

# **Picking Winners: Assessing the Costs of Technology-Specific Climate Policy for U.S. Passenger Vehicles**

**by  
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B.A (Economics), McGill University, 2010

Research Project Submitted in Partial Fulfillment  
of the Requirements for the Degree of  
Master of Resource Management

Report No.: 575

In the  
School of Resource and Environmental Management  
Faculty of Environment

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**SIMON FRASER UNIVERSITY**

**Summer 2013**

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**FYdcfhBc":** 575

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## Abstract

Policymakers implementing climate policies that aim to direct technological change must decide the extent to which such policies will be technology-neutral or technology-specific. There is a debate over the effect that such alternative designs will have on a policy's expected cost-effectiveness. Researchers have investigated this question in top-down models that focus on the early phases of technological change (R&D), but no one has yet compared technology-neutral and technology-specific policy designs for the later stages of technological change (commercialization and diffusion), in a model that includes explicit energy technologies. I model these policy designs using a case study of the US passenger vehicle sector in a hybrid simulation model that is not only technology explicit, but behaviourally-realistic and that possesses some degree of macroeconomic feedbacks. I find that technology-specific vehicle mandates results in lower policy cost-effectiveness than a carbon tax on vehicle fuel because the vehicle mandate has a higher risk of policymakers "picking the wrong winner." However, I find as well that a technology-specific electric vehicle mandate is able to meet a key adoption threshold for getting low-cost emission reductions from PHEVs. Key limitations of my model include: consumers have zero foresight, exogenous assumptions for fuel supply and cost, and assumptions that seem to implicitly favour the adoption of plug-in hybrid electric vehicles over biofuels. The implications of my results are that further research should investigate ways in which technology-neutral and technology-specific policies can be combined to increase expected policy cost-effectiveness and minimize the risk of "picking the wrong winner."

**Keywords:** Climate Policy, Passenger Vehicles, United States, Technology-neutral, Technology mandate

## **Acknowledgements**

I am very gracious for the guidance, patience, and support granted to me by my supervisors: Dr. Jonn Axsen and Dr. Mark Jaccard. I would like to thank my parents, Lawrence and Nancy, and my younger brother, Eli, for their ongoing support. I am very grateful as well to all of the excellent colleagues I have had the pleasure of working and exchanging ideas with in the Energy and Materials Research Group and in SFU's School of Resource and Environmental Management. Finally, I acknowledge the financial funding granted to me by the Social Sciences and Humanities Research Council of Canada, The British Columbia Automobile Association, the Government of British Columbia, and the Energy and Materials Research Group.

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## List of Acronyms

AEO	<i>Annual Energy Outlook</i>
BAU	Business as usual
CC	Command-and-control policy
CIMS-US-PV	CIMS-US passenger vehicle
CO <sub>2</sub> e	Carbon dioxide equivalent
EIA	Energy Information Administration
ESUB	Elasticity of substitution
EV	Electric vehicle
FC	Financial cost
GHG	Greenhouse gas
HEV	Hybrid-electric vehicle
HFV	Hydrogen fuel cell vehicle
MB	Market-based policy
PC	Perceived cost
PHEV	Plug-in hybrid electric vehicle
R&D	Research and development
VKT	Vehicle kilometer travelled
ZEV	Zero-emission vehicle

# 1. Introduction and Background

In order to meet long-term targets for greenhouse gas (GHG) emissions reductions, governments seek to implement climate policies that will direct technological change towards new low-emission technologies. To direct technological change, climate policies must induce consumers and firms to develop and adopt new technologies. Some economists and policymakers argue that it will be less costly for societies to design climate policies to be “technology-neutral,” meaning that policies would be set relative to an emissions target, without specifying which particular technologies should be developed or adopted to achieve that target. For example, a carbon price is a technology-neutral policy design because a carbon price is set relative to a common feature of technologies (the level of GHGs emitted), and is in theory applied at the same rate for all technologies in an economic sector. Thus, a carbon price does not “pick” a winning technology, but instead lets the market decide which technologies should emerge.

According to its proponents, technology-neutral policy design minimizes the expected social costs of climate policies. This is because technology-neutrality allows consumers to adopt the most preferred technologies available to meet an emissions reduction goal. The problem with policies that support specific technologies is that uncertainty over future cost reductions, the evolution of consumer preferences, the roll-out of supportive infrastructure and other factors create a risk that such policies will lead firms and consumers to invest in and adopt new technologies that turn out to be inferior to non-supported technologies or, in other words, “pick the wrong winners.” For these reasons, some economists argue that “technology-specific” policies should not have a role in climate policy (Jaffe, Newell, and Stavins 2005; Nordhaus 2009).

Other researchers (Azar and Sandén 2011; Stern 2007; Carrillo-Hermosilla 2006) have critiqued this view. They argue instead that to lower the expected social costs of climate policy, near-term technology-neutral policies must be coupled with long-term

policies that support specific technologies. These researchers argue that long-term technology-specific policies, such as regulations that force manufacturers to meet sales quotas for new technologies, are necessary to overcome market barriers that will delay the adoption of new technologies by “forcing” the initial technology adoption.

Technological adoption is often driven by a process in which a technology becomes more attractive to consumers as more consumers adopt it. Researchers refer to this process as increasing returns to adoption (Arthur 1989), where the social costs of production and adoption can be significantly reduced once a certain threshold of adoption is passed. Increasing returns to adoption is the culmination of several other observed processes including manufacturers learning by doing (Arrow 1962), economies of scale, and changes in consumer preferences (Axsen, Mountain, and Jaccard 2009; Mau et al. 2008). For example, EVs would become more attractive as production costs decrease, as consumers get more exposure to the technology, and as recharging infrastructure becomes more widespread. The EV regulation mentioned in the previous paragraph may thus stimulate increasing returns to adoption for EVs and potentially reach a threshold where societal climate abatement costs are substantially reduced in the passenger vehicle sector. Due to the potential of such thresholds, some argue in favour of using technology-specific instruments to promote specific technologies instead of relying solely on an economy-wide carbon tax and broad-based subsidies for research and development (R&D) (Sandén and Azar 2005; Sierzchula et al. 2012).

In a sense, economists are arguing about what approaches to climate policy inflict the least costs on society. Most of the studies that do evaluate the costs of technology-specific policy designs do so with respect to policy that impacts only the initial phases of technology development. These studies find that the addition of technology-specific support for the research and development (R&D) of new technologies lowers the social costs of an economy-wide carbon price (Kalkuhl, Edenhofer, and Lessmann 2012; Fischer and Newell 2008). Less work has been done, however, to quantitatively assess the relative costs of technology-neutral and technology-specific policy designs for climate policies that directly affect the later phases of technology development, between when technologies are first introduced to the consumer market and when they either fail or succeed to gain widespread consumer acceptance.

Moreover, there is room to build upon the results of previous studies by better incorporating uncertainty through multiple random, or “stochastic,” model input parameters. The crucial factor in the debate over technology-neutral versus technology-specific climate policy is uncertainty (Fischer et al. 2012). We cannot be completely sure of the emissions reductions that will result from climate policies in practice, the extent and rate at which the costs of new technologies will decline, or the future evolution of consumer preferences. Alternative climate policies that impact technological change should be compared not just based on select scenarios but on how they perform across the best current estimate of the full range of possible future outcomes (Bastani, Heywood, and Hope 2012).

In this research paper, I use a hybrid energy-economy simulation model that possesses technology-explicitness, behavioural-realism, and some macroeconomic feedbacks to compare the social costs and GHG emissions reductions among technology-neutral and technology-specific policy designs. I contribute to the debate over the long-term impacts of technology-specific policies by looking at long-term system dynamics for a realistic set of current and future vehicle propulsion technologies. In addition, I incorporate multiple random uncertain (or “stochastic”) input parameters into my model in order to explore a wide range of possible future outcomes. I undertake a case study of the US market for different passenger vehicle propulsion technologies up to the year 2050. In the following sections I describe the background to this research as well as my main research objectives.

## **1.1. US Passenger Vehicle Policy**

In 2010, the transportation sector produced 27% of total US GHG emissions, and light-duty vehicles made up 62% of this sector (US Environmental Protection Agency 2010). Part of the US federal government’s strategy for reducing light-duty vehicle emissions is to significantly increase the market share of low-emission vehicles within the next few decades. Advocates have proposed gasoline-electric hybrid vehicles (HEVs), plug-in hybrid vehicles (PHEVs), pure electric vehicles (EVs), hydrogen fuel cell vehicles (HFVs), and internal combustion engines adapted to burn biofuels (E85 ethanol) all as potential vehicle propulsion technologies that policy could target. These

technologies can be divided into two broad categories: evolutionary and disruptive technologies (Christensen 1997). Evolutionary technologies (HEVs and E85 ethanol) are new technologies that provide a substitute for the service of an existing technology but do not require new infrastructure and are relatively familiar to consumers. In contrast, disruptive technologies (PHEVs, EVs, and HFVs) often require new infrastructure and a significant amount of learning by consumers prior to mass adoption (Christensen 1997; Mau et al. 2008).

Alternative policies for increasing the market share of low-emission technologies can be classified according to compulsoriness, or the extent to which the government requires firms and consumers to undertake certain behaviour. Mallory (2007) groups passenger vehicle emission policies into three broad categories: less compulsory *market-based policies*, more compulsory *command-and-control policies*, and hybrid policies that fall in between these two extremes.

In this study, I take a selection of both market-based (MB) and command-and-control (CC) policies and group them into technology-neutral and technology-specific categories. Technology-specific policy design is an attribute that is generally independent of a policy's level of compulsoriness (both MB and CC policies fall into both categories). I view my categorization as preliminary because researchers have yet to exactly define what it means for a given policy to be more or less technology-specific than alternative policies. And some researchers (Azar and Sandén 2011) question whether any climate policies can indeed be technology-neutral in practice. I avoid this debate by looking only at the question of policy design: whether or not policymakers intend for a given policy to be technology-neutral or technology-specific.

Market-based policies induce firms and consumers to change behaviour, and develop and adopt low-emission technologies through financial self-interest (Stavins 2001). Emission taxes do so by putting a price on GHG emissions and thus increasing the price of GHG-intensive fuels and technologies. Purchase subsidies decrease the upfront cost for targeted technologies with the intention of inducing greater numbers of consumers to adopt such technologies. R&D subsidies induce firms to increase their investment in producing knowledge, potentially leading to improvements in existing technologies as well as the entry of entirely new technologies into the consumer market.

Emission taxes are a technology-neutral policy design because, in theory, a tax targets the GHG intensity of fuels and technologies, which is a feature of technologies, as opposed to the technologies themselves. Purchase subsidies, however, are technology-specific because they are applied directly to a specific technology or set of technologies. According to my initial categorization, the fewer the technologies that a subsidy affects, the more technology-specific a subsidy is. For example, a subsidy that applies only to EVs is more specific than a subsidy that can be used by consumers for either EVs, PHEVs, or HEVs. Similarly, R&D subsidies are also inherently technology-specific. Typically, governments allocate R&D subsidies to specific technology groups or research areas because, to be effective in practice, governments and research bodies must set research priorities that favour some technologies or groups of technologies over others (Azar and Sandén 2011).

Command-and-control policies regulate either specific emissions reduction levels or low-emission technologies that firms and consumers must adopt. Governments typically enforce these regulations through financial or legal penalties for non-compliance. Some command-and-control regulations, such as performance standards, are designed to be technology-neutral because the standard is based on a level of emissions performance and do not specify the kinds of technologies that firms and consumers can or cannot adopt to meet this level of performance. For example, a performance standard would only indicate that all vehicles must be below a maximum amount of GHG emissions per km travelled. In contrast, technology mandates, “force” manufacturers to sell a minimum quantity of certain technologies and are thus inherently technology-specific. In general, the more technologies that a regulation allows to compete for market share under a regulation such as a mandate, the less technology-specific the regulation is. The inclusion of credit trading with a technology mandate both reduces the compulsoriness of the policy and makes the mandate less technology-specific because it gives producers greater flexibility in meeting the regulation’s requirements.

An example of a real-world command-and-control regulation that over time has varied in its level of technology-specificity is California’s Zero-emission Vehicle (ZEV) program. Technically, the ZEV mandate is a technology standard (manufacturers must sell a certain quantity of vehicles) that is combined with a performance standard (the

vehicles sold must classify under the regulation’s definition of a “zero-emission vehicle”). Implemented in 1990, the original ZEV mandate was designed to force a disruptive low-emission technology (EVs)<sup>1</sup> into the automobile market to try and direct technological change. From the start, the ZEV mandate was coupled with low-emission vehicle regulations (LEV) designed to lower emissions for existent vehicle technologies. The original ZEV mandate required major automobile manufacturers to have ZEVs make up at minimum 2% of annual new vehicle sales in 1998-2000, 5% of sales in 2001-2002, and 10% of sales from 2003 on. These targets made the original ZEV mandate relatively aggressive, technology-specific, and inflexible. Because manufacturers later convinced the California Air Resources Board that they could not meet expected cost declines for electric vehicle propulsion technology, the scope of the ZEV mandate was expanded in the late 1990s to cover more potential advanced vehicle technologies at less aggressive levels of emissions performance. In 2003, regulators granted manufacturers even more flexibility by creating an alternative compliance pathway (Bedsworth and Taylor 2007). In its current incarnation—based on amendments made in 2008—the Californian ZEV mandate requires an increasing percentage of new cars sold to be ZEVs by the 2025 model year. The complex categories and credit trading within the regulation, however, obfuscate any current prediction of the exact number of EVs, PHEVs, and HFVs that will be sold to consumers under the mandate in future years. It is likely that other US states, as permitted by federal law, will implement their own versions of California’s ZEV mandate. In this study, I model regulations similar to the California’s ZEV mandate in order to investigate the effect of different policy designs on future technological change.

## **1.2. Technological change, diffusion of new technologies, and increasing returns to adoption**

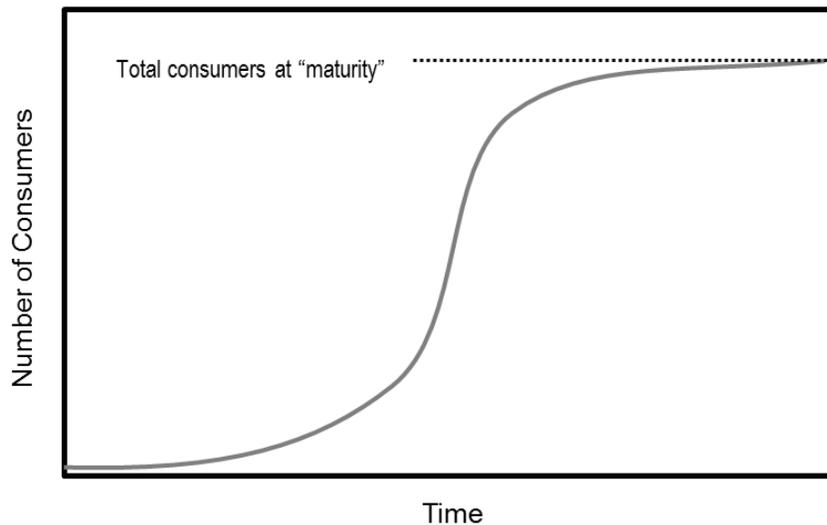
Technological change is the process by which evolutionary and disruptive new vehicle technologies enter the consumer market. Technological change occurs in three

<sup>1</sup> During the 1990s, EVs were the only vehicle technology that could possibly meet the zero-emission performance requirement of the ZEV mandate (Bedsworth and Taylor 2007).

general stages: invention, innovation, and diffusion (Schweitzer 1961). First, new technologies are invented, meaning that a person or group of people produces a new product or process. Second, new technologies become innovations when they are first made available for purchase on a market, or “commercialized.” Together, researchers refer to the innovation and invention stages as R&D. The third broad stage of technological change is diffusion. Diffusion refers to the mass adoption by firms or individual consumers of a successful innovation. Within each of these phases there is a high rate of failure; only a small percentage of new inventions become widely adopted.

Historical case studies show that diffusion often occurs gradually (Jaffe, Newell, and Stavins 2002). The reason for this is that consumer preferences for technologies—which are driven by factors such as education, marketing, and shifts in cultural norms—evolve over time (Norton, Costanza, and Bishop 1998). A key observed pattern is that the portion of potential adopters who become users of a new technology tends to follow a sigmoid or “s-shaped” curve (Figure 1). The number of adopters rises slowly at first, enters a period of rapid growth, and then slows as most of the potential adopters have switched to the now more “mature” technology (Rogers 2003; Geroski 2000).

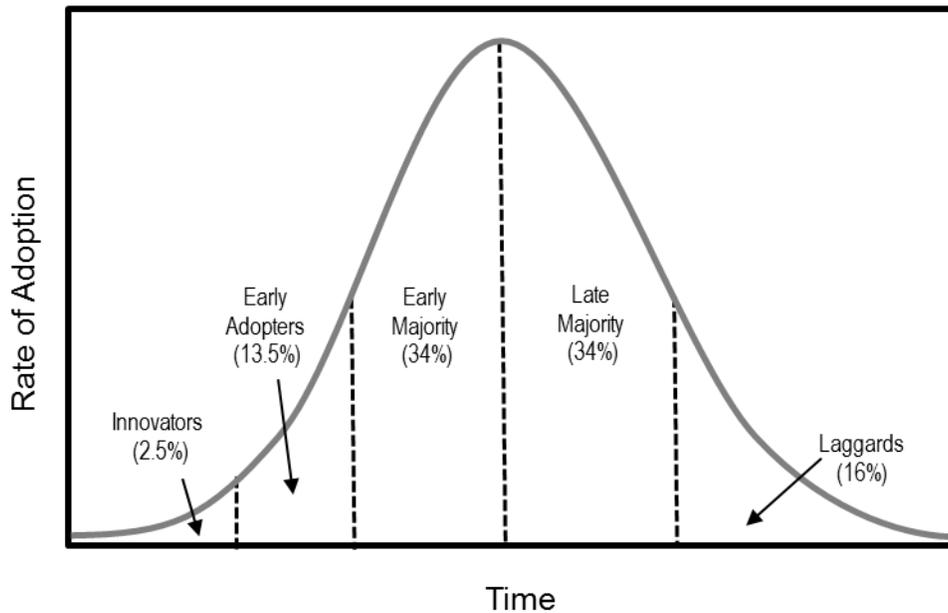
**Figure 1: Cumulative Adoption of Typical New Technology (S-shaped curve)**



Source: adapted from (Rogers 2003, pg. 11)

Over time, the actual adoption rate (the slope of the curve in Figure 1) follows a bell-shaped distribution. Rogers (2003) divides this bell-curve into five broad categories based on the preferences different groups of consumers have for new technologies: innovators (2.5%), early adopters (13.5%), early majority (34%), late majority (34%), and laggards (16%) (Figure 2). This classification offers an intuitive explanation of why many new technologies fail to become widespread: if only a small number of innovators and early adopters adopt a new technology, then that technology will not achieve sufficient popularity to be adopted by the early majority and majority consumer groups.

**Figure 2: Adopter Categories by Rate of Adoption**



Source: adapted from Rogers (2003 pg. 281)

Two main forces produce the s-shaped pattern of technology diffusion. The first is that consumers have varied or “heterogeneous” perceptions of whether or not a new technology is superior to existing technologies that provide the same service. A larger portion of consumers may view a new technology to be inferior to existing technologies for reasons unrelated to observed financial costs. For example, a conventional gasoline vehicle may be preferred over an electric vehicle that can travel only 100 miles with a full battery—even if the financial costs are equal. The second is that consumers view the adoption of a new technology to be riskier than the adoption of existing technologies, and it takes time for information that will better inform consumer perceptions of risk to become widespread (Jaffe, Newell, and Stavins 2002).

Because of the s-shaped pattern of consumer adoption, the diffusion of new technologies tends to be a non-linear, path-dependent process. This means that the actual sequence of events matters and can restrict the set of possible future scenarios for technological change. Thus it is possible for a market to “lock-in” to a dominant technology that gains almost the entire market share for a particular economic service. A key example of locking-in both to a dominant technology and to a specific technological

pathway is that vehicle owners have been locked-in to internal combustion engine (ICE) technology since the initial mass adoption of automobiles in the US during the 1920s. Key historical events, such as the invention of suburban living in the 1920s creating a certain image for automobiles, and increasing returns to adoption drive the phenomenon of locking-in to a dominant technology (Arthur 1989; 1994).

Increasing returns to adoption refers to the process by which a technology becomes more attractive to consumers the greater the number of consumers that use it. The term increasing returns to adoption represents the combined effect of several processes: learning by doing, economies of scale, and “the neighbour effect.” Learning by doing is the process by which firms achieve innovation and cost reductions per unit the more they repeat a production process (Arrow 1962). Economies of scale is the process by which cost reductions are achieved as firms achieve greater scales of production. Thus, the more consumers adopt a technology, the more its production increases and manufacturers achieve greater economies of scale, leading to cost savings. Finally, the neighbour effect is the process by which consumer preferences favour a technology the more that the technology is adopted by other consumers (Axsen, Mountain, and Jaccard 2009; Mau et al. 2008). The neighbour effect is driven by changes in social concerns, increased credibility, the spread of information about user experiences, education, marketing, shifts in cultural norms, and the requirement of some technologies for complementary infrastructure (van der Vooren, Alkemade, and Hekkert 2012; Yang and Allenby 2003; Norton, Costanza, and Bishop 1998). The neighbour effect is related to the phenomenon that other researchers (Katz and Shapiro 1985; Kemp, Schot, and Hoogma 1998; Sandén and Azar 2005) refer to as “network externalities” in which the utility of good or service increases with the number of users.

While it is helpful to understand, in general, the dynamics of technology commercialization and diffusion, understanding how this process is affected by both technology-neutral and technology-specific policy designs requires the use of energy-economy models.

### **1.3. Modeling technological change in a hybrid simulation model**

Energy-economy models are useful tools for assessing the impacts of climate policies on technological change. In particular, energy-economy models are useful because such models can simulate endogenous technological change, meaning that the development and adoption of new technologies are determined by the interaction of various model parameters and not by a fixed baseline forecast. Hybrid simulation models combine features found in two other categories of energy-economy models: top-down and bottom-up models (Loschel 2002).

Top-down models describe aggregate substitution relationships between macroeconomic factors of production for entire economic sectors. They simulate endogenous technological change through elasticity of substitution parameters that determine the extent to which markets substitute between alternative technologies as prices change. Modellers derive these ESUB parameters from historical data and, because of this, top-down models can contain a high degree of behavioural-realism. Because top-down models describe the circular flow of resources through multiple economic sectors, they also simulate full macroeconomic feedbacks. The main critique of top-down models is that they tend to overestimate the social costs of GHG emissions reductions because they assume that without any policy interventions, the economy is always in an optimal state and any change from this state results in increased costs to society due to a suboptimal outcome.

In contrast, bottom-up models are technologically-explicit, meaning that they contain detailed cost and performance information for large sets of current and future energy technologies. Conventional bottom-up models such as optimization models lack behavioural-realism because they assume that consumers make decisions purely based on financial costs, ignoring the effects of heterogeneous consumer preferences, perceptions of risk, and differences in the non-financial attributes of technologies. Bottom-up models also lack macroeconomic feedbacks because they do not account for changes in the relative prices of substitutable technologies or services. Thus, bottom-up models tend to underestimate the costs of GHG emissions reductions because they overestimate the rate at which consumers adopt new low-emission technologies.

Hybrid models combine the features of top-down and bottom-up models to more accurately simulate technological change and forecast the cost of climate policy. Generally, hybrid models are developed by either adding technology-explicitness to a top-down model (Karplus et al. 2013), or by adding behavioural-realism and macroeconomic feedbacks to a bottom-up model. CIMS-US is a hybrid energy-economy model of the US economy that embodies the latter approach to achieving a high degree of technological explicitness, behavioural-realism, and macroeconomic feedbacks (Bataille et al. 2006).

CIMS-US includes detailed, explicit representations of cost and fuel consumption characteristics for a varied set of individual technologies in the United States. For example, the model includes a variety of competing vehicle propulsion systems: conventional gasoline ICE, HEVs, EVs, PHEVs, diesel vehicles, HFV, and E85 ethanol vehicles. CIMS-US includes macroeconomic feedbacks by estimating shifts in supply and demand for different economic sectors that are caused by changing prices. Finally, CIMS-US incorporates behavioural-realism by including functions that simulate observed consumer preferences. The parameters in these functions are informed by empirical research (Axsen, Mountain, and Jaccard 2009; Horne, Jaccard, and Tiedemann 2005)

CIMS-US simulates technological change using two main functions for specific technologies: a learning curve for the declining capital costs of technologies and a declining intangible cost function that represent the neighbour effect. Together these equations give the model increasing returns to adoption and, thus, the ability to simulate path-dependent outcomes and technological lock-in. The declining capital cost learning curves relate declines in a technology's capital cost to its cumulative production. These learning curves capture both economies of scale and learning by doing for new technologies. The declining intangible cost function relates decreasing intangible costs to increasing market share of new technologies (the "s-shaped" cumulative adoption rate show in Figure 1). Intangible costs are empirically-informed estimates of consumer perceptions of the quality, reliability, availability, and social desirability of new technologies as well as any other factor that affects consumer purchase decision not accounted for by financial costs. In CIMS-US, the declining intangible cost function represents the neighbour effect.

## 1.4. Using CIMS-US to estimate policy costs

Because of its characteristics as a hybrid simulation model, CIMS-US has the potential advantage of more accurately estimating the cost of emissions reduction policies than either purely top-down or bottom-up models. Other studies that assess the potential cost of technology-neutral and technology-specific climate policies for R&D use top-down models (Kalkuhl, Edenhofer, and Lessmann 2012; Fischer and Newell 2008). These models estimate policy costs by determining the optimal technological and behavioural pathway for an economy in the absence of policy, and assume costs always occur when an emissions policy forces the economy to deviate from this optimal pathway. Because top-down models must solve to an economic equilibrium in every model period (for computational reasons), they are limited in how they can portray market failures and barriers to entry for specific technologies. Although such models are able to simulate market failures in the market for innovation, they must always do so relative to a model's equilibrium state. Also, these models do not include explicit technologies and instead group energy technologies into a small number of representative technology groups: looking at substitution between an incumbent technology and one or two "low" to "zero-carbon" technologies."

Analysis using the hybrid CIMS-US model can therefore complement existing research comparing technology-neutral and technology-specific policy designs in top-down models. Investigating such policy designs in CIMS-US is useful because CIMS-US possess a more detailed representation of the process of technology diffusion, instead of concentrating more heavily on the dynamics of R&D. Also CIMS-US can evaluate this policy design issue using a different modeling methodology than previous studies. In contrast to top-down models, CIMS-US is a hybrid simulation model<sup>2</sup> originally based on a bottom-up model architecture, which means that it does not assume that the absence of any climate policies results in an optimal pathway for technological change. Therefore,

<sup>2</sup> Other researchers use terms such as "system dynamics model" (Herbst et al. 2012) or "energy system simulation" model (Mundaca et al. 2010) instead of "hybrid simulation model."

it is theoretically possible in CIMS-US for an emissions policy to have a negative cost, if there are significant market failures and barriers to entry in the BAU scenario. For example, there could be a low-emission vehicle propulsion technology that consumers do not prefer in early years of a model forecast because they are unfamiliar with it, but may prefer over conventional vehicles in later years if the technology does achieve mass adoption, accompanied by significant reductions in capital cost and increases in positive consumer perceptions.

Despite the advantages that a hybrid simulation model such as CIMS-US presents in combining the strengths of both bottom-up and top-down models, it is more challenging to calculate the cost of policies in CIMS-US than in top-down models. This is because, unlike top-down models, CIMS-US does not contain a unique mathematical function that determines the extent to which consumers value the allocation of an economy's resources. Like other studies that use hybrid simulation models (Small 2012; Mallory 2007), I have to infer the components of a policy's expected social cost from the demand and cost relationships within an economic sector of CIMS-US—which are determined by empirically-informed behavioural parameters. However, because of these behavioural parameters, CIMS-US is able to calculate policy costs without having to assume that either all consumers are rational, cost-minimizing agents (like in bottom-up models) or that market always acts in the best interest of consumers (like in top-down models).

## **1.5. Incorporating stochastic input parameters into CIMS-US**

Research on technology-neutral versus technology-specific climate policy however, has yet to fully incorporate uncertainty in modeling exercises and policy cost simulations. Because CIMS-US possesses a high degree of behavioural-realism, it is a useful model for exploring a wide range of future outcomes using stochastic input parameters. Moreover, because of the model's level of technological detail, CIMS-US can explore the effect of uncertainty over the future attributes of individual technologies, which is an additional way that analysis in CIMS-US can complement previous work done in top-down models.

Modeling stochastic input parameters possesses several advantages over the alternative technique of using discrete deterministic scenarios, such as an upper bound, lower bound, and middle scenario to account for uncertain input parameters.<sup>3</sup> Using only discrete scenarios to characterize uncertainty is useful to test extreme model scenarios, but only provides a few select samples of the potential outcome distribution for possible model results. In contrast, characterizing uncertain input assumptions as stochastic parameters allows CIMS-US to identify an exact range of possible outcomes as well as the probability with which each outcome occurs within the model.

One technique for incorporating stochastic input parameters into a hybrid simulation model is Monte Carlo analysis. Monte Carlo analysis is a method that comes from the decision analysis literature. Decision or risk analysis involves quantitative techniques often applied to policy analysis that rank decisions based on the magnitude (in terms of costs and benefits) and probability of possible outcomes (Howard 1968). For example, uncertainty over the future costs over vehicle batteries will in turn lead to different scenarios for the costs of PHEVs and EVs. This will lead to different outcomes for the consumer adoption of such technologies, which in turn leads to different scenarios (or uncertainty) for overall policy costs. Monte Carlo analysis is one such method of accounting for multiple uncertainties, and it is an appropriate technique if there are many uncertain model inputs (Morgan and Henrion 1990). The advantage of incorporating stochastic input parameters through Monte Carlo analysis is that it allows a hybrid simulation model, such as CIMS-US, to produce a full outcome distribution for policy cost and emissions reduction results. The disadvantage of using Monte Carlo analysis is that it is difficult to link existing risk analysis software to the current programming structure of the full CIMS-US model. Thus, I find it necessary to build a CIMS-based sub-model in order to benefit from the full capabilities of existing risk analysis software.

<sup>3</sup> An example of a previous study in CIMS that is based on uncertainty analysis with discrete scenarios is Muncaster (2008).

## 1.6. Research objectives

Whether or not technology-specific policies are needed in addition to technology-neutral climate policies is an issue debated by researchers. Previous studies find that, under certain conditions, governments should implement technology-specific policies to overcome market failures for R&D investment. A remaining question, though, is how future uncertainties and the potential effects of increasing returns to adoption may impact the relative cost-effectiveness of technology-neutral and technology-specific policy designs that are directed towards the full life cycle of technological change: from initial commercialization to widespread adoption. US passenger vehicles present a useful case study to analyze this question, as regulations such as California's ZEV program aim to benefit from increasing returns by "forcing" the creation of niche markets for low-emission vehicle propulsion technologies. In this paper I use a hybrid simulation model, CIMS-US, to evaluate this case study. CIMS-US is well suited to modeling technology diffusion in a manner that is behaviourally-realistic, technology-explicit, and factors in some macroeconomic feedbacks. I use CIMS-US to pursue the following research objectives:

1. To represent uncertainty in technology change by incorporating stochastic input parameters directly into a CIMS-based model by building a sub-model (CIMS-US-PV) for the US passenger vehicle sector
2. To use this sub-model to compare the cost-effectiveness of both technology-neutral and technology-specific policy designs for a case study of policies that aim to reduce tailpipe GHG emissions by directing technological change towards new vehicle propulsion technologies
3. To use the results of this case study to comment on my methodology for comparing technology-neutral and technology-specific policy designs in hybrid simulation models and suggest areas for future research

## **2. Methods**

### **2.1. The Model**

To achieve the research objectives posed in the last chapter, I built a simulation model (CIMS-US-PV) in Microsoft Excel based on the passenger vehicle node in the personal transportation sector of CIMS-US (hereafter referred to as the “full CIMS-US model”). CIMS-US-PV simulates how such climate policies influence the adoption of new vehicle propulsion technologies relative to a business as usual scenario (BAU). The BAU scenario is calibrated with the passenger vehicle sector forecast of the U.S. EIA’s *Annual Energy Outlook 2012*.

I chose to build a sub-model of CIMS-US instead of using the transportation sector in the full CIMS-US model because doing so allowed me to incorporate quantitative risk analysis into the model without significantly adding to the model’s computation time. The disadvantage of building a sub-model is that it cannot recreate the wide set of interrelated energy sectors and technologies in the CIMS-US model. However, building a sub-model allows me to integrate stochastic model parameters in a way that is impossible within the full CIMS-US. Thus, because my research question focus only on passenger vehicle propulsion technologies, I deem having stochastic parameters to be more important than many energy sectors/technologies.

For its principal outputs, CIMS-US-PV estimates cumulative well-to-wheels GHG emissions and the total cost to consumers of consuming vehicle kilometers travelled

(VKTs).<sup>4</sup> The model divides the continental US into 4 broad regions to represent differences across the US in terms of the GHG intensity of electricity generated. The model simulates the evolution of the passenger vehicle stock in five-year time steps starting in the year 2005 and ending in the year 2050. The initial input into this simulation is a forecast for VKTs, which is first calibrated to the full CIMS model and then, after the model year 2010, follows an annual growth rate of 1.4% (U.S. Energy Information Administration 2012). In the CIMS-US-PV model, the demand for VKT represents the overall demand for vehicle use in the entire US economy. I assume that each vehicle has a maximum lifespan of 15 years, at which point the model retires vehicles from the total vehicle stock. At the start of every model time period, new vehicles enter the total vehicle stock in order to meet the overall market demand for VKT. The model then assigns these new vehicles to specific propulsion technologies based on the technology competition algorithm (explained in the next Section) for allocating new vehicle market share. In this manner, the model forecasts the turnover of different “vintages” of vehicle propulsion technologies in the US passenger vehicle sector.

I specify the initial forecast for VKTs as an exogenous assumption in the business as usual (BAU) scenario, which means that this forecast is pre-specified and cannot be altered by other model parameters. In policy simulations, though, the total VKT demanded does adjust endogenously relative to the static BAU forecast—meaning that its deviation from the BAU forecast is determined through the interaction of parameters within the model—based on estimated consumer reactions to changing vehicle and overall driving costs (referred to in this study as “feedback effects”). Another key model element that changes endogenously is the rate of technological change. In the following sub-sections, I detail how I specify the technology competition for market

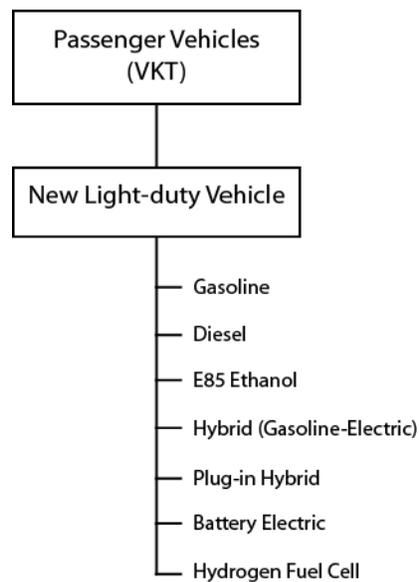
<sup>4</sup> The measure of tailpipe GHG emissions accounts solely for those emissions released from the direct combustion of passenger vehicle fuel. In reality, more GHG emissions are associated with the extraction, production, and transportation (the upstream processing) of all vehicle fuels. Thus, I include estimates for the well-to-wheels lifecycle emissions, which include all greenhouse gases emitted over the lifecycle of that fuel before it enters an automobile’s engine. My estimates for these values are taken from Samaras and Meisterling (2008), Farrell et al. (2006), Schmer et al. (2008), and California Air Resources Board (2012) for liquid fuels; and Weber et al. (2010) for regional US electricity grids.

share, endogenous technological change, feedback effects in driving and vehicle purchase behaviour, and the four different US geographic regions in CIMS-US-PV.

### 2.1.1. *Technology Competition*

The only technology competition in the model is that among different vehicle propulsion systems. Because this study focuses on the adoption of low-emission vehicle propulsion technologies, I do not look at other vehicle features such as vehicle size, occupancy, and the propensity of consumers to choose between cars and light trucks. The different vehicle technologies are defined by capital cost, fuel type, and efficiency. Figure 3 shows the vehicle technologies that compete for market share in the model. In Section 2.3.2, I describe the specific technical and cost characteristics for each technology.

**Figure 3: New passenger vehicle node in CIMS-US-PV**



To meet the overall demand for new passenger VKT (VKT demand that cannot be met by the existing stock of vehicles) the model simulates a competition among the vehicle propulsion systems listed in Figure 3. Below is the mathematical function that defines this competition.

$$MS_j = \frac{\left[ CC_j * \frac{r}{1 - (1 + r)^{-n}} + MC_j + EC_j + i_j \right]^{-v}}{\sum_{k=1}^K \left\{ \left[ CC_k * \frac{r}{1 - (1 + r)^{-n}} + MC_k + EC_k + i_k \right]^{-v} \right\}} \quad \text{Equation 1}$$

I take this function directly from the full CIMS-US model. Equation 1 accounts for the principle factors affecting consumers' vehicle purchase decisions: capital costs, maintenance costs, energy costs, the perceived intangible costs of new technologies with which consumers have little user experience, and a private discount rate for each decision-maker. The algorithm allocates new market shares ( $MS$ ) amongst  $K$  technologies.  $CC_j$ ,  $MC_j$ , and  $EC_j$  represent the capital, maintenance, and energy costs of technology  $j$ , respectively. The capital cost is the purchase price that consumers pay for the propulsion system. The maintenance cost is an estimate of the annual amount consumers will have to pay to maintain the vehicle technology over its lifespan. Finally, the energy cost is an estimate of the annual cost of fuel.

The technology competition function also contains three behavioural parameters,  $i$ ,  $r$ , and  $v$  that define consumer preferences over competing vehicle propulsion technologies. The values for these parameters are drawn from previous empirical research (Axsen, Mountain, and Jaccard 2009; Mau et al. 2008; Horne, Jaccard, and Tiedemann 2005). I discuss modeling consumer preferences further in Section 2.3.2. The  $i_j$  parameter is the perceived intangible cost of technology  $j$ . In the CIMS model, intangible costs represents factors that are not reflected in the financial costs of a particular technology but nonetheless affect the choices of consumers.

The  $r$  parameter is the perceived private discount rate, which determines how consumers perceive the future costs that are associated with a technology in the current time period (Train 1985). In both CIMS-US-PV and the full CIMS-US model, the  $r$  for vehicles is 25.7%, which is a relatively high discount rate compared with the discount rates for other energy technologies (Axsen, Mountain, and Jaccard 2009; Horne, Jaccard, and Tiedemann 2005). Factors that contribute to this high discount rate are limited time for consumers to make decisions, the perception of a greater risk of failure

for a new product, and the value of waiting for more information (de Groot, Verhoef, and Nijkamp 2001; Dixit and Pindyck 1994; Hassett and Metcalf 1993).

In the CIMS technology competition function, the  $v$  parameter (alternatively referred to as the “decision rule”) represents the heterogeneity in the market or, in other words, the extent to which different consumers perceive varying life cycle costs (LCC) for the same technology. The technology competition function is an inverse power function that determines a technology’s market share. The  $v$  parameter determines the shape of this function. Theoretically the  $v$  parameter can take any value between just approaching zero to infinity. If  $v$  has a high value, the technology with the lowest LCC will capture almost the entire new market share. As  $v$  approaches infinity, the technology competition function approaches a step-wise function in which the cheapest technology captures 100% of the new market share. If  $v$  has a low value, market share will be allocated more evenly among the competing technologies. As  $v$  approaches 0, the market share given to any competing technology will approach  $1/n$ , where  $n$  is the number of competing technologies (Bataille et al. 2006).

The set of vehicle propulsion technologies in the model is a simplification of what technologies, in reality, will likely be available to consumers over the next several decades. The CIMS-US-PV model has only one vehicle propulsion system type for each alternative technology and includes efficiency increases for each propulsion system according to a baseline forecast.<sup>5</sup> The assumptions I make for the increasing efficiency in gasoline, diesel, and E85 ethanol motors are relatively optimistic: by 2030 every new

<sup>5</sup> This baseline forecast is a different method than the one that the full CIMS-US model uses to forecast efficiency increases. The programming structure of the full CIMS-US model does not allow for individual technologies to increase in efficiency over time. Thus, CIMS-US models efficiency advances by having more efficient versions of the same technology compete against the original lower efficiency version. The purpose of not doing this and instead using a baseline forecast is to focus the CIMS-US-PV model more closely on the adoption of low-emission vehicle technologies under technology-neutral and technology-specific policy designs

propulsion system is at the highest possible efficiency attainable in the full CIMS-US model for that particular technology.<sup>6</sup>

### **2.1.2. Increasing Returns to Adoption**

In CIMS-US-PV, technological change is driven by two equations taken from the full CIMS-US model (Jaccard 2009). I include increasing returns to adoption in the model through the  $CC_j$  and  $i_j$  parameters in the CIMS technology competition function Equation 1. The two functions that determine increasing returns to adoption—the process by which new technologies become more desirable to consumers as they become more widely adopted—for each vehicle propulsion technology are the declining capital cost function and the declining intangible cost function.

CIMS-US-PV models learning by doing through log-linear experience curves for the capital cost of certain new vehicle technologies. Equation 2 describes a typical experience curve, or what is termed in CIMS-US as the “declining capital cost function.”

$$CC_j(t) = CC(t_0) \left( \frac{N_j(t)}{N_j(t_0)} \right)^{\log_2 PR} \quad \text{Equation 2}$$

The variable  $CC_j$  denotes the capital costs of a given technology  $j$ . For CIMS-US-PV,  $CC_j$  represents the purchase price for different vehicles.<sup>7</sup> In CIMS-US-PV, four different vehicle propulsion technologies possess declining capital costs: HEVs, PHEVs, EVs, and HFVs.  $CC_j(t)$  represents the capital cost of technology  $j$  at time  $t$ .  $CC_j(t_0)$  is the initial capital cost of the technology at  $t_0$ , the beginning of the simulation period. The variable

<sup>6</sup> I take the upper limit for gasoline, diesel, and E85 ethanol efficiencies from the “high efficiency” motor attributes in the full CIMS-US model.

<sup>7</sup> I look only at differences in the purchase prices for vehicle propulsion systems as I assume all other attributes of vehicles to be fixed in the model (thus any price differences between vehicles would only come from having alternative propulsion system technology).

$N_j(t)$  represents the cumulative production of technology  $j$  up to but not including time  $t$ .  $N_j(t_0)$  represents the “base stock” for the production of technology  $j$  and  $PR$  denotes the progress ratio. The progress ratio determines the extent to which the capital cost declines every time there is a doubling in cumulative production relative to the base stock (the level of cumulative production acts as a proxy for production experience in the model).

In CIMS-US-PV mature vehicle propulsion technologies (ICE, diesel, E85 ethanol) do not have declining capital cost functions. Of the remaining new technologies that do experience declining capital costs, HEVs, PHEVs, and EVs are grouped together in same “technology class.” This means that, for these three technologies, production experience for any one technology is cumulative for the entire group. Thus even if only HEVs are produced in the model, the capital costs for PHEVs and EVs will still decline as well because all of these vehicle technologies depend on variations of the same technology: vehicle batteries, motors, and electronics.

**Table 1: Technology classes in CIMS-US-PV**

Technology Class	Vehicle Propulsion Technologies included
Mature technologies	Conventional gasoline (ICE), Diesel vehicles, E85 ethanol
Battery vehicles	Hybrid-electric (HEV), Plug-in hybrid (PHEV), Electric (EV)
Hydrogen vehicles	Hydrogen Fuel Cell (HFV)

The neighbour effect is included in CIMS-US-PV through the declining intangible cost function. The neighbour effect is the observed phenomenon that, independent of cost declines from learning by doing, consumers tend to adopt new technologies according to an exponential “s-shaped” curve: as market share increases, the receptivity of consumers to new technologies accelerates until it eventually reaches a peak rate and then decelerates until it reaches its theoretical long-term market share. This phenomenon is driven by changes in consumers’ psychological perceptions of brand new technologies. In CIMS-US-PV, this means that the upfront intangible costs of new technologies decrease according to an exogenously defined curve as a given technology’s market share increases. Equation 3 defines this curve:

$$i_j(t) = i_{Fj} + \frac{i_j(t_0)}{1 + Ae^{k*MS_j(t-1)}}$$

**Equation 3**

The variable  $i_j(t)$  represents the total intangible cost of technology  $j$  at time  $t$ . The first parameter in Equation 3,  $i_{Fj}$ , is the annual fixed intangible cost which is not dynamic (affected by the market share) and thus remains at the same value throughout the simulation period. The annual fixed intangible cost simulates observed patterns in consumer preferences that seem to be permanent despite the widespread availability of a given technology (i.e. anxiety that consumers have over the limited range of EVs). The variable  $i_j(t_0)$  is the initial upfront intangible cost of technology  $j$ , which does vary according to that technology's market share. The variable  $MS_j(t-1)$  is the market share of the technology at time  $t-1$ , the previous five-year time period in the model simulation. The  $A$  and  $k$  parameters are fixed values that define the shape of the intangible cost curve and the rate of change in intangible cost from an increase (or decrease) in market share, respectively.

### **2.1.3. Feedback effects**

CIMS-US-PV simulates changes in the demand for VKTs in policy simulations by dividing the VKT demand in a given model period into two different markets that adjust to supply and demand equilibrium: the market for new vehicles and the market for travel from the existing vehicle stock. CIMS-US-PV simulates a demand curve for each of these markets based on an elasticity parameter which is an uncertain input assumption in the model. Thus in a policy simulation, any time the average price for VKTs in either of these markets changes relative to the average price in the BAU simulation, consumers respond by adjusting the overall quantity demanded of VKTs. In other words, if the average price of new vehicles increases relative to the BAU, consumers respond by demanding fewer new vehicles. Similarly, if the average cost of driving for the existing vehicle stock rises, consumers respond by cutting back on demand for travel (vehicle-km per year) from existing vehicles. The equations that define these feedback relationships are based on previous work by Mallory (2007) and Peters (2006).

Equation 4 simulates the demand curve in the market for new vehicles for a given model time period ( $t$ ).

$$D_{vehiclesPOL}(t) = \frac{(\sum PC_{jBAU} * MS_{jBAU} - \sum PC_{jPOL} * MS_{jPOL})}{\sum PC_{jBAU} * MS_{jBAU}} * e_{vehicles} * D_{vehiclesBAU}(t) \quad \text{Equation 4}$$

The parameters in this equation are as follows.  $D_{vehiclesPOL}(t)$  and  $D_{vehiclesBAU}(t)$  are the demand for vehicles in the business-as-usual (BAU) and policy (POL) scenarios at time  $t$ , while  $PC_j$  and  $MS_j$  are the perceived cost (per unit of VKT) and the market share of each technology  $j$ , respectively. By multiplying  $PC_j$  and  $MS_j$ , the model calculates the average perceived cost for all new vehicles in each model period. The parameter  $e_{vehicles}$  is the elasticity of for new vehicle demand, or the percentage change in demand caused by a percentage change in price. A 1% change in the average PC of new vehicles in the policy scenario (relative to the BAU scenario) will change the demand for new vehicles in the policy scenario by the elasticity  $e_{vehicles}$ .

Equation 5 simulates the demand curve for vehicle travel (VKT) from the existing vehicle stock in a given model time period ( $t$ ).

$$D_{VKT POL}(t) = \frac{(\sum PC_{kBAU} * MS_{kBAU} - \sum PC_{kPOL} * MS_{kPOL})}{\sum PC_{kBAU} * MS_{kBAU}} * e_{VKT} * D_{VKTBAU}(t) \quad \text{Equation 5}$$

In this equation, the average cost of driving varies inversely with the demand for travel from existing vehicles. Because of this feedback relationship, policies that tend to raise the fuel efficiency of vehicles experience a “rebound effect” because the lower average cost of driving from higher fuel efficiency then increases the overall demand for vehicle travel (Hymel, Small, and Van Dender 2010). For each five-year time period, CIMS-US-PV calculates the average cost of driving for the existing vehicle stock and compares this to same value in the BAU scenario. The parameters in Equation 5 are similar to those in Equation 4 except that the model takes them from the existing vehicle

stock and not from new vehicle stock in each time period. The parameter  $e_{VKT}$  is the elasticity of demand for existing VKT: a 1% change from the BAU average fuel cost will lead to a change in VKT demand from existing vehicles of  $e_{VKT}$ .

#### **2.1.4. Regional Disaggregation of the US Electricity Grid**

In the CIMS-US-PV model I divide the US into four broad regions to capture the potential impact of different electricity grid compositions across regions. Each region has its own average well-to-wheels GHG intensity for electricity. In reality, the US electricity grid is much more varied than the division shown below. However, using these four regions allows me to include some regional variation without unnecessary model complexity. Consumer preferences for new vehicle technologies remain identical across regions. I list the key attributes of each region's electricity supply in Table 2.

**Figure 4: Map showing four US regions in CIMS-US-PV**



**Table 2: US Electricity Regions in CIMS-US-PV**

Region	Average GHG Intensity of Electricity Generated (tonnes CO <sub>2</sub> e/GJ)	Approximate Share of US Passenger Vehicle Fleet <sup>a</sup>	Initial Price of Electricity (2005 CDN/GJ) <sup>b</sup>
Northeast	0.125	18%	\$41.95
South	0.234	32%	\$25.93
Central	0.189	34%	\$23.05
West	0.151	16%	\$32.96

<sup>a</sup> Passenger vehicle share is based on a region's proportion of the US population

<sup>b</sup> (U.S. Energy Information Administration (EIA) 2012)

### **2.1.5. Summary of the Model**

Table 3 summarizes the key inputs, algorithms and outputs of CIMS-US-PV (I highlight exogenous assumptions in bold). The model takes a set of inputs to determine the vehicle technology competition in each of the model's five-year iterations (from the base year of 2005 until 2050). Thus, the model provides an approximate forecast of the stock of vehicle propulsion technologies over time. I have not yet explain many of these input assumptions, but Section 2.3 contains a detailed description of the model's inputs. Endogenous technological change occurs in the model through two main mechanisms: learning by doing and the neighbour effect. Policies affect the model by increasing the energy cost of certain fuels, altering the purchase price for vehicle propulsion systems, or by constraining the technology competition among new vehicle propulsion systems.

**Table 3: Summary of CIMS-US-PV showing exogenous inputs in bold**

Inputs	Key Algorithms	Outputs
<ul style="list-style-type: none"> <li>• <b>VKT annual growth rate</b></li> <li>• <b>VKT and vehicle demand elasticity (policy scenarios only)</b></li> <li>• Vehicle propulsion system attributes (including capital and intangible costs)</li> <li>• <b>Fuel costs</b></li> <li>• <b>Fuel emission factors</b></li> <li>• <b>Vehicle retirement rate</b></li> </ul>	<ul style="list-style-type: none"> <li>• Declining capital cost function</li> <li>• Declining intangible cost function</li> <li>• VKT and vehicle demand feedback functions (policy scenarios only)</li> </ul>	<ul style="list-style-type: none"> <li>• Perceived cost</li> <li>• Financial cost</li> <li>• Well-to-Wheels GHG emissions</li> <li>• Tailpipe GHG emissions (no upstream emissions)</li> </ul>

## 2.2. Analysis of Policies

I use the CIMS-US-PV model to evaluate three different kinds of policies; each designed to reduce tailpipe GHG emissions. The three policies I simulated are: a carbon tax on vehicle tailpipe emissions (fuel carbon tax), a technology-specific electric vehicle mandate (EV standard), and a technology-specific near-zero emission vehicle mandate (NZEV standard) that includes a greater variety of low-emission technologies under its mandate than the EV standard. I chose this set of policies to directly compare the effects of constraining policies in CIMS-US-PV to be more or less technology-specific.

### 2.2.1. Policy Stringency

In this section, I describe the stringency of the policies that I model in greater detail, as well as the technique I use for determining policy cost-effectiveness. Rather than using a shared policy target, I compare policies of similar stringencies in order to compare their expected outcomes. In previous studies using CIMS-US, such as Mallory (2007), all policies are set to meet the same GHG emissions reduction target in the last model year. In contrast, because the focus of this study is to compare technology-neutral and technology-specific policy designs across a range of uncertain future outcomes, I compare two vehicle mandates with identical stringencies but different sets of mandated vehicle technologies as well as a carbon tax on vehicle fuel. I set the level of the fuel

carbon tax based on current proposals (under the assumption that a higher tax level would be politically unacceptable). In this study, I model policies that aim to reduce tailpipe vehicle GHG emissions. In addition, for most of the results I compare in this paper, I assume that a clean electricity standard policy is applied to the electricity sector in order to reduce GHG emissions from electricity generation (which in CIMS-US translates to approximately a 3% annual reduction in the carbon intensity of electricity). Overall though, I compare policies based on the cost-effectiveness of cumulative well-to-wheels lifecycle GHG reductions.

In my choice of methodology there is an inherent trade-off. By not constraining each policy to meet a specific target, I am better able to incorporate uncertainty by comparing differences in the output distributions for policy simulations. I am unable, however, to compare the cost of policies relative to same benefit (the exact same cumulative amount of reduced GHG emissions), which means that my policy comparison does not account for the declining marginal benefit of reducing GHG emissions. What matters more for my research objectives though is the relative ranking of policy cost-effectiveness and this ranking's sensitivity to uncertain input assumptions.

### ***2.2.2. Calculating Policy Cost-Effectiveness***

I measure the social costs of policies by calculating the net change in the total costs incurred by consumers between the policy and business-as-usual (BAU) scenarios. The technique I use for doing so, which was developed specifically for CIMS (Peters 2006), is similar to a method that has already been applied to the passenger vehicle sector for another hybrid US model, the National Energy Modeling System (NEMS) (Small 2012). Small (Small 2012) uses service demand elasticities in NEMS for vehicle use and new vehicle demand and assumes a flat supply curve to geometrically calculate net changes in the area lost beneath the demand curves for the two linked markets of vehicle use and new vehicle demand. While not a complete welfare analysis, estimating changes under the demand curve is a useful way to estimate policy costs for a model with dynamic technology assumptions that is also non-deterministic.

In each five-year model period, CIMS-US-PV records costs according to two definitions: the bottom-up financial cost and the top-down perceived cost. The

bottom-up financial cost measures costs associated with a technology that can be estimated prior to investment: the change in total consumer spending on the capital, energy, and operating costs for vehicle technologies (a subset of Equation 1 parameters). This financial cost estimate does not include any of the model's behavioral parameters ( $v$ ,  $i$ , and  $r$ ). CIMS-US-PV then measures the change in financial cost for any consumers who happen to switch to a new technology in the policy scenario relative to the BAU scenario. The total financial cost is thus estimated as the difference between the total financial costs of the forecasted technology mix in the policy scenario with that of the BAU scenario. Equation 6 shows how the model calculates the financial cost  $FC$  for a technology  $k$  in time period  $t$ .

$$FC_{k,t} = \frac{CC_k * \frac{d}{1 - (1 + d)^{-n}} + OC_k + EC_k}{20,000 \text{ VKT/Year}} * TotalVKT_{k,t} \quad \text{Equation 6}$$

where  $CC_k$  is the capital cost,  $d$  is the social discount rate of 5%,  $OC_k$  the annual operating cost,  $EC_k$  is the annual energy cost, and  $TotalVKT$  is the total VKT provided by the entire technology stock in that time period. Equation 7 shows how I calculate the total financial cost for a policy simulation and discount all future values relative to the year 2012.

$$FC = \sum_{t=2015}^{2050} \frac{FC_{POL,t} - FC_{BAU,t}}{(1 + d)^{t-2015}} \quad \text{Equation 7}$$

From an economic perspective however, the bottom-up financial cost method has several drawbacks: it assumes that market conditions are homogenous for all individual consumers, it does not factor in macroeconomic feedbacks, and it assumes that technologies that provide the same energy service are perceived by consumers as perfect substitutes (Murphy and Jaccard 2011b; Jaccard 2009; Hourcade et al. 2006;

Loschel 2002). Therefore, to more accurately account for total societal costs, CIMS-US includes a second cost measure, called the perceived cost, which factors in heterogeneous and dynamic consumer preferences, macroeconomic feedbacks, and consumers' perception that many technologies are imperfect substitutes for one another. By measuring the perceived cost, I seek to account for real-world patterns of consumer behaviour in the same manner as an aggregate top-down energy-economic model.

In CIMS-US I calculate the perceived cost by adding the behavioural parameters in CIMS-US to the financial cost calculation: the  $v$ ,  $i$ , and  $r$  parameters (Equation 1 and Equation 2). Specifically, the perceived cost includes upfront and annual intangible costs for each technology ( $i$ ), a private discount rate for decision-makers ( $r$ ) that is above the social discount rate, and heterogeneous technology preferences ( $v$ ). In each model period, the perceived cost is calculated as the sum of three cost measures: the perceived (intangible) cost of technology switches, the lost consumer surplus—an economic measure of consumer satisfaction—caused by the policy in the market for new vehicles (increased purchase price of vehicles and reduced vehicle demand), and the lost consumer surplus in the market for vehicle travel from existing vehicles (increased price of vehicle travel and reduced travel demand). Equation 8 shows the components of the total perceived cost (*Total PC*) for  $K$  technologies in model period  $t$ ,

$$Total\ PC_t = \sum_{j=k}^K PC_k * SwitchNS_{k,t} + \Delta W_{VKT,t} + \Delta W_{NewVehicles,t} + \Delta W_{VKTSwitch,t} \quad \text{Equation 8}^8$$

where  $PC_k$  is the annualized perceived cost per VKT for technology  $k$ ,  $SwitchNS_k$  is the net technology switch relative to the BAU for technology  $k$ ,  $\Delta W_{VKT}$  is the consumer surplus lost as a result of policy in the market for vehicle travel from existing vehicles,

<sup>8</sup> The perceived cost is also discounted to its current value in in the year 2012 using the same calculation shown in Equation 7.

$\Delta W_{NewVehicles}$  is the consumer surplus lost as a result of policy in the market for new vehicles, and  $\Delta W_{VKTSwitch}$  is the welfare lost based on the additional perceived cost of alternative modes of transportation.

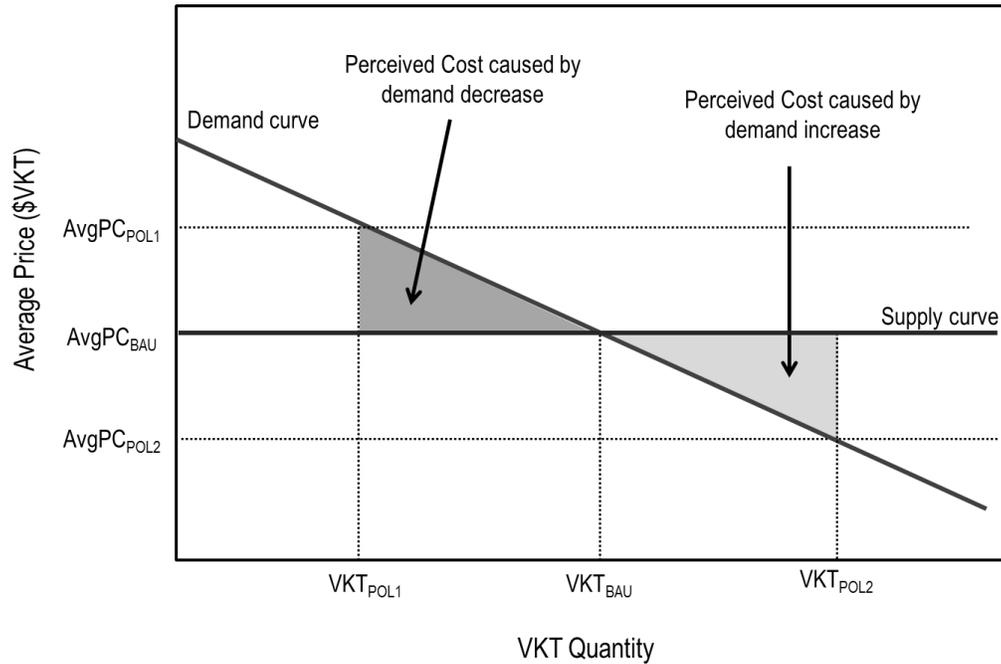
I calculate  $SwitchNS_k$ , the net technology switches under policy, using the following equation:

$$SwitchNS_{k,t} = NSPOL_{k,t} - (MSBAU_{k,t} * TNSPOL_{k,t}) \quad \textbf{Equation 9}$$

$NSPOL_{k,t}$  is the new stock of technology  $k$  in the policy simulation,  $MSBAU_{k,t}$  is the market share for technology  $k$  in the BAU simulation, and  $TNSPOL_{k,t}$  is the total stock of new vehicles in the policy simulation. By using the market share from the BAU scenario, Equation 9, isolates the costs that come from changes in consumer technology choices from fluctuations in service demand.

I calculate two components of the total perceived cost in Equation 8,  $\Delta W_{VKT,t}$ ,  $\Delta W_{VKTSwitch,t}$ , and  $\Delta W_{VKTSwitch,t}$ , by estimating the total area lost underneath the demand curve for each market in the policy scenario. The demand in each of these service markets changes in the model every time the market's average price under policy deviates from the average price in the BAU scenario. I assume a flat supply so that I can estimate this value by calculating the area of triangles shown in Figure 5.

**Figure 5: Perceived costs from demand shifts in CIMS-US-PV service markets**



I use Equation 10 to calculate the area of the triangle for either an increase or decrease in the demand for either vehicle travel over new vehicles.

$$\Delta W_t = ABS \left[ (AvgPC_{POL,t} - AvgPC_{BAU,t}) (Q_{POL,t} - Q_{BAU,t}) \left( \frac{1}{2} \right) \right] \quad \text{Equation 10}^9$$

In Equation 10,  $\Delta W_t$  is the total perceived cost in model period  $t$ ,  $AvgPC_{POL,t}$  is the average perceive cost in the market under the policy scenario,  $AvgPC_{BAU,t}$  is the average perceive cost in the market under the BAU scenario,  $Q_{POL,t}$  is the quantity (either travel or

<sup>9</sup> I take the absolute value of the product because, under the assumption that the service demand market is in equilibrium in the BAU, any shift away from that equilibrium will result in a loss of consumer surplus and thus a perceived private cost. To see this graphically, refer to Peters (2006).

new vehicles) demanded in the market under the policy scenario, and  $Q_{BAU,t}$  is the quantity demanded in the market under the BAU scenario.

One modification that I make to the CIMS-US cost-accounting method is that I add a third market representing all other transportation alternatives to passenger vehicle travel that is linked to the VKT demand and demand for new vehicles. I assume that the overall VKT demand for any time period in the model is fixed: when consumers reduce their demand for either new vehicle VKTs or existing VKTs, they instead must use VKTs in the alternative transportation market. In contrast to the equations for the other two service demand markets, I include a random uncertain parameter in the cost calculation for VKT “switched” to the market for transportation alternatives ( $AvgPC_t$ ) as show in the following equation.

$$\Delta W_t = ABS \left[ (AvgPC_t)(VKT_{POL,t} - VKT_{BAU,t}) \left( \frac{1}{2} \right) \right] \quad \text{Equation 11}$$

In Equation 11,  $AvgPC_t$  is the perceived cost of other transportation options for the entire forecast period,  $VKT_{POL,t}$  is the total VKT in the policy scenario in model time period  $t$ ,  $VKT_{BAU,t}$  is the total VKT in the BAU scenario.

Similar to top-down models, CIMS-US calculates a perceived cost for any deviation that policy causes from the technology and service demand choices in the BAU (whether it is an increase or decrease in a particular energy service demand). This assumption, though, ignores research that shows regulations can increase consumer welfare (Moxnes 2004), and that technology preferences can change over time and in response to policy (Duke and Kammen 1999). Because of this, I calculate a midpoint between the financial cost and the perceived cost according to the following equation so that I do not overstate the “optimality” of consumers’ present choices:

$$\text{Total Cost of Policy} = \text{Total FC} + ((\text{Total PC} - \text{Total FC}) * w) \quad \text{Equation 12}$$

where  $w$  is a weighting factor that has a base value of 0.75. The value of 0.75 is based on our judgement that approximately 25% of the perceived cost is purely the product of market failures and bounded rationality and thus represents a “false” social cost. I base this judgement on the previous finding that consumers do not always make perfect choices in a BAU scenario (Moxnes 2004). Admittedly, our assumption for  $w$  lacks a strong empirical basis which is why I later test the sensitivity of model results to a range of weighting values between 0 and 1.

For each policy simulation, I calculate the cost (weighted by  $w$ ) in each model time period and calculate a cumulative cost over the forecast period (2005-2050), discounting the total cost in each period at a 5% social discount rate with 2012 as the base year. I calculate the ratio between the net present value of total policy costs and reduced tonnes of WTW GHG reductions over the forecast period. An important feature of our cost-effectiveness estimate is that it is based on dynamic long-term technology assumptions. For cost-effectiveness, a higher number indicates a less favourable outcome. This ratio can also be negative, if a policy results in overall cost savings through greater fuel efficiency and fuel switching.

There are several factors not included in the definition of the economic resource cost. First, I do not include emissions charges as these are transfers from consumers to government that ultimately stay within the economy. Second, the administrative cost of enforcing each policy is not included. It should be noted though that the vehicle mandate policies are likely to have higher administrative costs than a carbon tax on vehicle fuels. Third, the model does not include the infrastructure costs related to the diffusion of a new technology, such as the construction of new refueling infrastructure. Fourth, my cost calculations do not include any marginal benefits from emission reductions—I assume each ton of CO<sub>2</sub>e reduced relative to the BAU has an identical, unspecified benefit to society. Fifth, the model does not factor in macroeconomic costs which may arise from a

policy decreasing economic activity in certain sectors. At the same time, though, the model also does not include macroeconomic benefits if a policy encourages economic growth that would otherwise not take place (i.e. if battery vehicle technology takes off and increases overall employment). Finally, I do not factor in the potential for negative externalities in the market for vehicle travel. Examples of these would include social costs caused by increased passenger vehicle travel, including traffic congestion and vehicle fatalities

## **2.3. Input Assumptions**

I include a number of input assumptions in the CIMS-US-PV model in order to simulate the US passenger vehicle sector. In this section, I provide an overview of key input assumptions as well as relevant sources for the base values of and uncertain distributions of such assumptions. An integral part of my methodology is incorporating uncertainty through the technique of Monte Carlo simulations, which I discuss in Section 2.5.

### **2.3.1. *Vehicle Demand Forecast***

The model runs from years 2005 to 2050, and the demand for vehicle use is measured in passenger VKTs, based on data generated by the US EIA. The VKT demand for years 2005 to 2010 is based on historical data while the demand from 2010-2050 is based on a projected annual growth rate of 1.4% (U.S. Energy Information Administration (EIA) 2012).

Based on the full CIMS-US model, I assume that the maximum vehicle lifespan is 15 years (although small percentages of vehicles are retired after 5 and 10 years according to a technology retirement function taken from the full CIMS-US model). In addition, I assume that each vehicle travels on average 20,000 VKT/year and that this value remains static in the model forecast.

### **2.3.2. Vehicle Technology Characteristics**

Each vehicle propulsion technology in the model is defined by a series of unique attributes: the introduction year, the capital cost and fuel efficiency of the technology for each time period, the parameters that define each technology's fixed and declining intangible costs (the neighbour effect), and the parameters that define each technology's declining capital cost (learning by doing).

Because the main difference in the costs for alternative vehicle options is the total lifecycle cost differential among vehicle propulsion technologies, this is the value that I compare between model simulations. I assume other attributes of passenger vehicles (size, cars vs. trucks etc.) remain relatively constant across all simulations. What is crucial for this study's policy comparison is the cost differential between the policy and BAU scenarios, not the absolute cost of either. I take the capital costs for vehicle technologies from the full CIMS-US model.

I also draw on the full CIMS-US model for the fuel efficiency of each vehicle propulsion technology. In the BAU, I model the current US EPA's Corporate Annual Fuel Economy (CAFE) standards which, in their current form, are expected to run until 2025. I only include a simplified approximation of the CAFE standards in order to maintain model simplicity because the focus of my study is technology adoption, not fuel economy improvements. I approximate the CAFE standards by setting the fuel efficiency of current vehicle propulsion types (gasoline, diesel, gasoline-electric hybrid, and E85 fuel vehicles) to autonomously improve until 2025 (at which point all new vehicles have the highest fuel efficiency attainable in the full CIMS-US model). In addition, I use a shadow price on vehicle efficiency in the BAU scenario that increases the cost of vehicles inversely proportional to their fuel efficiency. The shadow price—which is an estimate of the implicit tax that fuel economy standards place on vehicles that are of below-average efficiency—increases the forecasted market share for more fuel efficient vehicle technologies. Overall, I calibrate the CAFE standard approximation by ensuring that my CIMS-US-PV model BAU simulation produces a similar outcome for new vehicle market share as the reference case in the US EIA's *Annual Energy Outlook 2012*.

Two vehicles in the model use two different fuels. The ethanol vehicle propulsion technology has a 15/85 split between gasoline and ethanol fuel. The PHEV propulsion

technology also has a 15/85 split but between gasoline and electricity, respectively. For the PHEV I assume that, at the model year 2040, the gasoline portion of the fuel demand is replaced by ethanol, significantly reducing the emissions intensity of plug-in hybrids at the end of the simulation period.

I determined whether or not to include the declining capital costs for vehicle propulsion technologies based on the stage of each vehicle propulsion technology's development. Mature technologies—specifically ICE gasoline, diesel, and E85 ethanol vehicles—do not have declining capital costs. I assume that since these technologies are widespread (diesel propulsion systems are widespread in other uses) they do not benefit from learning by doing. I include declining capital cost functions for HEVs, EVs, PHEVs, and HFVs because none of these technologies have yet achieved high levels of market penetration. As each technology is more readily adopted, accumulated experience produces economies of scale and cost savings until technologies reaches their minimum capital cost (if at all). A key assumption is the cost of each vehicle propulsion technology at maturity, which I set as a pre-specified value relative to the gasoline ICE vehicle. This cost at maturity is included as an uncertain parameter in the Monte Carlo analysis. For each cost at maturity, I specify a normal distribution because I deem that there are sufficient existing studies with point estimates close to the base values for these parameters in CIMS-US-PV (Bandivadekar et al. 2008; Eyzaguirre 2004)

Another crucial parameter is the learning rate or “progress ratio” for vehicle propulsion technologies. Commonly, learning rates are based on experience with past similar technologies, but this does not guarantee that one can accurately predict the learning rate for new technologies in the future, such as the vehicle propulsion technologies in this study. I chose the base value for the learning rate for battery vehicle technology class (HEVs, PHEVs, and EVs) to be 0.88 based on econometric analysis from Weiss et al. (2012). This value leads to cost declines that are congruent with other literature sources (Cheah and Heywood 2010; Kromer and Heywood 2007). Overall, though, I test a range of learning rates along a uniform distribution as I judge there is insufficient data to justify an alternative probability distribution. I specify a learning index with endpoints for the progress ratio of 0.75 and 0.98.

Table 2 provides a summary of vehicle characteristics including uncertainty parameters.

**Table 4: Summary of vehicle propulsion technology baseline parameters for CIMS-US-PV with Monte Carlo distribution assumptions**

Technology	Year Introduced	Initial Capital Cost (2005 CDN)	Cost at Maturity (% Initial CC)	Initial Fuel Efficiency (GJ/VKT)	Progress Ratio (experience curve)
Gasoline	2005	$\sim N(5000, 1000)^a$	-	0.003482	-
Diesel	2005	$\sim N(8000, 1000)$	-	0.003098	-
E85 Ethanol	2005	$\sim N(5677, 1000)$	-	0.003886	-
Plug-in Hybrid (gasoline and electricity)	2015	$\sim N(17926, 1000)$	$\sim N(44, 2.5)$	0.001792	$\sim U(0.75, 0.98)$
Gasoline-Electric Hybrid	2005	$\sim N(12650, 1000)$	$\sim N(52, 2.5)$	0.002015	$\sim U(0.75, 0.98)$
Hydrogen Fuel Cell	2015	$\sim N(150437, 1000)$	$\sim N(25, 2.5)$	0.00262	0.7 <sup>b</sup>
Electric	2015	$\sim N(38672, 1000)$	$\sim N(50, 2.5)$	0.00126	$\sim U(0.75, 0.98)$

<sup>a</sup>  $\sim N(\mu, \sigma)$  denotes a normal distribution centered on mean  $\mu$  and with a variance of  $(\mu)$  while  $\sim U(a, b)$  denotes a cumulative uniform distribution with minimum  $a$  and maximum of  $b$ .

<sup>b</sup> Even with a very optimistic progress ratio of 0.7, Hydrogen Fuel Cell motors are barely adopted by consumers in CIMS-US-PV

The last crucial set of parameters differentiating vehicle propulsion technologies is the set of parameters that defines the declining and fixed intangible costs. I base the parameters in CIMS-US-PV on several studies that use and develop empirical methods to estimate intangible cost parameter values (Axsen, Mountain, and Jaccard 2009; Mau et al. 2008; Horne, Jaccard, and Tiedemann 2005)

The intangible cost function has two components: the fixed component that is an annual cost not affected by any other model parameters, and the upfront intangible cost which changes based on that vehicle technology's market share in the previous model period. The intangible cost accounts for the fact that the features of some technologies, for example the lower maximum range of electric vehicles, will always have some intangible cost associated with them relative to current conventional vehicles. A negative

number for the fixed intangible cost (as is the case with gasoline vehicles) indicates that consumers perceive a significant benefit from that technology not reflected in the financial cost. I account for the uncertainty surrounding the values for these intangible costs parameters in my Monte Carlo simulations by specifying normal distributions as show in Table 5. I choose to specify normal distributions for these values because they come from previous empirical research.

**Table 5: Summary of intangible costs for vehicle propulsion technology in CIMS-US-PV with Monte Carlo input assumptions**

Vehicle Type	Fixed Intangible Cost (2005 CDN)	Upfront Variable Intangible Cost (2005 CDN)	A	K
Gasoline	$\sim N(-3400, 500)^a$	-	-	-
Diesel	$\sim N(2000, 500)$	$\sim N(4000, 1000)$	0.4	65
Ethanol	$\sim N(1500, 500)$	$\sim N(2000, 500)$	0.4	65
Gasoline-electric Hybrid	-	$\sim N(7000, 1000)$	0.4	65
Plug-in Hybrid	-	$\sim N(15000, 1000)$	0.4	65
Hydrogen Fuel Cell	-	$\sim N(10000, 1000)$	0.4	65
Electric	$\sim N(2000, 500)$	$\sim N(13000, 1000)$	0.4	65

<sup>a</sup>  $\sim N(\mu, \sigma)$  denotes a normal distribution centered on mean  $\mu$  and with a variance of  $(\mu)$

### 2.3.3. Other Key Model Parameters

Several additional parameters influence the technology competitions within the model. The first such parameter is the private discount rate ( $r$ ) for consumers. The discount rate defines the trade-off that vehicle consumers make between costs and benefits in the present time period, and costs and benefits in the future. According to the literature on consumer vehicle purchase decisions, this discount rate tends to be high: consumers weight their decisions much more heavily on the relative technology costs in the present time period than on future costs. In CIMS-US-PV, I apply the current discount rate from the full CIMS-US model passenger sector (25.70%) which is based on several previous studies (Axsen, Mountain, and Jaccard 2009; Mau et al. 2008; Home, Jaccard, and Tiedemann 2005).

The market heterogeneity or variance parameter ( $v$ ) enables the model to produce forecasts that are more behaviourally realistic than simply portraying consumers

solely as choosing the vehicle technology with the least cost. The higher the  $\nu$  parameter, the closer the technology competition algorithm approaches allocating 100% of new market share to the least cost technology. At the other extreme, a very low value for  $\nu$  will lead to an even allocation of market share between competing technologies regardless of differences in life-cycle costs. In the full CIMS-US model, the value for the  $\nu$  parameter within the passenger vehicle class in CIMS is set at 15. I adjust this down to a value of 10 because it better calibrates with the *Annual Energy Outlook 2012* reference case for new vehicle market share and based on earlier work suggesting an even lower value for the  $\nu$  parameter of 2.4 to 6.1 by Axsen, Mountain, and Jaccard (2009); Mau et al. (2008); and Horne, Jaccard, and Tiedemann (2005). I chose though to keep the base value for the  $\nu$  parameter at 10 because, at lower values, the technology competition algorithm loses its sensitivity to policy. In the Monte Carlo analysis, I test a range of values for the  $\nu$  parameter using a normal distribution to account for the uncertainty inherent in this decision. My choice of a normal distribution over a uniform distribution in this case is arbitrary.

The vehicle demand and VKT demand feedbacks are important feedback effects in the model. The vehicle demand own-price elasticity represents the response of consumer demand for new vehicles to overall vehicle prices. I use a base value of  $-0.5^{10}$  from Mallory (2007) and account for a range of values by specifying a normal distribution from which a value for vehicle demand elasticity is randomly drawn during the Monte Carlo simulations. An elasticity value of  $-0.5$  means that, for every 1% increase in the average cost of new vehicles, there is a 0.5% decrease in the demand for new vehicles.

The VKT demand from existing vehicles feedback represents the response of consumers with existing vehicles to changes in the average cost passenger vehicle travel. I use a value of  $-0.2$  (also from Mallory [2007]) for the elasticity of existing vehicle

<sup>10</sup> Other researchers find the following estimates overall own-price elasticity of automobile demand:  $-0.87$  (McCarthy 1996),  $-1.0$  (Kleit 1990), and  $-1.55$  to  $-2.0$  (Bordley and McDonald 1993)

use parameter. I place a normal distribution around this assumption as well because of previous studies that find values that are close to the base value of -0.2.<sup>11</sup>

**Table 6: Other key model parameter input assumptions**

Parameter	Distribution in Monte Carlo Simulations
Discount rate (r)	$\sim N(0.257, 0.05)$
$\nu$ (Market Heterogeneity)	$\sim N(10, 1.5)$
Vehicle Demand Elasticity	$\sim N(0.5, 0.05)$
Elasticity of Exist. Vehicle Use	$\sim N(0.2, 0.02)$

### 2.3.4. Fuel Costs and Characteristics

I input fuel costs into the model as exogenous forecasts show below in Table 7.

**Table 7: BAU Fuel Cost Forecast (2005 CDN/GJ)**

Fuel	2005	2010	2015	2020	2025	2030	2035	2040	2045	2050
Biodiesel	29.93	41.25	45.01	50.11	50.91	47.87	45.48	43.25	41.13	39.12
Diesel	19.83	15.83	25.32	28.77	29.20	30.71	30.71	30.71	30.71	30.71
Electricity (average)	28.75	29.51	30.83	31.50	32.46	34.52	34.52	34.52	34.52	34.52
Ethanol	26.75	26.24	26.81	30.76	30.97	31.70	32.30	32.30	32.30	32.30
Gasoline	20.48	19.16	28.28	32.39	32.93	34.58	34.58	34.58	34.58	34.58
Hydrogen	55.59	46.64	45.19	42.68	42.68	42.68	42.68	42.68	42.68	42.68

I vary fuel costs as uncertain parameters by simulating four scenarios for each fuel cost forecast. In the Monte Carlo specification, each scenario is weighted with a 0.25

<sup>11</sup> A literature review of econometric studies of the rebound effect (Small and Van Dender 2007) find the following range of estimates for the VKT rebound effect: 20-30% (or -0.2 to -0.3).

probability. The four fuel cost scenarios are: no change from the BAU, a -30% reduction, a 30% increase, and a 60% increase relative to the BAU scenario.

A unique feature of CIMS-US-PV is the specification of ethanol fuel. I assume that there is an upper limit to how much corn ethanol fuel the US economy can produce. *The Energy Independence and Security Act (2007)* established a federal Renewable Fuels Standard (RFS) and placed an upper limit of approximately 15 billion barrels (1.4 billion GJ) for annual US corn ethanol production (to mitigate the risk of increasing food prices). Thus, I set 2.0 billion GJ as the upper limit for annual corn ethanol fuel consumption in the model.<sup>12</sup> If, in a given model period, the quantity of ethanol consumed exceeds this upper limit, then the price of ethanol rises sharply in the following model period—simulating a highly inelastic supply curve. There are, however, two scenarios for ethanol fuel built into the Monte Carlo analysis. The first scenario is one in which there is no breakthrough in cellulosic ethanol, meaning that the well-to-wheels lifecycle GHG intensity of ethanol fuel stays the same in the model and the upper limit for corn ethanol production remains binding. The second scenario is that there is a breakthrough in cellulosic ethanol that becomes commercialized in 2030, meaning that in this model year the well-to-wheels lifecycle GHG intensity of ethanol decreases from 0.073 to 0.005 tonnes CO<sub>2</sub>e/GJ and that there is no longer an upper limit to how much ethanol can be produced (because cellulosic ethanol—in theory—will not affect food crop production in the US). In Monte Carlo analysis, the model chooses between these scenarios based on an external probability.<sup>13</sup>

I use two sets of emission factors for each fuel in the full CIMS-US-PV model (all emissions in the model come from fuel consumed by passenger vehicles—I assume that emissions produced in the production of vehicles remains the same regardless of vehicle type). First, the direct emission factors, or “tailpipe” emissions, describe the number of

<sup>12</sup> I chose to raise the corn ethanol limit from 1.4 to 2.0 billion GJ to give the model more flexibility in accounting for advances in corn ethanol production and the initial production of cellulosic biofuels.

<sup>13</sup> See Appendix C. Table 12 row 9.

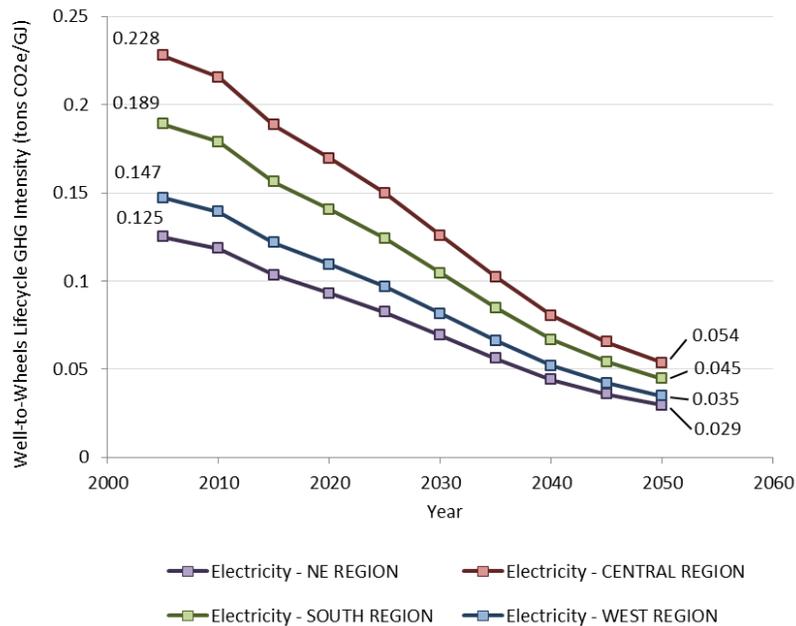
tonnes of CO<sub>2</sub>e released into the atmosphere from the direct combustion of a given fuel inside the vehicle engine. I take these emissions factors from data in the full CIMS-US model. I summarize these emission factors along with the well-to-wheels emissions factors in Table 8.

**Table 8: Direct/“Tailpipe” emission factors**

Vehicle Fuel	Direct Emissions (tonnes of CO <sub>2</sub> e/GJ)	Well-to-Wheels Emissions (tonnes of CO <sub>2</sub> e/GJ)
Gasoline	0.0681	0.086
Diesel	0.0706 <sup>a</sup>	0.091
Biodiesel	0	0.020
Ethanol	0	0.073 (cellulosic=0.005)
Hydrogen	0	0.76
Electricity	0	Region-dependent (see Figure 6)

The second set of emission factors I include are well-to-wheels lifecycle emission factors for each fuel. These factors include the GHGs emitted in the process of producing a fuel and transporting it to the point at which it enters a vehicle. I use three principle sources to determine my well-to-wheels emissions factors. First, I take values for corn and cellulosic ethanol from Farrell et al. (2006) and Schmer et al. (2008), and for biodiesel and hydrogen from California Air Resources Board (2012). Second, I calculate the emission factors for my four US grid regions based on data from Weber et al. (2010). Third, I forecast emission intensity declines in the US grid according from modeling of EMF 24 scenarios in the full CIMS-US model. These scenarios include different combinations of economy-wide policies such as clean electricity regulations and a cap-and-trade system. The EMF scenarios are a standard set of scenarios used to compare results in many of world’s leading energy policy models (Jaccard and Goldberg 2013). I show the US6 clean electricity standard scenario that is the basis for the policy comparisons I present in my results section in Figure 6.

**Figure 6: Forecasted well-to-wheels lifecycle GHG intensity of US electricity by region (EMF US 6 scenario: clean electricity standard)<sup>14</sup>**



In this study, I focus mainly on the cumulative well-to-wheels lifecycle emissions reductions for alternatives vehicle policies because this is the result that matters more for the level of overall national emissions. I contribute to previous research on the impact of plug-in electric vehicles in different US regional electricity grids (Samaras and Meisterling 2008; Axsen et al. 2011) by including a forecast of the GHG intensity of electricity grids several decades into the future (Jaccard and Goldberg 2013).

Except for ethanol (in the scenario that cellulosic ethanol does become available) and electricity, I assume that the well-to-wheels emissions factors for vehicle fuels remain static over the forecast period. I do so because CIMS-US-PV focuses on effect of policies that target vehicle propulsion technology choices as opposed to the GHG-intensity of fuel. I do not explicitly factor in future US oil exports from the Canadian oil sands, which would likely increase the upstream GHG intensity of gasoline (although

<sup>14</sup> Electricity scenario 2 is based on simulation results of the EMF 24 US 6 scenario in the full CIMS model Jaccard and Goldberg (2013).

CIMS-US-PV also does not include gasoline that is blended with small amounts of ethanol, which would reduce the overall well-to-wheels GHG intensity of gasoline). I deem exploring alternative scenarios and uncertainties for the well-to-wheels GHG emission factors in CIMS-US-PV to be an important addition for future studies but out of the scope of this research paper.<sup>15</sup>

## 2.4. Policies Assessed

In this study, I consider three different policies—each at three varying levels of stringency for the purpose of sensitivity analysis. Each policy is implemented in the year 2015 and continues at increasing stringency until 2050. The policies I simulate are:

- A tax on greenhouse gas emissions applied to the direct emissions of vehicle fuels (Fuel Carbon Tax)
- A near-zero emission vehicle mandate that mandates the adoption of zero-emission vehicles but forces mandated technologies to compete against one another (NZEV Standard). The vehicle propulsion technologies included are:
  - Hydrogen Fuel Cell (HFV)
  - Plug-in Hybrid Electric (PHEV)
  - Electric (EV)
  - E85 Ethanol
- An electric vehicle mandate that mandates the adoption of only plug-in electric vehicles (EV Standard). Thus the only vehicle propulsion technologies included are:
  - Plug-in Hybrid
  - Electric

I do not test any policy combinations because I choose to focus my analysis on the effect of increasing technological-specificity in a direct policy-to-policy comparison. In

<sup>15</sup> Mallory (2007) forecasts exogenous scenarios that factor in economy-wide cap-and-trade in which there are very marginal declines in the upstream emissions for vehicle fuels. Based on the marginal change in emissions factors in her study, I chose to keep my values static.

reality, it is possible that a combination of different policies will lead to the lowest relative costs for reducing GHG emissions from passenger, but this research question is beyond the scope of this paper. Rather than setting policies to meet a specific emissions reduction goal, I instead set the stringency level of policies based on recent political proposals. I account for the relative arbitrariness of this modeling assumption by also looking at high and low scenarios for policy stringency. In Table 9, I describe each policy and its respective scenarios in greater detail.

**Table 9: Summary of Policies Assessed**

Policy	Policy Lever	Policy Stringency Scenario	Policy Level (by year)		
			2015	2035	2050
Fuel Carbon Tax	Tax applied to the direct GHG emissions of gasoline and diesel fuels (2005 CDN/ton of CO <sub>2</sub> e)	Low	\$15	\$100	\$175
		Medium	\$30	\$200	\$350
		High	\$100	\$500	\$800
NZEV Standard	Regulation mandating that a percentage of new vehicles sold in a given year must be low emission vehicles (HFVs, PHEVs, EVs, or E85 Ethanol)	Low	5%	25%	40%
		Medium	8%	35%	65%
		High	8%	40%	100%
EV Standard	Regulation mandating that a percentage of new vehicles sold in a given year must be either PHEVs or EVs)	Low	5%	25%	40%
		Medium	8%	35%	65%
		High	8%	40%	100%

I select the middle stringency for policies based on current political proposals. I set the fuel carbon tax at an initially low level of \$30/tonne in 2015 (a value that is identical to the current level of the British Columbia’s carbon tax) that increases to \$200/tonne by 2035 and \$350/tonne by mid-century, which are both values within the range of estimates for marginal cost abatement curve for greenhouse gas emissions (although they are closer to upper-bound of such estimates [Tol 2011; Murphy and Jaccard 2011; Clarke et al. 2009]). For the purpose of sensitivity analysis I also model a much lower carbon tax and one that is much higher: several hundred dollars above current proposals. I model this relatively “politically unacceptable” carbon tax to see how

the model reacts to such an extreme value and to look at the level for emissions reductions such a high carbon tax can achieve.

I set the middle stringency for the vehicle mandates policies at a level slightly higher than that of the current ZEV mandate in California, which mandates that approximate 15% of all new vehicles sold in the 2025 model year must classify under the regulation's definition of "zero-emission vehicle."<sup>16</sup> I set the mandate in 2025 at 20% of new vehicles. The three stringency levels for the portfolio standard differ mainly by how aggressively the policy increases the mandated market share for non-conventional vehicles. The low, middle, and high stringency cases results in mid-century mandated new vehicle market shares of 40%, 65%, and 100%, respectively.

It is important to recognize that this policy comparison will depend on key, highly uncertain assumptions about the evolution of future consumer preferences, the scale-up costs, and declining costs for ethanol, hydrogen, and electric vehicle technologies. In the following section, I discuss the Monte Carlo algorithm for integrating these uncertainties as stochastic input parameters.

## **2.5. Incorporating Uncertainty**

Like all models, CIMS-US-PV is an abstraction from reality that is useful for investigating particular policy questions. As such, it is crucial to understand the implications of uncertainty on the model's forecasts, and particularly because the CIMS-US-PV model attempts to simulate dynamics in the US passenger vehicle sector over a relatively long time period. While it is important to find that a given policy may be more cost-effective than another, it is at least equally important to understand what assumptions lead to this outcome. Moreover I must re-examine the efficacy of the

<sup>16</sup> Because of complex credit mechanisms and alternative compliance pathways under California's ZEV program, it is uncertain what actual percentage of ZEV vehicles will actually be adopted under a 15% mandate.

assumptions that act as inputs into the model that most impact the cost and emission results.

In Monte Carlo analysis, a value is drawn at random from a pre-defined probability distribution for each model input. After the software algorithm assigns each uncertain input a value, the model iterates and produces outputs. This process is then repeated a pre-specified number of times ( $m$ ), producing  $m$  unique combinations of different input assumption. As a final result, the Monte Carlo analysis produces an output distribution for each output variable with  $m$  data points (Morgan and Henrion 1990).

In this study, I undertake Monte Carlo analysis using the @Risk software package which is add-on to Microsoft Excel. In total I specify 36 uncertain model inputs. I apply normal distributions for inputs that are derived from previous empirical research, cited as point estimates in other literature, or taken from the existing full CIMS-US model. For parameters for which I do not have the same basis to apply a normal distribution—for example, where other researchers site a possible range of values—I specify a uniform distribution using a minimum and maximum value I judge to be within reasonable bounds. For each Monte Carlo analysis simulation, I run the model through exactly 10,000 iterations. In Table 10, I provide a summary of key input parameters (I provide a complete list of all uncertain input assumptions in the model and the probability distributions I specified for each in the Monte Carlo simulations in Appendix C on pg. 91).

**Table 10: Summary of Uncertain Input Parameter Specification for Monte Carlo Analysis**

Number	Parameter	Base Value	Type of Distribution	Distribution Values
1	VKT Annual Growth Rate	1.4%	Normal	$\mu=1.4\%$ $\sigma=0.2\%$
2	Discount Rate (r)	25.70%	Normal	$\mu=0.257\%$ $\sigma=0.05\%$
3	Market Heterogeneity (v)	10	Normal	$\mu=10$ $\sigma=1.5$
10	Plug-in Hybrid Vehicle Capital Cost	\$17,926	Normal	$\mu=\$17,926$ $\sigma=\$1,000$
11	Vehicle Demand Elasticity	0.5	Normal	$\mu=0.5$ $\sigma=0.05$
12	VKT Elasticity	0.2	Normal	$\mu=0.2$ $\sigma=0.05$
13	Breakthrough in Cellulosic Biofuels	0 (No)	Binomial	0 (No)=60% 1 (Yes)=40% <sup>17</sup>
14	Plug-in Hybrid Vehicle Upfront Intangible Cost	\$15,000	Normal	$\mu=\$15,000$ $\sigma=\$1,000$
17	Vehicle Battery Progress Ratio (Declining Capital Cost)	0.88	Uniform	Minimum=0.75 Maximum=0.98

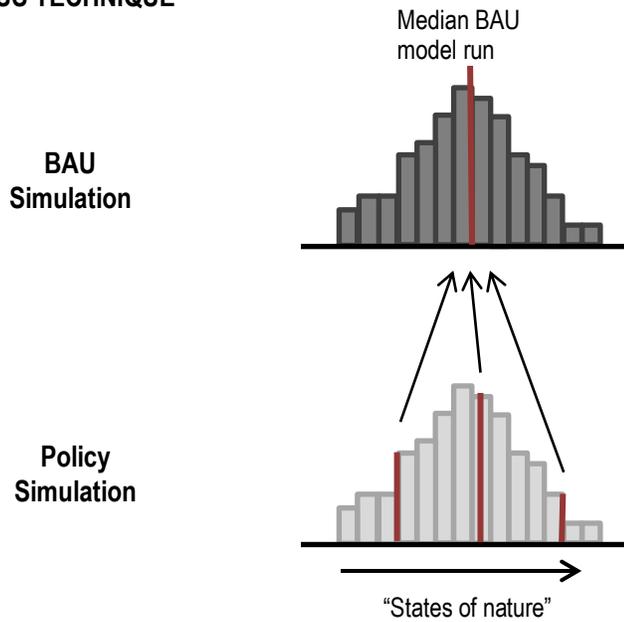
In previous studies in which stochastic risk analysis was conducted within a CIMS-based model, policy scenarios were compared with the median model run for the BAU model (Mallory 2007). In contrast, my methodology allows both the BAU and policy models to use the same input assumptions simultaneously in the Monte Carlo simulations. Thus, the model reports the difference between the outputs of these two

scenarios across all the random “states of nature” fed through the model. States of nature are unique sets of input assumptions. A simple example is that in some states of nature, the cost of vehicle batteries declines significantly whereas in other states of nature vehicle batteries remain very expensive.

To illustrate this difference in simple terms, let us consider a single simulation of a policy and BAU scenario under both the old and new simulation methods. With the old method, the model first runs through 10,000 states of nature for the BAU scenario. Using the subsequent cost and GHG emissions result distributions, a computer program then calculates the median values for policy costs and emissions in each time period. Then, the model runs through 10,000 states of nature for the policy scenario, comparing the cost and GHG emissions results in each of the 10,000 iterations to the median value from the previous BAU simulation. With the new method, the model runs through the 10,000 states of nature for the BAU scenario and policy scenarios at once. Thus in each of the 10,000 iterations, the model compares the policy cost and GHG emissions results with the BAU results for that individual iteration, and not the BAU median result calculated from a previous simulation. I show this in a diagram in Figure 7.

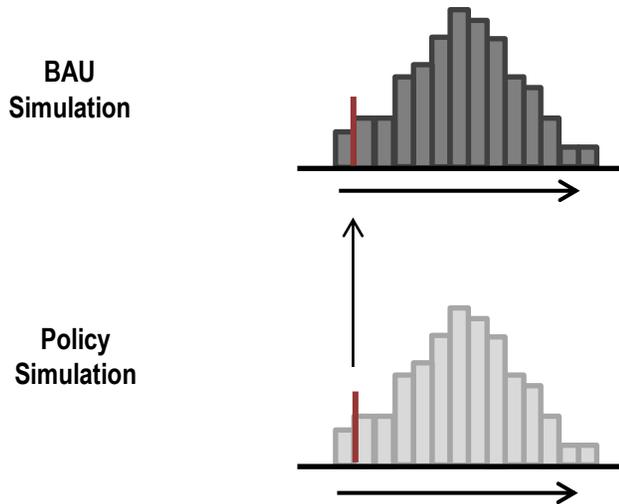
**Figure 7: Diagram explaining new linked Monte Carlo analysis technique**

**PREVIOUS TECHNIQUE**



As the policy simulation moves along different “states of nature,” the policy results (total cost and GHG emissions) are always compared with the median run for the BAU

**NEW TECHNIQUE**



With each model run, the model compares each policy scenario model run with the BAU model run for the same randomly drawn states of nature. Therefore, the comparison moves across both simulations simultaneously as opposed to comparing one moving simulation with the median result of the first simulation

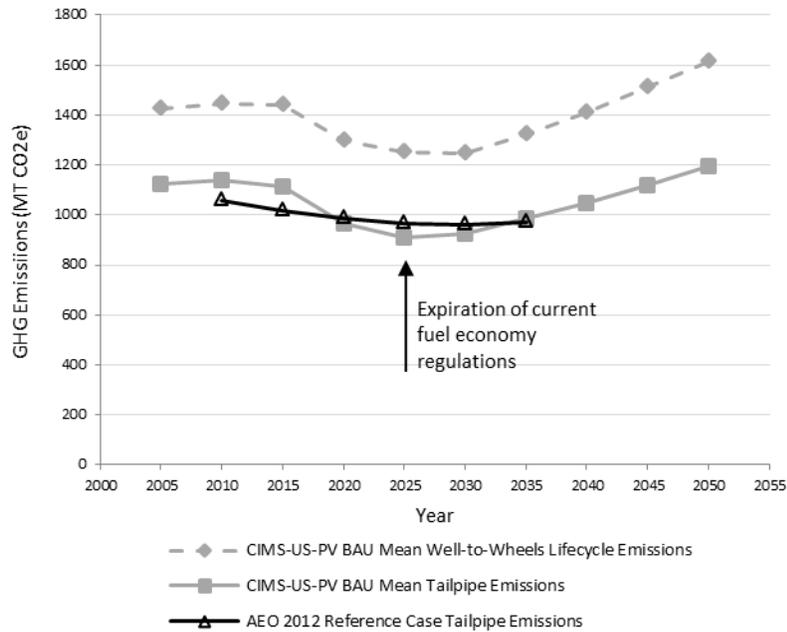
## 3. Results and Discussion

### 3.1. Business as Usual Forecast

The business as usual (BAU) simulation of the model forecasts the greenhouse gas emission (GHG) released from US passenger vehicles assuming that no further policies are implemented for the US passenger vehicle sector. Policies in the BAU include a CAFE standard regulation that ends in the year 2025 (when almost all new vehicle propulsion technologies entering in the model reach their maximum efficiency) and small subsidies in the early model periods that simulate the tax-credits initially given to consumers for purchasing HEVs, PHEVs, and EVs. Emissions from electricity generation in the BAU scenario are determined by simulations of the Energy Modelling Forum (EMF) 24 US 1 scenario in the full CIMS-US model, which corresponds to approximately a 0.9% reduction/year in the carbon intensity of all electricity generated in the US. The US 1 scenario does not include nuclear generation and carbon capture and storage as low-emission generation options and assumes a relatively optimistic scenario for wind and solar generation, bioenergy, and technologies that would reduce end-use energy consumption or better facilitate end-use fuel switching (Jaccard and Goldberg 2013). In the BAU, I also assume that all ethanol is produced from corn using a process that always produces 0.073 tonnes of CO<sub>2</sub>e/GJ (Farrell et al. 2006; Schmer et al. 2008), rather than lower-emissions cellulosic processes.

In the Monte Carlo analysis, the BAU forecast changes based on different input assumption for each of the individual 10,000 model runs. Here, I show the mean results for the BAU. Using the base values for uncertain input parameters, I calibrate the mean BAU forecast to the US Energy Information Administration's (EIA) *Annual Energy Outlook 2012* (AEO) reference case for passenger vehicles based on two model outputs: vehicle tailpipe GHG emissions and new vehicle market share. I show this comparison in Figure 8, as well as the associated well-to-wheels lifecycle GHG emissions forecast in CIMS-US-PV.

**Figure 8: Calibrating CIMS-US-PV vehicle tailpipe emissions to the AEO 2012 reference case**



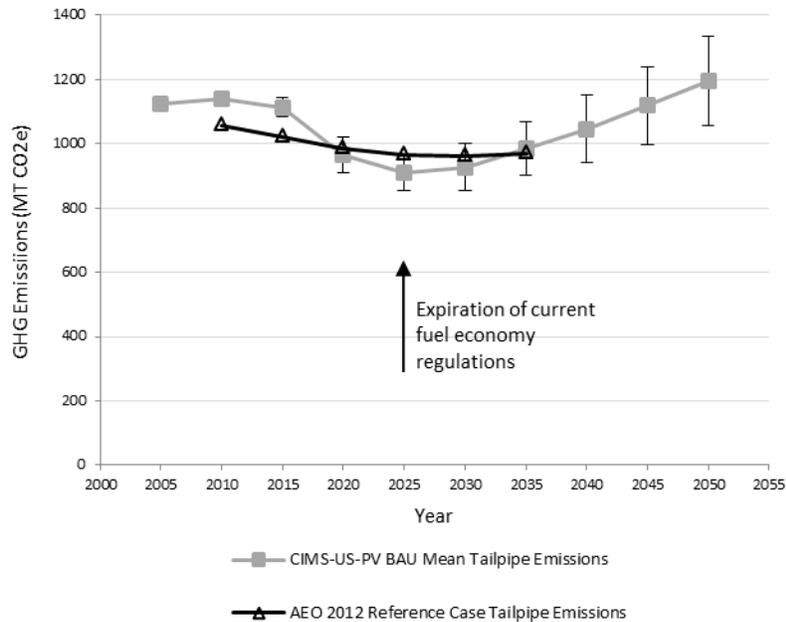
The CIMS-US-PV forecast shows the mean values from the 10,000 model runs from the Monte Carlo simulation. The same forecast is shown in Figure 9 with error bars for the standard deviation. The range of the distribution increases in the later model time periods indicating that the uncertainties of predicting passenger vehicle tailpipe GHG emissions amplify over time.

The AEO 2012 forecast is for tailpipe GHG emissions which is a measure that does not include emissions from electricity generation and fuel production. The CIMS-US-PV forecast tailpipe GHG emissions<sup>18</sup> are relatively close to the AEO 2012 reference case forecast tailpipe GHG emissions and especially so between the years 2020-2035. Between these years, the forecasts are within 5% of each other and show decreasing

<sup>18</sup> The AEO 2012 forecast for the passenger vehicle sector only reports tailpipe GHG emissions as the emissions that would comprise well-to-wheel GHG emissions are reported in other economic sectors. This is why I calibrate CIMS-US-PV to the AEO 2012 using tailpipe emissions and not well-to-wheel emissions.

emissions because of the current US CAFE standard fuel economy regulations (which expire in 2025). The CIMS-US-PV forecast shows increasing emissions from 2035 until 2050, which are years that the AEO 2012 does not investigate.

**Figure 9: Uncertainty in BAU vehicle tailpipe GHG emissions forecast**



In both BAU forecasts, conventional ICE vehicles remain relatively dominant in terms of market share (representing the current state of technological lock-in for ICE gasoline passenger vehicles). As the simulation progresses, ICE gasoline vehicles lose some market share to E85 ethanol vehicles and hybrids. Diesel vehicles rise to and remain at a relatively constant market share just below 4% of new vehicles. Most notably, EVs and PHEVs vehicles capture less than 2% of new market share by the year 2035. HFVs are adopted in such small numbers that they do not show up in any of the results.

The new vehicle market share forecast for CIMS-US-PV largely parallels that from the EIA between the years 2005-2035. The main difference between these two forecasts is that the EIA models predicts a higher market share for E85 (ethanol) flex fuel vehicles and a lower market share for HEVs. Both forecasts are similar with respect to the market penetration of low-emission vehicles. The variation in E85 ethanol vehicle

uptake can probably be accounted for based on different cost and behavioural assumptions in each model. Another point to highlight is that the EIA NEMS<sup>19</sup> model includes ethanol vehicles as “flex fuel” vehicles that are able to use either gasoline or E85 as fuel whereas CIMS-US-PV does not allow E85 ethanol vehicles to use only gasoline.

### **3.2. Results of Policy Comparison**

Figure 10 shows the Monte Carlo simulation results for the clean electricity standard scenario.<sup>20</sup> I find the fuel carbon tax policy to be much more cost-effective than either of the vehicle mandates, regardless of the level of policy stringency. For many of the simulations, the fuel carbon tax even achieves a negative cost-effectiveness. This result means that for some set of assumptions the gains from increasing average vehicle fuel efficiency and reducing VKT demand make the policy beneficial to consumers in the long-run, even when including intangible costs and heterogeneous consumer preferences. A second key finding is that, in a majority of the simulations, the EV standard is more cost-effective than the NZEV standard, especially as policy stringency increases. Moreover, according to the upper uncertainty bars (showing the 95<sup>th</sup> percentile), the NZEV standard is more likely to be significantly more costly than the other two policies.

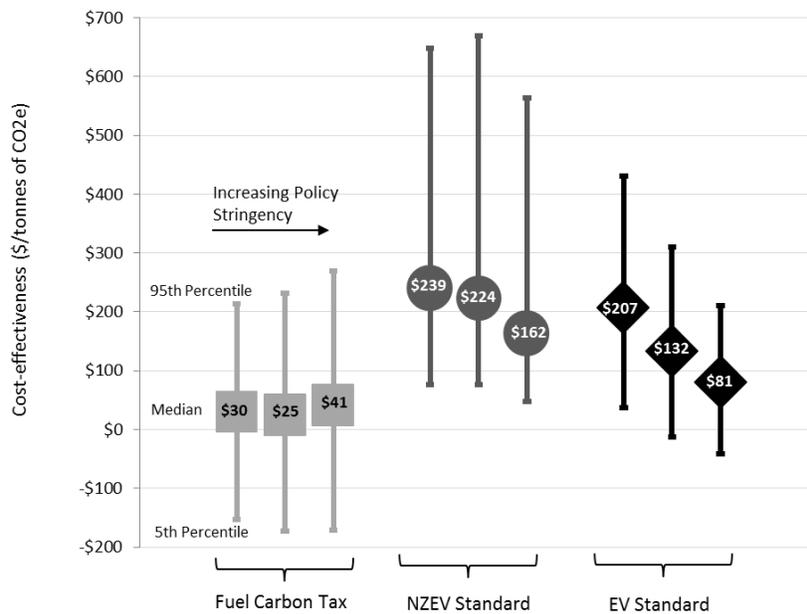
There are three potential drivers within the model that may contribute to this finding. First, the increasing returns to adoption for PHEVs and EVs could be so great in a majority of the model iterations that this outweighs the other model iterations in which vehicle battery technology has a very low progress ratio (leading to relatively insignificant declines in EV and PHEV capital cost). Increasing returns to adoptions in CIMS-US-PV means declining capital and intangible costs. Second, the NZEV standard

<sup>19</sup> National Energy Modelling System

<sup>20</sup> All the electricity scenarios are adapted from Jaccard and Goldberg (2012) who simulate Energy Modelling Forum (EMF) 24 policy scenarios in the full CIMS-US model.

may lead to more instances of the vehicle market locking into an inferior technological pathway because of input assumptions in the model about the availability of cellulosic ethanol and the relative weakness of increasing returns to adoption for E85 ethanol vehicles in the model. Third, the EV standard may results in lower overall financial costs (by incentivizing higher technologies that are more fuel efficient) than the NZEV standard. To look more clearly at the results, I analyze the two components of policy cost-effectiveness in isolation: total policy cost and cumulative lifecycle GHG reductions.

**Figure 10: Monte Carlo results for policy cost-effectiveness of “well-to-wheels” lifecycle GHG reductions under Clean Electricity Standard<sup>21</sup>**



### 3.2.1. Total Policy Cost

As I describe in section 2.2.2, I calculate total policy cost using the economic resource cost, a weighted average of the financial cost and the perceived cost. The

<sup>21</sup> All future policy costs presented are discounted at a rate of 5% (d=0.05) to their present value in the year 2012. This applies for all findings presented in this paper.

financial cost describes the cost of a particular policy relative to the BAU scenario based solely on the change in total expenditure on the capital, energy, and operating costs for vehicle technologies. In contrast, the perceived cost includes intangible costs and a higher private discount in addition to the existing financial costs and, thus, provides an estimate of the value of lost consumption when a policy causes consumers to choose vehicle technologies that they otherwise would not have chosen in the BAU.

Figure 11 shows a significant difference in the median perceived cost among the two vehicle technology mandates and the fuel carbon tax. The most important observation is the significant difference between the outcome distributions for the NZEV standard and the EV standard: in a majority of the simulations, the NZEV standard has a steadily increasing perceived cost over the forecast period while the EV standard median perceived cost reaches a peak and then descends to a comparable level as the perceived cost of the fuel carbon tax by the model year 2045.

**Figure 11: Median perceived cost (middle policy stringency, clean electricity standard)**

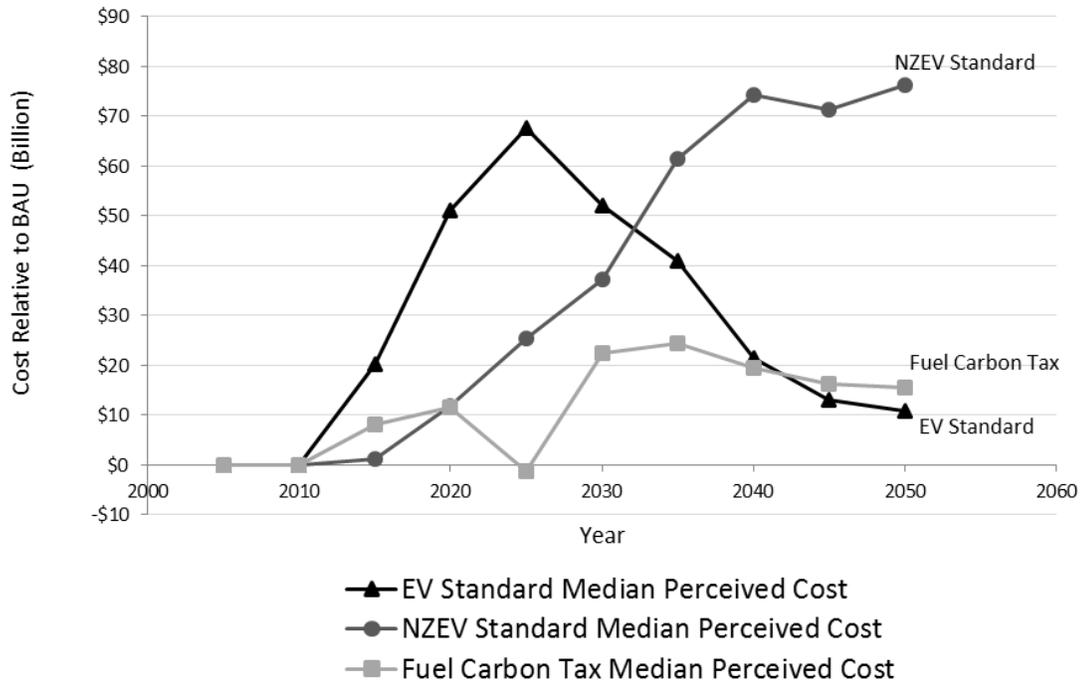


Figure 12 shows the median results for the financial costs of each policy (all of which are negative because of cost-savings that come from consumers adopting higher efficiency vehicle propulsion technologies). Again, the fuel carbon tax tends to have a lower cost than either of the vehicle mandates. The difference between the results for the two vehicle mandates is less drastic than for the outcome distribution for the perceived cost. Initially, the EV standard leads to lower financial costs, but then rises back to a similar level as the NZEV standard. Overall, the magnitude between the financial costs for the two standards is not as great as that between the perceived costs. This suggests that intangible cost parameters, which are not included in the financial costs, have a relatively larger impact on the policy costs results than other model parameters.

**Figure 12: Median financial cost (middle policy stringency, clean electricity standard)**

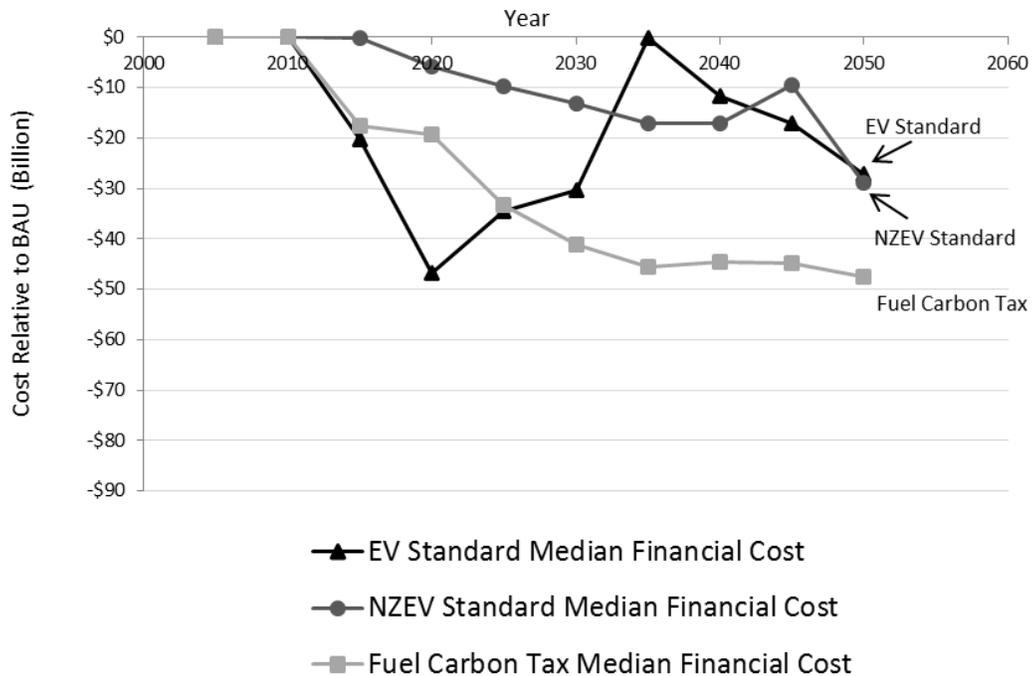
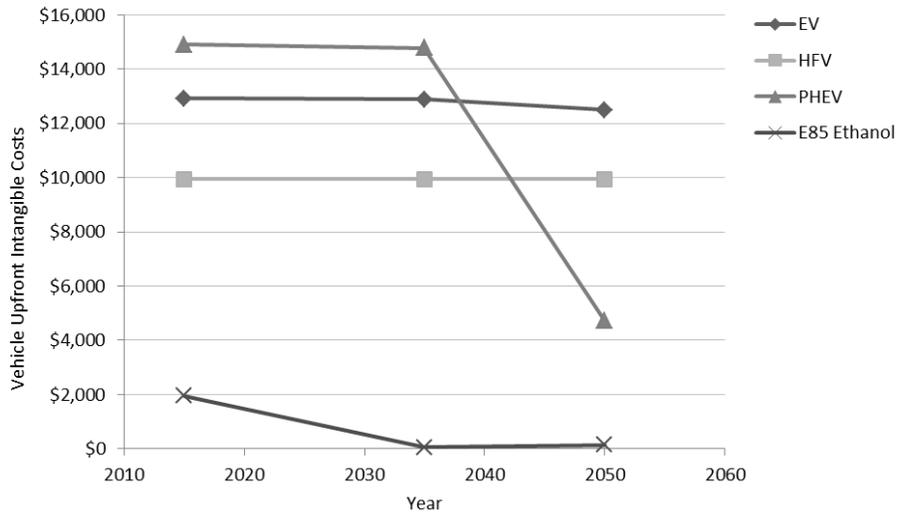
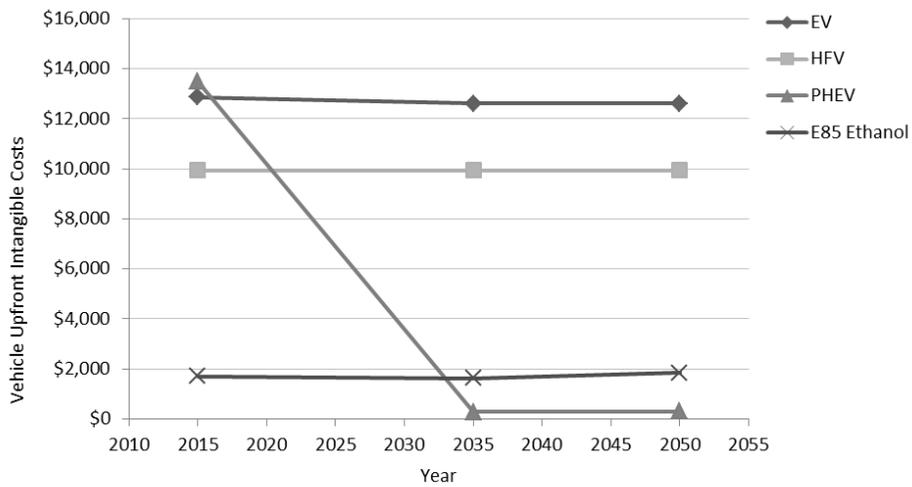


Figure 13 and Figure 14 show the mean intangible costs for the NZEV standard and EV standard respectively at three intervals over the model forecast (model years 2015, 2035, and 2050). In other words, Figure 13 and Figure 14 show the extent that different vehicle propulsion technologies benefit from the neighbour effect under technology-specific policy designs. The results show that the two vehicle mandates differ based on just two technologies: the plug-in hybrid electric and E85 ethanol vehicles. Under NZEV standard, the initial uptake of E85 ethanol vehicles delays the adoption of PHEVs and thus widespread consumer acceptance of PHEVs through the neighbour effect. Under the EV standard, PHEVs achieve widespread consumer acceptance (upfront intangible costs close to \$0) by the model year 2035.

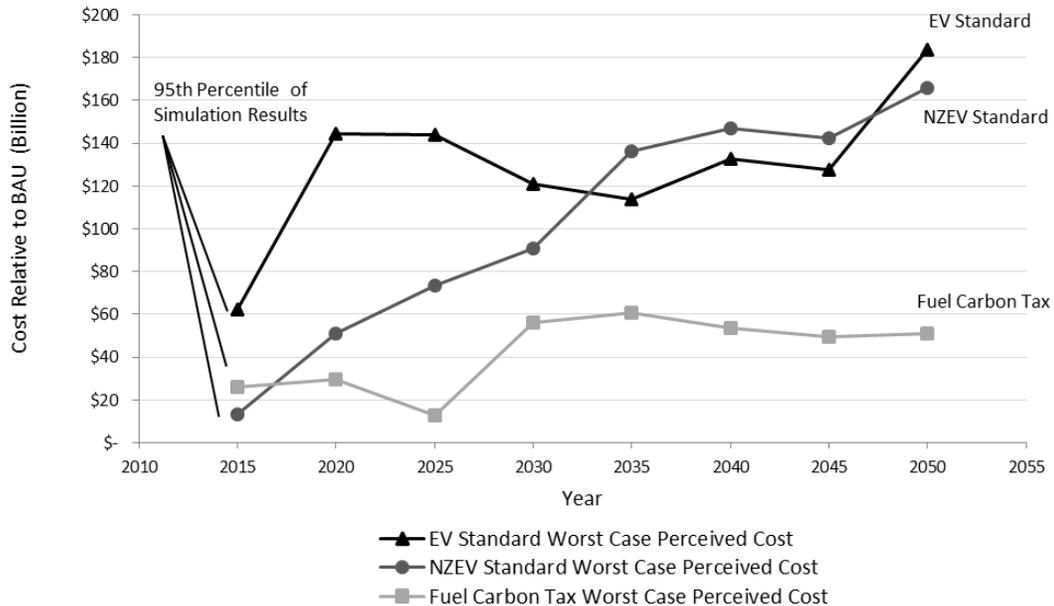
**Figure 13: Mean upfront intangible costs under NZEV standard (middle policy stringency, clean electricity standard)**



**Figure 14: Mean upfront intangible costs under EV standard (middle policy stringency, clean electricity standard)**



**Figure 15: Comparing the “worst case” PPC Scenarios for each policy simulation (Middle Policy Stringency, Electricity Scenario 2)**



In Figure 15, I compare the upper 95<sup>th</sup> percentile of each policy’s output distribution or, in other words, “the worst case” scenario. In terms of the results in later model time periods (2035-2050), there is not much of a difference between the two vehicle mandates. This is an important result because it indicates that, in the model, the NZEV standard and EV standard seem to have a similar negative result if both E85 ethanol vehicles and PHEVs turn out to be “technological losers” (although the EV standard worst case scenario is significantly more costly in the first two decades of the model forecast). In CIMS-US-PV, designing a vehicle mandate to be more technology-neutral does not seem to lessen the high cost of forcing an inferior technological pathway. It is worth noting however, that the fuel carbon tax does present a much cheaper worst case scenario than either of the vehicle mandates because it tends to encourage the lowest-cost mix of vehicle technologies. Overall, Figure 15 shows how impactful the model assumptions on the strength of increasing returns to adoption are on the long-term costs on different policies.

### 3.2.2. Cumulative lifecycle well-to-wheels GHG emissions

The denominator in the equation for policy cost-effectiveness is the cumulative lifecycle “well-to-wheels” GHG emissions reduced relative to the BAU scenario. Thus, I also investigate the simulation results for each policy’s cumulative GHG reductions to better understand the cost-effectiveness results I show in Figure 10.

**Figure 16: Comparison of policy cumulative lifecycle “well-to-wheels” lifecycle GHG reductions (showing 3 levels of policy stringency)**

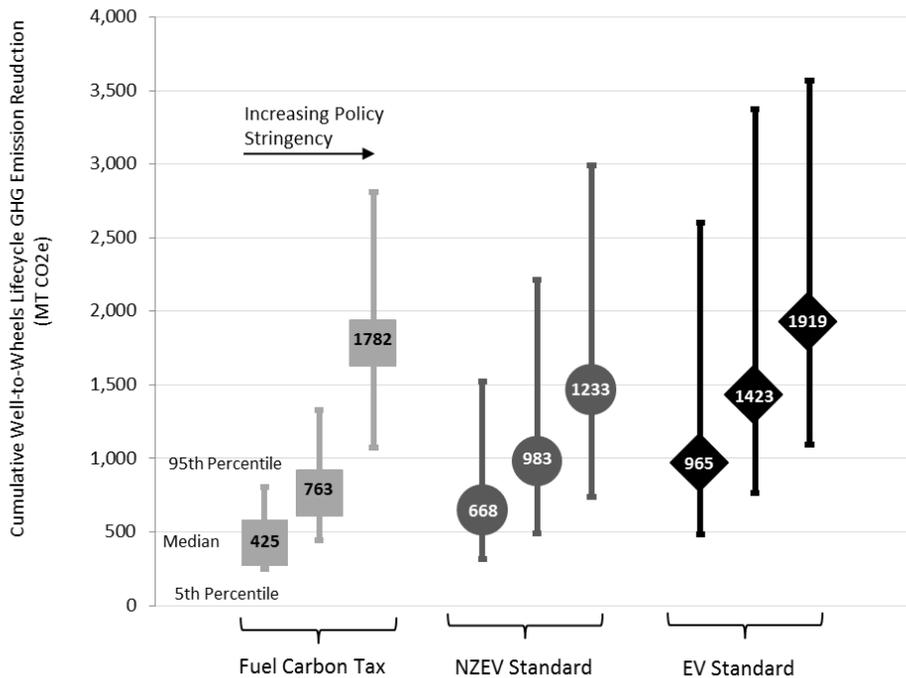
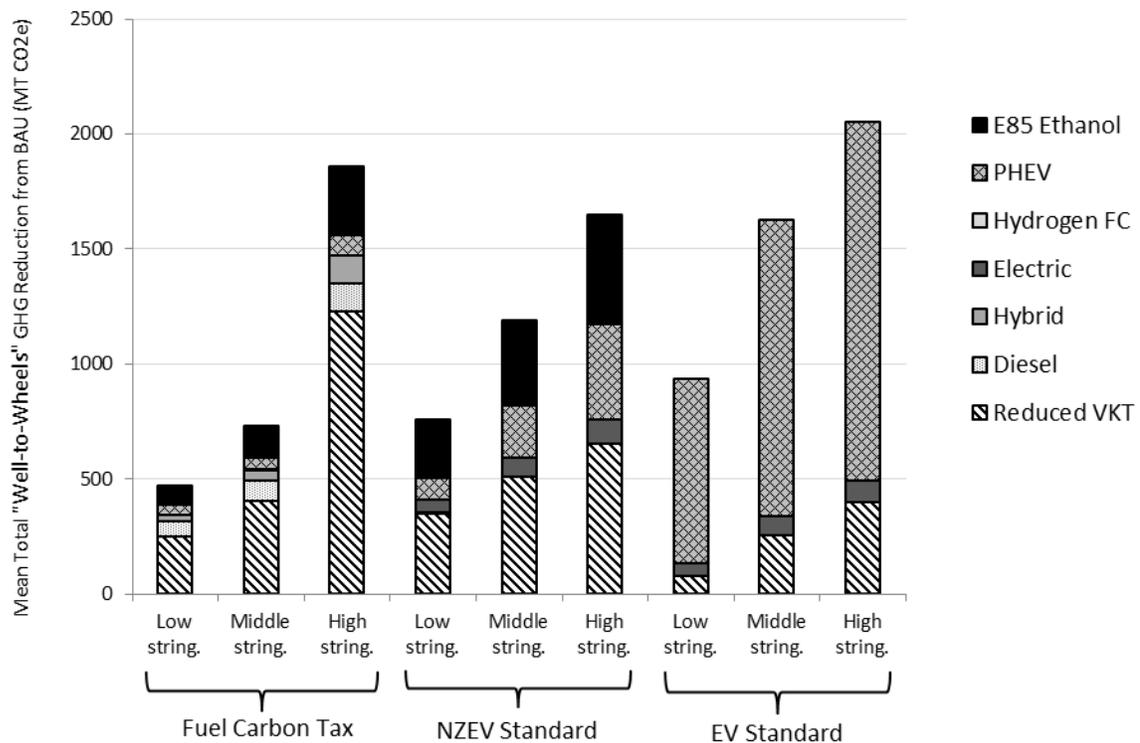


Figure 16 shows a further reason why, in most of the simulations in CIMS-US-PV, the EV standard is more cost-effective than the NZEV standard: the EV standard is more likely to achieve greater GHG reductions than the NZEV standard at an equivalent level of policy stringency. Another interesting, and somewhat unexpected result, is that the very high fuel carbon tax achieves a considerably higher level of GHG reductions than one would expect looking at the two lower stringency tax policies. This is because raising the level of a carbon tax at some point triggers a threshold at which consumers start adopting a new abatement technology.

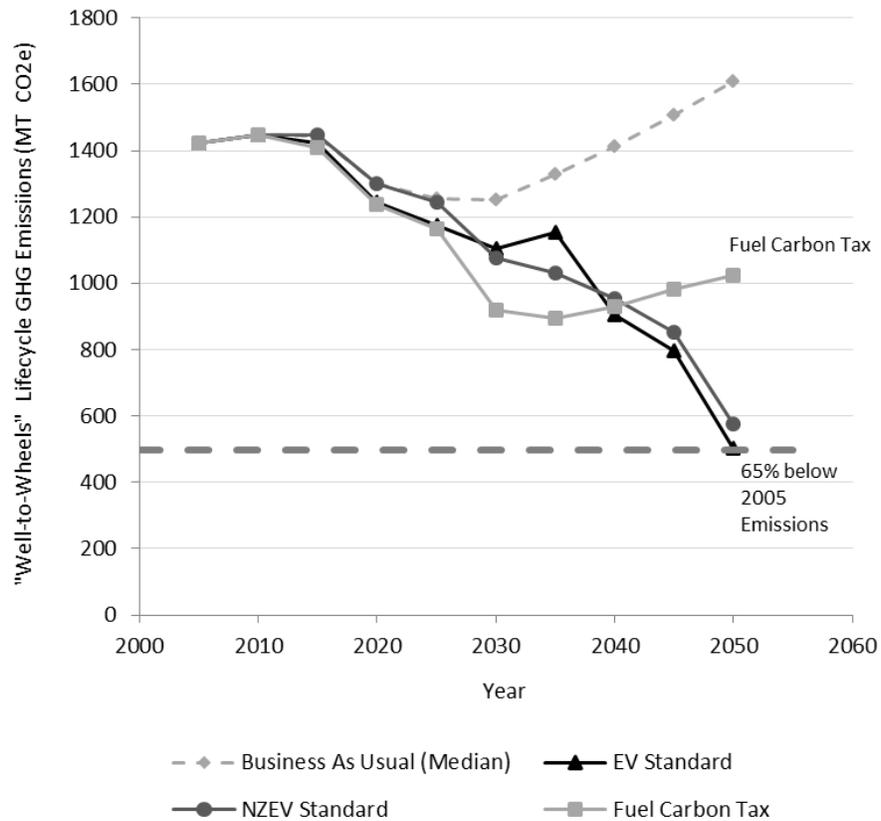
In order to further understand differences between the cumulative emissions results, I break down the results for mean GHG emission reductions into two key components: reductions from reduced/switched VKT and reductions from low-emission vehicle adoption. In Figure 17, I show this breakdown for the same three levels of policy stringency for each of vehicle policies. In Figure 17, we see a significant difference between the fuel carbon tax policies on the left (which achieve most of their emission reductions through reduced VKT) versus the EV standards on the right (which achieve most of their reductions through PHEV adoption). In contrast the NZEV standard tends to produce a roughly equal amount of reductions from reduced VKT and NZEV adoption. What these results show is a trade-off within the model between having a large set of vehicle technologies each contributing a small amount of emission reductions versus relying on a single vehicle technology to achieve the bulk of emission reductions.

**Figure 17: Mean GHG reductions from new vehicle adoption and VKT reductions (Electricity Scenario 2)**



In Figure 18, I look at the “best-case” emissions reduction scenario for each policy in CIMS-US-PV. I set each policy to have electricity scenario with the greatest degree of decarbonisation (4.6% annual reduction in GHG intensity of electricity) and allow for widely-available cellulosic biofuel. I find that, for the levels of policy stringency that I model, the vehicle mandates have a much higher upper-potential for GHG reductions over the entire model period. While the high-stringency fuel carbon tax does achieve lower emissions than either of the portfolio standards in earlier model periods, this tax policy is not able to achieve the same dramatic reductions after 2040. This is because achieving such deep emission reductions in CIMS-US-PV requires the mass adoption of PHEVs that eventually run on biofuels, EVs, or E85 ethanol vehicles (if cellulosic biofuel is available).

**Figure 18: Policy Comparison of “Best-Case” Scenario for GHG Emission Reductions**



This figure requires two important qualifications. The first is that I only test a fuel carbon tax policy that is applied to the tailpipe GHG emissions for vehicles. If a carbon tax was applied to upstream emissions as well, then it is very possible that such a comprehensive tax would be able to achieve the 65% reduction target in 2050 in CIMS-US-PV, and probably at a lower social lower cost than either of the vehicle mandates. I do not model an upstream tax, however, because the intention of this study is to compare policies that focus purely on tailpipe emissions. A second qualification is that a fuel carbon tax on vehicle tailpipe emissions is able to reach the 65% target if that tax rises to \$900/tonne by 2035 and then up to \$1700/tonne by 2050. Such a fuel carbon tax level is well above current proposals that would be deemed, “politically acceptable.” It is likely though that the rate of a comprehensive carbon tax (that is also applied to upstream emissions) that achieves the 65% reduction target would be much closer to or within the range of political acceptability.

### **3.3. Sensitivity Analysis**

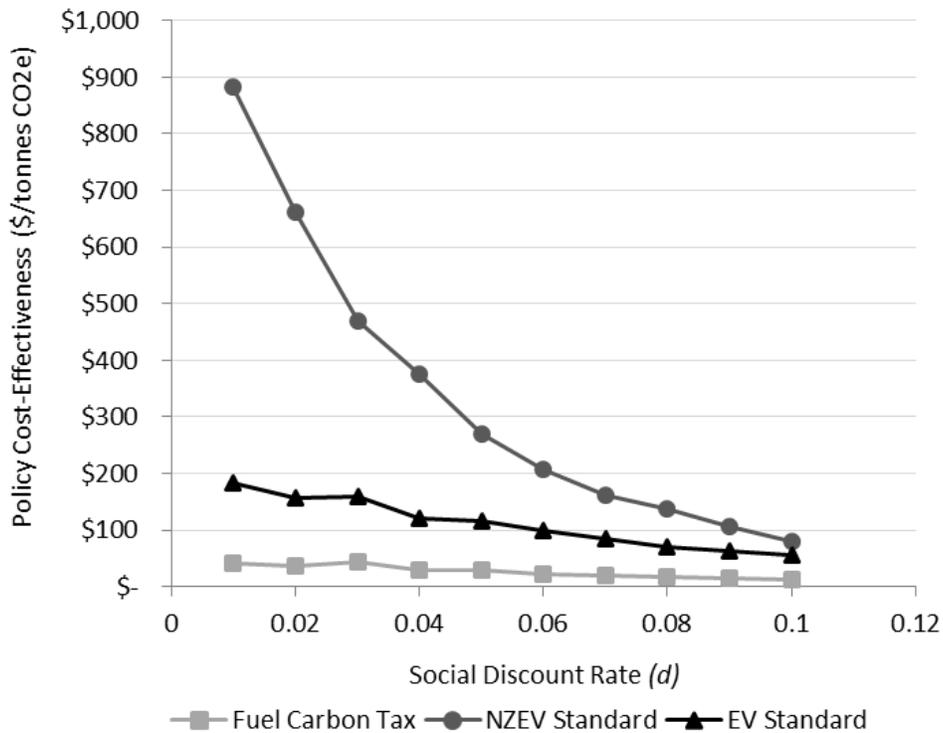
In the following figures, I present analyses to determine how sensitive the policy simulation results are to uncertain input parameters. First, I undertake single parameter sensitivity analysis for the social discount rate ( $d$ ). The social discount is the rate at which an entire economy discounts the future costs and benefits of climate policies. This is different than the private discount rate ( $r$ ), which in CIMS-US-PV represents the extent to which individual consumers discount the future costs when deciding which vehicle propulsion technology to purchase.

The base value I used for the social discount rate is 5% per year (the same value used by the US EIA and by Small [2012]).<sup>22</sup> In Figure 19, I show the base cost-effectiveness result for each policy model simulation as I adjust the social discount rate from 1% to 10%. This comparison shows that the ranking of results for relative policy

<sup>22</sup> U.S. Energy Information Administration, *Energy Market and Economics Impacts of the American Power Act of 2010*, pg. 15.

cost-effectiveness is not sensitive to my choice of the social discount rate ( $d$ ). The magnitude for the cost-effectiveness of the NZEV standard, though, does increase significantly relative to the other policies as I adjust the social discount rate downwards toward 1%. This pattern indicates that the NZEV standard policy tends to have very high policy costs in the later periods of the model forecast.

**Figure 19: Sensitivity of mean policy cost-effectiveness to the social discount rate (Electricity Scenario 2, Middle Policy Stringency)**



Another type of sensitivity analysis I undertake is tornado analysis, which is a method that draws from the results of a Monte Carlo simulation to rank uncertain input assumptions based on how much they affect a model outcome. For the tornado analysis in this study, I linked policy models together in “meta-simulations” in order to produce a Monte Carlo output for the likelihood that a specific ranking for policy cost-effectiveness occurs in CIMS-US-PV.

Figure 20 shows the tornado diagram for the meta-simulation I run that tests the relative ranking of two vehicle mandates (and thus excludes the fuel carbon tax policy). The x-axis represents the probability that the EV standard is more cost-effective than the NZEV standard. The mean value of the diagram is 86% which, from the Monte Carlo simulation, is the overall probability that the EV standard is more cost-effective than the NZEV standard. The left side of the diagram lists the uncertain input assumptions to which this result is most sensitive. For example, the chart shows that a higher value for the elasticity of VKT demand for existing vehicles decreases the likelihood that the EV standard will be more cost-effective than the NZEV standard. Figure 20 lists the top five most influential parameters for the relative ranking of the two vehicle mandates.

**Figure 20: Sensitivity of the EV Standard having a superior cost-effectiveness to the NZEV standard (clean electricity standard, middle policy stringency)**

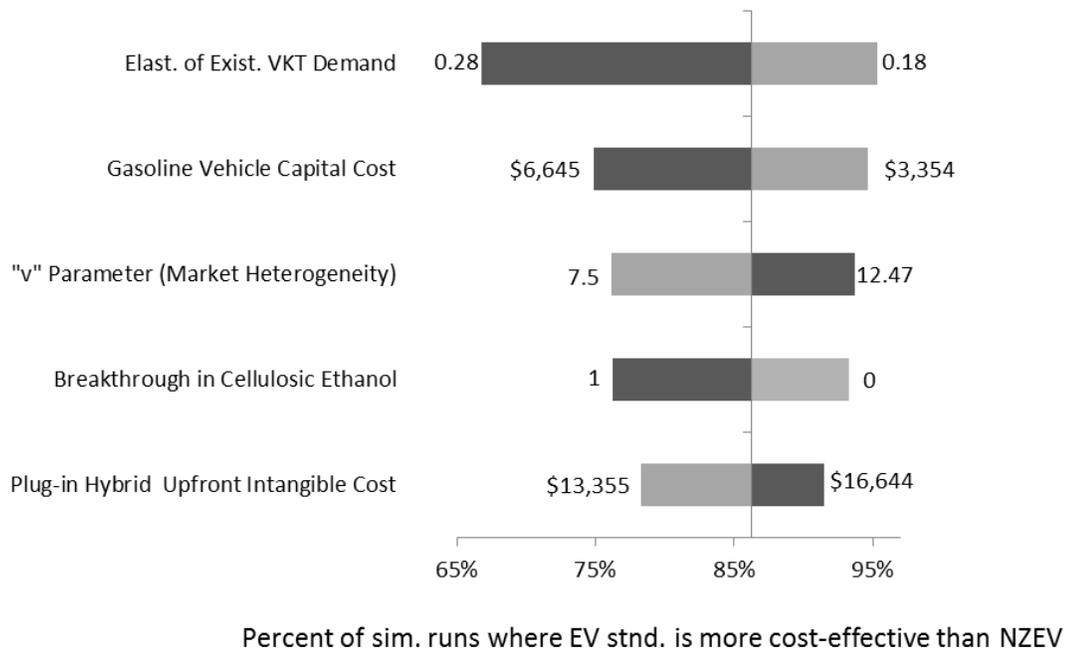
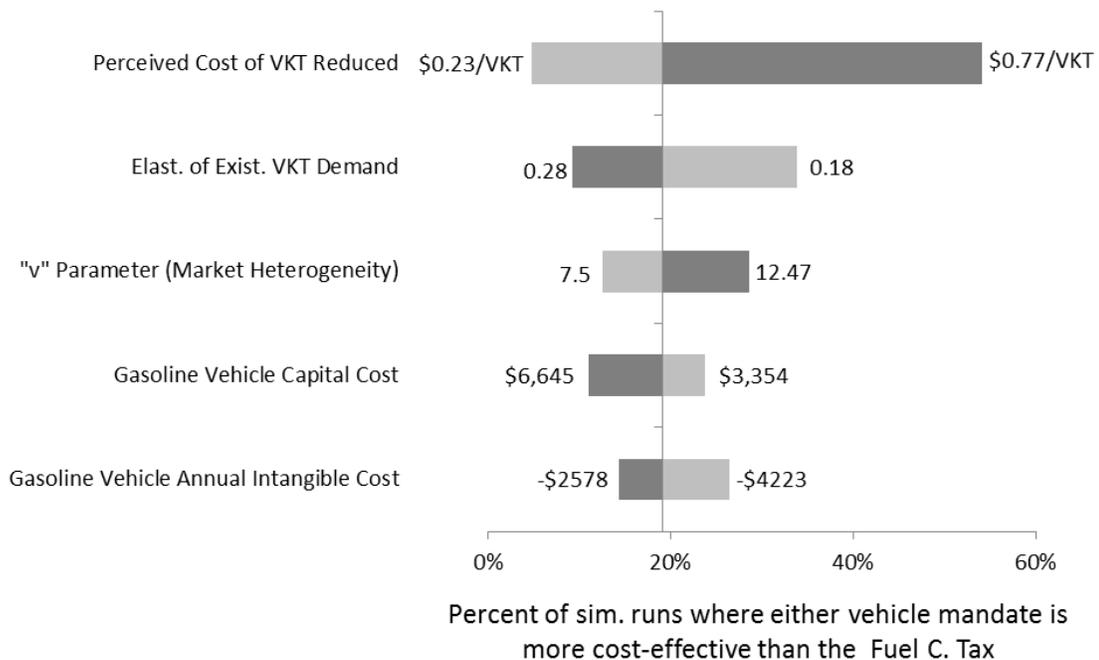


Figure 20 shows as well that, even with the elasticity for existing VKT demand set very high (0.28), the EV standard still outperforms the NZEV standard in approximately 70% of the joint-model runs. Thus, for this case study in the CIMS-US-PV, the benefit of “forcing” the neighbour effect for PHEVs mostly outweighs risk of plug-in hybrid vehicles turning out to be a “technological loser.”

Figure 21 shows the tornado diagram for the second meta-simulation that I run. In it, I evaluate the likelihood that either one of the vehicle mandates is more cost-effective than the fuel carbon tax. As denoted by where the y-axis intersects with the x-axis of the chart, there is just an approximately 20% likelihood that one of the vehicle mandates is more cost-effective than the fuel carbon tax. Unlike the previous tornado analysis of the ranking of just the two vehicle mandates, this analysis finds the “perceived cost of VKT reduced” to be the uncertain input parameter to which the relative ranking of all three policies is most sensitive. What this means is that the higher the perceived cost of switching to alternative transportation modes (such as public transit or biking), the greater the likelihood that one of the mandates is more cost-effective than the fuel carbon tax.

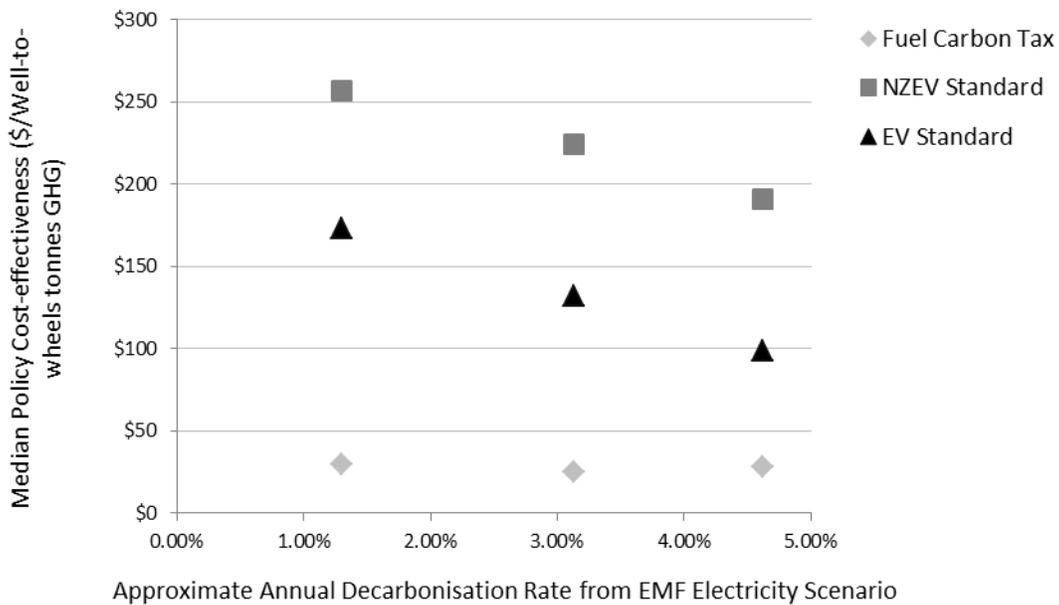
**Figure 21 Sensitivity of either vehicle mandate having a superior cost-effectiveness to a Fuel Carbon Tax (clean electricity standard, middle policy stringency)**



The final uncertainty analysis I undertake is that run the middle policy stringency level for each policy under high and low electricity scenarios. Instead of using the US 6 EMF scenario results from the full CIMS-US model (which show an

approximate 3.13% annual decline in the GHG intensity of electricity), I run the policy simulations based on the US13 and US4 scenarios,<sup>23</sup> which lead to low and high approximate annual decarbonisation rates of 1.3 % and 4.6%, respectively.<sup>24</sup> I show the results below in Figure 22 for the median cost-effectiveness of the three policies based on the three electricity scenarios. For these high and low scenarios electricity scenarios, there is no change in the relative ranking of policy cost-effectiveness.

**Figure 22: Sensitivity of median policy cost-effectiveness to high and low electricity decarbonisation scenarios (middle policy stringency)**



<sup>23</sup> The US4 scenario assumes a 50% cap-and-trade policy and includes all electricity generation technologies, including carbon capture and storage and nuclear. The US13 scenario assumes no policy and optimistic cases for all electricity generation technologies.

<sup>24</sup> As a means of reference the reduction in carbon intensity for the US electricity grid in 2011 was approximately 4.0% (U.S. Energy Information Administration 2013).

## 3.4. Discussion

### 3.4.1. *Main Findings*

This study is an initial attempt at comparing technology-neutral and technology-specific policy designs in a hybrid simulation model. As such, the results I present are relatively preliminary and most useful in that they indicate important areas for future research.

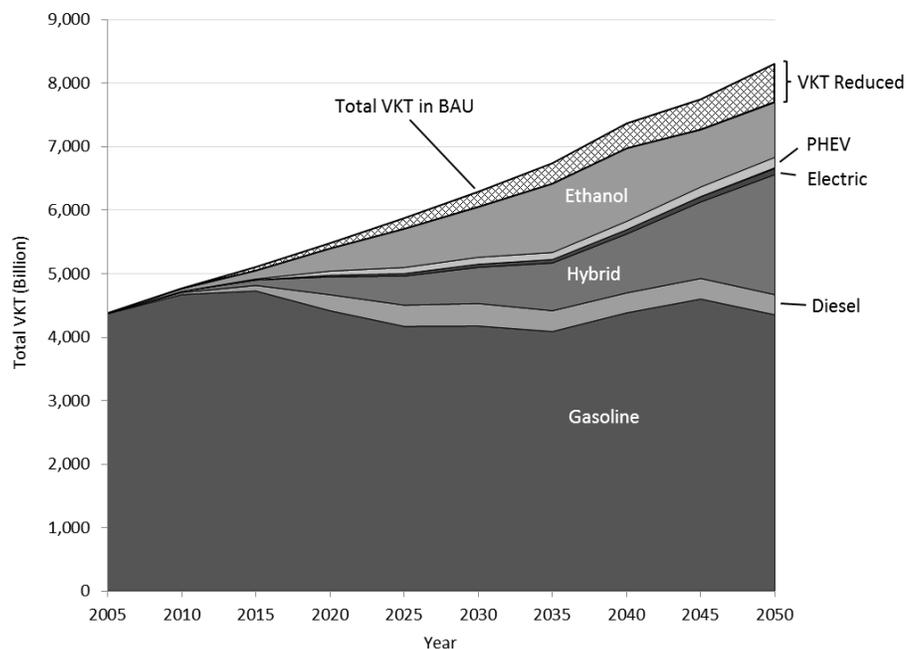
It is important to acknowledge that these results are derived from a case study of US passenger vehicles with a particular set of vehicle propulsion technologies; they may very well not hold for other economic sectors or technology sets. These results are useful though in how they compare and contrast with theoretical arguments forwarded by economists and technology experts. First, the policy cost results for both of the vehicle mandates show that it is indeed possible that “picking the wrong winner” could lead to a substantial social cost. The results show as well that a policy designed to be technology-neutral (the fuel carbon tax) results in a much more favourable “worst case” scenario than the alternative technology-specific policies. Therefore, I do find that the technology-specific vehicle mandates perform poorly across uncertain future outcomes when viewed as substitutes for a technology-neutral fuel carbon tax.

However, my results are also consistent with Azar and Sandén's (2011) argument that technology-specific climate policies can produce benefits by “forcing” the creation of niche markets for new disruptive low-emission technologies. The EV standard simulations show that a technology-specific policy can exploit the potential of increasing returns to adoption for a technology (PHEVs) and that the creation of this initial niche market is otherwise an unlikely outcome under a technology-neutral tax policy. This effect is best demonstrated by comparing the mean vehicle stock market shares under the fuel carbon tax and EV standard, which I present in Figure 23 and Figure 24, respectively. It would take a much higher carbon tax in CIMS-US-PV to produce the same kind of niche market for PHEVs that the EV standard creates prior to the year 2030. A carbon tax that would create such a niche market in CIMS-US-PV

would probably have to be set at a level well above what is now considered to be politically acceptable.

Such a carbon tax (which places a low cost on all consumers) would also have a much larger effect on the average cost of driving for all vehicles than the establishment of a niche market through a technology-forcing mandate (which concentrates a high cost on a small number of consumers). This is an important factor to consider because rising average prices lead to consumers driving less, and the costs that consumers perceive when they switch from passenger vehicle travel to alternative modes of transportation is a key future uncertainty.

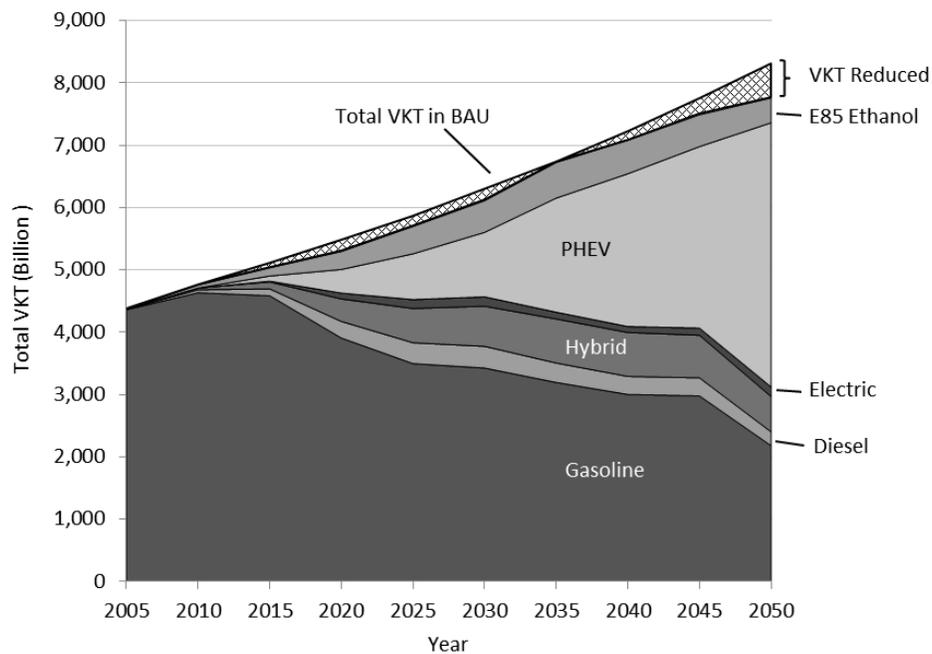
**Figure 23: Average vehicle stock under Fuel Carbon Tax (middle policy stringency, clean electricity standard)**



In addition, the results for the less technology-specific NZEV standard show that it is important to consider the trade-off between incentivizing the adoption of evolutionary versus revolutionary technologies. With the set of technology and fuel assumptions that I make for this study, delaying the introduction an initially expensive but promising revolutionary technology (PHEVs) in favour of what is more likely to be an initially cheaper but less environmentally-effective evolutionary technology (E85 ethanol)

significantly decreases policy cost-effectiveness for the NZEV standard. This is because of the several decades it can take for a new revolutionary technology to actually benefit from increasing returns to adoption. Thus, designing a vehicle mandate to be less technology-specific can create an elevated risk of high policy costs by delaying an important threshold in transitioning to a low-emission technology.

**Figure 24: Average vehicle stock under EV Standard (middle policy stringency, clean electricity standard)**



### 3.4.2. Model Limitations

In its current form, CIMS-US-PV possesses important limitations that impact my results. First, firms and consumers are completely myopic in the model; they have zero foresight of future taxes or regulations and thus make vehicle technology and fuel choices based only on the cost information in that present year. The result of this assumption is that CIMS-US-PV probably underestimates the adoption of low-emission technologies under a carbon tax. The reason for this is that, if consumers see that a carbon tax will rise in the future, then that expectation will affect their current vehicle purchase decisions because they will—to some extent—anticipate increases in fuel costs for GHG-intensive vehicles. There exists already an equation in the full CIMS-US model for consumer

carbon tax foresight that I do not include in CIMS-US-PV. This is a key model limitation. It is possible that with some extent of consumer foresight, a fuel carbon tax would be much more successful at nurturing a niche market for disruptive vehicle technologies than portrayed in the current model results.

A second limitation of CIMS-US-PV is how the model deals with vehicle fuels. Unlike the full CIMS-US model, there are no separate supply sectors for such fuels. Thus, both the price and GHG-intensity of fuels are input into CIMS-US-PV as exogenous assumptions. In particular, I place a production ceiling on corn ethanol production (the ceiling is much more optimistic than the near-term production limit outlined in existing US legislation). The advantage of this technique is that it is simple to input into the model. The model, however, would portray future scenarios more accurately if it instead used a rising supply cost curve for corn ethanol; it is unlikely that the actual supply curve for this fuel will be as inelastic as I specify with the production limit. The same holds for all of the fuels included in CIMS-US-PV. The inclusion of such supply cost curves would allow fuel prices in the model to adjust endogenously instead of being inputted as exogenous forecasts. The model could also be improved by using additional discrete modeling scenarios for the forecasted well-to-wheels GHG content of specific fuels.

A third limitation of CIMS-US-PV is that it uses the standard log-linear functional form for declining capital cost experience curves. These experience curves do not explicitly account for cost-declines that come from R&D activities or, “learning by searching.” This omission neglects an important policy lever for cost declines. The single function used for experience curves also does not allow a modeller to test whether or not unit cost declines could be better portrayed by a different kind of function than a log-linear curve (for example, an “s-shaped” curve).

A fourth limitation of CIMS-US-PV is that it does not explicitly account for the new refueling infrastructure that will be essential for the successful diffusion of new disruptive vehicle technologies. The version of CIMS I use for this study only addresses infrastructure indirectly through the intangible cost parameters.

A fifth limitation relates to the characterization of PHEVs in the model. Specifically, CIMS-US-PV assumes that PHEVs can run on ethanol in later model periods so that these vehicles can become relatively “zero-emission.” It is important to note that, without this assumption, both vehicle mandates and especially the EV standard policy result in lower expected cumulative well-to-wheels GHG emissions reductions.

Another limitation that relates more to the design of this study is that I do not test more extreme scenarios for the cost assumptions of low-emissions vehicles. For example, I do not model any scenario in which hydrogen fuel-cell vehicles become even close to cost-competitive with other vehicles. Furthermore, I only look at a specific vehicle mandate for electric vehicles and not at all for hydrogen or ethanol vehicle technologies. Although a future technological breakthrough in hydrogen fuel cell vehicles may be unlikely, it is important to run such a scenario in order to have a more complete picture of all potential model results. As such, the design of this study provides only a partial and incomplete picture of how technology-specific vehicle mandates might affect the passenger vehicle sector.

### **3.4.3. Policy Implications**

Although the model I use in this study does have key limitations, my results do lead to some important policy implications. I show that, in the absence of significant GHG reductions in the electricity sector, the carbon tax is on average more cost-effective than a technology-specific standard—even one that emphasizes the “winning” technology (in this case PHEVs). However, the cost-effectiveness advantage of the carbon tax policy in my simulations of the passenger vehicle sector is not overwhelming. Given the improbability of most regions enacting a stringent carbon tax on vehicle fuel (due to political unacceptability), vehicle portfolio standards may present a more politically realistic avenue for climate abatement.

I find that the potential of increasing returns to adoption for vehicle propulsion technologies means that policymakers should be cautious of increasing the scope of a standard to include more vehicle technologies, such as the NZEV standard I simulate. Allowing multiple alternative vehicle powertrains to directly compete for market

share may prevent or delay the adoption thresholds necessary to substantially bring down the costs of transitioning to a “winning” low-carbon technology (in this case: PHEVs). Rather, policymakers should consider the specific incentives that a more technology-neutral mandate creates for individual technologies. This study shows that the long-run cost-effectiveness of inducing increasing returns to adoption for vehicle technologies through targeted incentives might, in some situations, outweigh the cost-effectiveness of trying to induce free-market competition within a mandate. The lesson here is that policymakers should carefully design such policies to balance two risks: the risk of picking a “losing” technology and also the risk of failing to achieve a key adoption threshold for a “winning” technology.

## 4. Conclusion

### 4.1. Summary

This case study for US passenger climate policy seeks to contribute to the debate over technology-neutral versus technology-specific policy design in a hybrid energy-economy simulation model. Through the method of Monte Carlo analysis, I apply multiple stochastic inputs to a hybrid model that is technology-explicit, behaviourally-realistic, and that contains some macroeconomic feedbacks. I show that modeling long-term dynamics complicates the forecasting of relative policy cost-effectiveness. For the model specifications and parameters that I used, I find that technology-specific vehicle mandates tend to be less cost-effective than a technology-neutral carbon tax on vehicle tailpipe emissions. The vehicle mandate policies present a risk that policymakers will “pick the wrong winner,” leading to a very high social cost for emissions reductions. This is consistent with the view of researchers that climate policy should be designed to be as technology-neutral as possible.

At the same time, however, the presence of high non-financial costs and the assumption of no consumer foresight of future carbon prices lead to a low probability in my model that niche markets for new revolutionary low-emission technologies will develop under a carbon tax. This confirms the argument made by other researchers that some technology-specific policies might be necessary to unlock the abatement potential of promising new technologies by accelerating adoption. My results show that the potential benefits of technology-specific policies in terms of increasing policy cost-effectiveness are strongly linked to the extent of increasing returns to adoption and future cost declines for a specific technology (PHEVs). Overall, I find that policymakers should design technology-specific climate policies to balance two risks: the risk of picking a “losing” technology and the risk of failing to sufficiently incentivize a “winning” technology.

The hybrid model I use for this study is useful for simulating technological change for US passenger vehicles but possesses key limitations in terms of consumers with no foresight of future carbon prices, the lack of endogenous fuel supply curves, and assumptions that seem to implicitly favour the adoption of plug-in hybrid electric vehicles over biofuels. These findings lead to new research questions for hybrid models on how to best combine technology-neutral and technology-specific policies.

## **4.2. Areas for Future Research**

This study indicates several directions for future research comparing technology-neutral and technology-specific in hybrid simulation models. Future research should investigate different combinations of technology-specific policies with technology-neutral carbon prices. The main research question for this would be whether or not technology-specific policies can increase the expected cost-effectiveness of a carbon price.

Another promising extension of this study in CIMS-US-PV is to model technology-specific standards for other vehicle technologies (hydrogen fuel cell and E85 ethanol vehicles). In addition, future work in CIMS-US-PV should also investigate the effect of promoting “technological variety” by modeling a vehicle mandate in comparison to an equivalent series of individual standards targeted at each individual vehicle placed under the mandate.

Future research should also broaden the scope of this study by comparing technology-specific and technology-neutral policies in other economic sectors, specifically sectors that have longer and shorter stock turnovers than the passenger vehicle sector.

A future study could also focus on California’s ZEV program, and adapt the CIMS-US-PV to analyze the effect of changing the design of this ZEV mandate. For example, what are the potential effects of offering more alternative compliance paths to manufacturers (other than selling the required amount of ZEVs)? This would require a better understanding of the ZEV regulations as well as some modifications and improvements to CIMS-US-PV, but would clarify a real-world policy problem. Another

study could adapt variations of the model to specific US states and analyze the emissions effects of states other than California adopting the ZEV regulations.

There are also many methodological improvements that could be made to the CIMS-US-PV model. The most pressing improvement is to input either simple vehicle supply sectors or better informed supply cost curves into the model. One improvement would be to incorporate existing equations from the full CIMS-US model to factor in some extent of consumer foresight. In the context of this study, an interesting question is whether consumer foresight would also impact the results of vehicle mandates (for example, can consumers foresee a future neighbour effect or will they delay purchasing a new technology if they expect its upfront price to decline in later model periods?). However, because such mandates mainly target vehicle manufacturers, including some extent of consumer foresight in the model would probably have more of an effect on consumer behaviour under a carbon tax policy than under vehicle mandates. Another improvement would be to estimate two-factor experience curves (with R&D and cumulative production as the two factors as done by Mallory [2007]) and to test the sensitivity of model results to other functional forms for experience curves, such as “s-shaped” curves.

It would be interesting as well to evaluate costs of similar policies in a hybrid simulation with all energy sectors (such as the full CIMS model) that is soft-linked to a CGE model to produce a more comprehensive welfare analysis for policies.

Other researchers (van der Vooren, Alkemade, and Hekkert 2012) use a model that includes the stock of complementary infrastructure for new vehicle technologies. Another area for future research would be to look into tying the intangible cost parameters in CIMS-US-PV to a stock of refueling infrastructure that has cost attributes. Currently, CIMS-US-PV is unable to explore the implications of policies that specifically target building refueling infrastructure to help encourage the adoption of disruptive vehicle technologies.

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## **Appendices**

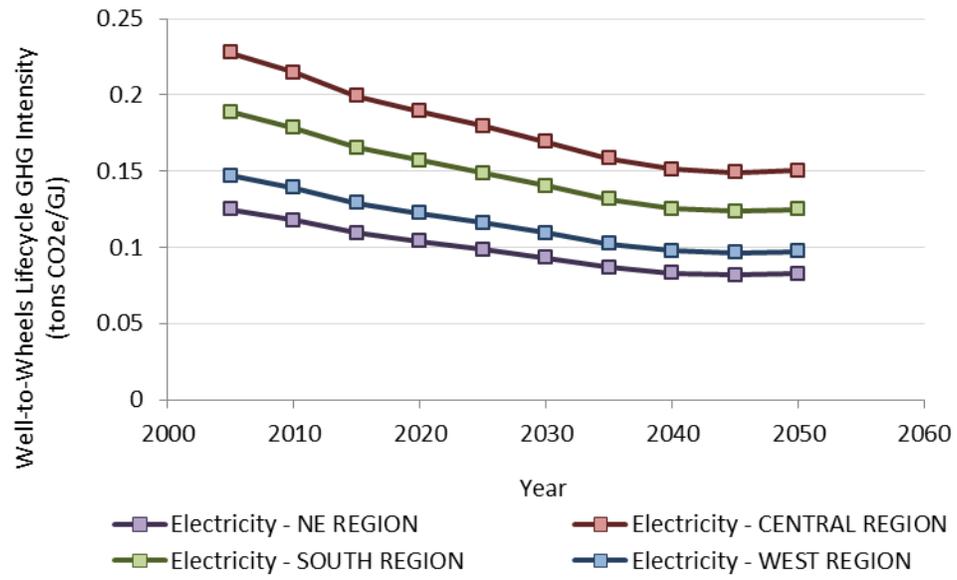
## Appendix A. Policy results across electricity scenarios (middle policy stringency)

*Table 11: Cost-effectiveness of Well-to-Wheel GHG reductions*

Policy	Electricity Scenario	Annual reduction in GHG intensity	Median (\$/CO <sub>2</sub> e)	5 <sup>th</sup> Percentile (\$/CO <sub>2</sub> e)	95 <sup>th</sup> Percentile (\$/CO <sub>2</sub> e)
Fuel Carbon Tax	1 (EMF US13)	1.30%	30	-179	244
	2 (EMF US6)	3.13%	25	-173	231
	3 (EMF US4)	4.62%	28	-162	218
NZEV Standard	1 (EMF US13)	1.30%	257	82	744
	2 (EMF US6)	3.13%	224	77	669
	3 (EMF US4)	4.62%	191	67	605
EV Standard	1 (EMF US13)	1.30%	173	-31	497
	2 (EMF US6)	3.13%	132	-12	310
	3 (EMF US4)	4.62%	99	-17	220

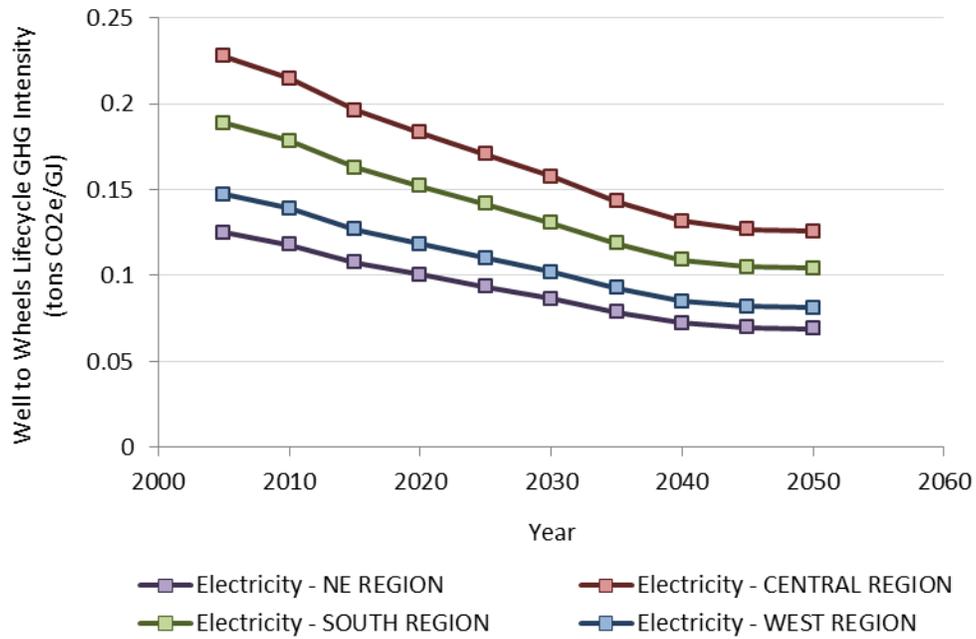
## Appendix B. Electricity Scenarios from EMF 24 in CIMS-US<sup>25</sup>

**Figure 25: BAU Electricity Scenario (EMF 24 US 1 Scenario: Baseline with no nuclear generation or carbon capture and storage )**

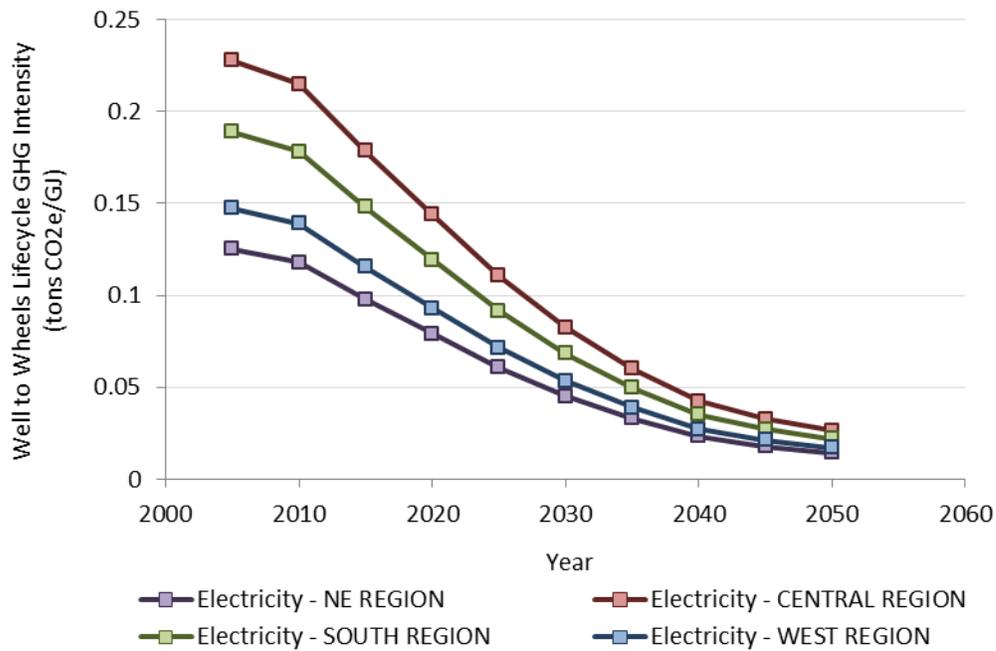


<sup>25</sup> All data for this section is taken from Jaccard and Goldberg (2013)

**Figure 26: Electricity Scenario 1 (EMF 24 US 13 Scenario: Baseline with optimistic technology assumptions)**



**Figure 27: Electricity Scenario 3 (EMF 24 US 4 Scenario: 50% Reduction from Cap-And-Trade Policy)**



## Appendix C. Full List of Uncertain Input Parameters in Monte Carlo Analysis

Unless otherwise stated in a footnote all values in Table 12 are drawn from Mallory (2007). The intangible cost for plug-in hybrids and the “v” parameter are adjusted based on an unpublished study done within the Energy and Materials Research group in late 2007.

**Table 12: Uncertain Input Parameter Specification for Monte Carlo Analysis**

Number	Parameter	Base Value	Type of Distribution	Distribution Values
1	VKT Annual Growth Rate	1.4%	Normal	$\mu=1.4\%^{26}$ $\sigma=0.2\%$
2	Discount Rate (r)	25.70%	Normal	$\mu=0.257\%$ $\sigma=0.05\%$
3	Market Heterogeneity (v)	10	Normal	$\mu=10$ $\sigma=1.5$
4	Diesel Vehicle Capital Cost	\$8,000 <sup>27</sup>	Normal	$\mu=\$8,000$ $\sigma=\$1,000$
5	Battery Electric Vehicle Capital Cost	\$38,672	Normal	$\mu=\$38,672$ $\sigma=\$1,000$
6	E85 Ethanol Vehicle Capital Cost	\$5,677	Normal	$\mu=\$5,677$ $\sigma=\$1,000$
7	Gasoline Vehicle Capital Cost	\$5,000	Normal	$\mu=\$5,000$ $\sigma=\$1,000$
8	Hybrid Vehicle Capital Cost	\$12,650	Normal	$\mu=\$12,650$ $\sigma=\$1,000$

<sup>26</sup> U.S. Energy Information Administration (2012)

<sup>27</sup> All monetary values are in 2005 Canadian dollars.

9	Hydrogen Fuel Cell Vehicle Capital Cost	\$150,437	Normal	$\mu=\$150,437$ $\sigma=\$1,000$
10	Plug-in Hybrid Vehicle Capital Cost	\$17,926	Normal	$\mu=\$17,926$ $\sigma=\$1,000$
11	Vehicle Demand Elasticity	0.5	Normal	$\mu=0.5$ $\sigma=0.05$
12	VKT Elasticity	0.2	Normal	$\mu=0.2$ $\sigma=0.05$
13	Breakthrough in Cellulosic Biofuels	0 (No)	Binomial	0 (No)=60% 1 (Yes)=40% <sup>28</sup>
14	Fuel Cost Scenarios	0 (BAU)	Discrete	0 (BAU) = 25% 1 (BAU*0.7) =25% 2 (BAU*1.3) =25% 3 (BAU*1.6)=25%
18	Perceived Cost of VKT Reduced	\$0.5/VKT	Uniform	Minimum=0.2 Maximum=0.8
19	Diesel Annual Intangible Cost	\$2,000	Normal	$\mu=\$2,000$ $\sigma=\$500$
20	Diesel Upfront Intangible Cost	\$4,000	Normal	$\mu=\$4,000$ $\sigma=\$1,000$
21	Gasoline Annual Intangible Cost	-\$3,400	Normal	$\mu=-\$3,400$ $\sigma=\$500$
22	Hybrid Upfront Intangible Cost	\$7,000	Normal	$\mu=\$7,000$ $\sigma=\$1,000$
23	Battery Electric Vehicle Annual Intangible Cost	\$2,000	Normal	$\mu=\$2,000$ $\sigma=\$500$
24	Battery Electric Vehicle Upfront Intangible Cost	\$13,000	Normal	$\mu=\$13,000$ $\sigma=\$1,000$
25	Hydrogen Fuel Cell Vehicle Upfront Intangible Cost	\$10,000	Normal	$\mu=\$10,000$ $\sigma=\$1,000$

<sup>28</sup> Baker and Keisler (2009)

26	Plug-in Hybrid Vehicle Upfront Intangible Cost	\$15,000	Normal	$\mu=\$15,000$ $\sigma=\$1,000$
27	E85 Ethanol Vehicle Annual Intangible Cost	\$1,500	Normal	$\mu=\$1,500$ $\sigma=\$500$
28	E85 Ethanol Vehicle Annual Intangible Cost <sup>29</sup>	\$2,000	Normal	$\mu=\$2,000$ $\sigma=\$500$
29	Vehicle Battery Progress Ratio (Declining Capital Cost)	0.88	Uniform	Minimum=0.75 Maximum=0.98
30	Exogenous Annual Capital Cost Decline	1%	Uniform	Minimum=0.25% Maximum=1.5%
31	Battery Electric Vehicle Minimum Capital Cost	50% <sup>30</sup>	Normal	$\mu=50\%$ $\sigma=2.5\%$
32	Hybrid Vehicle Minimum Capital Cost	52%	Normal	$\mu=52\%$ $\sigma=2.5\%$
33	Hydrogen Fuel Cell Vehicle Minimum Capital Cost	25%	Normal	$\mu=25\%$ $\sigma=2.5\%$
34	Plug-in Hybrid Vehicle Minimum Capital Cost	44%	Normal	$\mu=44\%$ $\sigma=2.5\%$

<sup>30</sup> Percentage of initial capital cost