and percent acceleration improvement vs. dollar value. Note that Bjelkengren only reported the value change due to an *improvement* in performance from the reference vehicle's performance. To plot these curves I have assumed that the value of losing performance is equal in magnitude and opposite in sign to the value of gaining performance. This assumption was necessary because some of the modeled vehicles analyzed in this thesis have worse performance than the reference car Bjelkengren used to derive the market share relationship, depending on the engine option chosen here.

An inspection of the value curves which are plotted as a function of percent performance changes reveals that all three car markets value fuel economy changes linearly, with the luxury car market most sensitive to fuel economy variations from the reference level. (Figure 37) Yet the acceleration value curve portrays a different story. Figure 38 indicates that the small car market is most sensitive to acceleration changes from reference, but that this trend decreases as acceleration changes grow, until the small car market becomes indifferent to acceleration improvements or reductions of +20%/-20% from the reference 0-60 time. The mid-size car market follows a similar pattern though it is less sensitive to a given acceleration change than the small car market. The luxury car market, in contrast to the other two, continues to value acceleration changes linearly over the range of acceleration variations studied.

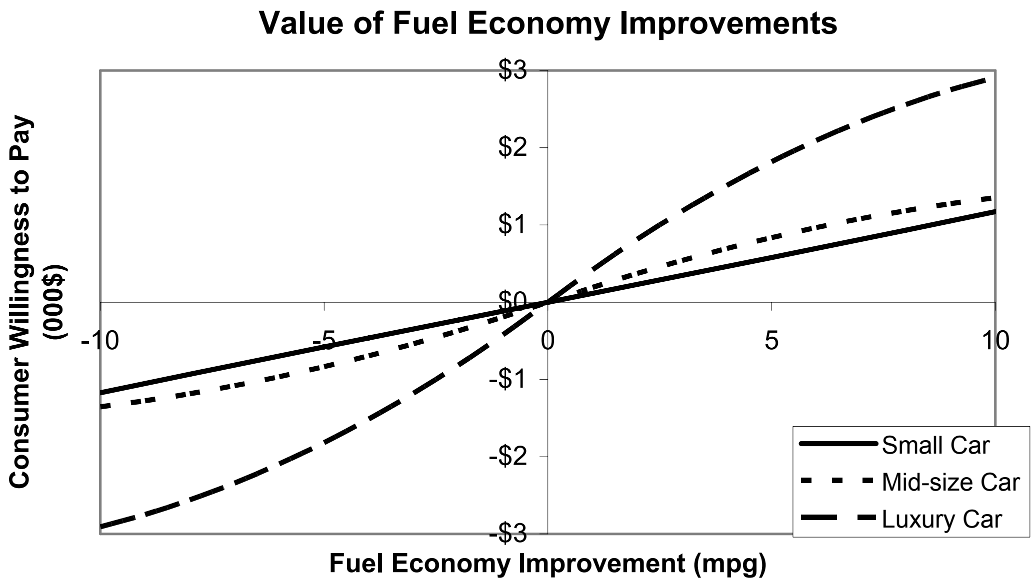


Figure 35 Value of fuel economy improvements

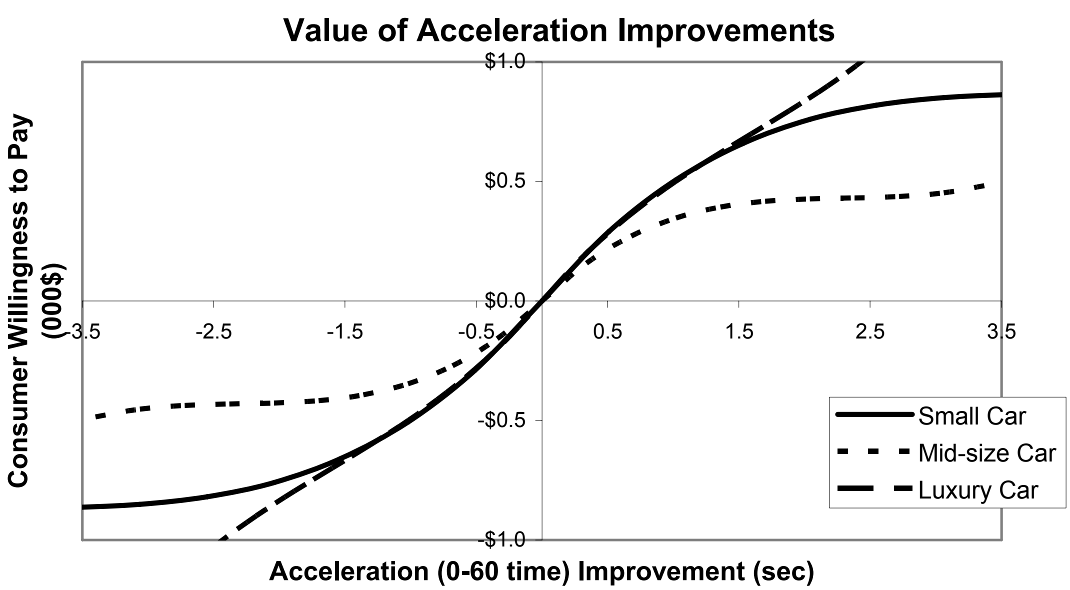


Figure 36 Value of acceleration improvements

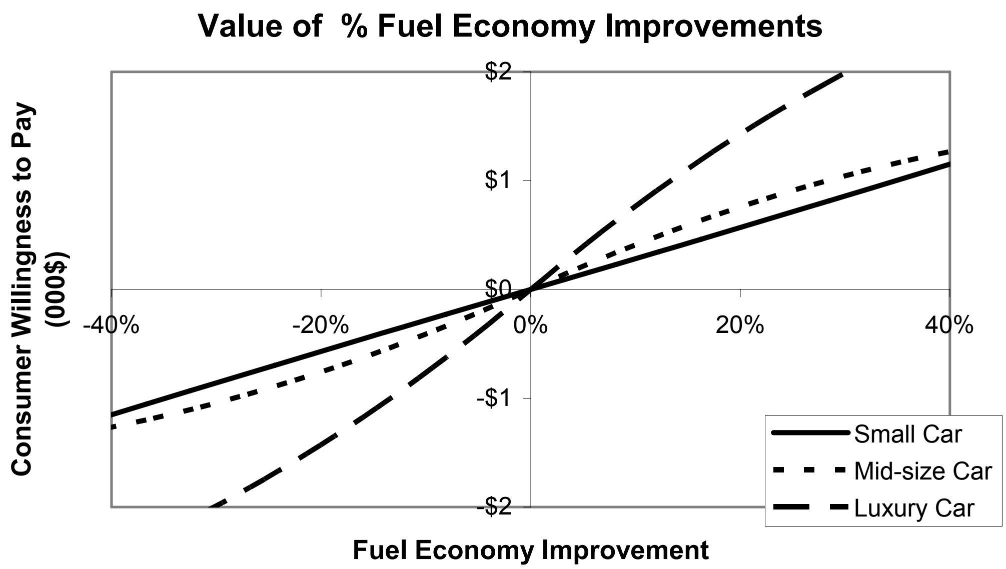


Figure 37 Value of (percent) fuel economy improvement

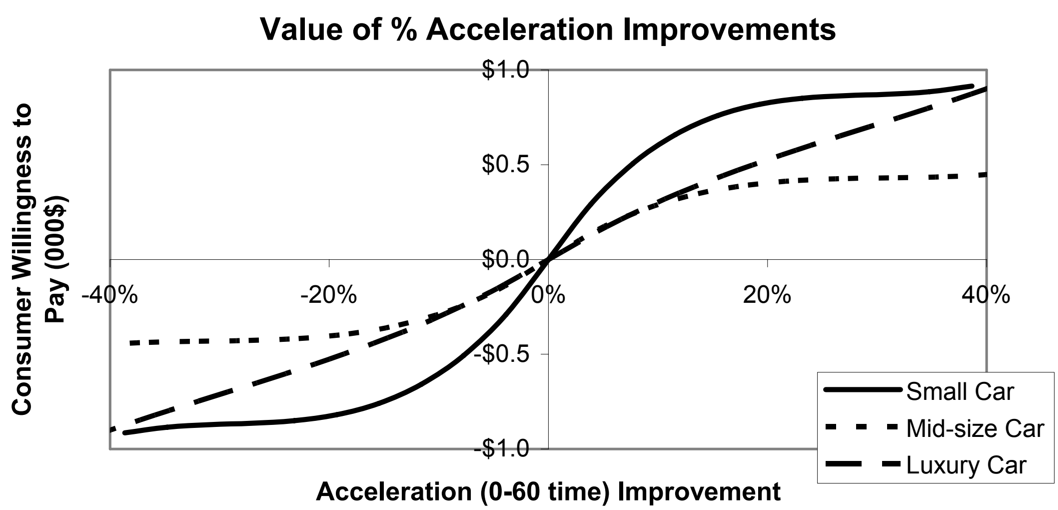


Figure 38 Value of (percent) acceleration improvement

Table 25 uses these value curves as a guide to walk through a back of the envelope cost-value analysis for using either steel or composite closures in the mid-size car with a steel body and a 95 kW engine at the reference market size.

	Market Reference Mid-size car	*95 kW Mid-size Car Steel Body Steel Closures*	*95 kW Mid-size Car Steel Body Composite Closures*
Closure Set Mass (kg)		124.8	79.3
Total Vehicle Mass (kg)		1502.2	1422.9
Δ Vehicle Mass (kg)			-45.2 (-3%)
Acceleration (0-60 sec)	8.1	10.6	10.3
Δ Acceleration (sec)		-2.5	-2.2
Value Due to Δ acc		**-$430**	**-$430**
Fuel Economy (mpg)	22.2	28.6	28.9
Δ Fuel Economy (mpg)		6.4	6.7
Value Due to Δ fe		**$1045**	**$1080**
Total Value		**$615**	**$650**
		at ~170,000 APV	
Net Value of Using Composites		**$45**	
Cost Penalty of Using Composites		**-$150**	

Table 25 Cost-value analysis for composite and steel closures in mid-size car at reference market size

As the table indicates, using the composite closure set saves 45 kg, or 3% of total vehicle mass compared to the car with steel closures. The 45 kg savings is large relative to the mass of steel closures, but small when the total car is considered.

Next, the acceleration and fuel economy of the cars using steel and composites are determined by means of the performance model. (The results printed in the table are an output of the ADVISOR-based statistical regressions detailed in Chapter Three.) Note that the 95 kW engine used in the modeled mid-size cars is likely much smaller than the engine used in the reference mid-size car from which the market share relationships were determined, which causes the acceleration of the modeled vehicles to be much slower and the fuel economy to be much higher, relative to the reference. The most important factor for this analysis, however, is the *relative* difference between the performance of the steel and composite vehicle, not the overall difference between either modeled vehicle and the reference car. For example, while each modeled vehicle is much slower than the reference car (the steel car is 2.5 seconds slower and composite car is 2.2 seconds slower), using composites improves the 0-60 time by three tenths of second (10.3 sec vs. 10.6 sec) compared to using steel. This is roughly a 3% difference, which is consistent with the 10-10 rule approximation that holds that a 3% mass reduction should improve fuel acceleration time by 3%. (In this case, the 3% mass reduction is the total vehicle mass reduction afforded as a result of using composite closures instead of steel.)

But this performance advantage isn't translated into any value advantage because the mid-size car acceleration-value curve flattens out beyond acceleration improvements or reductions of +2 and -2 seconds relative to the reference car (Figure 36). Even though composites only improve performance by 0.3 sec, or 3%, compared to steel, the absolute difference between composites and the reference car is more than 2 seconds (about 25% of the 8.1 seconds reference acceleration for the mid-size car). The underlying causes of the shapes of these value curves (and the market share curves from which they are derived) should be investigated further,[8] but for now this result suggests that the reference cars and the technology options should have been chosen such that the anticipated range of the technology-influenced performance variations in the modeled vehicles occurs within a domain where the associated market responses are non-zero. Better still; one of the modeled engines should have been chosen to mimic the actual engine of the reference

[8] At the lower extreme this behavior probably doesn't make sense. If acceleration is truly awful the market share (and thus the value) should approach zero.

car, which would have yielded some car options that replicated the performance of the reference car. Then the performance shift due to a lightweight materials-influenced mass reduction (in a modeled car with engine similar to the reference car) would have occurred around the origin of the performance-market share curves where the response is non-zero and also probably most accurate. In the end, the both of the modeled vehicles have a value loss of about $430 due to acceleration.

This problem is less significant for fuel economy because the fuel economy-value curves are approximately linear over a large range of fuel economy changes from the reference value (origin). As the table indicates, the modeled vehicle with the steel closures has a fuel economy of 28.6 mpg, while the fuel economy of the composite closure vehicle is 28.9 mpg, both more than 6 mpg greater than the reference car. The fuel economy advantage of using composites compared to steel is 0.3 mpg, approximately 1.0% better than steel. This is fairly consistent with the relevant engineering rule of thumb (10-5 rule for fuel economy) which holds that a 3% total vehicle mass reduction should improve fuel economy by about 1.5%. In relation to the reference car, the fuel economy improvements yield $1045 of value for the car with steel closures and $1080 of value for the car with composite closures.

Considering the value loss from slower acceleration and the value gain from improved fuel economy, the total performance-derived value is $615 for the car with steel closures and $650 for the car with composite closures. The net value of using composites is the difference between these two figures, $45. The net cost of using composites is the production cost penalty associated with manufacturing composite closures at the reference market scale, corresponding to approximately 170,000 units per year. At this volume, the average production cost of the composite closure set is about $150 more than steel. As the net cost of using composites ($150) is greater than the net value of using composites ($45), steel is the better choice. Similar estimates show that steel is preferred for the body of the mid-size car and both the closures and body for the small car.

Finally, note that the small and mid-size cars are equipped with the small engine while the luxury car has the more powerful option. Table 26 presents a cost-value analysis to examine the factors affecting engine choice (heeding the finding that CAFE is not constraining), using the case of an all-composite luxury car.

	Market Reference Luxury Car	***95 kW Luxury Car All Composite***	***155 kW Luxury Car All Composite***
Engine Mass (kg)		123.0	160.0
Total Vehicle Mass (kg)		1611.5	1648.5
Δ Vehicle Mass (kg)			-37 (-2%)
Acceleration (0-60 sec)	6.95	11.2	7.58
Δ Acceleration (sec)		-4.3	-0.63
Value Due to Δ acc		**-$2,600**	**-$340**
Fuel Economy (mpg)	18.7	27.8	21.2
Δ Fuel Economy (mpg)		6.4	6.7
Value Due to Δ fe		**$2,765**	**$1000**
Total Value		**$165**	**$660**
Net Value of Using 155 kW engine		**$495**	
Cost Penalty of Using 155 kW engine		**-$360**	

Table 26 Cost-value analysis for small and large engine in luxury car at reference market size

As the table shows, using the smaller engine saves mass (the table reports that the car with the larger engine is 37 kg heavier) and offers much better fuel economy—but much slower acceleration than the reference car, resulting in a net value of $165. The larger engine, by contrast, yields similar acceleration and slightly better fuel economy than the reference car, affording a $660 relative value increase. The net value of the larger engine is thus $495, which is greater than its $360 cost penalty (the marginal cost difference of the two engines is $1,700 - $1,360), making it the preferred choice. Note that the production cost of the engines are assumed to be constant, regardless of production volume, so this analysis should hold for any market scale, assuming no additional regulation costs. However, this choice could go the other way if the cost penalty of the large engine were only $140 more, implying that the result is sensitive to engine costs and suggesting that an investigation of the robustness of the engine cost relationship used in this thesis would be insightful.

Two important points should be made before continuing to discuss the rest of the results. First, the cost-value analysis for the engine further reveals that the performance of some modeled car combinations is vastly different than the reference cars used to construct the market share relationships, suggesting that the market response to these atypical modeled vehicles might be questionable. For example, the previous table implies that using a 95 kW (127 hp) engine in a $50,000 luxury car to achieve 11.2 seconds 0-60 mph time will only result in a $2,600 value loss per car, but no luxury car has been sold in recent years with such sluggish performance. The true value loss from such an engine choice could easily be much higher. Second, while the previous analyses are useful to get a quick idea of the directional effects caused by different technology choices, they do not fully explain the optimization results because they do not present an exhaustive treatment of all marginal options. For example, the decision to use composite or steel closures in the mid-size car depends on their marginal costs and benefits considering the rest of the technology decisions which affect fuel economy and acceleration. In the sample calculation this was defined as a 95 kW engine and steel body-in-white, but the analysis will look different if the closure choices are compared in a car with a 95 kW engine and composite body-in-white, because the market values acceleration changes nonlinearly. In the case where the rest of the vehicle includes a composite body, the car's acceleration will start at a higher point even before the closures materials option is considered. This might mute the effect of further acceleration increases that could be realized by choosing to manufacture the closure set from lightweight composites. This type of marginal analysis is accomplished in the optimization model because the NPV of every technology combination is calculated.

The optimization results presented in this section hold for the reference market size, but changes to this market size (and thus the associated production volumes) reveal more of the competitive dynamics of composites and steel, which have already been shown to vary at least on a cost basis.

4.1.2 Optimal Fleet Sensitivity to Market Size

Table 27 presents the optimal fleet choices at five different reference market scales: 20%, 40%, 60%, 80%, and 100% of the reference market size. In each of these cases, the market size for each car was reduced by the stated percentage. Given that the interesting cost dynamics between composites and steel occur at low production volumes, only lower market size sensitivities are presented here. However, it should be noted that optimizations were run at market sizes between 100% and 150% of the reference size without observing any changes to the optimal fleet choices.

As the table shows, the optimal fleet choices at the reference market size are robust until the market is reduced to 20% of the reference size, at which point the small and mid-size cars become all composite vehicles. This result isn't surprising, given that the annual production for these vehicles at 20% of the reference market size is approximately 49,000 APV and 35,000 APV, respectively. These production volumes are well below the cost-competitive point of composite body production and composite closure production. However, note that the optimal fleet as a whole isn't profitable at this scale, yielding a $0.6 billion loss to the firm over the life of the project.

optimal fleet	**No Demand Uncertainty Baseline CAFE**				
percent of reference market size	***0.2***	***0.4***	***0.6***	***0.8***	***1.0***
Small car					
Body-in-White	**composite**	steel	steel	steel	steel
Closures	**composite**	steel	steel	steel	steel
Engine	95 kW	95 kW	95 kW	95 kW	95 kW
Capacity	110%	110%	110%	110%	110%
Fuel Economy (mpg)	31.5	30.4	30.4	30.4	30.4
Acceleration (0-60 sec)	8.4	9.1	9.1	9.1	9.1
Expected Year 1 Sales	48,634	92,453	138,679	184,906	231,132
Mid-size car					
Body-in-White	**composite**	steel	steel	steel	steel
Closures	**composite**	steel	steel	steel	steel
Engine	95 kW	95 kW	95 kW	95 kW	95 kW
Capacity	110%	110%	110%	110%	110%
Fuel Economy (mpg)	29.6	28.9	28.9	28.9	28.9
Acceleration (0-60 sec)	9.7	10.3	10.3	10.3	10.3
Expected Year 1 Sales	35,076	68,988	103,481	137,975	172,469
Luxury car					
Body-in-White	**composite**	**composite**	**composite**	**composite**	**composite**
Closures	**composite**	**composite**	**composite**	**composite**	**composite**
Engine	**155 kW**	**155 kW**	**155 kW**	**155 kW**	**155 kW**
Capacity	110%	110%	110%	110%	110%
Fuel Economy (mpg)	21.2	21.2	21.2	21.2	21.2
Acceleration (0-60 sec)	7.6	7.6	7.6	7.6	7.6
Expected Year 1 Sales	5,657	11,314	16,971	22,628	28,284
Fleet CAFE (mpg)	29.9	28.8	28.8	28.8	28.8
PV(CAFE penalty)	$0	$0	$0	$0	$0
Fleet E[NPV]	-$0.6b	$0.1b	$1.0b	$1.7b	$2.5b

Table 27 Optimal fleet choice sensitivity to market size

To closely examine the competitive dynamics between composites and steel, more narrow production volume crossover regimes were determined by running multiple optimizations using market scaling factors between 20% and 40% (for the small and mid-size car), and well above 100% for the luxury car. If necessary, the NPV of competing projects (small car with composite body and small car with steel body, for example) were themselves plotted over a range of market sizes to better characterize the causal trends.

4.1.3 Competitive Crossovers without Uncertainty

One of the general hypotheses underlying this work is that the effects of two factors: (1) performance-derived value and (2) asymmetric returns due to demand uncertainty and capacity limits, may advantage composites compared to steel in automotive applications. This implies that when these effects are considered, the production volume at which it becomes economically efficient to transition from using composites to using steel shifts from the cost-competitive production volume to a higher one.

However, using an optimization model with several production capacity options confounded this examination because the competitive production volume crossovers sometimes move in unanticipated ways—even in the absence of demand uncertainty, which can be illustrated by a simplified example. First consider two competing projects: steel and composites. At small market sizes,[9] composites are less expensive than steel and offer some performance-derived value, implying that the NPV of the composite project is higher than steel. (See Figure 39, which presents a simple plot of production cost and NPV on the same market size axis.) As market size (and production volume) increase, the

[9] Cost-competitive crossovers are usually discussed in terms of annual production volume, but the NPV model used in this thesis scales by total market size because demand (production volume) is determined as a percent of this size, subject to market preferences for vehicle performance. Given one market size, the demand/production volume for a steel car and composite car can be different if they have different performance.

production cost benefit that composites enjoy decreases until they cost the same as steel. Yet there is still some value to using composites because of the performance gains that lightweighting affords, so the NPV of the composites project will still be higher than steel until some point after the cost-competitive crossover. The relative cost of using composites continues to increase until it is greater than the value of using composites, at which point the efficient choice transitions to steel. This crossover shift (from the cost-competitive point to a higher one) is illustrated in Figure 39 by the shift of *cr* to *cr'*.

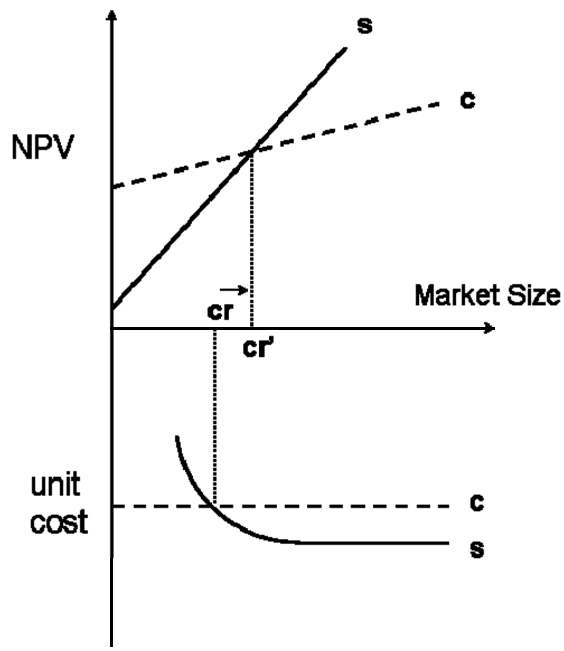


Figure 39 Performance-derived value of composites shifts the competitive crossover to higher market size/production volume (not to scale)

Now consider the effect of increasing the production capacity of both projects by 10% without any additional sales This reflects the case in the baseline scenario in which each car project builds plant capacity to 110% of expected annual sales without any possibility of selling above 100% of expected sales. The extra 10% capacity is thus unutilized. As capital costs are greater but revenues remain constant, the NPV of a project built with capacity of 110% of expected sales should be shifted down from the NPV of a project built to exactly 100% expected sales. Furthermore, steel is more capital-intense than composites, so the cost spent on 10% extra capacity for the steel project is greater than the cost spent on 10% extra capacity for the composites, which causes the steel NPV curves to shift more than the composite NPV curves. Figure 40 graphs the resulting NPV plots. As a graph shows, the steel NPV curve shifts more, from *steel 100%* to *steel 110%*, than the composite curves do, *composite 100%* to *composite 110%*. This moves the crossover point from *cr'* to *cr''* at a higher production volume.

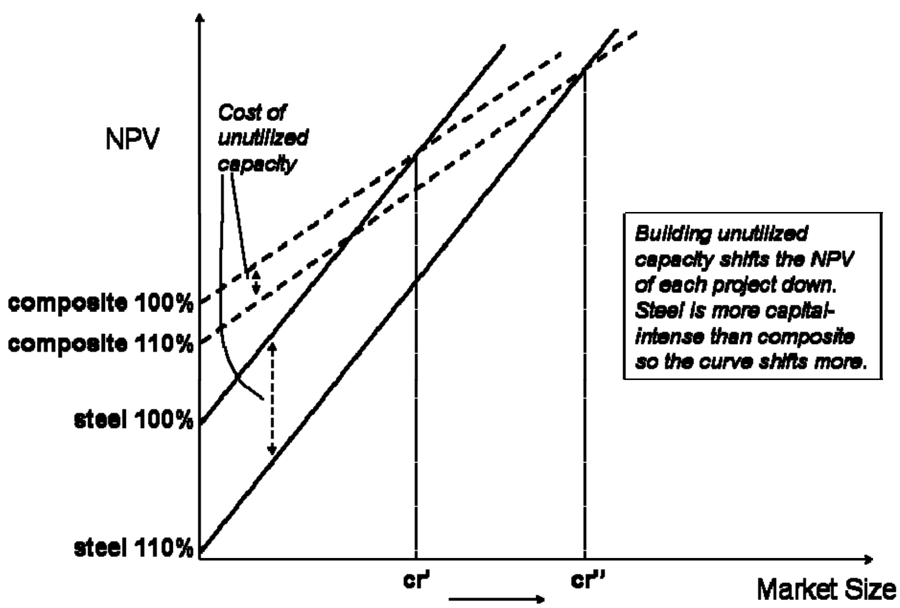


Figure 40 Building unutilized capacity shifts the crossover to higher market size/production volume (not to scale)

However, this simplification ignores the fact that recurring costs can lead to discontinuous NPV jumps. For example, the tool costs that composite body-in-white production entails are modeled in this thesis as a $10,000,000 investment every 20,000

APV of production capacity.[10] When this cost is lumped into total cost and spread over all units produced over the life of the project, as is done in the unit cost curves, it isn't very noticeable, but when it is viewed in absolute terms it appears as a sharp downward spike in the total composite NPV, shown in Figure 41.

Furthermore, when plant capacity is built to accommodate 110% of expected sales, the expected production volume at which another unit tool investment is required will be smaller than the case for which plant capacity is built to 100% of expected sales. Table 28 helps explain.

Expected Sales/Prod. Vol:	**17,000 APV**	**18,000 APV**	**19,000 APV**	**20,000 APV**
	purchase $10m tools for every 20,000 APV of capacity			
Build Capacity to:				
100% of Expected Sales				
Plant Capacity (APV)	17,000	18,000	19,000	20,000
Required Tool Investment	$10m	$10m	$10m	$20m
110% of Expected Sales				
Plant Capacity (APV)	18,700	19,800	20,900	22,000
Required Tool Investment	$10m	$10m	$20m	$20m

Table 28 Composite body tool investments at 100% capacity and 110% capacity

The table presents the required tool investments for two strategies: building plant capacity to 100% of expected sales and building capacity to 110% of expected sales, at four expected sales levels. As the table shows, when the expected sales level is 19,000 APV, the strategy which calls for building plant capacity to 110% of this level plans for a plant capacity of 20,900 APV, meaning that two unit tool investments of $10 million must be made. By contrast, the strategy which builds only to 100% of expected sales does

[10] Recall that all tool investments are assumed to be made at once, at the beginning of the project based on the planned plant scale—not as the tools wear out.

not plan to make the second unit tool investment until the expected sales level reaches 20,000 APV.

This implies that not only is the NPV of the composite project at 110% capacity shifted down from the 100% composite NPV curve (because of the added cost of unutilized capacity), but each investment spike also occurs at a smaller market scale. If the steel NPV curves happen to intersect the composite NPV curves along the discontinuity, it can appear that the crossover has shifted left, contrary to the above case without recurring investments.

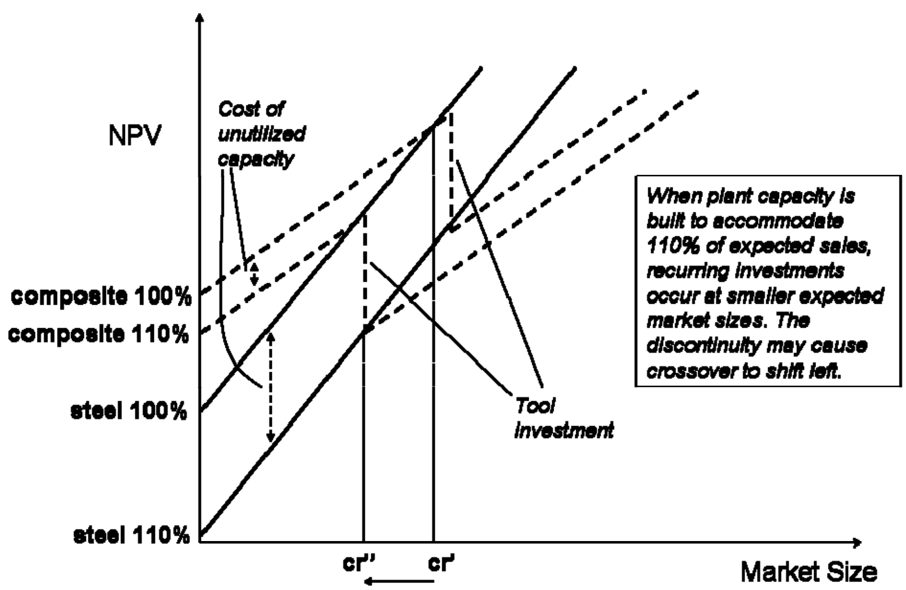


Figure 41 Tool investment discontinuity causes crossover to shift to lower market size/production volume (not to scale)

To understand how large this effect can be, competitive NPV crossovers were observed (via the optimization model) for the body-in-white and closures for each car at 110% and 125% production capacity—in addition to 100% production capacity. These crossovers are presented in Table 29 along with the crossover predicted by the cost model only (which effectively assumes 100% production capacity).

As mentioned previously, the NPV model predicts crossovers at market sizes, not production volumes, because the production volume is discontinuous over the technology crossover. (After switching to steel along the market size crossover, vehicle performance deteriorates and demand falls.) But in the aim of making this information easier to comprehend, I have presented the crossover points by production volume, not market size. The values listed in Table 29 correspond to the demand level for the composite material option at the market scale just before the NPV model predicts a switch to steel.

	Cost Model Predicted Crossover	**NPV Optimization Model Predicted Crossover** No Demand Uncertainty Baseline CAFE		
annual production volume		***Small Car***	***Mid-size Car***	***Luxury Car***
Body	~54,000			
100% Capacity		~58,000	~56,000	~98,000
110% Capacity		~54,000	~54,000	~90,000
125% Capacity		~51,000	~50,000	~93,000
Closures	~64,000			
100% Capacity		~80,000	~70,000	no crossover
110% Capacity		~77,000	~67,000	no crossover
125% Capacity		~75,000	~66,000	no crossover

Table 29 Comparison of cost-competitive crossover and NPV crossover at three capacities

As the technology decisions have been shown to be unconstrained by the baseline CAFE policy, the NPV crossovers reported here are similarly unaffected by fuel economy policy. Therefore, the table primarily documents two effects: (1) by considering market value, the crossovers are shifted to higher production volumes compared to the cost-competitive points, but (2) adding unused capacity often makes composites *less* competitive due to the effect of recurring investments explained above.

The magnitude of the crossover shift due to the first effect, performance-derived market value, depends on the vehicle application. The body-in-white crossover is shifted just 2,000 to 4,000 APV in the small and mid-size car, but more than 40,000 APV (to 98,000 APV) in the luxury car when capacity is limited to 100%. The crossovers are even higher for the closure set: 80,000 in the small car, 70,000 in the small car, and there is no crossover predicted for the luxury car, implying that the value of using composites in this application is always greater than their cost for any production volume.

The difference in the magnitude of the crossover shift from one car to another is due to the relative value that each vehicle market places on performance improvements, while the difference between the body and the closures is due to the rate at which each becomes less cost-competitive with steel as market size (or production volume) increases. Figure 42 and Figure 43 expand the production cost plots of the body-in-white and the closure set around the cost-competitive point to illustrate the latter distinction. As the figures show, at a point 20,000 APV beyond the cost-competitive crossover for body-in-white production, composites are at a $500 disadvantage, while at a point 20,000 APV beyond the cost-competitive crossover for closure production, composites are only at a $50 disadvantage. Furthermore, the composite closure cost disadvantage never gets much greater than $180, even at very high production volumes (see Figure 25).

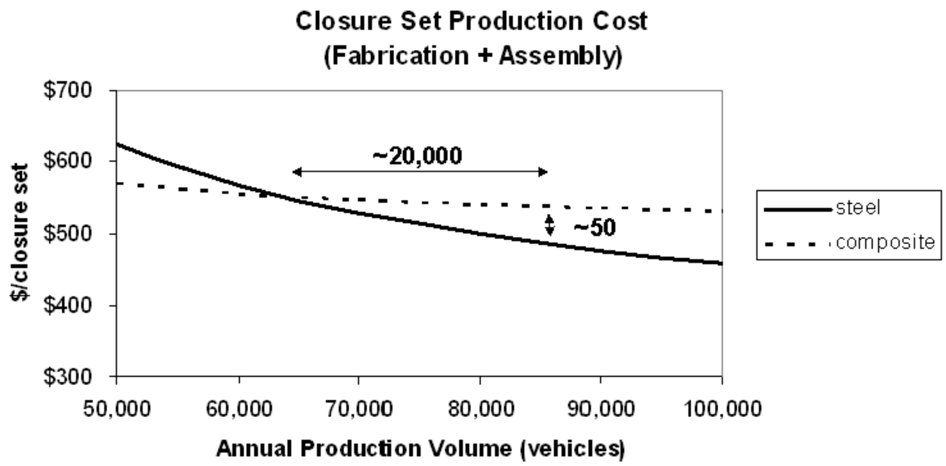


Figure 42 Expanded view of steel and composite closure production cost

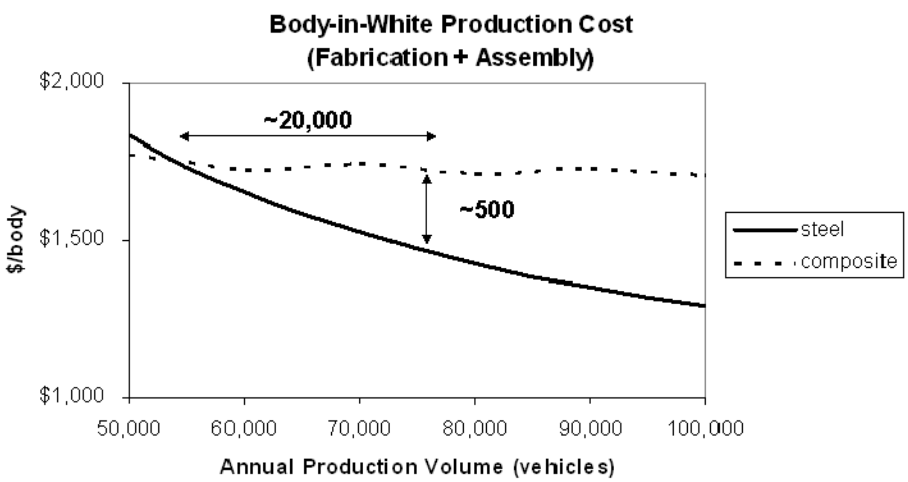


Figure 43 Expanded view of steel and composite body-in-white production cost

Yet as documented earlier, many modeled mid-size car variations have predicted acceleration times that are far worse than the reference car and lie in a regime on the mid-size car performance-value curve that is essentially flat, meaning that the small but important predicted acceleration advantage of using composites compared to steel in the mid-size car is worthless in terms of its calculated NPV. As a consequence, the mid-size car crossovers predicted by the baseline analysis are probably too conservative. To study how this modeling problem can be mitigated, the next section presents the crossover results following the implementation of a variation to the mid-size car performance model.

4.1.4 Crossover Sensitivity to Market Model (Value) Adjustment

Table 30 presents the NPV competitive crossovers for the mid-size car at 110% capacity following a re-centering of the reference car's acceleration from 8.1 seconds to 10.1 seconds. By increasing the reference acceleration, the acceleration of the modeled mid-size cars using either steel or composites are much closer to the origin of the performance-value curve, where even small variations (the acceleration gain from using lightweight composites) yield nonzero market value responses. This improves the net value of using composites (compared to steel) and shifts the crossover point for both the body-in-white and the closures to higher production volumes. Note that the closure crossover shifts much more than the body-in-white crossover because the cost penalty of using composite closures increases more slowly than the cost penalty of using a composite body. (See previous figures)

annual production volume	Cost Model Predicted Crossover	NPV Optimization Model Predicted Crossover No Demand Uncertainty, 110% Capacity Baseline CAFE		
		Small Car	***Mid-size Car***	***Luxury Car***
Body	54,000			
No Adjustment		~54,000	~54,000	~90,000
Mid-size Car + 2 sec			~58,000	
Closures	64,000			
No Adjustment		~77,000	~67,000	no crossover
Mid-size Car + 2 sec			~93,000	

Table 30 Mid-size car crossover shift due to a re-centering of the reference car acceleration

4.1.5 Optimal Fleet Choice under Demand Uncertainty

Having investigated the effects of performance-derived value and excess unutilized capacity on the competitive dynamics between steel and composites, the NPV optimization model was re-run including the demand uncertainty simulation, still holding CAFE at the baseline scenario. The optimal fleet choice results at five market sizes under this scenario are presented in Table 31. At this market size resolution the only observable differences between the optimal choices without uncertainty and with uncertainty are the production capacity of the luxury car and the production capacity of the mid-size car after it transitions to an allnsteel vehicle. The optimal production capacity choice is now 125% of expected sales for these cars, implying that they are better suited to capture the upside of demand uncertainty.

The underlying reason relates to the profit margin on each vehicle. The low profit margin on the small car (6% when capacity is at 110% of expected sales) means that the marginal profit of selling more cars is small compared to the cost of adding even more excess capacity. By contrast, the mid-size steel car has a profit margin of 10% and the luxury car has a profit margin of 21% (each calculated at 110% of expected sales), meaning that the benefit of adding extra capacity to capture potential upside sales can be large.

optimal fleet	**With Demand Uncertainty Baseline CAFE**				
percent of reference market size	***0.2***	***0.4***	***0.6***	***0.8***	***1.0***
Small car					
Body-in-White	**composite**	steel	steel	steel	steel
Closures	**composite**	steel	steel	steel	steel
Engine	95 kW	95 kW	95 kW	95 kW	95 kW
Capacity	110%	110%	110%	110%	110%
Fuel Economy (mpg)	31.5	30.4	30.4	30.4	30.4
Acceleration (0-60 sec)	8.4	9.1	9.1	9.1	9.1
Expected Year 1 Sales	48,634	92,453	138,679	184,906	231,132
Mid-size car					
Body-in-White	**composite**	steel	steel	steel	steel
Closures	**composite**	steel	steel	steel	steel
Engine	95 kW	95 kW	95 kW	95 kW	95 kW
Capacity	110%	125%	125%	125%	125%
Fuel Economy (mpg)	29.6	28.6	28.6	28.6	28.6
Acceleration (0-60 sec)	9.7	10.6	10.6	10.6	10.6
Expected Year 1 Sales	35,076	68,988	103,481	137,975	172,469
Luxury car					
Body-in-White	**composite**	**composite**	**composite**	**composite**	**composite**
Closures	**composite**	**composite**	**composite**	**composite**	**composite**
Engine	**155 kW**	**155 kW**	**155 kW**	**155 kW**	**155 kW**
Capacity	125%	125%	125%	125%	125%
Fuel Economy (mpg)	21.2	21.2	21.2	21.2	21.2
Acceleration (0-60 sec)	7.6	7.6	7.6	7.6	7.6
Expected Year 1 Sales	5,657	11,314	16,971	22,628	28,284
Fleet CAFE (mpg)	29.9	28.8	28.8	28.8	28.8
PV(CAFE penalty)	$0	$0	$0	$0	$0
Fleet E[NPV]	-$0.6b	$0.1b	$1.0b	$1.7b	$2.5b

Table 31 Optimal fleet choice under uncertainty, baseline CAFE

The information that isn't conveyed in the table above, though, is whether the crossovers have shifted at all under demand uncertainty, and if in fact the hypothesis that demand uncertainty improves the competitive position of composites compared to steel is supported.

4.1.6 Crossover Sensitivity to Demand Uncertainty

Analyzing the crossover shifts due to demand uncertainty is not straightforward given the way the problem has been framed and the unexpected capacity effects explained previously. When the optimization model simulates demand uncertainty and offers two production capacity decisions, the best choices for a given car may transition from composites at 110% capacity to steel at 125%, in which case the crossover point may be affected by the capacity effect. Likewise, the best production capacity choices for a given car will always be 110% without uncertainty, but if the best choice is 125% with uncertainty (for either the steel or composite option around a crossover), the crossover point may similarly have moved in unanticipated ways.

Table 32 highlights these concerns, as the crossovers predicted by the NPV model appear to have moved to a lower production volume for several vehicle applications. The notable exception is the crossover for the closures in the small car, which has shifted from 77,000 APV at 110% capacity without uncertainty to 80,000 APV at 110% capacity with uncertainty.

	Cost Model Predicted Crossover	NPV Optimization Model Predicted Crossover Baseline CAFE		
		Small Car	***Mid-size Car***	***Luxury Car***
annual production volume		*(composite capacity – steel capacity)*		
Body	~54,000			
No Uncertainty		~54,000 (110%-110%)	~54,000 (110%-110%)	~90,000 (110%-110%)
With Uncertainty		~54,000 (110%-110%)	~54,000 (110%-125%)	~93,000 (125%-125%)
Closures	~64,000			
No Uncertainty		~77,000 (110%-110%)	~67,000 (110%-110%)	no crossover
With Uncertainty		~80,000 (110%-110%)	~66,000 (125%-125%)	no crossover

Table 32 Crossover shifts under demand uncertainty

To better understand the competitive dynamics of different projects under uncertainty, the case of the mid-size car closures is investigated in detail. Figure 44 presents the NPV of the three competing options around the mid-size car closure crossover in terms of the difference between the competing project and the low-volume choice, without uncertainty. That is, the NPV of the composite closures at 110% capacity is taken as a reference because it is the optimal choice at small market sizes in the absence of uncertainty. Then, the NPV of each of the three other alternatives: steel with 110% capacity, composites with 125% capacity, and steel with 125% capacity, are plotted in terms of the difference between the NPV of the reference project (composites at 110%) and the respective alternative.

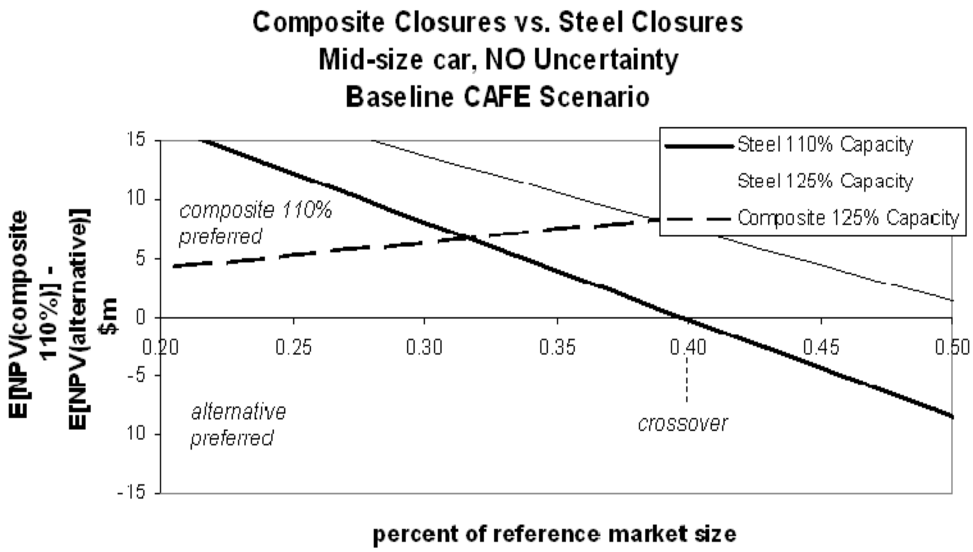


Figure 44 Mid-size car NPV crossover for closure set, no uncertainty

Any project plotted with an NPV difference below $0 in Figure 44 should be preferred to the reference project because the negative NPV difference implies that the NPV of the alternative project is greater than the reference. Thus, the line plotting the difference between the NPV of the reference project and the NPV of composites with 125% capacity is always positive because in the absence of uncertainty, the extra unused capacity makes the 125% composites project less valuable. However, the NPV of the alternative steel projects are downward sloping because they are becoming more competitive with composites as market size (and production volume) increase. The crossover occurs at a market scale of just under 40% of the reference size (~67,000 APV), when the efficient choice transitions to steel with 110% capacity.

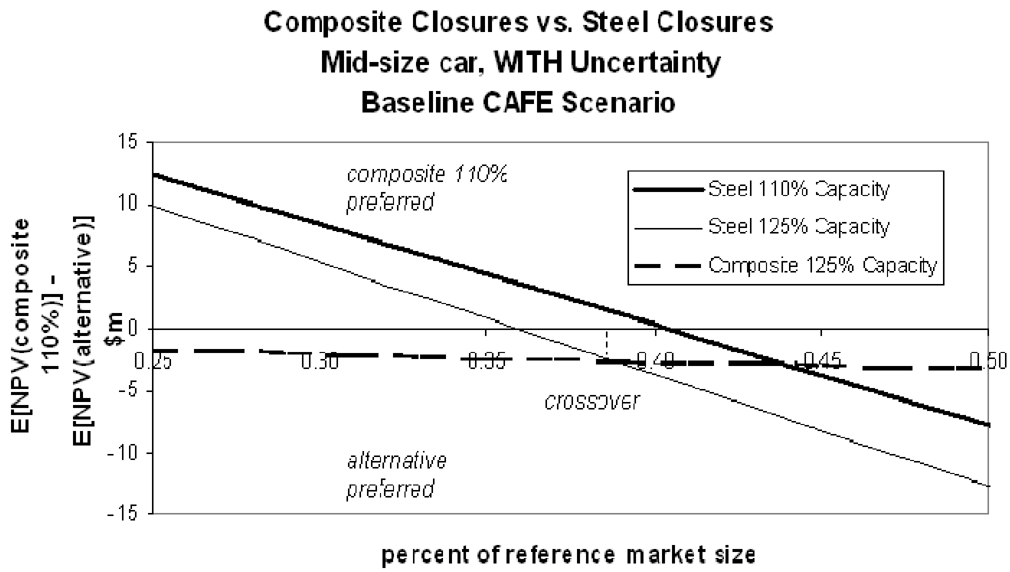


Figure 45 Mid-size car NPV crossover for closure set under uncertainty

The competitive dynamics look different under uncertainty, as shown in Figure 45. Now the composites project with 125% capacity is preferred to the reference composites project with 110% capacity at small market sizes (the NPV difference line is negative) because of the profit margin effect explained earlier—the mid-size car has a high enough profit margin to be able to take advantage of building 125% capacity. The crossover now occurs when the NPV curve for composites with 125% capacity crosses the NPV curve for steel with 125% capacity at a market scale of approximately 0.39 (~66,000 APV). This is a small shift of 1,000 APV to a smaller production volume.

Even if opposing effects would otherwise cause the crossover point to shift to higher production volumes, the above analysis suggests that the dominant effect causing the mid-size car closure set crossover to shift to a smaller production volume under uncertainty is the unanticipated movement caused by capacity-influenced recurring investment schedules. For further proof, note that without uncertainty, the crossover point for the mid-size car closure set also shifted to smaller production volumes when capacity was increased from 110% to 125% (Table 29). As the optimal choice under uncertainty similarly switches from 110% capacity to 125% after the crossover here, the underlying causes are likely related.

Yet if the capacity effects can be mitigated—by studying the crossovers at the same production capacity with and without uncertainty—the effect of demand uncertainty on the crossover point can be isolated. Figure 46 presents the results of such an analysis, plotting the NPV difference between composite closures in the mid-size car with 110% capacity and steel closures with 110%, with and without uncertainty. The solid line plots the NPV difference between composites and steel without uncertainty and shows that the crossover point is, as documented above, at a market size just below 40% of the reference size. When the NPV model simulates demand uncertainty, however, the NPV difference curve shifts to the right and the crossover moves to a market scale just greater than 40% of the reference size. This crossover shift corresponds to an annual production volume of about 1,500 APV.

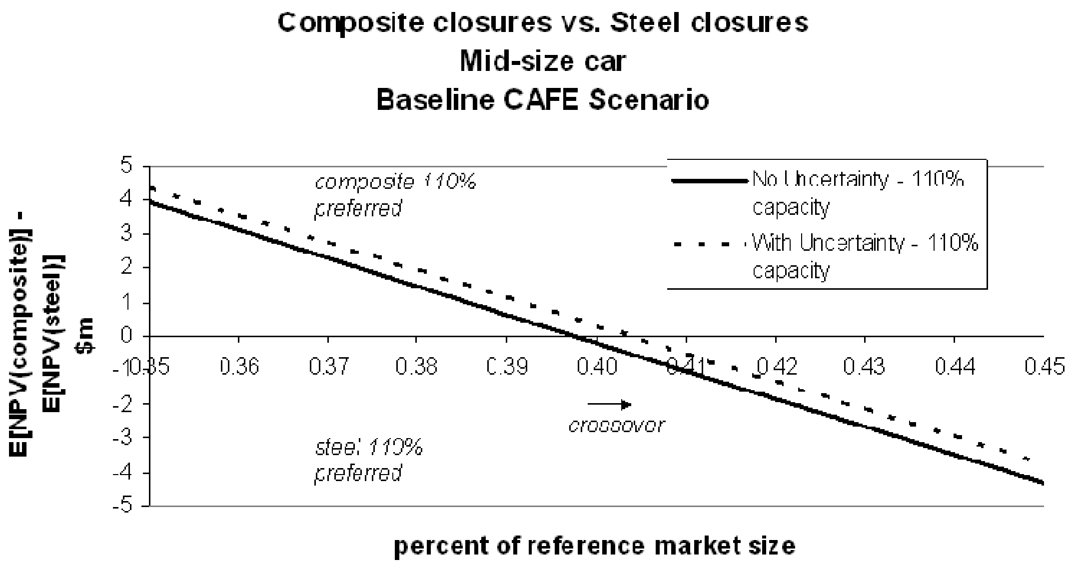


Figure 46 Crossover shifts right under uncertainty at same production capacity

The magnitude of this shift is small but the direction is consistent with the hypothesis that was originally posited: composites are more competitive compared to steel in an environment of demand uncertainty. Investigating the above case further reveals the mechanics that underlie the competitive shift, as calculated by the NPV simulation.

Figure 47 plots the difference of the year five cash flow NPV for each project, without uncertainty. When demand uncertainty is considered at any expected market size, the simulation model calculates the probability of discrete cash flows according to the distribution established by the binomial lattice model for period five, subject to the constraint that capacity is limited to 110% of the sales level at the expected market size.

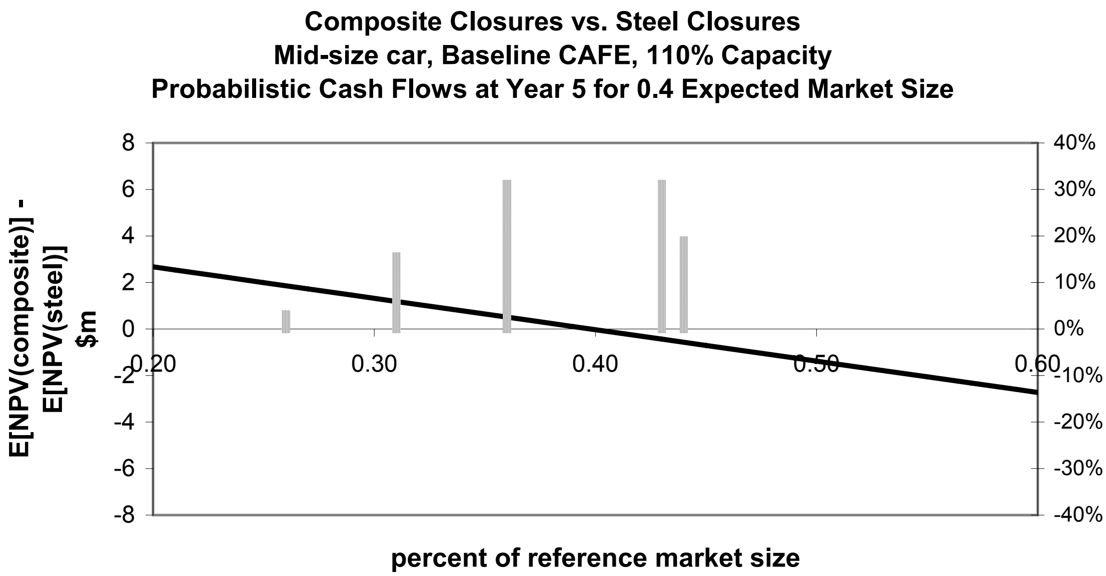


Figure 47 NPV composites – NPV steel and discrete probabilities for 0.4 expected market size

For an expected market size of 0.4, the location of each of the probabilistic year five cash flows is indicated by a light grey bar. The height of the bar represents the cash flow's likelihood. Table 33 walks through the uncertainty simulation. In year five there are six demand observations with likelihood 3.1%, 15.6%, 31.2%, 31.2%, 15.6%, and 3.1%. Each demand observation is represented by a different market scale that corresponds to the spread of the binomial lattice at year five, assuming that 0.4 is the starting lattice value (instead of 1.0). These observations are 0.26, 0.31, 0.36, 0.43, 0.44, and 0.44. The last two values are constrained by the production capacity of the plant (110% of 0.4 = 0.44), given the assumption that demand will always equal production volume up to the capacity of the plant. These constrained demand observations are the analytical representation of the primary asymmetry which was used to support the hypothesis that composites should become more competitive under uncertainty.

Composite Closures vs. Steel Closures Mid-size Car, Year 5 Cash Flows at 0.4 mean Market Scale, 110% capacity, Baseline CAFE							
	no uncertainty	*with uncertainty*					
		obs 1	obs 2	obs 3	obs 4	obs 5	obs 6
Probability	100%	3.1%	15.6%	31.2%	31.2%	15.6%	3.1%
Market Scale	0.40	0.26	0.31	0.36	0.43	0.44	0.44
PV(composite)-PV(steel)	$0.05m	$1.90m	$1.19m	$0.60m	-$0.43m	-$0.65m	-$0.65m
E[NPV Δ]	$0.05m (composite preferred)	$0.17m (composite preferred)					

Table 33 NPV calculation under uncertainty for 0.4 expected market size

As the table reports, after multiplying the demand observations with their associated probabilities, the expected NPV difference between composites and steel is slightly larger with uncertainty than without. ($0.17m vs. $0.05m) This indicates that composites are more competitive near this market size and will exhibit a crossover to steel at higher production volumes.

Although the effect is small and often muddled by opposing effects, this analysis confirms that when projects with similar capacities are compared, composites can be more competitive in an environment of demand uncertainty.

4.2 Alternative CAFE Scenarios

The next sections report the optimization results for scenarios that consider alternative CAFE policies: a 35 mpg standard and $5.50 penalty, a 35 mpg standard with a $15.00 penalty, and a 35 mpg standard with a $50.00 penalty. All of these analyses assume no demand uncertainty.

4.2.1 35 mpg

As Table 34 indicates, raising CAFE to 35 mpg without changing the CAFE penalty induces the firm to use the small engine in the luxury car at all production volumes and appears to alter the firm's materials strategy slightly (the firm is now choosing composites for the closure application in the mid-size car at 40% of the reference market size). On closer inspection, the crossovers for the closures in both the small and mid-size car have indeed shifted, making composites more competitive, but only the crossover for the body-in-white in the luxury car has moved (see Table 35 on the page following the fleet decisions chart).

Note that the firm still transitions to steel in the small and mid-size car at higher production volumes even as this strategy lowers its CAFE value and increases its CAFE penalties. With respect to the firm's total NPV, fleets at 20% and 40% of the reference market size are now unprofitable, compared to the baseline case in which only the 20% market size case lost money.

These results suggest that (1) increasing CAFE alone can improve the competitiveness of composites and (2) altering the engine is the CAFE-complying technology strategy which causes the smallest NPV reduction for the simulated automaker.

optimal fleet	**No Demand Uncertainty 35 mpg CAFE Standard, $5.50 CAFE Penalty**				
percent of reference market size	***0.2***	***0.4***	***0.6***	***0.8***	***1.0***
Small car					
Body-in-White	**composite**	steel	steel	steel	steel
Closures	**composite**	steel	steel	steel	steel
Engine	95 kW	95 kW	95 kW	95 kW	95 kW
Capacity	110%	110%	110%	110%	110%
Fuel Economy (mpg)	31.5	30.4	30.4	30.4	30.4
Acceleration (0-60 sec)	8.4	9.1	9.1	9.1	9.1
Expected Year 1 Sales	48,634	92,453	138,679	184,906	231,132
Mid-size car					
Body-in-White	**composite**	steel	steel	steel	steel
Closures	**composite**	**composite**	steel	steel	steel
Engine	95 kW	95 kW	95 kW	95 kW	95 kW
Capacity	110%	110%	110%	110%	110%
Fuel Economy (mpg)	29.6	28.6	28.6	28.6	28.6
Acceleration (0-60 sec)	9.7	10.6	10.6	10.6	10.6
Expected Year 1 Sales	35,076	68,988	103,481	137,975	172,469
Luxury car					
Body-in-White	**composite**	**composite**	**composite**	**composite**	**composite**
Closures	**composite**	**composite**	**composite**	**composite**	**composite**
Engine	95 kW	95 kW	95 kW	95 kW	95 kW
Capacity	110%	110%	110%	110%	110%
Fuel Economy (mpg)	27.8	27.8	27.8	27.8	27.8
Acceleration (0-60 sec)	11.2	11.2	11.2	11.2	11.2
Expected Year 1 Sales	5,494	10,989	16,483	21,978	27,472
Fleet CAFE (mpg)	30.51	29.5	29.5	29.5	29.5
PV(CAFE penalty)	$83m	$200m	$300m	$400m	$500m
Fleet E[NPV]	-$0.7b	-$0.1b	$0.6b	$1.3b	$2.0b

Table 34 Optimal fleet choice at 35 mpg CAFE and $5.50 CAFE penalty

annual production volume	Cost Model Predicted Crossover	NPV Optimization Model Predicted Crossover No Demand Uncertainty, 110% Capacity		
		Small Car	***Mid-size Car***	***Luxury Car***
Body	54,000			
27.5 mpg, $5.50 CAFE		~54,000	~54,000	~90,000
35 mpg, $5.50 CAFE		~54,000	~54,000	no crossover
Closures	64,000			
27.5 mpg, $5.50 CAFE		~77,000	~67,000	no crossover
35 mpg, $5.50 CAFE		~90,000	~80,000	no crossover

Table 35 Crossover shifts under 35 mpg CAFE, $5.50 penalty

4.2.1 35 mpg, $15.00 penalty

When the CAFE standard is increased to 35 mpg and the CAFE penalty is raised to $15.00, the firm continues to alter its materials strategy. The small engine is still used in the luxury car at all production volumes, but now the firm chooses composite closures at least up to 60% of the reference market size (Table 36). In fact, as Table 37 on the page following the fleet decisions shows, all crossovers for the body-in-white and closure set have shifted significantly. The NPV crossovers for the body-in-white have moved to 69,000 APV for the small car, 64,000 APV for the mid-size car, and there is now no crossover predicted for the luxury car body. Furthermore, the NPV crossovers for the closure set have shifted to 128,000 APV for the small car and 110,000 APV for the mid-size car.

optimal fleet	**No Demand Uncertainty 35 mpg CAFE Standard, $15.00 CAFE Penalty**				
percent of reference market size	***0.2***	***0.4***	***0.6***	***0.8***	***1.0***
Small car					
Body-in-White	**composite**	steel	steel	steel	steel
Closures	**composite**	steel	steel	steel	steel
Engine	95 kW	95 kW	95 kW	95 kW	95 kW
Capacity	110%	110%	110%	110%	110%
Fuel Economy (mpg)	31.5	30.4	30.4	30.4	30.4
Acceleration (0-60 sec)	8.4	9.1	9.1	9.1	9.1
Expected Year 1 Sales	48,634	92,453	138,679	184,906	231,132
Mid-size car					
Body-in-White	**composite**	steel	steel	steel	steel
Closures	**composite**	**composite**	**composite**	steel	steel
Engine	95 kW	95 kW	95 kW	95 kW	95 kW
Capacity	110%	110%	110%	110%	110%
Fuel Economy (mpg)	29.6	28.9	28.9	28.6	28.6
Acceleration (0-60 sec)	9.7	10.3	10.3	10.6	10.6
Expected Year 1 Sales	35,076	69,335	104,003	137,975	172,469
Luxury car					
Body-in-White	**composite**	**composite**	**composite**	**composite**	**composite**
Closures	**composite**	**composite**	**composite**	**composite**	**composite**
Engine	95 kW	95 kW	95 kW	95 kW	95 kW
Capacity	110%	110%	110%	110%	110%
Fuel Economy (mpg)	27.8	27.8	27.8	27.8	27.8
Acceleration (0-60 sec)	11.2	11.2	11.2	11.2	11.2
Expected Year 1 Sales	5,494	10,989	16,483	21,978	27,472
Fleet CAFE (mpg)	30.5	29.8	29.6	29.5	29.5
PV(CAFE penalty)	$220m	$520m	$800m	$1,000m	$1,400m
Fleet E[NPV]	-$0.8b	-$0.4b	$0.1b	$0.6b	$1.2b

Table 36 Optimal fleet choice at 35 mpg CAFE and $15.00 CAFE penalty

annual production volume	**Cost Model Predicted Crossover**	**NPV Optimization Model Predicted Crossover** No Demand Uncertainty, 110% Capacity		
		Small Car	***Mid-size Car***	***Luxury Car***
Body	54,000			
27.5 mpg, $5.50 CAFE		~54,000	~54,000	~90,000
35 mpg, $15.00 CAFE		~69,000	~64,000	no crossover
Closures	64,000			
27.5 mpg, $5.50 CAFE		~77,000	~67,000	no crossover
35 mpg, $15.00 CAFE		~128,000	~110,000	no crossover

Table 37 Crossover shifts under 35 mpg CAFE, $15.00 penalty

4.2.1 35 mpg, $50.00 penalty

Under the most aggressive CAFE policy, the firm chooses composite bodies-in-white up to 126,000 APV for the small and mid-size car and uses composite closures for all vehicles at all production volumes. However, note that all fleets are significantly unprofitable. Raising the CAFE penalty from $15.00 per 0.1 mpg infraction per car to $50.00 per 0.1 mpg infraction per car (an increase of more than 300%), reduced the expected NPV of each fleet by at least 300% as well

optimal fleet	**No Demand Uncertainty 35 mpg CAFE Standard, $50.00 CAFE Penalty**				
percent of reference market size	***0.2***	***0.4***	***0.6***	***0.8***	***1.0***
Small car					
Body-in-White	**composite**	**composite**	steel	steel	steel
Closures	**composite**	**composite**	**composite**	**composite**	**composite**
Engine	95 kW	95 kW	95 kW	95 kW	95 kW
Capacity	110%	110%	110%	110%	110%
Fuel Economy (mpg)	31.5	30.4	30.8	30.8	30.8
Acceleration (0-60 sec)	8.4	9.1	8.9	8.9	8.9
Expected Year 1 Sales	48,634	97,276	141,297	188,396	235,495
Mid-size car					
Body-in-White	**composite**	**composite**	**composite**	steel	steel
Closures	**composite**	**composite**	**composite**	**composite**	**composite**
Engine	95 kW	95 kW	95 kW	95 kW	95 kW
Capacity	110%	110%	110%	110%	110%
Fuel Economy (mpg)	29.6	29.6	29.6	28.9	28.9
Acceleration (0-60 sec)	9.7	9.7	9.7	10.3	10.3
Expected Year 1 Sales	35,076	70,152	105,228	138,670	173,338
Luxury car					
Body-in-White	**composite**	**composite**	**composite**	**composite**	**composite**
Closures	**composite**	**composite**	**composite**	**composite**	**composite**
Engine	95 kW	95 kW	95 kW	95 kW	95 kW
Capacity	110%	110%	110%	110%	110%
Fuel Economy (mpg)	27.8	27.8	27.8	27.8	27.8
Acceleration (0-60 sec)	11.2	11.2	11.2	11.2	11.2
Expected Year 1 Sales	5,494	10,989	16,483	21,978	27,472
Fleet CAFE (mpg)	30.5	30.5	30.1	29.8	29.5
PV(CAFE penalty)	$800m	$1,500m	$2,400m	$3,400m	$4,300m
Fleet E[NPV]	-$1.3b	-$1.5b	-$1.7b	-$1.8b	-$1.9b

Table 38 Optimal fleet choice at 35 mpg CAFE and $50.00 CAFE penalty

annual production volume	**Cost Model Predicted Crossover**	**NPV Optimization Model Predicted Crossover** No Demand Uncertainty, 110% Capacity		
		Small Car	***Mid-size Car***	***Luxury Car***
Body	54,000			
27.5 mpg, $5.50 CAFE		~54,000	~54,000	~90,000
35 mpg, $50.00 CAFE		~126,000	~126,000	no crossover
Closures	64,000			
27.5 mpg, $5.50 CAFE		~77,000	~67,000	no crossover
35 mpg, $50.00 CAFE		no crossover	no crossover	no crossover

Table 39 Crossover shifts under 35 mpg CAFE, $50.00 penalty

4.3 Summary of Competitive Crossovers

The following table summarizes the competitive NPV crossover predicted by the optimization model under the primary market demand and policy scenarios studied. This table provides a useful reference, but recall that the cost-competitive crossover is derived from an analysis at 100% capacity while the reported results are at either 110% or 125% capacity, which have different crossover dynamics.

		Cost Model Predicted Crossover	**NPV Optimization Model Predicted Crossover**		
	annual production volume		***Small Car***	***Mid-size Car***	***Luxury Car***
Body		~54,000			
Baseline CAFE	No Uncertainty		~54,000	~54,000	~90,000
	With Uncertainty		~54,000	~54,000	~93,000
Alternative CAFE	35 mpg, $5.50		~54,000	~54,000	none
	35 mpg,$15.00		~69,000	~64,000	none
	35 mpg, $50.00		~126,000	~126,000	none
Closures		~64,000			
Baseline CAFE	No Uncertainty		~77,000	~67,000	none
	With Uncertainty		~80,000	~66,000	none
Alternative CAFE	35 mpg, $5.50		~90,000	~80,000	none
	35 mpg,$15.00		~128,000	~110,000	none
	35 mpg, $50.00		none	none	none

Table 40 Summary of competitive crossovers for major scenarios

In general, the crossover results reported in Table 40 indicate that the studied policy scenarios have a much greater impact on the competitiveness of composites relative to steel, compared to the impact of demand uncertainty.

Chapter 5: Conclusions

5.1 Thesis Summary

This work was motivated by two trends in the market for and regulation of U.S. passenger vehicles which might foreshadow a shift in the competitiveness of lightweight alternative materials relative to incumbent steels in automotive applications. First, the study hypothesized that consumers' increasing demand for fuel efficient vehicles, together with the federal government's recent action to update new car CAFE standards, may advantage lightweight materials because these actions increase the value of fuel economy improvements that can be realized by vehicle lightweighting. Second, the study hypothesized that the volatile nature of market demand and the unsettled future of further fuel economy policy creates an environment favorable to certain classes of lightweight materials, such as composite polymers, which entail production processes that are less capital-intense than typical high investment steel production. This argument is based on the conjecture that rising and falling demand yield asymmetric effects given plant capacity constraints. While the high fixed cost, low variable cost characteristics of steel parts production affords steel part manufacturing firms economies of scale that improve their competitiveness relative to composite part manufacturing firms when demand rises, the benefit is limited by plant capacity. When demand falls however, the higher investments that steel production entails leaves steel part manufacturing firms exposed to large downside losses that are only limited by the size of the initial investment.

The present study tested these hypotheses by first developing a novel methodology to evaluate materials selection and engine technology decisions on the basis of their contribution to the net present value of vehicle projects, and then by applying this methodology to a relevant case study. The modeling methodology comprises a framework of five integrated models: (1) a performance model that predicts vehicle fuel economy and acceleration given total vehicle mass, engine power, and transmission tuning, (2) a market model that predicts the expected annual sales for the first year of production given fuel economy and acceleration, (3) a cost model that maps technology decisions and sales levels to fixed and variable costs, (4) a demand uncertainty model that projects a probabilistic distribution of demand/sales levels for future years, and (5) a regulatory model that determines compliance with or assesses penalties due to violation of a simplified CAFE policy. The integrated NPV model simulates all possible vehicle fleet combinations given a set of technology decisions and finds the optimal decisions by finding the vehicle fleet for which NPV is maximized.

The case study was designed to apply this methodology to a set of technology and production decisions that illuminate the competitive dynamics between incumbent steel and lightweight composite materials in two vehicle subsystems and three different vehicle markets. In total, four decisions were formulated: materials choice for body (either stamped steel or SRIM-type composite), materials choice for closure set (either stamped steel or a mixed design of SMC and RIM-type composite), engine (either 95 kW or 155 kW), and production capacity (either 110% or 125% of expected demand in the first year). These decisions were exercised for each car in a three-car fleet: a small car, a mid-size car, and a luxury car. Optimization simulations were performed in several scenarios: under a CAFE policy mimicking current CAFE with and without demand uncertainty, and then under three more stringent CAFE policies in the absence of demand uncertainty.

Several data implementation strategies were employed to carry out the case study. The performance model is based on the results of ADVISOR simulations of the default small car that is natively programmed in that software. Several ADVISOR fuel economy and acceleration tests were run across a range of values for each technical parameter that was studied (total vehicle mass, engine power, and final drive ratio), and the results were then transformed to analytical relationships between technical parameters and performance metrics (fuel economy and acceleration) by means of statistical regression.

The market model is based on the work of Catarina Bjelkengren, a contemporary MIT colleague. Bjelkengren studied current market survey data available commercially from Market Insight to derive relationships between changes in fuel economy, acceleration, and price, with predicted changes in market share for three reference cars (a small, mid-size, and luxury car). Given a selling price, these relationships were used to map the vehicle performance of a modeled car to the market share it is expected to garner in the first year of production.

The cost model primarily derives from technical cost models of materials production processes that have been previously developed at the Materials Systems Laboratory at MIT. However, instead of directly embedding these process based cost models into the NPV optimization model, the results of the more detailed PBCMs were used to formulate simple parametric relationships between production capacity and fixed costs, and between production volume and variable costs. Engine costs were determined from a relationship between engine power and cost found by Michalek. Additional costs for the remaining vehicle segments were estimated with advice from industry experts.

The demand uncertainty model was constructed using a recombining binomial lattice, similar to the approach used to model asset price uncertainty in financial options. The implemented binomial lattice model assumes that demand starts at an expected value in year zero and can move up by u percent or down by $-u$ percent in the next year at some likelihood p and $1-p$, respectively. The u and p values were calibrated by observing annual U.S. sales trends for several vehicles in the compact and subcompact car classes (by EPA definition). Annual sales data for each car were normalized by its sales level in the first full year of production and the resulting spread of sales over the next five years for all cars was matched to the outcome of a binomial lattice model with $u = 0.08$ and $p = 0.5$.

The regulatory model is a simplified version of U.S. CAFE policy. Firm CAFE is calculated by determining the sales-weighted fuel economy for the entire fleet. If the firm's CAFE is lower than the specified CAFE standard, a penalty is assessed for every 0.1 mpg infraction per car sold.

The principal findings of this research follow.

5.2 Principal Findings

1. This thesis successfully developed a method to evaluate automotive materials selection decisions considering production cost and vehicle performance-derived benefits, using established technical cost modeling techniques and readily

available market data. The current method improves on other selection methods that ignore the benefits of designing products with lightweight materials and, in addition, it incorporates the capability to study the effects of demand uncertainty and alternative regulatory policy as they affect materials selection choices.

The underlying method treats materials selection decisions like conventional business decisions. Assuming that competing designs in alternative materials are functionally sufficient (that is, that each design meets basic functional requirements), a firm's optimal design choice is the material/design which maximizes NPV.

The NPV calculation can be decomposed into the investments and operating costs required for manufacturing parts from a certain material, and the revenue or value streams that the firm expects based on the final performance of the product. As this decomposition reveals, ignoring the value differences between product designs in alternative materials obscures the true competitiveness between materials and limits the ability of a firm to understand its best product strategy.

This limitation is present in several prior analyses of automotive materials competitiveness (Kang 1998; Kelkar, Roth et al. 2001; Fuchs, Field et al. 2008), which only report the cost-competitive character of lightweight materials, not their full market competitiveness considering the performance gains achieved through mass reduction. Furthermore, analyses which attempt to place a value on vehicle lightweighting by considering only the benefit of discounted fuel savings ignore both the value of increased sales due to higher demand and the value of acceleration improvements. This work corrects these limitations because it considers the market value of fuel economy and acceleration improvements by directly incorporating performance-market relationships derived from consumer responses to detailed marketing surveys.

The current method is not far removed from Field's materials selection method, which proposes employing utility functions to determine the value of alternative materials designs (Field 1985). However, the present technique views value in light of consumer's willingness to pay for product attributes that materials choice affects, while Field's method views value in light of a material's ability to abide a diverse set of design factors which the product engineer must confront. Both methods suffer from an imperfect information problem: engineers understand the technical tradeoffs of alternative designs but perhaps not the market tradeoffs of product attributes—while consumers understand how they value alternative product attributes in the market but are mostly ignorant to the underlying technical designs.

In Field's method, this problem is manifested in the utility function itself, which is constructed from a survey of the engineer-designer's preferences for materials characteristics. Inevitably, the engineer's utility will imperfectly reflect consumer's preferences for product attributes that materials choice affects. In the current method, the imperfect information problem is manifested in the definition of the alternative designs which have been tested by their ability to provide consumer value. Except for the stated differences in acceleration and fuel economy, each design has been assumed to be equivalent from a technical perspective (and the consumer's perspective), although in fact some design alternatives may provide additional technical advantages which consumers are ignorant to or unable to value.

The current method thus doesn't solve the information problem outright, but it does present a method for incorporating consumers' utility (by means of their willingness to pay) directly into the materials selection method. While such market data may not be available for all products that require a materials selection process, this thesis has demonstrated how readily available market data can be applied to the automotive materials selection case.

Moreover, by integrating a demand uncertainty model and a regulation policy model, the current methodology allows researchers to investigate how volatile sales markets and varying fuel economy policy impinge on optimal automotive materials choices, a practical and novel advancement.

2. The value of acceleration improvements may be greater than the value of fuel economy improvements due to a vehicle mass reduction achieved by using lightweight materials.

Expanding on the engineering rule of thumb that a 10% vehicle mass reduction yields a 5% fuel economy improvement, this work suggests a corollary rule: a 10% vehicle mass reduction also yields a 10% acceleration improvement (in seconds of 0-60 mph time). Applying these rules to the reference small car studied in this thesis shows that a 10% mass reduction improves fuel economy from 24.6 mpg to 25.8 mpg and improves acceleration time from 9.6 seconds to 8.6 seconds. Using Bjelkengren's value curves presented in Chapter Four, the 5% fuel economy increase represents approximately $100 in added value, while the 10% acceleration improvement is worth approximately $500.

This observation further highlights the importance of considering all lightweighting benefits when analyzing an automotive materials selection problem. Moreover, it is interesting to note that this result holds for all three cars studied, including the economy small car. This suggests that the dominant business case for materials-enabled vehicle lightweighting that can be made currently, regardless of the type of vehicle considered, centers on acceleration improvements, not fuel economy improvements.

3. The marginal benefits of vehicle lightweighting depend on the remaining set of vehicle technology decisions. The value figures referenced above are true for performance changes from the reference car's performance, but they may be greater or smaller in magnitude if the reference performance shifts, given that the market often does not value performance changes linearly.

For example, if the vehicle in which a lightweight materials application is being considered is already equipped with a powerful engine that enables a fast acceleration time, the marginal benefits of increasing the acceleration time by materials lightweighting may be small, depending on the specific car market being considered. As Bjelkengren's value curves indicate, the markets for the small and mid-size car markets studied in this work are indifferent to acceleration improvements beyond 20% from the reference value. This result underscores the need to evaluate materials selection decisions in light of other vehicle technology decisions that influence salient performance measures such as fuel economy and acceleration.

4. When the value of acceleration and fuel economy improvements are included in a comparison of incumbent steel and lightweight composites across a range of production volumes, the competitive position of composites improves from the cost-competitive production volume to a higher one. The magnitude of this crossover shift depends on two factors: (1) consumer demand for acceleration and performance in the specific car market being studied, and (2) the rate at which composites become relatively more costly than steel as production volume increases.

With respect to the body-in-white application in the small and mid-size car, the competitive crossover considering total NPV did not shift significantly from the cost-competitive crossover at 54,000 APV, but in the luxury car this crossover shifted to approximately 90,000 APV. The notable discrepancy is due to the difference in the ways that each car market values performance improvements. While the small car and mid-size car market grow indifferent to performance improvements beyond a certain degree (their value curves flatten out), the luxury car market continues to value performance improvements for the entire range of acceleration and fuel economy studied.

Furthermore, the lack of a crossover shift for the body in the small and mid-size car is primarily a result of the marginal benefits observation described above. As most of the modeled mid-size car combinations had acceleration times that were much slower and fuel economy values that were much greater than the reference car, the market was indifferent to marginal performance differences between the modeled steel and composite mid-size car variations. However, when the mid-size car reference acceleration was increased by two seconds (to locate it closer to the range of acceleration values of the modeled mid-size car combinations), the body-in-white NPV crossover shifted from approximately 54,000 APV to approximately 58,000 APV. This shift occurred because the mid-size car market is indifferent to marginal acceleration changes that are more than two seconds from the reference value. (A 2.5 second acceleration improvement from reference is valued as much as a 2 second acceleration improvement.) Thus when the reference acceleration is 2 seconds closer to the acceleration of the modeled mid-size cars the marginal acceleration improvement of using composites results in a notable marginal benefit that is reflected in the shifted crossover point.

With respect to the closure set application, the NPV crossover shifted from the cost-competitive crossover of approximately 64,000 APV to approximately 77,000 APV in the small car, to approximately 67,000 APV in the mid-size car, and there was no crossover predicted for the luxury car (composites always preferred). When the reference mid-size car acceleration value was increased by two seconds, the closure set crossover shifted even farther, to approximately 93,000 APV.

These more pronounced crossover shifts observed for the closure set applications, relative to the body-in-white, are a consequence of the slower rate at which composite closures become more costly than steel closures. While the composite closure suffers just a $50 cost disadvantage per unit at 20,000 APV beyond the cost-competitive volume crossover, the composite-body-in-white is at a $500 disadvantage per unit by that same point 20,000 APV past its cost-competitive crossover. As the composite closures suffer a much smaller cost penalty for a given production volume step, they are competitive across a greater range of production volumes than the composite body-in-white application.

5. Demand uncertainty slightly improves the competitive position of composites relative to steel in automotive applications when projects with the same production capacity are compared and plant capacity is fixed at 110% of expected annual sales. Under these conditions, the volatility of annual sales levels observed in some segments of the U.S. car market is large enough to generate asymmetric returns to an automaker after one year. For the closure set application that was studied, the expected returns favor composites and shift the NPV competitive crossover approximately 1,500 APV for mid-size car and 3,000 APV for the small car.

This result is narrowly constructed because much of the present uncertainty analysis was confounded by difficulties related to framing problems. As the problem was solved by optimization and two possible production volumes were available, the optimal choice sometimes transitioned from 110% of expected capacity to 125% of expected capacity when uncertainty was considered. This muddied the examination of uncertainty effects because it was discovered that crossovers may shift in either direction (to higher or lower production volumes) when production capacity increases. Yet in cases where the capacity did not change after optimization (as for the small car closure set), or a separate analysis with only one capacity option was studied (as for the mid-size car closure set), the uncertainty effect could be isolated and this result reported.

With respect to the modeling of automotive demand uncertainty, the binomial lattice model well approximated the observed sales volatility. The output of the calibrated binomial lattice indicates that if the expected annual sales for a vehicle in the compact and subcompact U.S. car market were modeled as a random variable, it would be characterized by an overall growth rate of approximately 0% per year and a standard deviation of approximately 18% after five years.

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6. Over all scenarios studied in this thesis, the consideration of more stringent fuel economy policies improved the competitive position of composites to a greater degree than did the consideration of demand uncertainty.

This result suggests that the transition from the current 27.5 mpg CAFE standard to the updated 35 mpg CAFE standard will have a greater impact on the competitiveness of composites in the U.S. car market than any effects of demand uncertainty, assuming that the magnitude of demand uncertainty is and remains similar to the magnitude of demand uncertainty modeled in this work. However, it is plausible that the market will become even more volatile as the transition to a more fuel-efficient fleet intensifies.

7. The case study presented in this thesis can improve fuel economy regulators' understanding of the costs and benefits of vehicle lightweighting using composite materials, from an automaker's perspective. Moreover, the results of the alternative CAFE policy scenarios that were simulated characterize the relative industry impact that raising the standard from 27.5 mpg to 35 mpg might have versus the impact of penalty increases from $5.50 to $15.00 to $50.00 per 0.1 mpg infraction per car sold.

The last major government-sponsored work to consider the subject of lightweight materials and their potential to meet more stringent fuel economy requirements presented the subject in broad terms that simplified the production economics and generalized the benefits associated with vehicle lightweighting. (National Academy of Sciences 2002)

The study presented here, by contrast, illustrates the production cost characteristics of aggressive lightweighting strategies, their resultant performance improvements, and the attendant value added to the automaker. The results indicate that lightweight composites may be more competitive in the U.S. market than is implied by their low market penetration, yet much of this competitiveness derives from the acceleration benefit that lightweighting affords, not its fuel economy benefit. In fact, the possibility of using costless transmission tuning to favor acceleration instead of fuel economy leaves open the possibility that automakers will employ lightweight composites to achieve acceleration gains *without* fuel economy gains. This issue has been identified as an interesting direction for future work.

The case study has also demonstrated that CAFE penalty increases to $15.00 and $50.00 per 0.1 mpg violation per car can induce dramatic shifts in a firm's technology strategy, but at potentially enormous cost. With the CAFE standard at 35 mpg, an increase from $5.50 to $15.00 (approximately 275%), increased the NPV crossover by approximately 10,000 APV for the composite body-in-white and 30,000 APV for the composite closure set, although assessed CAFE penalties also rose by about 275%—from $500 million to $1.4 billion at the reference market size. Under the most aggressive penalty increase, to $50.00 (a 333% increase over the $15.00 penalty), composites totally dominate steel at all production volumes in the closure set application and luxury body—and shift the crossover to 126,000 APV for the small car and mid-size car body.

However, this dramatic result is paired with a $4.3 billion penalty at the reference market size and unprofitable (negative NPV) fleets at all reference sizes.

5.3 Directions for Future Work

Several alternative analyses performed with the methodology developed in this thesis might advance the knowledge gained from the current case study. Foremost, the impact of transmission tuning should be investigated to understand whether a firm would ever tune a vehicle to favor fuel economy when the market values acceleration more highly. Other interesting cases to study include the addition of more materials options (more classes of materials and smaller subsystem applications) and more engine options such as unconventional power sources like hybrid and plug-in hybrid platforms. Other scenarios that could be analyzed include a study of demand uncertainty and alternative CAFE policy effects in tandem (in light of the fact that they were investigated separately in this thesis), and the impact of different types of fuel economy policies such CO_2 emissions regulation or fuel taxes.

The structure and assumptions of the methodology itself should also be tested further. For example, the current work assumed that the volatility implied by the market for compact and subcompact cars is equivalent to the volatility in the market for mid-size and luxury cars, though this may not be accurate. In addition, the NPV calculation method considered tax but ignored the effect of depreciation, which lowers taxes for projects that have higher capital investments.

Finally, some of the most significant practical issues not addressed by this work pertain to the barriers that may still prevent an automaker from adopting the materials strategies implied by the results of the case study. While the case study reports that composite bodies-in-white and composite closure sets are competitive with steel in luxury cars at typical sales volumes observed in the U.S. market, only a fraction of luxury cars sold in the U.S. are actually designed with structural composites. Other work by this author and several collaborators has suggested that some of the dominant barriers to the use of lightweight automotive materials include firm inertia and supply chain inadequacy (Cirincione, Roth et al. 2007), though this research topic is not complete. As automakers and materials suppliers confront the results of this thesis—not to mention the ever-changing market that initially motivated the work—it will be interesting to see if, when, and how the automotive materials paradigm shifts.

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