The Environmental Benefits of Electric Vehicles as a Function of Renewable Energy

The Environmental Benefits of Electric Vehicles as a Function of Renewable Energy

Ryan Cornell

A Thesis in the Field of Sustainability and Environmental Management for the Degree of

Master of Liberal Arts in Extension Studies

Harvard University

May 2017

Abstract

This project analyzes the relative benefits of electric vehicles (EV) as compared to their internal combustion engine (ICE) counterparts. Specifically, I contrast the air pollutant related social costs that can be quantified and assigned to each type of vehicle. These costs are based on the externalities (per metric ton) associated with carbon dioxide, sulfur dioxide, nitrous oxide, particulate matter, and volatile organic compounds. The difference in social costs is defined as the appropriate EV Subsidy, where a positive EV Subsidy indicates that the social costs for an electric vehicle are less than the social costs for an internal combustion engine vehicle. My research was centered around answering the question: What impact does the percentage of renewable energy have on the appropriate subsidy for an electric vehicle and how does the percentage of renewable energy impact the GHG mitigation potential for electric vehicles? I hypothesized that the negative environmental impact for a 100% renewable energy powered electric vehicle would be lower than the impact from an internal combustion engine vehicle with an efficiency of 80 miles per gallon, that the appropriate federal subsidy for a 100% renewable energy powered electric vehicle would be over $3,000 (when compared to an internal combustion engine vehicle with an efficiency of 25.4 miles per gallon), and that a 100% renewable energy powered electric vehicle would produce 50% fewer greenhouse gas emissions than an internal combustion engine vehicle with an efficiency of 80 miles per gallon.

I employed Argonne National Laboratory's GREET Model, the AP2 Model, and a variety of meta-analyses to determine these social costs. Each cost is a function of a variety of factors. Social costs for the internal combustion engine vehicle strongly correlate with the vehicle's miles per gallon, while the social costs for an electric vehicle strongly correlate with the percentage of renewable energy. Many studies look at a static grid, but I analyzed the impact that renewable energy has on the disparity in social costs between electric vehicles and gasoline-powered vehicles. Additionally, my model disaggregates grid-based and non-grid-based production costs, which allows production-based social costs to accurately reflect that percentage of renewable energy that is entered into the model. I conclude that the environmental benefits of electric vehicles are directly related to the level of renewable energy in the grid. The EV Subsidy for the 2016 grid (13.3% renewable energy) and an average internal combustion engine vehicle (25.4 miles per gallon) was $2,376, while the EV Subsidy for a 100% renewable energy grid reached $3,988. A 100% renewable energy grid also produced an electric vehicle with significantly lower social costs than a gasoline-powered vehicle with an efficiency of 80 miles per gallon (EV Subsidy = $1,071).

Acknowledgements

I am incredibly fortunate to have been surrounded by an amazing group of people that made this project possible. I want to start by thanking Dr. Mark Leighton. His guidance was invaluable and he was there for every step of this journey: from the great conversations that we had in Tuscany, to the formation of the thesis proposal, to the finished product.

I also want to thank my friends and family members that looked over, proofread, and added insight to the project: Renee Cornell, Paul Cornell, Chad Cornell, Rob Cornell, and Jeff Simpson. I also want to thank Rob Cornell for planting a seed in my mind that grew into an integral part of my model.

My Harvard SEM classmates have been an inspiration. I can't imagine a more altruistic group of people and I am looking forward to the positive changes that these individuals bring about. I want to give a special "thank you" to Emily Holleran for her insight and friendship throughout this process. Emily's comments and critiques helped to shape the foundation of my project and I only hope that I can return the favor.

I am indebted to my extraordinary thesis direction: Dr. Jennifer Clifford. Jennifer was always available to help (even when she was on vacation) and her detailed insightful comments went above and beyond any expectations that I could have add. Thank you!

I cannot thank my wife, Lisa, enough. She is my motivation, my support system, and the inspiration behind my project. Lisa's innate altruism inspires me to make the world a better place and I can only hope that this project will have such an impact.

Table of Contents

List of Tables

List of Figures

Chapter I

Introduction

The use of electric vehicles (EVs) has expanded significantly in the past five years: in 2012 there were 12,000 electric vehicles sold, while in 2015 it is estimated that 430,000 were purchased (Shahan, 2015). The electric vehicle has been touted as a potential solution to anthropogenic climate change; although some have argued that electric vehicles running off the current grid are no cleaner than standard automobiles (Lomborg, 2013). This point is hotly debated (Holland, Mansur, Muller, & Yates, 2015), but there is no argument over the fact that the current grid produces a non-trivial amount of carbon emissions per kWh. This situation can be remedied by combining electric vehicles and low carbon renewable energy. A nationwide fleet of electric vehicles would cause a significant increase in the demand for electricity, but this demand could be assuaged by a nationwide adoption of renewable energy programs (rooftop photovoltaics, grid-scale solar, wind power, hydropower). Subsequently, the carbon emissions related to the new renewable energy would be dramatically less than combusting gasoline, in addition to the emissions of other pollutants (including sulfur dioxide, nitrous oxide, particulate matter, and volatile organic compounds). Thus, a combination of electric vehicles and renewable energy has the potential to be a potent climate change mitigation strategy.

There is undeniably merit to this proposition, yet society cannot ignore the fact that electric vehicles are only as "clean" as the grid they are tied to. A wholesale adoption of electric vehicles would lead to a large increase in electrical demand, and subsequently, would be responsible for the greenhouse gas emissions associated with this increase. Thus, the climate change mitigation potential of an electric vehicle is directly linked to the grid from which it draws its energy: a low carbon grid will lead to low carbon vehicle. However, multiple studies, including a recent working paper by the National Bureau of Economic Research (NBER), analyzes the efficacy of electric vehicles based solely on our current grid. This is a severe research gap, as we cannot fully understand the potential for electric vehicles unless we pair them with a grid that unlocks their capability.

Research Significance and Objectives

Therefore, my research objectives are to:

- Demonstrate how a combination of electric vehicles and renewable energy can be used to dramatically decrease transportation-related carbon emissions, and consequently, mitigate climate change
- Establish the correlation between the appropriate subsidy for electric vehicles and the percentage of renewable energy

This study analyzed data from the National Renewable Laboratory (NREL), the U.S Environmental Protection Agency (EPA), and other government sources to determine the environmental impact related to driving electric vehicles. This impact is greatly influenced by the mixture of electricity generation that powers the grid, and thus, I researched the environmental impact related to five different electricity generation scenarios: our current grid (in 2016), a grid with 20% renewable energy, a grid with 50% renewable energy, a grid with 80% renewable energy, and a grid that is comprised of

100% renewable energy. Argonne National Laboratory's GREET model was used to calculate the pollutants per kWh that would be associated with each scenario (Argonne National Laboratory, 2015). There are undeniable social costs related to pollutants such as carbon dioxide (CO2), sulfur dioxide (SO2), nitrous oxide (NOX), volatile organic compounds (VOCs), and particulate matter (PM). The costs for these pollutants may lie outside the standard market, but they are still quantifiable. A popular model called the AP2 Model was used to determine the social costs per kWh for each pollutant. These costs were summed to determine the social cost (externality) per kWh that is associated with each of the above-mentioned energy scenarios. A similar process was followed to determine the social cost per gallon of gasoline burned in a standard internal combustion engine vehicle. These unit-based social costs were distributed over 150,000 miles to estimate the social cost for an electric vehicle (for each electricity generation scenario) and an internal combustion engine vehicle (kWh/100 miles and miles per gallon efficiencies will also be taken into account). The difference between these social costs represents the social benefit that could be derived from a specific driving scenario and a comparison of these scenarios elucidates the true benefits of electric vehicles as we move toward a low-carbon grid.

This study will provide value to policymakers of all levels, as it addresses the feasibility of a transition to a low-carbon transportation model. The current grid does not allow electric vehicles to reach their full climate change mitigation potential, but the results of this study may encourage policymakers to implement the changes that would facilitate a low-carbon future. The true significance of this study does not relate to where we are now, but to where we are headed.

Background

The COP21 Conference in Paris reasserted the world's drive to reduce greenhouse gas emissions. Many of the goals that emerged from the conference are not binding and are not attached to specific mechanisms for reducing greenhouse gas emissions (United Nations Conference on Climate Change, 2015). Thus, there is still a significant amount of debate surrounding the most effective means for reducing emissions.

Countless proposals exist for how the United States of America should reduce emissions, but many of the ideas relate to two key areas: power plants and transportation. The Obama Administration's recent "Clean Power Plan" is one example of the prior Administration's efforts to reduce the emissions related to America's power plants. This is no small feat, as power plants account for 2,215 million metric tons of yearly emissions, which is 31% of America's total greenhouse gas emissions. A large portion of this electricity powers the nation's commercial and residential buildings, which account for 34% of America's greenhouse gas emissions. Yet, transportation comes in at a close second, accounting for 27% of greenhouse gas emissions (Environmental Protection Agency, 2013). Transportation's large share of total greenhouse gas emissions makes the industry a prime target for anyone who is looking for a means to reduce overall emissions.

Electric Vehicles

An "electrification" of the American automobile fleet is one of the key ideas for reducing transportation related emissions. The Obama Administration had a goal of putting 1 million electric vehicles on the road (Institute for Energy Research, 2011) and the state of California instituted multiple programs that incentivize electric vehicle adoption (DriveClean, 2015). Additionally, the federal government currently gives a $7,500 tax credit to anyone who purchases a new electric vehicle, and there are multiple states that offer monetary incentives in addition to the federal subsidy (IRS, 2015). These subsidies exist to promote the sale of electric vehicles and the zero "tail-pipe" emissions that they embody.

The public has responded to the government's push for electric vehicles and sales of electric vehicles have increased dramatically over the past five years. This growth is not exclusive to the United States: the worldwide census of electric vehicles reached the one million mark in September of 2015 (Shahan, 2015). One of the key drivers of growth has been the proliferation of electric vehicle options. There were initially few choices for individuals who wanted to purchase an electric vehicle, but this is no longer the case. Multiple manufacturers now offer electric vehicles and exciting new options from Tesla, Chevrolet, BMW, and Ford have hit the market. Chevrolet recently announced at the Consumer Electronics Show in Las Vegas that they would be producing the first $30,000 electric vehicle with a 200-mile range and the first "Chevrolet Bolts" were able to hit the market in late 2016. This is a key price point and experts suspect that it will go a long way toward bringing electric vehicles to the masses (Davies, 2016).

Electricity Generation and Emissions

The news surrounding electric vehicles is not all positive and they do have their detractors. Some experts have bemoaned the high prices and limited range, but the new electric vehicle options from manufacturers have begun to silence these critics. Each year the electric vehicle options become cheaper and offer significantly greater range. Hence, a far more credible concern relates to the emissions that can be attached to each electric vehicle. While electric vehicles do not produce any direct greenhouse gas emissions, they are powered by stored electricity that comes from the local grid.

This has allowed individuals such as Bjorn Lomborg to make the case that electric vehicles are actually dirtier than standard internal combustion engine vehicles (Lomborg, 2013). His argument is centered on a 2012 life-cycle analysis (LCA) comparing electric and conventional vehicles (Hawkins, Majeau-Bettez, & Stromman, 2013). This LCA estimated that the production phase for electric vehicles was responsible for over double (30,000 compared to 14,000 lbs) the carbon dioxide emissions of conventional vehicles. Lomborg believes that it will take an individual 80,000 miles to recoup the difference in production-related carbon dioxide emissions, as electric vehicles are only responsible for 6 fewer ounces of carbon dioxide emissions per mile (Lomborg, 2013). Lomburg's opinions have drawn strong rebuttals from other experts. Max Baumhefner of the National Resource Defense Council took issue with this conclusion and referred to another LCA by the Argonne National Laboratory that estimated production-related carbon dioxide emissions (for EVs) to be nearly three times less than the number cited by Lomborg (Baumhefner, 2013). Additionally, Don Anair of the Union of Concerned Scientists criticized Lomborg's assumption that the vast majority of electricity would come from coal power (Anair, 2015). While Lomborg's critique may be imperfect, there is no denying the fact that power plant emissions must be accounted for when measuring the environmental impact of an electric vehicle.

The environmental impact of an electric vehicle also varies from region to region. An analysis of American energy generation shows that greenhouse gas emissions per kWh vary widely from state to state (U.S. Energy Information Administration, 2015). Thus, a car driving in Washington (where most electricity comes from hydropower) will account for far fewer greenhouse gas emissions per mile than a car driving in Ohio (where most electricity comes from coal power). A National Bureau of Economic Research (NBER) working paper quantified the wide range of environmental benefits from driving an electric vehicle. For example, the benefit was as high as $3,025 in California and as low as -$4,773 in North Dakota (Figure 1).

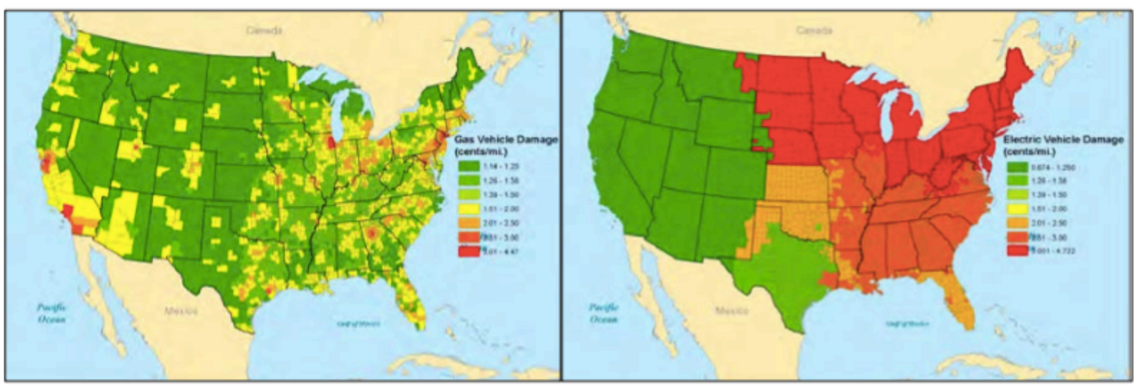


Figure 1. Marginal damage for gas and electric cars by county. Left image is for gas-powered cars and the right image is for electric vehicles. Red signifies more damage and green signifies less damage. Data source: Holland et al., 2015.

This analysis looked at the externalities from air pollution that can be tied to driving a vehicle. The paper quantified the damage done by emissions of carbon dioxide, particulate matter, and other pollutants and used this information to determine the level of externalities per kWh (for electric vehicles) and per gallon (for internal combustion automobiles). Some may consider these results to reflect negatively on electric vehicles, but in truth, the NBER results demonstrate the potential of an electric vehicle when it is tied to a low-carbon grid (Holland et al., 2015). Hence, the true beauty of electric vehicle technology is not its current state, but what it can become when tied to renewable energy resources. The modern electric vehicle should by no means be looked at as a finished product, but as a facilitator of positive change.

The Coupling of Renewable Energy and Electric Vehicles

An electric vehicle's potential for positive environmental impact is truly unlocked when the vehicle is tied to clean energy. There is no theoretical means for an internal combustion engine to run off of renewable energy; even a hybrid car with an efficiency of 100mpg is still burning gasoline and emitting carbon dioxide. This does not have to be the case for an electric vehicle. A car that is running on solar, wind or hydropower will have marginal greenhouse gas emissions that approach zero (Moomaw, Burgherr, Lenzen, Nyboer, & Verbruggen, 2011). This clearly illustrates the importance of coupling electric vehicles with an adoption of renewable energy.

Multiple low-carbon sources of energy generation exist that could be used to charge an electric vehicle. Wind, solar, and hydropower all have many positive characteristics. For example, rooftop photovoltaics can produce a tremendous amount of energy and it is estimated that the United States could produce 818 TWh (Lopez, Heimiller, Blair, & Porro, 2012). Thus, it is theoretically possible that a residential adoption of photovoltaics could happen simultaneously with the adoption of electric vehicles. In some cases, this is already happening: a 2014 survey of electric vehicle owners in California showed that 32% of respondents already had photovoltaic systems on their home and 15% were planning to install systems in the near future (California Air Resources Board, 2014). One can imagine a future where every house has a photovoltaic panel on the roof and an electric vehicle in the garage.

The low-carbon renewable energy sector extends far beyond photovoltaics. Concentrated solar power (CSP) is another form of solar energy that uses solar energy to produce steam that turns a turbine. (NREL, 2016). NREL (2015) and the EIA (2015) both predict that there will be large increases in the capacity of CSP as the United States moves toward a higher percentage of renewable energy. Wind power is another energy source that possesses the ability to generate electricity while emitting minimal levels of pollution.

Figure 2. Land-based wind power over time. The cost of wind power (blue bar graphs) has decreased exponentially, while wind capacity (orange line) has increased exponentially. Data source: U.S. Department of Energy (2016).

The per kWh cost of wind power has dropped precipitously since 1980, while overall wind capacity has increased year after year (Figure 2). In 2015, wind power added more electricity generating capacity than any other type of power plant (EIA, 2015). Furthermore, the United States' first off-shore wind power plant went online in 2016 and the sector represents an untapped resource that could see significant growth in the coming decades (Mai et al., 2012). On the other hand, hydropower is not expected to grow as quickly as wind or solar power. This does not imply that hydroelectric power plants should be ignored, as hydropower was the leader in generating capacity among all renewables in 2015 (EIA, 2016). Both NREL and the EIA predict that wind and solar power will eventually overtake hydropower, but hydropower plants will remain a key part of the American grid for the foreseeable future. A common thread among all renewables is the ability to produce energy with marginal emissions (carbon dioxide and other criteria pollutants) that approach zero. This is true for wind power, photovoltaics, hydropower, geothermal, and concentrated solar power (CSP). It is important to note that this does not indicate that renewable energy is completely pollutant free, as it is necessary to look at renewable energy from a life-cycle assessment standpoint to truly determine the pollutants per kWh. This is due to the fact that upstream emissions still exist (from production, transportation, and sectors) even when marginal emissions approach zero.

Renewable Energy and the Modern Grid

Electric vehicles and renewable energy technologies have a mutually beneficial relationship, but unfortunately, the supply and demand curves for electric vehicles and most forms of renewable energy do not align. Most electric vehicles charge at night (when owners are back from work), while wind power can fluctuate throughout the day and photovoltaic panels produce electricity only during daylight hours (Fattori, Anglani, & Muliere, 2014). A sample kWh demand curve for a single household is displayed in Figure 3. The graph displays a natural increase in demand during the later afternoon and a decrease in demand during the night. This is a common demand curve that reflects an increase in electricity demand during the hours that occupants are home, while decreasing during nighttime hours.

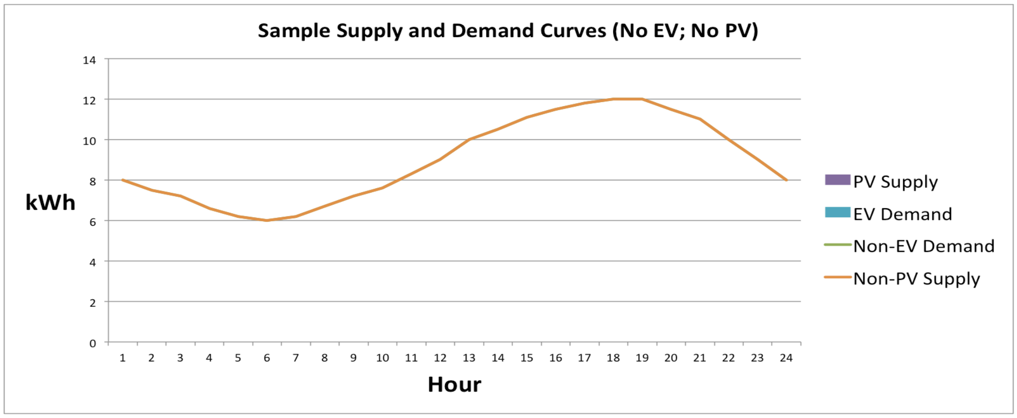


Figure 3. Sample supply and demand curves (No EV or PV). This displays a sample demand curve, with no electric vehicle charging and no photovoltaic generation.

The demand curve is dramatically altered when an electric vehicle is added to the picture. The impact of an electric vehicle charging can be seen in Figure 4 (sample assumes a complete charge of a 20kWh battery, providing upwards of 80 miles of range). The charging of the electric vehicle raises the non-photovoltaic (non-PV) energy demand during the night, which leads to a slight smoothing of the curve.

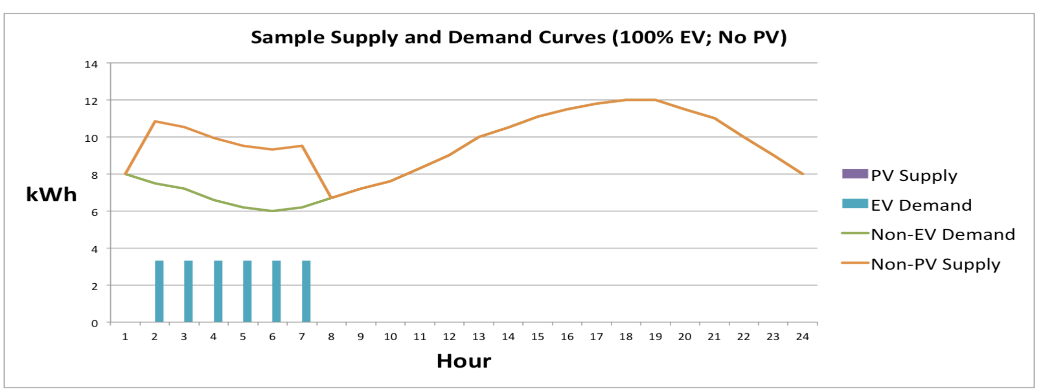


Figure 4. Sample supply and demand curves (EV but no PV). This displays a sample demand curve, with nighttime electric vehicle charging, but no photovoltaic generation.

While an electric vehicle can lead to a smoothing of the demand curve, photovoltaic panels only exacerbate the variability of the supply curve. Furthermore, photovoltaic panels can significantly lower the non-PV demand during the day, moving this demand a significant distance from its mean output (Figure 5).

The current level of technology in the American grid can only support a limited amount of renewable energy due to its inherent volatility (Fattori, Anglani, & Muliere, 2014). However, this is not a death knell for the potentially symbiotic relationship between electric vehicles and renewable energy.

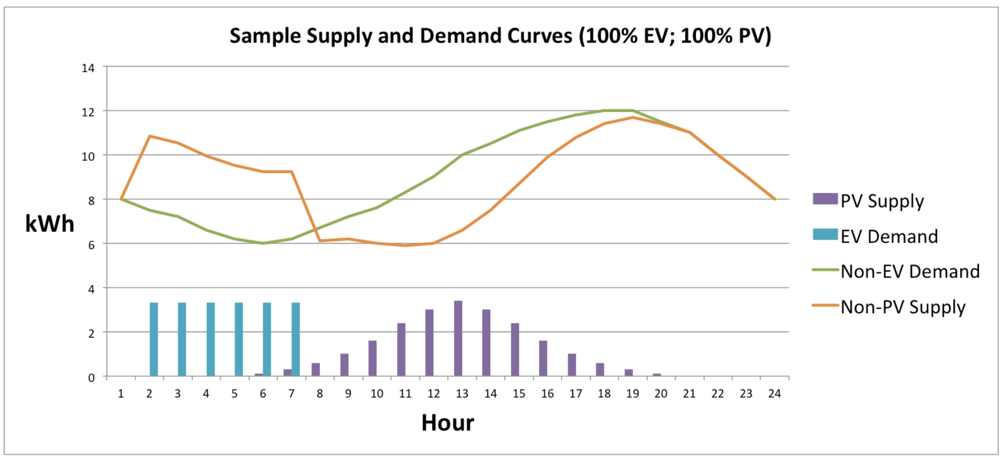


Figure 5. Sample supply and demand curves (EV and PV). This displays a sample demand curve, with nighttime electric vehicle charging and daytime rooftop photovoltaic generation.

Technology is rapidly changing, and what seems improbable today, may seem commonplace in the near future. A recent study suggests that by the year 2050 the grid will be capable of utilizing 80% renewable energy. This will be accomplished through the implementation of "smart grid" technologies that facilitate a more effective distribution of energy and through an increase in grid-scale battery facilities (Mai et al., 2012). This study (NREL, 2009, pg. 2) specifically states that:

> Within the limits of the tools used and scenarios assessed, hourly simulation analysis indicates that estimated U.S. electricity demand in 2050 could be met with 80% of generation from renewable electricity technologies with varying degrees of dispatch-ability, together with a mix of flexible conventional generation and grid storage, additions of transmission, more responsive loads, and changes in power system operations.

This scenario is very different than humankind's quest to produce a fusion power plant or to warp space-time. While both of those goals are theoretically possible, the technology to achieve them does not currently exist. On the other hand, the technology exists to facilitate a renewable energy future: photovoltaics, battery storage, off shore wind. Thus, this "future reality" needs to factor in to any analysis of technologies that rely on electricity (i.e. electric vehicles).

The Grid of the Future

While the grid of today may do a poor job taking advantage of technologies such as photovoltaics, CSP, wind power, and electric vehicles, the grid of tomorrow may be built around such technologies. This so-called "smart grid" could use the batteries within electric vehicles to send electricity back to the grid when demand is high and charge when demand is low (Habib, Kamran, & Rashid, 2015). Additional home-based battery systems will allow households to store excess energy from photovoltaics during the day and use the additional energy at night (Ritte, Mischinger, Strunz, & Eckstein, 2012). These systems would facilitate a smoothing of the demand curve and allow renewables to charge electric vehicles in a time-delayed manner. Thus, one can make an argument that an improved grid could expedite the transition toward a nationwide fleet of renewable energy charged electric vehicles.

Externalities and the Social Cost of Carbon

Renewable energy is commonly regarded as more expensive than other non-renewable forms of energy (Figure 6); however, this assumption does not take into account many of the true costs related to electricity generation.

There is the standard market transaction that takes place when a consumer purchases electricity: the utility sells electricity to the consumer for a specified price and the consumer purchases the electricity for said price. This transaction is easy to understand, as the costs are clearly laid out for the consumer.

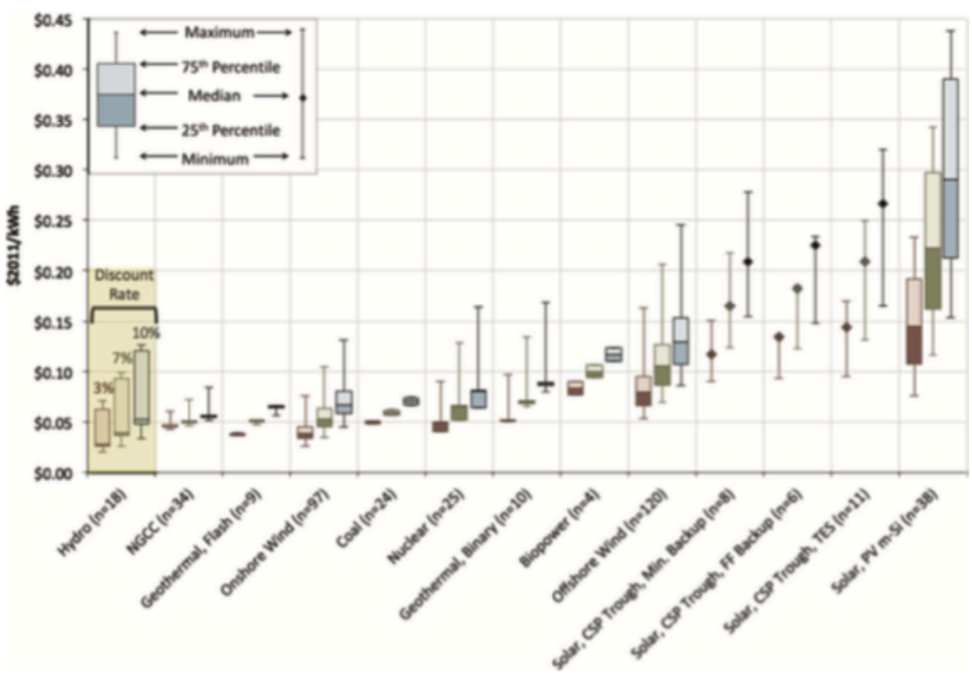


Figure 6. Levelized cost of electricity. Energy costs are calculated using NREL methodology, a 3-10% discount rate, and a 30-year lifetime. (copied from Klein & Whalley, 2015).

Unfortunately, there are numerous costs that do not show up on the electricity bill. These costs are "external" to the market transaction and are referred to as "externalities." These externalities include the negative impacts to tourism (as a result of fossil fuel extraction), deaths from coal-train accidents, climate change-related costs, and impacts to human health, all of which are undeniably true costs. Hence, it is important to quantify the true costs related to each source of electricity generation.

The Relationship Between Renewable Energy and Externalities

Holland et al. (2015) calculate the appropriate electric vehicle subsidy by analyzing the externalities associated with our current grid. The study takes an impressively detailed look at electricity generation throughout the country, but it gives little attention to the dynamic nature of this generation: i.e. the grid of today is different than the grid of tomorrow. While the study does an exhaustive analysis of the differences in externalities from one county to another, it pushes the potential of our future grid to one line in the sensitivity analysis. Furthermore, the sensitivity analysis for a "future grid" only makes the assumption that all coal power plants will be replaced with natural gas (Holland et al., 2015). This is a great starting point, but it begs to be explored further. What happens if we approach 50% renewable energy? What if we approach NREL's prediction of 80% renewable energy? What happens if the grid becomes carbon neutral? These scenarios may be far from reality, but the knowledge of these potentialities should guide our policies in the way that a map guides us to where we are going, not to where we currently reside.

Broad cultural realizations can, at times, lead humankind toward a flurry of innovation. Americans first had to realize that they were capable of going to the moon before they could be pushed to develop the multitude of technologies that would facilitate the journey. This same ideology holds true for renewable energy and electric vehicles. Transportation accounts for 1,806 million metric tons of American greenhouse gas emissions (27% of total) and renewable energy-powered electric vehicles could drastically reduce this number (EPA, 2013). Thus, it is important to understand the relationship between "clean energy" and the environmental impact of electric vehicles. This knowledge could be a catalyst for developing the technologies that would turn our capability, into reality.

Research Questions, Hypotheses, and Specific Aims

Therefore, my primary research question is: What impact does the percentage of renewable energy have on the appropriate subsidy for an electric vehicle and how does the percentage of renewable energy impact the GHG mitigation potential for electric vehicles? I will explore this question by testing the following hypotheses:

1. The negative environmental impact for a 100% renewable energy powered electric vehicle will be lower than the impact from an internal combustion engine vehicle getting 80 miles per gallon.
2. The appropriate federal subsidy for a 100% renewable energy powered electric vehicle will be over $3,000 when compared to an internal combustion engine vehicle with an efficiency of 25.4 miles per gallon (July 2016 average), and over

$1,000 when compared to an internal combustion engine vehicle with an efficiency as high as 80 miles per gallon.

3. A 100% renewable energy powered electric vehicle will produce 50% fewer GHG emissions than an internal combustion engine vehicle with an efficiency of 80 miles per gallon.

Specific Aims

The above-mentioned hypotheses necessitated the following specific research aims:

1. Creating a model to quantify the per kWh negative externality for air pollution on an electric vehicle.
2. Quantifying the per gallon negative externality for air pollution on an internal combustion engine vehicle.
3. Determining the appropriate federal subsidy for an electric vehicle, as a function of specific criteria: percentage of renewable energy used to charge the battery, cost of carbon, average miles per gallon for standard automobiles, and average kWh per 100 miles for an electric vehicle.

Chapter II

Methods

The primary focus of this study is to quantify the impact that the percentage of renewable energy has on the externalities associated with driving an electric vehicle. The environmental impact of an electric vehicle can then be compared to the impact of an internal combustion engine vehicle, elucidating the difference in social costs between these two types of vehicles (represented as the EV Subsidy). This analysis of the social costs for electric vehicles and internal combustion engine vehicles necessitated the creation of the following models: a model predicting the relationship between the percentage of renewable energy and the composition of the United States grid, a pollutant cost model, an emissions model for electric vehicles, an emissions model of internal combustion engine vehicles, and the EV Subsidy Model.

Renewable Energy and the United States Grid

It was necessary to create a model where a continuous input variable for renewable energy percentage (RE) could be entered into the model and it would output an accurate percentage breakdown for the corresponding grid. For example, an input of 50% renewable energy would output the percentages for wind, photovoltaic, concentrated solar power (CSP), biomass, geothermal, hydroelectric, oil, natural gas, coal, and nuclear power that would appropriately fit a grid with 50% renewable energy. I created three possible models and chose the model with the most accurate predictive qualities.

Proportional Model

The Proportional Model is based off of the EIA's 2016 percentages for wind, photovoltaic, concentrated solar power (CSP), biomass, geothermal, hydroelectric, oil, natural gas, coal, and nuclear power (EIA, 2016).

Table 1. Percentage of electricity generation by generation type for 2016.

Electricity Generation Type	Percentage
Wind	4.70%
Photovoltaic	0.30%
Concentrated Solar (CSP)	0.30%
Hydropower	6.00%
Geothermal	0.40%
Biomass	1.60%
Total Renewable:	13.30%
Oil	1.00%
Natural Gas	33.00%
Coal	33.00%
Nuclear	20.00%
Total Non-Renewable:	87.00%

In this model, hydroelectric power is held constant, as it is unrealistic to assume that hydroelectric power would increase proportionally with the rest of the renewable energy technologies. The EIA predicts that hydropower will remain nearly constant between 2016 and 2040 due to limited resources and the economic cost of building new dams (EIA, 2015). However, in this model, all other electricity generation types increase proportionally to one another. This was accomplished by determining the percentage of each energy generation source respective to the percentage of renewable energy or percentage of non-renewable energy (Table 1). It should be noted that the EIA data does not add up to exactly 100%. Fortunately, this was not a problem, as it was only necessary to determine their percentages relative to one another and the Proportional Model outputs values that add up to 100%.

Table 2. Percentage of renewable energy electricity generation for 2016.

Electricity Generation Type	Percentage
Wind	35.34%
Photovoltaic	2.26%
Concentrated Solar (CSP)	2.26%
Hydropower	45.11%
Geothermal	3.01%
Biomass	12.03%

Hydroelectric power was removed from the computation (Table 3) due to the fact that the percentage of hydropower will stay constant throughout the model. The other types of renewable energy generation (wind, photovoltaic, CSP, geothermal, and biomass) were then divided by the total percentage for non-hydroelectric renewable energy to determine their relative percentages (Table 3).

Table 3. Percentage of non-hydro renewable energy electricity generation for 2016.

Electricity Generation Type	Relative Percentage
Wind	64.38%
Photovoltaic	4.11%
Concentrated Solar (CSP)	4.11%
Geothermal	5.48%
Biomass	21.92%

The percentages in Table 3 were used to predict the breakdown for each possible renewable energy scenario. This was accomplished by subtracting the percentage of hydropower (HYD) from the percentage of renewable energy (RE) and multiplying the remaining value by the relative percentages (variable $IGrid_g$; g representing the index for all individual electricity generation types) in Table 3.

$$Renewable\ Percentage = (RE - HYD) \times IGrid_g$$

A similar process was followed for non-renewable energy, as the percentage for each non-renewable energy source (oil, natural gas, coal, and nuclear) was divided by the total percentage of non-renewable energy to quantify their relative percentages (Table 4).

Table 4. Percentage of non-hydro renewable energy electricity generation for 2016

Electricity Generation Type	Relative Percentage
Oil	1.15%
Natural Gas	37.93%
Coal	37.93%
Nuclear	22.99%

The relative percentage for each non-renewable energy source was then multiplied by the overall value entered for non-renewable energy.

$$NonRenewable\ Percentage = (1 - RE) \times IGrid_g$$

This model generates an output value for each electricity generation source that remains proportional to the 2016 values. For example, the percentage of wind power will always be close to an order of magnitude greater than the percentage of photovoltaics. The exception to this rule is hydropower, which is deliberately fixed to the 2016 value. This model exhibits one serious flaw: it is highly unlikely that the percentages of each renewable energy generation source will increase proportionally to their 2016 baseline. For example, the EIA predicts that solar power capacity (photovoltaic and CSP) will increase at a significantly greater rate than wind power capacity (EIA, 2016). It is also possible that a specific source could increase initially, but level off after the renewable energy percentage reaches a certain level. None of these scenarios factor into the Proportional Model.

National Renewable Energy Laboratory (NREL) Regression Model

The National Renewable Energy Laboratory (NREL) Regression Model is based on their 2015 Renewable Electricity Futures Study. The study explores high-penetration renewable energy scenarios and how these scenarios could be implemented. A potential breakdown for the percentage of each major energy generation type was included in the study and it detailed how each of these individual percentages would relate to multiple high-penetration renewable energy percentage scenarios (Table 5).

Table 5. NREL high penetration renewable energy projections.

% RE	Nuclear	Coal	Natural Gas	Biomass	Geo	Hydro	CSP	PV	Wind
30.00%	10.67%	49.22%	9.65%	4.47%	3.99%	8.49%	0.03%	2.43%	11.03%
40.00%	10.61%	42.90%	5.87%	6.13%	4.20%	9.48%	0.05%	3.10%	17.66%
50.00%	10.54%	34.39%	4.19%	7.12%	4.21%	9.91%	0.59%	4.59%	24.47%
60.00%	10.08%	25.68%	3.36%	10.48%	4.19%	10.14%	2.11%	5.00%	28.96%
70.00%	9.80%	16.55%	2.79%	13.83%	4.15%	10.93%	3.05%	5.40%	33.50%
80.00%	8.02%	8.68%	2.57%	15.20%	4.11%	11.36%	6.60%	6.44%	37.01%
90.00%	4.74%	2.93%	1.86%	14.81%	4.01%	12.48%	11.58%	7.07%	40.53%

The NREL Regression Model takes these values (Table 5) and uses the program XLSTAT to model the relationship between the independent variable (RE) and the dependent variable (the percentage for each energy generation type). All NREL values were entered into Excel, in addition to the 2016 EIA percentages (Table 1). The program

XLSTAT was used to determine the best-fit non-linear regression equation for each of the electricity generation types.

Multiple non-linear regressions were run in XLSTAT for each generation type (see Appendix 1) and the equation with the highest r^2 value was chosen for use in the model. All coefficients of determination were 0.97 or greater and the equations followed the NREL predictions with limited residuals. Then each of the regression-based formulas were used to output the appropriate percentages for each electricity generation type, based on the input percentage of total renewable energy. The only exception was oil, as NREL does not give data for oil power plants. Consequently, I fixed oil at 1/33 of coal power to reflect the oil-to-coal ratio that we see in 2016 (EIA, 2016).

Table 6. Formulas for electricity generation projections.

Electricity Generation Type	Function	Formula	R^2
Wind	Logit	$\frac{0.4264}{1+e^{2.7808-5.9686*RE}}$	0.997
Photovoltaic	Logit	$0.2933+\frac{-0.3078}{1+(\frac{RE}{2.6905})^{0.8859}}$	0.990
CSP	Logit	$4.6571+\frac{-4.6571}{1+(\frac{RE}{1.8971})^{4.9226}}$	0.996
Geothermal	Logit	$\frac{0.0414}{1+e^{6.5594-32.6158*RE}}$	0.998
Biomass	Logit	$\frac{0.1725}{1+e^{3.0073-5.8495*RE}}$	0.979
Hydropower	Logit	$0.4497+\frac{-0.4634}{1+(\frac{RE}{0.4237})^{0.3919}}$	0.979
Natural Gas	Logit	$0.0127+\frac{-0.7392}{1+(\frac{RE}{0.1167})^{2.1842}}$	0.999
Coal	Cubic	$3.9423RE^3-7.1886RE^2+3.3008RE+0.0162$	0.992
Nuclear	Quintic	$-8.0419RE^5+23.2378RE^4-26.6279RE^3+14.9043RE^2-4.0460RE+0.5301$	0.999

This model produces little deviation from the expected values, but in most cases the combined values for all renewable energy percentages will be slightly different than the input renewable energy percentage (Table 7). For example, when 13.3% is entered into the model, the sum of the values for all renewable energy sources equals 13.87%. This problem is solved by indexing the output values (OutputRE) for each energy source (g) to the input percentage of renewable energy (RE).

$$Indexed\ RE\% = \frac{OutputRE_g}{\sum_g (OutputRE_g)} \times RE$$

Table 7. Renewable energy generation percentages for 2016, based on regression formulas.

Electricity Generation Type	Percentage
Wind	5.14%
Photovoltaic	0.55%
Concentrated Solar (CSP)	0.002%
Geothermal	0.41%
Biomass	1.68%
Hydro	6.09%
Total	**13.87%**

Each percentage of renewable energy is divided by the regression-based total for renewable energy and then this value was multiplied by RE. This computation ensures that all output values will sum to the input value for renewable energy percentage (RE). The same process is then followed for non-renewable energy.

This model also has one very significant flaw: NREL includes values for coal power that are substantially higher than the current percentage of coal power and are far higher than the EIA's predictions. While the EIA's model does not look at high penetration renewable energy scenarios, it does predict the energy distribution through

2040, and these values contrast starkly to NREL's coal power predictions (EIA, 2016). NREL's percentage for coal is related to the fact that much of NREL's study was done prior to 2015, when coal production accounted for a far greater percentage of the overall grid (NREL, 2015).

The percentage of coal power has fallen tremendously in recent years and the EIA predicts that this trend will continue. Thus, it is unlikely that an increase in renewable energy will also coincide with a resurgence in the coal industry. The increase in coal power has a dramatic impact on the overall model for externalities associated with electric vehicles (demonstrated in the Results section), this results in a distortion of the central goal of this study: to determine the impact that renewable energy has on the environmental impact of electric vehicles. If this increase coincides with an increase in coal power, the potential benefit related to an increase in renewable energy will be confounded.

Combined Model

The Combined Model is based on the two prior models, as it uses the NREL-based regressions to predict the percentages for renewable energy, while it uses the Proportional Model to predict the percentages for non-renewable energy. This is done to eliminate the confounding impact of disproportionally high coal power on the overall NREL Regression based model. The Combined Model allows for the individual renewable energy generation methods to increase at the rate that NREL has deemed appropriate for each of the high penetration renewable energy scenarios. However, the benefits of renewable energy are not obscured by a dramatic increase relative to 2016 coal power output. An even more accurate model might include a decrease in coal power relative to natural gas, but within the scope of this study. The goal of this study is to isolate the variable for "renewable energy" and understand its impact on the environmental benefits of electric vehicles, ceteris paribus. Everything considered, the Combined Model is the best option for achieving this goal.

Social Cost: Electric Vehicle

This study is focused on the following pollutants: carbon dioxide (CO2), sulfur dioxide (SO2), nitrous oxide (NOX), particulate matter (PM 2.5), and volatile organic compounds (VOCs). These pollutants are at the forefront of environmental policy discussions and are responsible for the majority of air pollution-related damages (Holland et al., 2015). The study hinged on assigning a monetary value to the emissions of the above pollutants. I used the Environmental Protection Agency's (EPA) social cost of carbon (SCC), which was determined by the United States Government's Interagency Working Group on the Social Cost of Carbon (EPA, 2015). The EPA offers multiple costs of carbon based on different base years and discount rates, but all costs are given in 2007 dollars. I have chosen the year 2016 and a discount rate of 2.5% to get the value of $57 per metric ton of carbon dioxide (EPA, 2015). This value was converted to 2016 dollars to arrive at a final value of $66.26 per metric ton of carbon dioxide (Bureau of Labor Statistics, 2016).

The Air Pollution Emission Experiments and Policy(APEEP) Model was used to determine the per unit damages associated with SO2, NOX, PM 2.5, and VOCs. This "integrated assessment model" lists the damages for each pollutant in each county in the

United States (Muller, Mendelsohn, & Nordhaus, 2011, p. 1659). The model utilizes EPA data and peer-reviewed dose response algorithms to monetize the social costs related to the above-mentioned pollutants. This is accomplished for each county in the United States by assessing the marginal impact (mortality and morbidity) related to an additional ton of pollutant at each location (Muller et al., 2011). Essentially, the APEEP model puts a price tag on the social costs of one ton of pollution in every county in the United States and lists these values in an Excel file (Muller, 2016). In this study, these values were converted from year 2000 dollars to 2016 dollars and the median value was used to represent the social cost of each pollutant.

Table 8. Social cost of pollutants.

Pollutant	Source	Social Cost per ton (2016 $)
Carbon Dioxide	EPA	$66.26
Sulfur Dioxide	APEEP	$2,459.92
Nitrous Oxide	APEEP	$572.11
Particulate Matter 2.5	APEEP	$3,742.75
Volatile Organic Compounds	APEEP	$368.63

The monetary pollutant damages vary widely from county to county, but the median values (Table 8) make it possible to model the environmental impact of electric vehicles on a national scale. Furthermore, multiple sensitivity analyses and a Monte Carlo Simulation were performed to understand the impact related to costs of different pollutants. Particular attention was given to the impact that the social cost of carbon has on the overall environmental impact of electric vehicles and hence the appropriate subsidy for electric vehicles.

Power Plant Emissions

Power plant emissions were evaluated from a life cycle assessment perspective. This was especially important for renewable energy, as the marginal emissions from photovoltaics, CSP, and hydropower approach zero. Argonne National Laboratory's highly regarded life cycle assessment program "GREET 2015" was used to determine the emissions per kWh for coal (Figure 7), natural gas, oil, nuclear, and biomass power plants.

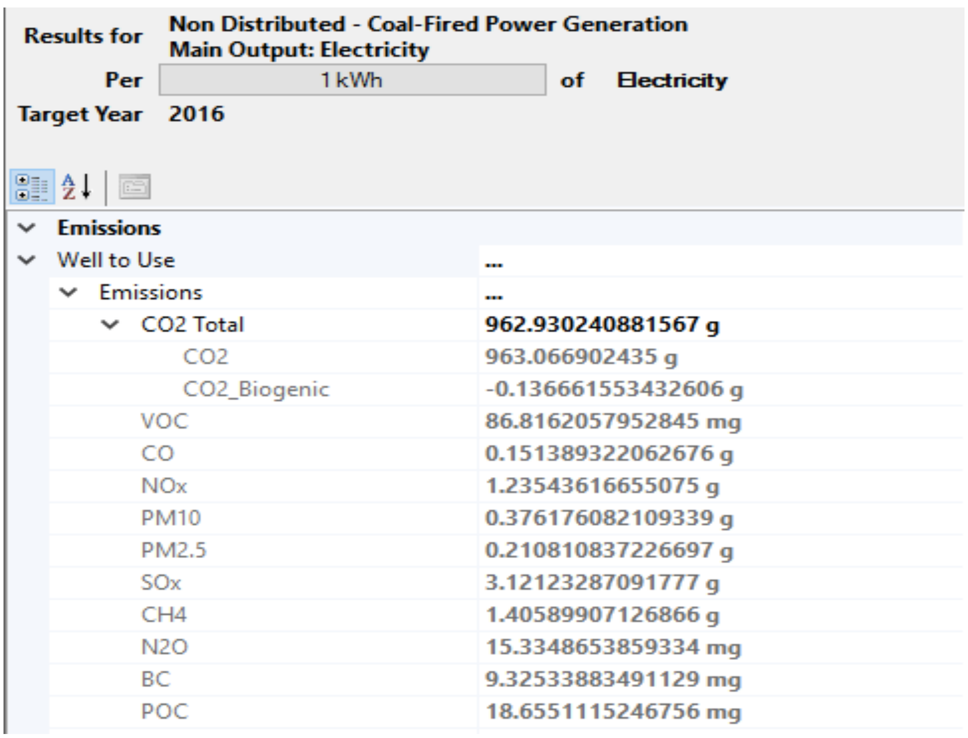


Figure 7. GREET output data for non-distributed coal-fired power plants. This figure is taken from GREET 2015 and displays emissions data per kWh for the pollutants detailed in this study.

GREET 2015 does not include LCA emissions data for the other renewable energy power plants. Therefore, a meta-analysis from Klein & Whalley (2015) was used to collect emissions data for photovoltaic, concentrated solar power, geothermal, and hydroelectric power plants. Klein & Whalley's paper provides meta-analysis data for CO2, SO2, NOX, and particulate matter for each type of renewable energy electricity generation and in each case the median/nominal value was recorded (Table 9). The meta-analysis does not include data related to VOCs and it was necessary to retrieve this information from a National Energy Technology life cycle comparison (Skone, Littefield, Cooney, & Marriott, 2013) and a NEEDS Project report (Frankl, Menichetti, Raugei, Lombardelli, & Prennushi, 2005).

Table 9. Power plant emissions.

Electricity Generation Type	CO2 (g)	SO2 (g)	NOX (g)	PM2.5 (g)	VOCs (g)
Wind	11	0.046	0.043	0.008	0.00881
Photovoltaic	48	0.307	0.178	0.308	0.088
Concentrated Solar (CSP)	35	0.042	0.107	0.017	0.0376
Hydropower	7	0.035	0.008	0.013	0.000016
Geothermal	58	0.08	0.025	0.026	0.000442
Biomass	30.78354	0.65794	1.06312	0.61202	0.14984
Oil	942.03924	3.08252	4.30114	0.13367	0.07418
Natural Gas	444.40070	0.09501	0.41317	0.01361	0.07294
Coal	962.93024	3.12123	1.23544	0.21081	0.08682
Nuclear	10.48254	0.02019	0.02530	0.00190	0.00374
Total:	2549.63627	7.48690	7.39917	1.34401	0.52239

Social Cost per kWh

The establishment of a cost per ton of pollutant and the quantity of pollutants per kWh facilitated the quantification of the social cost per kWh for each type of power generation. The pollutant data was collected in grams and milligrams, which necessitated a conversion to tons (see Appendix 2 for information on pollutant data per 150,000 miles). Once the pollutants per kWh were converted to tons, I was able to multiply each quantity (in tons) by the cost per ton of pollutant to arrive at a social cost per kWh for each pollutant and type of energy generation. For example, wind power produces 11 grams of CO_2 per kWh, which was divided by 1000000 to convert the value to tons. This was then multiplied by \$66.26 (the social cost of carbon, per ton) to arrive at a value of \$0.00072886. This indicates that each kWh of wind power produces \$0.00072886 worth of damages that can be associated with carbon dioxide emissions. The costs of each pollutant were summed to determine the overall damages associated with one kWh of each electricity generation type (Figure 8).

$$Electricity\ Generation\ Cost = \sum_{k} (PC \times Emissions)$$

The formula for the "Electricity Generation Cost" uses the variable PC to represent the cost per ton of pollutant, the variable Emissions to represent the quantity of emissions per kWh, and k is used to designate the pollutant index (CO_2, SO_2, NOX, PM 2.5, and VOCs).

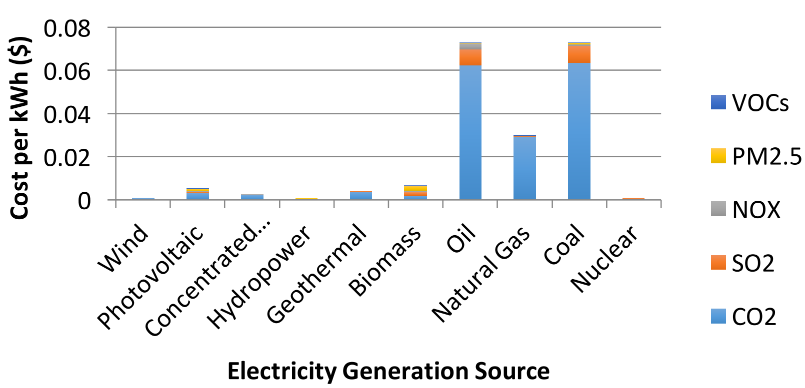


Figure 8. Social cost per kWh for different electricity generation sources.

The formula for Electricity Generation Cost (EGC) outputs the total social cost for the five specified pollutants (Table 10). This cost varies greatly from among power sources, as the EGC for coal power is \$0.07301, while the EGC for hydro power is \$0.00060.

Table 10. Social cost per pollutant for each electricity generation type.

Type	CO2	SO2	NOX	PM2.5	VOCs	Total
Wind	\$0.000729	\$0.000113	\$0.000025	\$0.000030	\$0.000003	**\$0.00090**
Photovoltaic	\$0.003180	\$0.000755	\$0.000102	\$0.001153	\$0.000032	**\$0.00522**
CSP	\$0.002319	\$0.000103	\$0.000061	\$0.000064	\$0.000014	**\$0.00256**
Hydropower	\$0.000464	\$0.000086	\$0.000005	\$0.000049	\$0.000000	**\$0.00060**
Geothermal	\$0.003843	\$0.000197	\$0.000014	\$0.000097	\$0.000000	**\$0.00415**
Biomass	\$0.002040	\$0.001618	\$0.000608	\$0.002291	\$0.000055	**\$0.00661**
Oil	\$0.062420	\$0.007583	\$0.002461	\$0.000500	\$0.000027	**\$0.07299**
Natural Gas	\$0.029446	\$0.000234	\$0.000236	\$0.000051	\$0.000027	**\$0.02999**
Coal	\$0.063804	\$0.007678	\$0.000707	\$0.000789	\$0.000032	**\$0.07301**
Nuclear	\$0.000695	\$0.000050	\$0.000014	\$0.000007	\$0.000001	**\$0.00077**

These costs were multiplied by the distribution of the national grid to determine the average national cost per kWh. For example, if wind power accounts for 4% of the national grid, then 4% would be multiplied by \$0.00090 (Table 10).

$$Social\ Cost\ per\ kWh = \sum_{g} \left(EGC_g \times Percentage \right)$$

The percentages were drawn from the Combined Model discussed earlier and vary based upon the input value for renewable energy percentage (RE). The summed value for all electricity generation types is equal to the Social Cost per kWh.

Social Cost for an Electric Vehicle

The social cost for an electric vehicle comes into focus once the social cost per kWh has been determined. The next step was to calculate how many kWh would be needed over the lifetime of an electric vehicle. This number is a function of two values: efficiency and total miles. This study used 150,000 miles, because it was the value used in NBER's 2015 white paper on the "Environmental benefits of electric vehicles" (Holland et al., 2015). The efficiency value of 32 kWh per 100 miles was used, as it is the weighted value for all 2016 model year electric vehicles that were also sold in 2015 (U.S. Department of Energy, 2016)).

$$Social\ Cost\ for\ an\ EV = \sum_{g} \left(EGC_g \times Percentage \times \frac{150000 \times Efficiency}{100} \right)$$

The total mileage (150,000) times the efficiency (32 kWh per 100 miles) divided by 100 is equal to the number of kWh that will be needed to power the vehicle over its lifetime.

Social Cost: Internal Combustion Engine (ICE) Vehicle

The gasoline emissions values were taken directly from the GREET 2015 software program, which breaks down emissions by well-to-pump (WTP) and well-to-wheels (WTW) emissions. I ran the simulation for the vehicle "Car: SI ICEV – E10 (Type 1 Conventional Material" and the year 2016. This designation refers to GREET's dataset for a standard internal combustion engine car using E10 gasoline (Figure 9). The WTW emissions were recorded, which take into account both WTP emissions and emissions from operation. This calculation was again based on 2016 technology and a lifetime range of 150,000 miles.

Car: SI ICEV - E10 (Type 1 Conventional Material)

Fuel Blend: E10

Target Year for Simulation 2016

Target Year for Vehicle Technology 2016

Functional unit: /MJ /100 km /mi /ton mi /tonne km /passenger mi /pass

Name	WTP	Mode - Regular (E10)	Non-Exhaust Emissions	Operation Only	WTW
Total Energy	1159.824331799...	4117.233163146...		4117.233163146...	5277.057494946...
Fossil Fuel	4921.967996974...	0 J/mi		0 J/mi	4921.967996974...
Coal Fuel	81.44724685718...	0 J/mi		0 J/mi	81.44724685718...
Natural Gas Fuel	670.1457861502...	0 J/mi		0 J/mi	670.1457861502...
Petroleum Fuel	4170.374963967...	0 J/mi		0 J/mi	4170.374963967...
Water_Reservoir ...	48.00042440221...				48.00042440221...
Water_Irrigation	298.6714663447...				298.6714663447...
Water_Cooling	31.38223688617...				31.38223688617...
Water_Mining	335.6140039953...				335.6140039953...
Water_Process	156.3757406001...				156.3757406001...
VOC	0.116680823928...	0.117236668852...		0.117236668852...	0.233917492780...
CO	79.91018876921...	2.567891914222...		2.567891914222...	2.647802102991...
NOx	0.169825507242...	0.110502020261...		0.110502020261...	0.280327527504...
PM10	15.22573456848...	5.290285494144...		5.290285494144...	20.51602006262...
PM2.5	9.966497012114...	4.679885298060...		4.679885298060...	14.64638231017...
SOx	0.141959144225...	0 g/mi		0 g/mi	0.141959144225...
CH4	0.338562030975...	7.903817804145...		7.903817804145...	0.346465848779...
CO2	75.19113464540...	294.9354427684...		294.9354427684...	370.1265774138...
N2O	11.52611280629...	4.893924520634...		4.893924520634...	16.42003732692...

Figure 9. GREET emissions data for a standard internal combustion engine automobile.

The per gallon emissions were then converted to lifetime emissions (Table 11). This was accomplished by determining the number of gallons that would be needed to power an ICE vehicle for 150,000 miles. This value was calculated by dividing 150,000 by the average miles per gallon.

Table 11. Emissions per gallon of gasoline.

Pollutant	WTW per Gal (g)	WTW per Gal (tons)	Emissions per 150,000mi (tons)
CO_2	10641.14	1.06E-02	62.841
SO_2	4.08	4.08E-06	0.024
NOX	8.06	8.06E-06	0.048
PM 2.5	0.42	4.21E-07	0.002
VOCs	6.73	6.73E-06	0.040

The University of Michigan (para. 3, 2016) tracks the "average sales-weighted fuel-economy rating of purchased new vehicles" based on data supplied by the EPA. This value has been steadily increasing and reached 25.3 miles per gallon in July 2016 (the most recent data at the time of writing). This value (25.3) was used in Table 11, but the variable for miles per gallon can be manipulated to determine the relationship between miles per gallon and the marginal benefits of an electric vehicle. This relationship is explored in the results section.

$$Lifetime\ Emissions\ per\ Pollutant = \ Emissions \times \frac{150000}{MPG}$$

Social Cost for an ICE Vehicle

The social cost for an ICE vehicle was calculated by multiplying the social cost per pollutant (PC) by the lifetime emissions per pollutant (Emissions) and summing the products for all pollutants (k).

$$Social\ Cost\ for\ an\ ICE = \sum_{k} \left(PC_k \times Emissions_k \times \frac{150000}{MPG} \right)$$

The same social costs per pollutant (Table 12) are used for both EV and ICE vehicles. These costs are based on median values derived from the APEEP model and refer to ground level emissions.

Table 12. Emissions and social cost per gallon of gasoline.

Pollutant	Emissions per Gallon (tons)	Social Cost per Gallon ($)
CO2	0.010641139	0.705081877
SO2	4.08133E-06	0.010039723
NOX	8.05942E-06	0.004610884
PM 2.5	4.21083E-07	0.001576012
VOCs	6.72513E-06	0.00247906

Non-Operating Costs

A non-trivial percentage of emissions for both electric vehicles and ICE vehicles occur outside the automobile's operating phase. These additional emissions can be attributed to the vehicle's components and the energy used during assembly, disposal, and recycling (ADR). This data was collected from GREET 2015, as the software breaks emissions down into multiple categories, including: components, ADR, and batteries. Once again, these emissions are based on 2016 technology and the 2016 grid. The vehicle "Car: SI ICEV – E10 (Type 1 Conventional Material)" was used to represent ICE vehicles and "Car: EV - Electricity (Type 1 Li-Ion/LMO Conventional Material)" was used to represent electric vehicles.

The central objective of this research is to determine the impact that renewable energy penetration will have on the environmental benefits of electric vehicles. Thus, it is important that non-operating emissions do not remain static and rather are based upon any treatments made to the independent variable (renewable energy percentage). It was necessary to break the non-operating emissions down into grid-dependent and grid-independent factions. I accomplished this by recording the initial emissions data and then altering the underlying assumptions within GREET 2015 so that the new grid produced zero emissions.

Table 13. Grid-based and non-grid based production emissions for an electric vehicle.

EV Components Emissions	2016 Grid WTP	No Carbon Grid WTP	WTP % from Grid
CO_2	40028.68995	26654.39259	33%
SO_2	224.763812	195.2109832	13%
NOX	52.64059036	36.37567004	31%
PM	10.84568612	8.560861129	21%
VOCs	34.55493882	33.04337142	4%

The decrease in emissions for each pollutant represents the percentage of emissions that could be attributed to the grid. For example, if 40mg of NOX was attributed to the "Components" in an ICE vehicle and this value decreased to 30mg in the zero carbon grid, it could then be assumed that 25% of emissions were derived from the grid (a sample of these values is shown in Table 13 and all values are included in Appendix 3).

A percentage was calculated for each pollutant originating from the following categories: Components, ADR, and Batteries. These percentages (EV% and ICE%) facilitated a breakdown of the emissions into grid-dependent and grid-independent emissions. The non-operating emissions for a specific category (Components, ADR, and Batteries) were computed by multiplying the grid-dependent emissions by an emissions factor derived from the input level of renewable energy and adding this value to the grid-independent emissions.

$$EV\ Cost\ = \sum_{k}\left[PC\times\left[\left((1-EV\%_k)\times ProdEV_k\right)+(ProdEV_k\times EV\%_k)\times\frac{Grid_k}{BaseGrid_k}\right]\right]$$

$$ICE\ Cost = \sum_{k}\left[PC\times\left[\left((1-ICE\%_k)\times ProdICE_k\right)+(ProdICE_k\times ICE\%_k)\times\frac{Grid_k}{BaseGrid_k}\right]\right]$$

The emissions factor ($\frac{Grid_k}{BaseGrid_k}$) adjusts based on the emissions per kWh for a given pollutant at the input renewable energy percentage ($Grid_k$) compared to the emissions per kWh for a given pollutant from the baseline 2016 grid ($BaseGrid_k$). Thus, a 50% reduction in emissions per kWh for a given pollutant will result in a 50% reduction in grid-dependent emissions for said pollutant. The per-pollutant emissions were then multiplied by the social cost of each pollutant (PC) and these values were summed within each category. The social cost related to Components, ADR, and Batteries were added together to determine the overall non-operating costs associated with each type of vehicle. The non-operating costs were added to the operating costs and the outcome was the overall social cost of the vehicle. The disaggregation of production costs allows my model to produce a production-based externality that responds to increases in renewable. This is my key contribution to the literature, as other studies use models with static production-based externalities.

Subsidy and Variables

The recommended EV subsidy was simply calculated by subtracting the social cost of an EV from the social cost of an ICE vehicle.

$$EV\ Subsidy = \ Social\ Cost\ for\ an\ ICE - Social\ Cost\ for\ an\ EV$$

A variety of treatments were then applied to the above methodology to understand the impact that specific independent variables have on the environmental impact of electric vehicles (as quantified by the EV Subsidy). The entire model was built into Excel and the “data table” feature was used to manipulate different independent variables. These variables included: percentage of renewable energy (RE%), miles per gallon, kWh per 100 miles, and the cost of carbon.

Monte Carlo Simulation

Furthermore, a Monte Carlo simulation was run using the Excel-based SimVoi software. This simulation modeled the effect of pollutant pricing on the overall EV subsidy. The Monte Carlo simulation consisted of 10,000 iterations that randomly selected data for SO2, NOX, PM 2.5, and VOCs from the APEEP model (social pollutant cost data for each county in the United States). Due to the uncertainty related to the social cost of carbon, the Monte Carlo simulation also randomly pulled data from a list of peer-reviewed "social costs of carbon." This data was taken from the widely-cited meta-analysis compiled by Havranek, Irsova, Janda, and Zilberman (2015). The meta-analysis included 809 estimates of the social cost of carbon from 101 different studies, although I only included the median value from each study. This was done to make sure that each study had the same probability of being selected during the Monte Carlo simulation (as opposed to favoring the studies with a large number of estimates). The individual social costs of carbon were then converted from 2010 dollars into 2016 dollars using the appropriate multiplier (1.11) taken from the Bureau of Labor Statistics (BLS, 2016). These specific values and the computations are listed in Ancillary Appendix 1.

Chapter III

Results

Electric vehicles are touted as an environmentally beneficial technology and this study aims to quantify these benefits. An electric vehicle's emissions are directly linked to the power grid from which it attains its electricity, and thus, this analysis looks at these benefits as a function of renewable energy. Furthermore, this study quantifies the carbon dioxide emissions associated with both electric vehicles and internal combustion engine vehicles.

Carbon Dioxide Emissions

I analyzed the carbon dioxide emitted during 150,000 miles of driving (operating phase), in addition to the emissions generated from production (production/non-operating phase). The GREET 2015 life-cycle assessment software indicated that an electric vehicle powered by the simulated 2016 power grid (13.3% renewable energy) would be responsible for 22.86 metric tons of carbon dioxide over its lifetime (Table 14). This number decreases significantly as the grid moves toward more renewable energy. An electric vehicle powered by 100% renewable energy (RE) would account for only 6.30 tons of carbon dioxide (Table 14), which represents a 79.5% decrease in total carbon emissions. It is important to note that the production emissions also decrease as the percentage of renewable energy increases. This is due to the fact that the model disaggregates production emissions into "grid-based" and "non-grid-based emissions."

The grid-based emissions are then linked to the percentage of renewable energy, which results in fewer production-based emissions as overall emissions per-kWh decrease (see Chapter II for greater detail).

Table 14. Carbon emissions as a function of renewable energy.

RE%	Usage Emissions	Production Emissions	Total Emissions
13%	22.86	7.968	30.83
20%	21.19	7.756	28.95
50%	13.63	6.793	20.42
80%	6.07	5.832	11.90
100%	1.10	5.200	6.30

Note: Carbon dioxide emissions are in metric tons over the lifetime of the vehicle.

The total carbon dioxide emissions exceed 165 metric tons (Table 15) for cars with an efficiency of 10 miles per gallon. This decreases to 68.38 metric tons for vehicles getting 25.4 miles per gallon (the July 2016 average) and eventually reaches 25.5 metric tons for vehicles with an efficiency of 80 miles per gallon (Table 15).

Table 15. Carbon emissions as a function of miles per gallon.

MPG	Usage Emissions	Production Emissions	Total Emissions
10	159.62	5.543	165.160
20	79.81	5.543	85.351
25	62.84	5.543	68.384
40	39.90	5.543	45.447
60	26.60	5.543	32.146
80	19.95	5.543	25.495

Note: Carbon dioxide emissions are in metric tons over the lifetime of the vehicle. Production emissions are not impacted by the efficiency of the vehicle (miles per gallon).

The Electric Vehicle (EV) Subsidy

The EV Subsidy is defined as the difference between the externalities associated with driving an internal combustion engine vehicle and the externalities associated with driving an electric vehicle. These externalities are based on the negative impacts of the following pollutants: carbon dioxide, sulfur dioxide, nitrous oxide, particulate matter, and volatile organic compounds. A positive value for the EV Subsidy would indicate that the pollution-related externalities from driving 150,000 miles in an electric vehicle are less than the pollution-related externalities from driving the same distance in an internal combustion engine vehicle.

Social Cost (SC) of Operating an Internal Combustion Engine Vehicle

The externalities associated with the operating phase of an internal combustion vehicle is calculated by summing the social costs related to the five pollutants specified in this study.

Table 16. Emissions data for internal combustion engine vehicles.

Pollutant	Emissions per Gallon (grams)	Emissions per Gallon (tons)	Social Cost per Ton	Social Cost per Gallon	Cost per 150,000mi
CO2	10641.1391	0.01064	$66.26	$0.705081	$4,163.87
SO2	4.0813	4.08133E-06	$2459.91	$0.010039	$59.29
NOX	8.0594	8.05942E-06	$572.11	$0.004610	$27.23
PM 2.5	0.4210	4.21083E-07	$3742.75	$0.001576	$9.31
VOCs	6.7251	6.72513E-06	$368.63	$0.002479	$14.64
			Total SC:	$0.723787	**$4,274.34**
			SC Per Mile:	$0.0285	$0.03

A car operating at 25.40 miles per gallon (the July 2016 average) would produce $4,274.34 worth (Table 16) of air pollution-related costs (University of Michigan, 2016). The vast majority of these costs ($4,163.87) are attributed to the emissions of carbon dioxide, while only $9.31 of the costs are a result of damages from particulate matter.

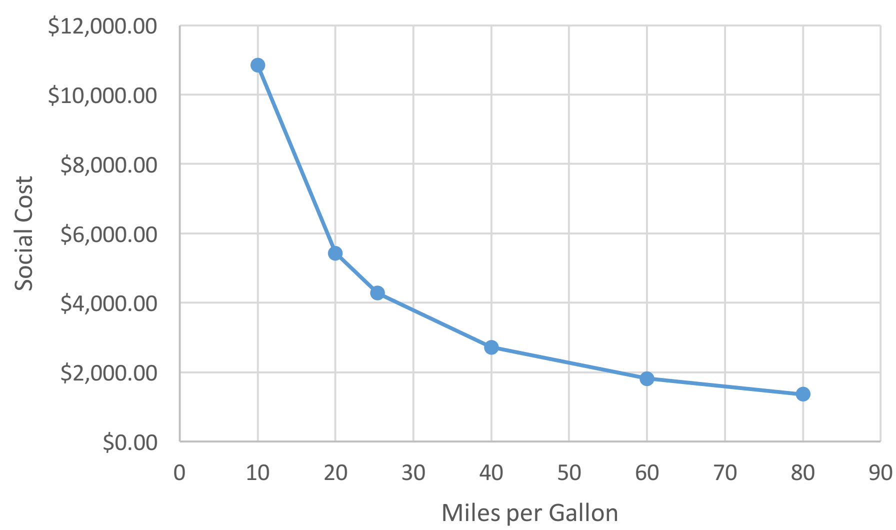


Figure 10. Social cost (usage phase) as a function of miles per gallon.

The social cost related to driving a gasoline-powered automobile for 150,000 miles decreases significantly as the vehicle become more efficient (Figure 10). A car operating at 10 miles per gallon will cause $10,856.81 of damage during its usage phase, while a car operating at 40 miles per gallon will only cause $2,714.20 of damage.

Social Cost of Operating an Electric Vehicle

The social cost of an electric vehicle is a function of the power grid from which a vehicle derives its electricity. The pollutants per kWh vary greatly from power plant to power plant (Figures 11 and 12), and thus, the air pollution-related externalities are dependent on the source of electricity generation.

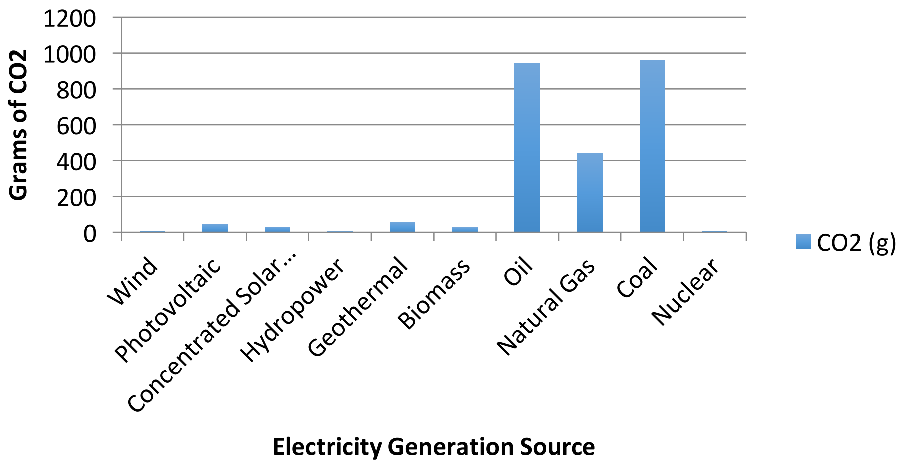


Figure 11. Carbon dioxide emissions per kWh.

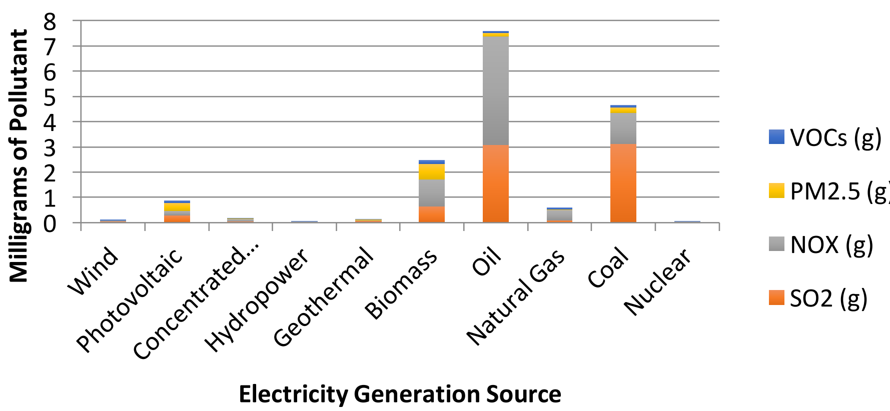


Figure 12. Pollutants per kWh.

The social cost per 150,000 miles is based on a mix that mirrors the current 2016 national grid. The Combined Model adjusted this mix based on the percentage of renewable energy that was entered into the model; this adjustment takes into account the current proportions and high penetration renewable energy predictions from the National Renewable Energy Laboratory (NREL, 2015).

Table 17. Power grid mix and social cost.

Electricity Generation Type	%	Social Cost per kWH (EGC)	Percentage Cost	Cost per 150,000 mi
Wind	4.93%	$0.0008998	$0.0000444	$2.13
Photovoltaic	0.53%	$0.0052227	$0.0000275	$1.32
CSP	0.00%	$0.0025611	$0.0000000	$0.00
Hydropower	5.84%	$0.0006032	$0.0000352	$1.69
Geothermal	0.39%	$0.0041517	$0.0000161	$0.78
Biomass	1.61%	$0.0066123	$0.0001063	$5.10
Oil	1.00%	$0.0729906	$0.0007274	$34.91
Natural Gas	33%	$0.0299939	$0.0098639	$473.47
Coal	33%	$0.0730096	$0.0240101	$1,152.48
Nuclear	20%	$0.0007672	$0.0001529	$7.34
		Total SC for an EV:	**$0.0349838**	**$1,679.22**
			SC Per Mile:	**$0.01119**

Note: The “cost per 150,000 miles” column is a function of the “social cost per kWh” and the “percentage.” For example, Oil and Coal have nearly the same “social cost per kWh,” but the “cost per 150,000 miles” for Coal is far greater because Coal powers 33% of the grid while Oil powers only 1%. The “total social cost” represents the social cost for a vehicle that derives power from a grid that perfectly models the 2016 national grid.

The model assumes an electric vehicle operating at 32 kWh per 100 miles, which is the weighted value of all 2016 model year electric vehicles (U.S Department of Energy, 2016). The outputs of this model are displayed in Table 17, which demonstrates that this electric vehicle would produce $1,670.22 of air pollution-related costs over its lifetime.

Table 18. Social cost as a function of the percentage of renewable energy.

Percentage of RE	Social Cost
13%	$1,679.22
20%	$1,550.31
30%	$1,357.90
40%	$1,165.49
50%	$973.08
60%	$780.66
70%	$588.25
80%	$395.84
90%	$203.43
100%	$11.02

This number changes significantly if the percentage of renewable energy increases (Table 18). The social cost moves under $1000 when the percentage of RE reaches 50% and goes under $300 once the renewable energy (RE) percentage approaches 85%. Furthermore, a car running on 100% RE would account for only $11.02 of air-pollution related damages.

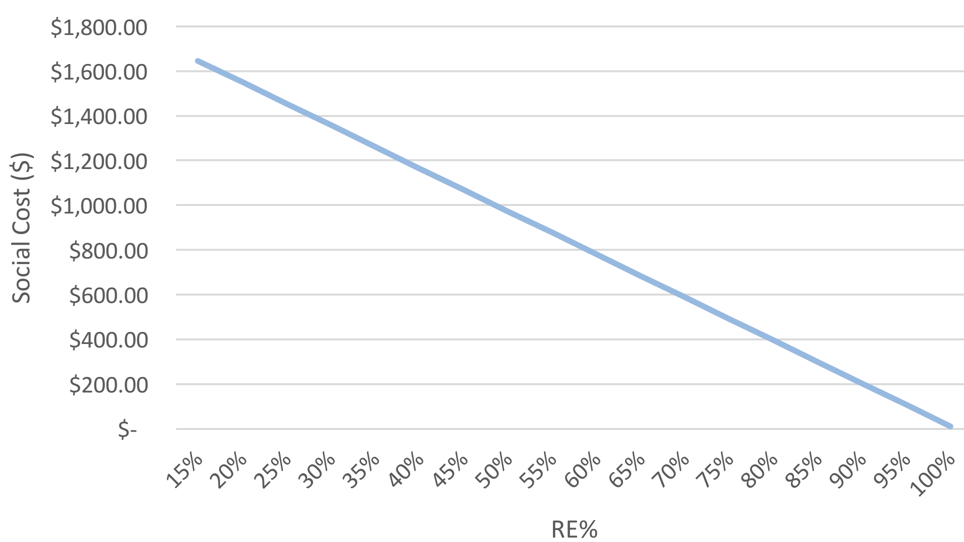


Figure 13. Social cost as a function of renewable energy.

For each 1% increase in RE%, the social cost decreases by $19.24. This inverse relationship demonstrates the impact that the RE% has on the social cost of an electric vehicle (Figure 13). An increase in renewable energy clearly leads to a decrease in air pollutants, and subsequently, a decrease in social costs.

Non-Operating Costs

Electric vehicles have greater production-based emissions (Table 19) due to the manufacturing of the battery pack. These packs require sophisticated components and their construction can be energy intensive; the cell components, cell manufacturing, and thermal management aspects of the battery all produce non-trivial levels of emissions (Kim et al., 2016).

Table 19. Production emissions for electric and internal combustion engine vehicles.

Total Emissions	EV Emissions	ICE Emissions
CO2	53120.48861	36951.90469
SO2	292.6073589	151.7208905
NOX	72.50415397	47.63524604
PM	15.10872758	9.708309352
VOCs	48.41777038	39.68165126

These emissions were converted into social costs, which resulted in $653.31 in social costs attributed to the production of an electric vehicle and $434.98 in social costs for a gasoline-powered vehicle (Table 20).

Table 20. Production social costs for electric and internal combustion engine vehicles.

Emissions	EV Costs	ICE Costs
Cost of CO2	$527.96	$367.26
Cost of SO2	$107.97	$55.98
Cost of NOX	$6.22	$4.09
Cost of PM	$8.48	$5.45
Cost of VOCs	$2.68	$2.19
Total Non-Operating	$653.31	$434.98

A significant portion of non-operating emissions are derived from the power grid, and thus, an increase in renewable energy will also decrease the non-operating costs (Figure 14).

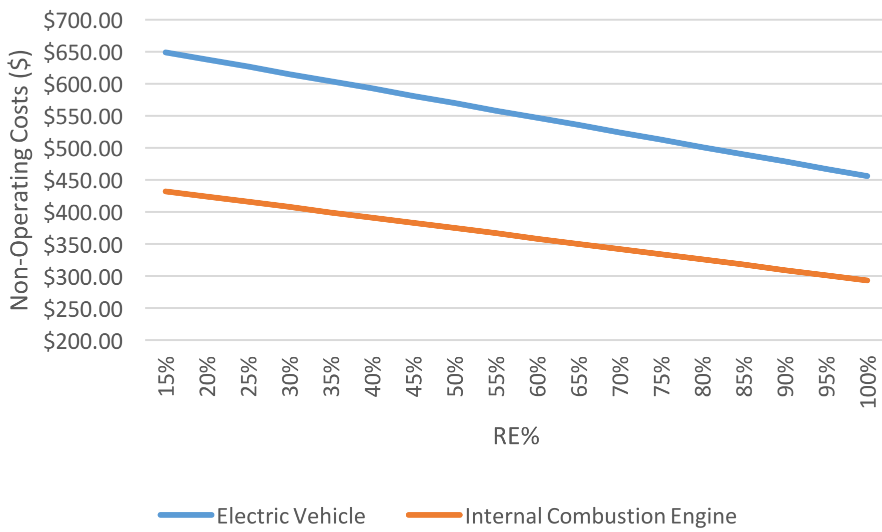


Figure 14. Non-operating costs as a function of renewable energy.

The Electric Vehicle Subsidy (Operation and Production Phase)

The EV Subsidy is computed by subtracting the social cost of an electric vehicle from the social cost of an internal combustion engine vehicle. The operating and non-operating (production) costs are added together to determine the total social costs for each type of vehicle.

Table 21. Social costs and the EV subsidy as a function of renewable energy.

RE%	ICE SC	EV SC	EV Subsidy
13%	$4,709.24	$2,332.43	$2,376.81
20%	$4,698.32	$2,197.30	$2,501.02
30%	$4,682.03	$1,995.64	$2,686.38
40%	$4,665.61	$1,792.57	$2,873.04
50%	$4,649.21	$1,589.77	$3,059.44
60%	$4,632.85	$1,387.40	$3,245.45
70%	$4,616.51	$1,185.32	$3,431.20
80%	$4,600.19	$983.33	$3,616.86
90%	$4,583.87	$781.29	$3,802.57
100%	$4,567.54	$579.13	$3,988.41

The subsidy changes dramatically once the RE% is manipulated (Table 21). This is due to the fact that the social cost of an EV decreases at a far greater rate than the social cost of an ICE vehicle, as the percentage of renewable energy increases.

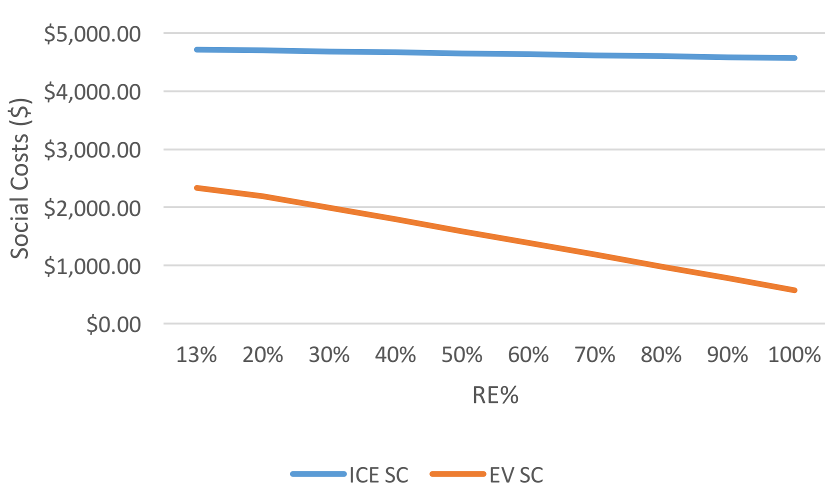


Figure 15. Social costs as a function of renewable energy

The social costs for an internal combustion vehicle do decrease as the RE% increases (Table 21), which is a result of the decreasing social costs of production. A percentage of production emissions are derived from the power grid, and thus, a cleaner grid will lead to a nominal decrease (Figure 15) in overall emissions. Unfortunately, the vast majority of ICE emissions, and subsequently, the social costs associated with an ICE, are a result of operating the vehicle. These social costs are not directly impacted by the cleaner grid. This stands in stark contrast with the electric vehicle. The non-operating social costs for an EV decrease nominally as RE% increases, but the social costs related to the operation phase of the vehicle decrease significantly (Table 21). The operation of an electric vehicle is powered by the grid, and thus, the externalities associated with driving an electric vehicle mirror the externalities associated with the grid itself.

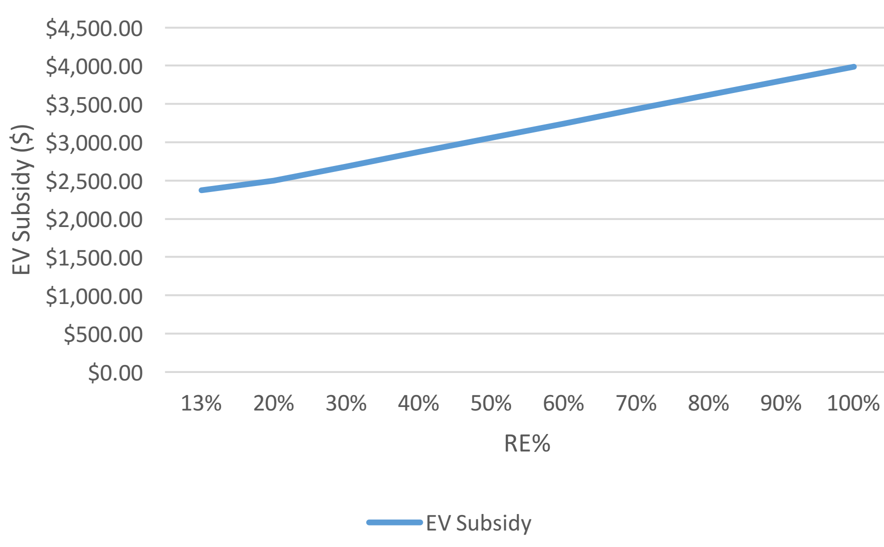


Figure 16. EV subsidy as a function of renewable energy.

The operating emissions for an EV approach 0, as the RE% approaches 100%. This results in an EV subsidy that is directly correlated to the percentage of renewable energy and we see an EV subsidy that nears $4,000 as the RE% reaches 100% (Figure 16).

Subsidy for an Electric Vehicle Powered by Photovoltaics

A national grid powered by 80% or 100% renewable energy is still a nascent idea and it may be many years before such a scenario becomes reality. Fortunately, this does not prevent an individual from charging an electric vehicle with 100% renewable energy in the year 2016. Photovoltaic panels can be installed today on a homeowner's roof which will provide the kWh necessary to power an electric vehicle.

The emissions for a 100% renewable energy national grid will differ slightly from the emissions assigned to a vehicle powered solely from rooftop photovoltaics. This is due to the fact that a 100% renewable energy grid will include a mixture of renewable energy technologies and there is some emissions variation amongst renewables. For example, photovoltaic power produces 48 grams of carbon dioxide per kWh, while wind power produces 11 grams of carbon dioxide per kWh (Klein & Whalley, 2015). These differences may be minimal, but it is important to incorporate them into an accurate assessment of the benefits of photovoltaic-powered electric vehicles.

Table 22. Photovoltaic emissions per-kWh.

Electricity Generation Type	CO2 (g)	SO2 (mg)	NOX (mg)	PM2.5 (mg)	VOCs (mg)
Photovoltaic	48	0.307	0.178	0.308	0.088

The life cycle assessment (LCA) based emissions for photovoltaics are incredibly low (Table 22), as all emissions are derived from the production of the panels. There a zero marginal emissions, but the LCA emissions cannot be ignored.

Table 23. Emissions data for photovoltaic powered electric vehicles

Pollutant	Emissions per kWh (tons)	SC per Ton	SC per kWh	Cost per 150,000mi
CO2	0.000048	$66.26	0.00318048	$152.66
SO2	3.07E-10	$2,459.92	0.00000076	$0.04
NOX	1.78E-10	$572.11	0.00000010	$0.005
PM 2.5	3.08E-10	$3,742.75	0.00000115	$0.06
VOCs	8.8E-11	$368.63	0.00000003	$0.00
		Total:	0.00318252	**$152.76**
		Per Mile:	0.00000002	**$0.0010**

These low emissions lead to a lifetime social cost of only $152.76 that can be assigned to the operation phase of the vehicle (Table 23). This stands in stark contrast to the externalities associated with operating an internal combustion engine vehicle: $4,273.34. The social costs for the internal combustion engine vehicle are nearly 28 times greater than the social costs for an electric vehicle powered by photovoltaics. The proper EV Subsidy was then determined by subtracting the social cost for a photovoltaic-powered EV ($152.76) from the social cost of an internal combustion engine vehicle ($4,273.34). Based on this analysis, an EV subsidy of $3,903.24 was deemed appropriate for a photovoltaic-powered electric vehicle.

Monte Carlo Simulation

There is undoubtedly some variation and uncertainty related to the specific costs assigned to different pollutants. The APEEP Model used in this study assigns costs for sulfur dioxide, nitrous oxide, particulate matter and volatile organic compounds based on geographic location, but these costs differ significantly from county to county (Muller, 2016). Furthermore, a meta-analysis of studies that analyzed the social cost of carbon demonstrates the uncertainty of this cost (Havranek, 2015). A Monte Carlo simulation considers this uncertainty in a probabilistic model. I used the SIMVOI software to create a simulation that consisted of 10,000 iterations, with each iteration randomly pulling data from the APEEP Model (Muller, 2016) and a meta-analysis on the social cost of carbon (Havranek, 2015). This data was entered into the EV Subsidy Combined Model and produced 10,000 different EV Subsidies; each of these subsidies was a function of the different costs that were randomly entered into it.

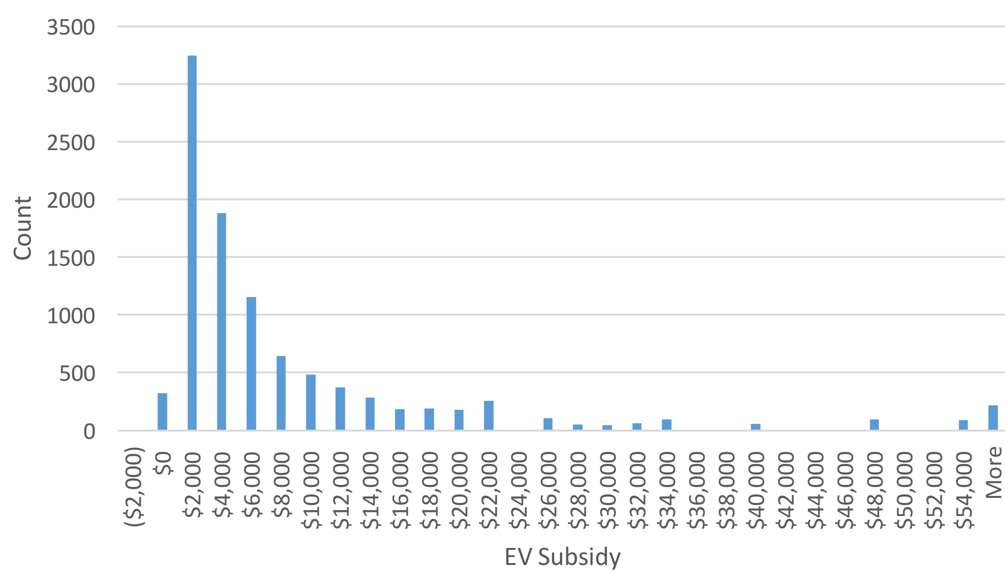


Figure 17. Monte Carlo simulation for 2016 grid (13.3% RE).

The majority of outputs appear in the $2,000 to $6,000 range (Figure 17), with a median value of $3,384.9. This median value can be compared to the determined EV Subsidy from the Combined Model (including production) of $2,376.81 and the closeness of these values substantiates the accuracy of the EV Subsidy discussed earlier in this chapter.

Table 24. EV subsidy percentile for Monte Carlo simulation.

Percentile	**Appropriate EV Subsidy (Combined):**
0.0%	-$1,229.89
0.5%	-$251.29
1.0%	-$170.93
2.5%	-$47.63
5.0%	$145.02
10.0%	$485.26
20.0%	$1,029.30
30.0%	$1,771.57
40.0%	$2,301.19
50.0%	$3,384.49
60.0%	$4,586.21
70.0%	$7,346.21
80.0%	$11,691.69
90.0%	$20,776.32
95.0%	$32,354.12
97.5%	$53,034.88
99.0%	$88,231.39
99.5%	$96,891.25
100.0%	$108,978.97

The Monte Carlo simulation is an effective tool for corroborating the output that emerges from a multivariate model, but its value is not specific to this singular purpose. The Monte Carlo simulation also illustrates the potential variation that lies within the system and the dangers that this presents. For example, 10% of the outputs (EV Subsidy) fell between -$1,229.89 and $485.26 (Table 24). This indicates that in 10% of the simulations the EV Subsidy was extremely low or negative. Alternatively, there were another 10% of the simulations where the EV Subsidy fell between $20,776.32 and $108,978.97 (Table 24). Thus, while it is possible that the EV Subsidy of $2,376.81 is slightly overestimating the benefits of an electric vehicle, it is also possible that this value is severely underestimating the benefits of an electric vehicle.

Variance of 10th Percentile to Median: $485.26 - $2,376.81 = -$1,891.55
Variance of 90th Percentile to Median: $20,776.32 - $2,376.81 = $18,399.51

Therefore, the simulation produced 1000 values (10th percentile) that were at least $1,891.55 below the median value, while the simulation also produced 1000 values (90th percentile) that were at least $18,399.51 greater than the median value. Once again, this underscores the potential advantages of electric vehicles and the non-trivial possibility that the EV Subsidy is severely underestimating these advantages.

Table 25. Measures of central tendency for Monte Carlo simulations

RE%	**Minimum**	**Maximum**	**Median**	**Mean**
13.30%	-$1,229.89	$108,978.97	$3,384.49	$8,729.21
20%	-$905.77	$114,024.63	$3,501.01	$9,281.62
50%	-$1,957.70	$136,792.74	$4,220.21	$11,457.82
80%	-$667.31	$159,562.10	$4,988.34	$13,518.93
100%	-$374.37	$174,473.88	$5,474.66	$14,425.89

Note: This table breaks down the measures of central tendency for each Monte Carlo Simulation. A separate simulation was run for each renewable energy scenario.

The Monte Carlo simulation was also run for a variety of different renewable energy penetration scenarios (Table 25). The median and mean values for these simulations increased as the percentage of renewable energy increased. This increase was expected and followed a similar pattern to what was demonstrated earlier in this chapter (when the percentage of renewable energy was manipulated).

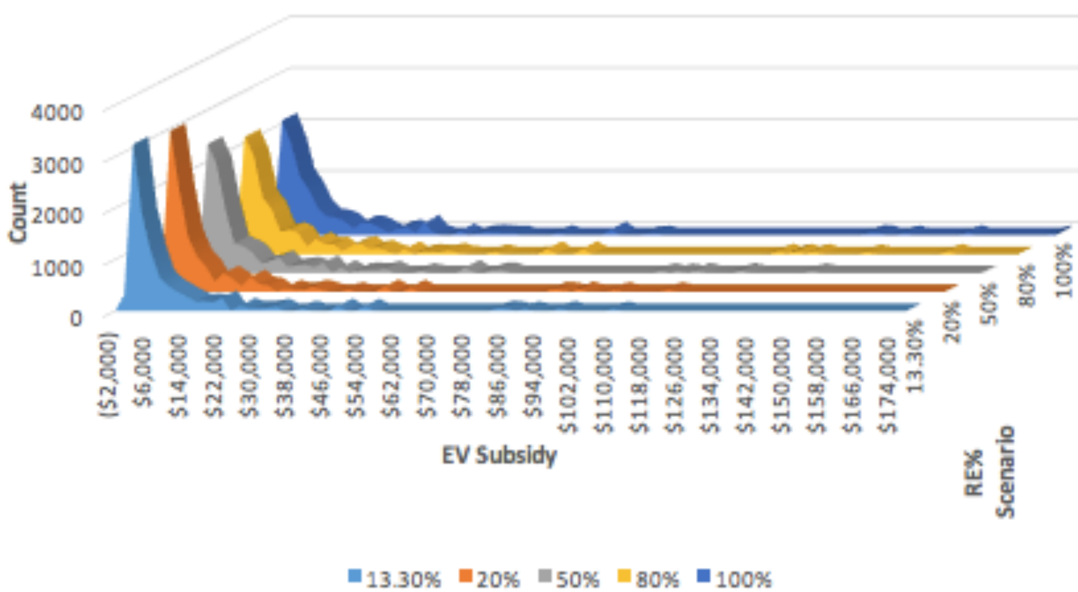


Figure 18. Monte Carlo comparison of different RE% scenarios

The majority of values are clustered around the medians (Table 25), but a non-trivial percentage of the simulations extend into the tens of thousands of dollars (Figure 18). This variability presents the possibility that electric vehicles running on renewable energy are far more beneficial to society than initial reports may indicate.

Monte Carlo Simulation for 100% Photovoltaic-powered EV

The renewable energy percentage scenarios are future scenarios and data from this study can be used to guide society towards these percentages. On the other hand, it is possible for an electric vehicle to be powered at home by electricity generated from 100% photovoltaics. Therefore, the Monte Carlo simulation for a 100% photovoltaic-powered EV can model a scenario that is applicable in 2016.

Table 26. EV subsidy percentile for PV-powered EV Monte Carlo simulation.

Percentage	EV Subsidy Including Production (100%PV):
0.0%	-$618.94
0.5%	-$496.53
1.0%	-$311.64
2.5%	-$192.10
5.0%	$133.00
10.0%	$601.33
20.0%	$1,487.69
30.0%	$2,692.10
40.0%	$3,593.77
50.0%	$5,333.62
60.0%	$7,314.68
70.0%	$11,714.81
80.0%	$18,985.18
90.0%	$33,454.14
95.0%	$51,814.67
97.5%	$86,687.95
99.0%	$142,105.66
99.5%	$175,376.11
100.0%	$175,625.05

The photovoltaic median value of $5,333.62 (Table 26) was nearly identical to the median value for the 100% renewable energy scenario ($5,474.66). Furthermore, 10% of the values were greater than $33,454.14 and 20% of the values were greater than $18,985.18. This affirms the possibility that solar-powered electric vehicles are more beneficial than we may realize.

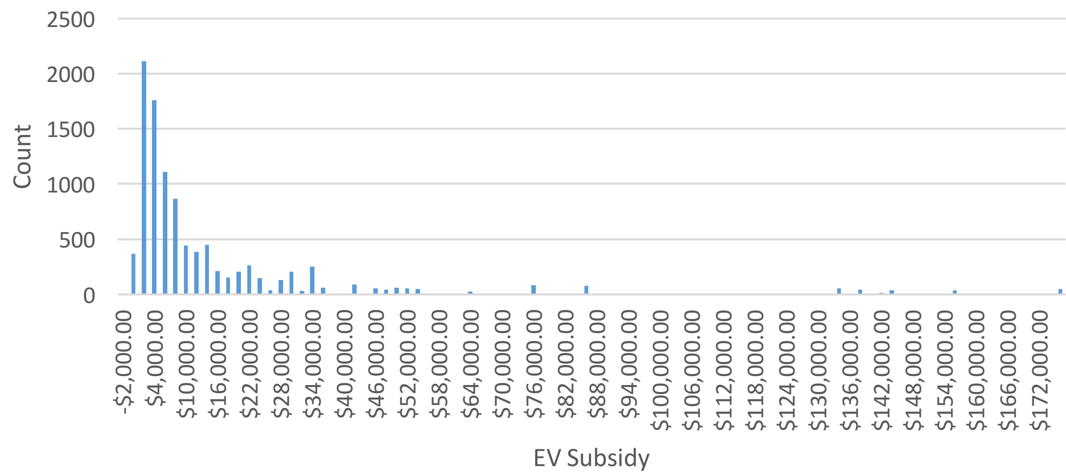


Figure 19. Monte Carlo simulation for 100% photovoltaic scenario

Carbon Dioxide Emissions

The carbon dioxide emissions associated with an electric vehicle running on the 2016 grid (13.3% renewable energy) were 55% less than an internal combustion engine with an efficiency of 25.4 miles per gallon (Table 27). This advantage disappeared when the electric vehicle was compared to an internal combustion engine automobile operating at 80 miles per gallon. In this scenario, the internal combustion engine vehicle was actually responsible for 21% fewer carbon emissions than the electric vehicle (Table 27). There are currently no cars on the market with efficiencies close to 80 miles per gallon, but it is important to compare the electric vehicle to an idealized version of the internal combustion engine vehicle. A 100% renewable energy grid is also an idealized scenario, but a comparison between these “utopian examples” can inform policy that will guide us down the path to an ideal transportation model.

Table 27. Carbon emissions comparison data for 2016 grid (13.3% RE).

	25.4mpg	**80mpg**
ICE Total LCA CO2:	68.38	25.49
EV Total LCA CO2:	30.82	30.83
CO2 Difference:	37.56	-5.34
CO2 Percentage Difference:	55%	-21%

An electric vehicle running off of 100% renewable energy produces far fewer greenhouse gas emissions than a vehicle based on the current grid: 6.30 tons of carbon dioxide compared to 30.82 tons of carbon dioxide. This is also substantially less than an internal combustion engine vehicle operating at 25.4 miles per gallon (68.38 tons of carbon dioxide) or a vehicle getting 80 miles per gallon (25.49 tons of carbon dioxide). The electric vehicle running on 100% renewable energy impressively produces 73% fewer carbon dioxide emissions than an internal combustion engine automobile with an efficiency of 80 miles per gallon (Table 28). This is greater than the 50% reduction that was hypothesized.

Table 28. Carbon emissions comparison data for 100% RE grid.

	25.4mpg	**80mpg**
ICE Total LCA CO2 (Tons):	66.40	23.51
EV Total LCA CO2 (Tons):	6.30	6.30
CO2 Difference:	60.10	17.21
CO2 Percentage Difference:	91%	73%

While the 100% renewable energy scenario is purely academic, it is feasible for an electric vehicle in 2016 to be 100% powered by rooftop photovoltaics. An electric vehicle powered from 100% photovoltaics will be responsible for 10.27 tons of carbon dioxide over its lifetime, which is 85% less than an internal combustion engine vehicle operating at 25.4 miles per gallon and 56% less than an internal combustion engine vehicle operating at 80 miles per gallon (Table 29).

Table 29. Carbon emissions comparison data for the 100% PV-powered EV.

	25.4 MPG	**80 MPG**
ICE Total LCA CO_2:	68.38	23.51
EV Total LCA CO_2:	10.27	10.27
CO_2 Difference:	58.11	13.24
CO_2 Percentage Difference:	85%	56%

Note: This scenario is based off of photovoltaic panels operating in the year 2016, and thus, the production emissions are from the 13.3% RE grid. This causes the carbon dioxide emissions to be higher than the 100% RE scenario in Table 28.

Environmental Impact of Electric Vehicles

The EV Subsidy is computed by subtracting the negative environmental impact of an electric vehicle from that of an internal combustion engine vehicle. A positive value would indicate that the electric vehicle had a lesser impact on the environment, while a negative value would indicate that the internal combustion engine vehicle had a lesser impact.

Table 30. Electric vehicle compared to ICE vehicle getting 25.4 mpg.

RE%	**EV Subsidy**	**MONTE CARLO Median Subsidy**
13.30%	$2,376.78	$3,384.49
20%	$2,500.99	$3,501.01
50%	$3,059.42	$4,220.21
80%	$3,616.83	$4,988.34
100%	$3,988.39	$5,474.66
100% PV	$3,907.52	$5,333.62

Table 31. Electric Vehicle compared to ICE vehicle getting 80 mpg.

RE%	EV Subsidy	MONTE CARLO Median SUBSIDY
13%	-$540.46	-$657.36
20%	-$416.24	-$485.41
50%	$142.18	$287.58
80%	$699.60	$1,026.51
100%	$1,071.15	$1,533.01
100% PV	$986.01	$1,286.45

Table 30 reveals that an electric vehicle in all RE% scenarios will have a lesser environmental impact than an internal combustion engine automobile with an efficiency of 25.4 miles per gallon. On the other hand, an internal combustion engine vehicle operating at 80 miles per gallon has a smaller environmental impact than an electric vehicle charged from a grid with 13.3% or 20% renewable energy (Table 31). This did not hold true for other RE% scenarios, as all RE% scenarios with 50% renewable energy or greater showed a positive EV subsidy. As hypothesized in Hypothesis #2, an electric vehicle charged with 100% renewable energy will have a lesser environmental impact than an automobile operating at 80 miles per gallon (Table 31). The appropriate 2016 EV Subsidy for a 100% renewable-powered EV came in at $3,988.39, which was also greater than the $3,000 that was hypothesized (Table 30).

Chapter IV

Discussion

There are a variety of factors that impact the EV Subsidy, including: emissions data, the cost per pollutant, miles per gallon, and the kWh per 100 miles. It is essential to understand which factors impart the greatest impact on the subsidy and to analyze the uncertainty within these variables. The SIMVOI software package produces coefficients of determination for each of the input variables within the Monte Carlo simulations (Table 32). This data helps to illuminate the relationships between the input variables (costs per pollutant) and the output variable (EV Subsidy).

Table 32. Monte Carlo simulation coefficients of determination. 13.3% RE scenario.

	Cost of Carbon	**Cost of SO2**	**Cost of NOX**	**Cost of PM**	**Cost of VOCs**
Appropriate EV Subsidy	1.0000	0.0005	0.0001	0.0003	0.0000

The Monte Carlo simulation in Chapter III produced coefficients of determination that highlighted the strong relationship between the social cost of carbon (SCC) and the EV Subsidy (Table 32). The impact of the cost of carbon was the primary determinant of the EV Subsidy and far exceeded the impacts of the other pollutants. This analysis did not take into account other input variables, such as “miles per gallon” and “kWh per 100 miles,” but I was able to build upon the initial simulation to create a new Monte Carlo simulation that included these variables. This new Monte Carlo simulation pulled pollutant cost data from the APEEP Model (Muller, 2016) and a meta-analysis for the social cost of carbon (Havranek et al., 2015), but it also randomly input data for "miles per gallon" and "kWh per 100 miles." The data was selected using SIMVOI's "RANDTRIANGULAR" function, which allows data to be selected from a triangular probability density function: the low, high. and "most likely" values were entered into the simulation. For "miles per gallon" a low value of 10, a high value of 80, and a most likely value of 25.4 were entered into the simulation. The "mostly likely" value of 25.4 was chosen because it represents that average miles per gallon (July 2016 value), while the low of 10 and high of 80 were chosen so that a wide range of values would be entered into the simulation. For "kWh per 100 miles" a low value of 20, a high value of 40, and a most likely value of 32 (weighted value of all 2016 model year electric vehicles) were input into the Monte Carlo simulation.

Table 33. Monte Carlo simulation coefficients of determination. 13.3% RE scenario. Including efficiency inputs.

	Cost of Carbon	**Cost of SO2**	**Cost of NOX**	**Cost of PM**	**Cost of VOCs**	**Mile per Gallon**	**EV Efficiency**
Appropriate EV Subsidy	0.2806	0.0001	0.0002	0.0002	0.0001	0.1313	0.0026

Note: The above values represent the coefficients of determination related to each of the independent variables (columns) as they relate to the dependent variable (Appropriate EV Subsidy).

Table 33 reveals that the cost of carbon still accounts for most of the variation in the EV Subsidy, but that "miles per gallon" is also significant. Hence, it is important to explore these two key inputs further.

Cost of Carbon

The social cost of carbon (SCC) is the most significant determinant for the EV Subsidy. However, it is also an input that is mired in uncertainty. The strong correlation between the social cost of carbon and the EV Subsidy (difference between the social cost of an ICE and an EV) was illustrated in the Monte Carol simulation (Figure 20).

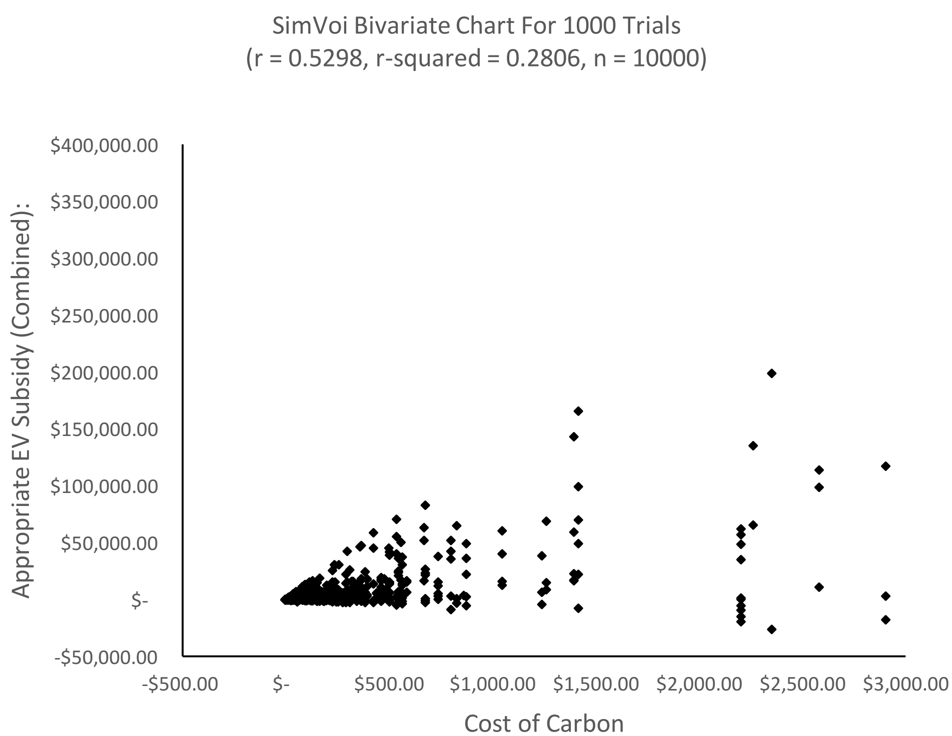


Figure 20. Scatterplot for Monte Carlo simulation (13.3% RE scenario). This graph demonstrates the relationship between the appropriate EV Subsidy and the cost of carbon.

The social cost of carbon has a greater impact on the EV Subsidy than any of the other pollutant costs, miles per gallon, or electric vehicle efficiency. While there is a relationship between the social cost of any of the pollutants and the EV Subsidy, the impact of carbon dioxide far exceeds that of the other pollutants. For example, a $10 increase in the social cost of carbon will increase the EV Subsidy by nearly $400, while a $1,000 increase in the social cost of sulfur dioxide will decrease the EV Subsidy by less than $30. Carbon dioxide is undoubtedly the main driver of the EV Subsidy and this is due to the fact that both EVs and ICE vehicles emit far more carbon dioxide than other pollutants (see Appendix 2). An electric vehicle running on the 2016 American grid would produce 22.96 metric tons of carbon dioxide over its lifetime (during the operation phase), while it would only produce 5.32×10^{-5} metric tons of sulfur dioxide over the same span of time. This indicates that an EV will be responsible for 429,311 times more carbon dioxide than sulfur dioxide over its lifetime (150,000 miles).

The relationship between the social cost of carbon and the EV Subsidy is perfectly linear: for every $1 increase in the social cost of carbon, the EV Subsidy increases by $37.56 (Figure 21).

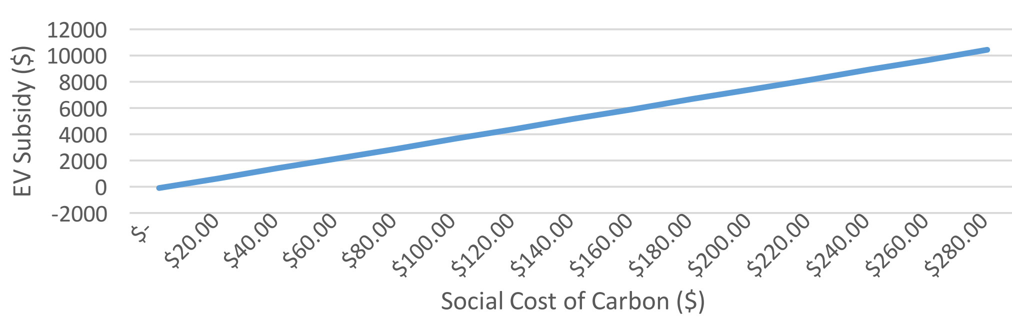


Figure 21. The EV subsidy as a function of the social cost of carbon.

As illustrated in Figure 21, the EV Subsidy could rise to over $10,000 if the social cost of carbon exceeds $280. This value is not unprecedented, as other studies have produced social costs of carbon that exceed $300 (Havranek et al., 2015).

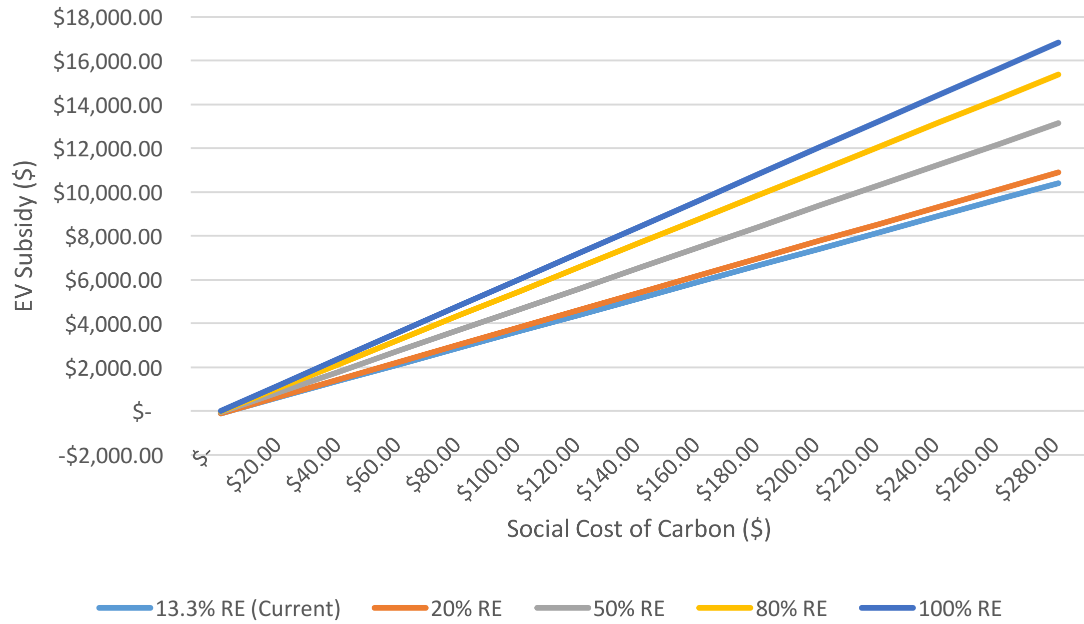


Figure 22. EV subsidy as a function of renewable energy and the social cost of carbon.

These values continue to grow if the percentage of renewable energy increases beyond 2016 numbers. In a 100% renewable energy scenario, the EV Subsidy will increase by $60 for every one-dollar increase in the social cost of carbon (Figure 22). If the cost of carbon reaches $280 (see Ancillary Appendix 1 for all values), it will lead to an EV Subsidy of nearly $17,000. It is undeniable that both the social cost of carbon, and the percentage of renewable energy, have a pronounced impact on the EV Subsidy.

A social cost of carbon exceeding $200 may be significantly higher than the current social cost of carbon used by many government institutions, but it is not outside the mainstream of the academic literature. The meta-analysis by Havranek et al. (2015) includes values that exceed $1,000 per ton and my Monte Carol simulation clearly demonstrated that these high values cannot be ignored. The high SCC values from Havranek et al. significantly impacted the Monte Carlo Simulation, as they caused the mean EV Subsidy value to greatly exceed the median EV Subsidy value. Botzen and van den Bergh (2014) make a strong case in “Nature Climate Change” that many SCC estimates are undervaluing the SCC by failing to account for the full external costs of carbon dioxide. Some of the costs that are unaccounted for include: biodiversity losses, impacts on long-term economic growth, political instability, extreme weather, and the possibility of low-probability/high impact climate change risks. Botzen and van den Bergh (2014) demonstrated that the inclusion of these costs would result in a social cost of carbon floor of at least $125, yet the true cost may exceed this value. Hence, I have incorporated the SCC value of $125 throughout my analysis. If the true cost of carbon is significantly greater than $125 per ton, it would mean that the current EV Subsidy is far too low. Furthermore, the risks of underpricing the social cost of carbon may be significantly less than the risks associated with overpricing it. This risk was demonstrated in the Monte Carlo Simulation, as low estimates for the SCC resulted in EV Subsidies (2016 grid) as low as -$1,229.89, while high estimates for the SCC led to EV Subsidies as high as $108,978.97 (see Table 25 in Chapter III).

Miles per Gallon

The social cost of carbon may have yet to enter the public lexicon, but “miles per gallon” is ubiquitous. The lesser known variable “SCC” had the most profound impact on the EV Subsidy, while “miles per gallon” had the second highest coefficient of determination among all the possible input variables entered into the Monte Carlo simulation.

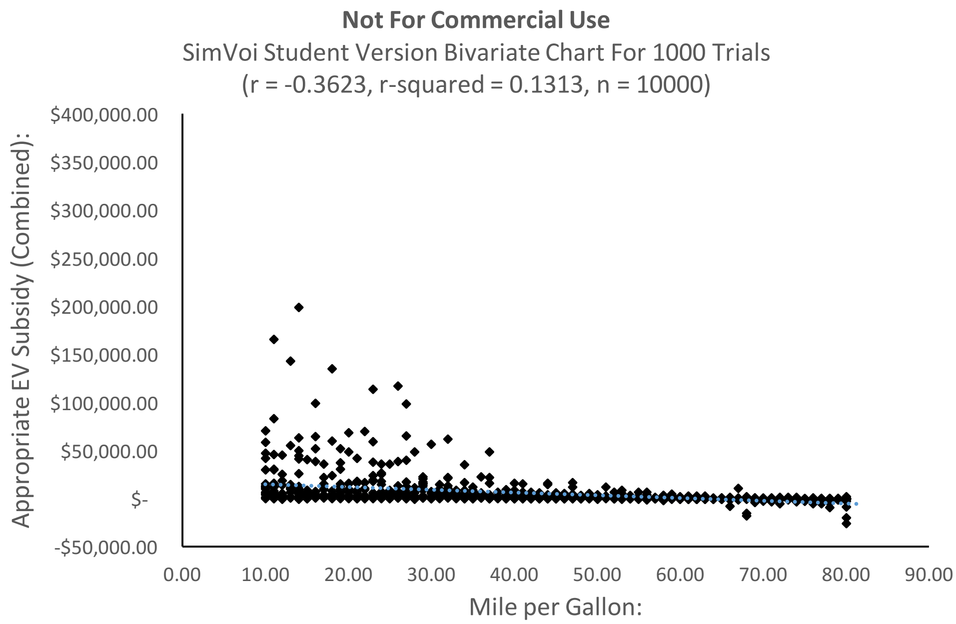


Figure 23. Scatterplot for Monte Carlo simulation of the relationship between the EV subsidy and miles per gallon (13.3% RE scenario).

The inverse relationship (r = -0.36) between miles per gallon and the EV Subsidy can be visualized in Figure 23. This relationship also occurred in my EV Subsidy model: I was able to manipulate the variable for miles per gallon to determine the outputs (EV Subsidy) for a range of ICE efficiencies (Figure 24).

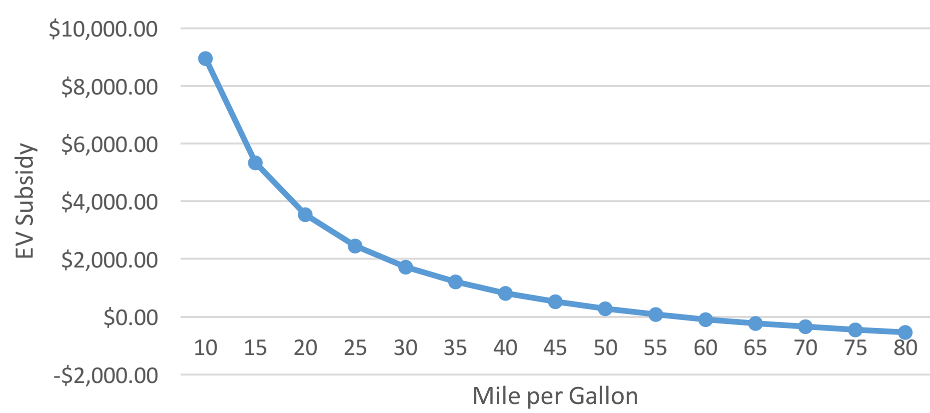


Figure 24. The EV subsidy as a function of miles per gallon.

The relationship between the EV Subsidy and the ICE efficiency is exponential: the impact on the EV Subsidy diminishes as the number of miles per gallon increases. Improving the efficiency from 10 mpg to 15 mpg reduces the EV Subsidy by $3,619, while increasing the efficiency from 40 to 45 mpg reduces the EV Subsidy by only $302. The environmental benefits of increased ICE efficiency are unequivocal, however this does not change one incredibly important fact: no matter how efficient an ICE vehicle becomes, it will still be combusting gasoline. A renewable energy powered EV can approach zero marginal emissions, while this is an unattainable goal for even the most efficient of ICE vehicles.

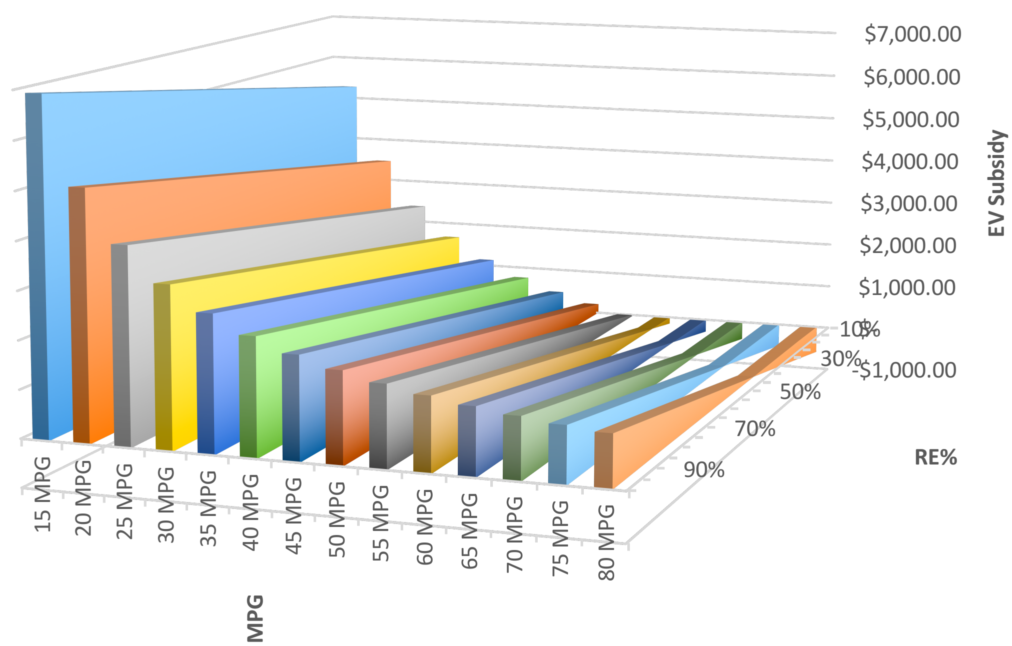


Figure 25. The EV subsidy as a function of RE% and mpg.

A combination of low RE% and high ICE efficiency will produce an EV Subsidy that dips into negative territory (Figure 25). This indicates that ICE vehicles would be environmentally advantageous in these specific scenarios. These possibilities cannot be ignored, but it is important to remember that the vast majority of scenarios produce a positive EV Subsidy. Furthermore, the ideal ICE scenarios (high MPG, low RE%) produce slightly negative EV Subsidies, while the ideal EV scenarios (low MPG, high RE%) produce large positive EV Subsidies.

Electric Vehicle Efficiency

The metric for electric vehicle efficiency (kWh per 100 miles) may initially seem counterintuitive, as a lower number indicates greater efficiency. This is due to the fact that a lower number is stating that it takes fewer kilowatt hours to travel the exact same distance (100 miles).

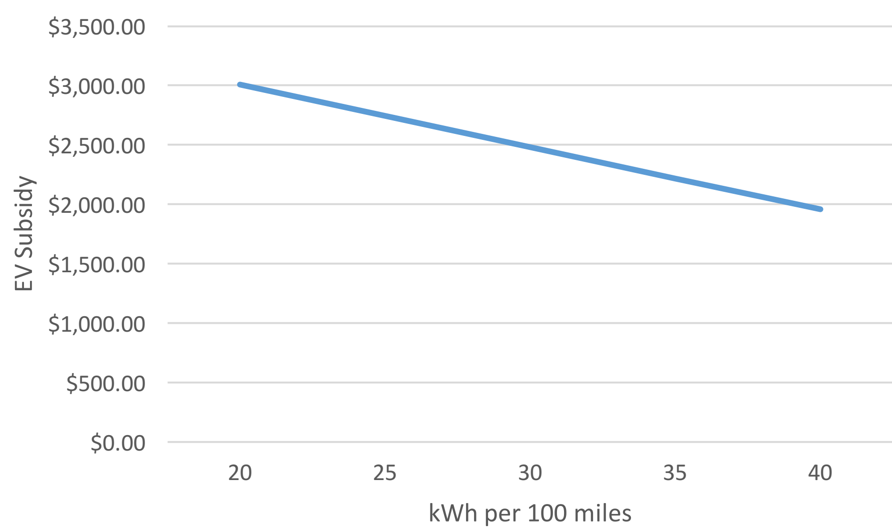


Figure 26. EV efficiency and the EV subsidy

Thus, there is an inverse relationship (Figure 26) between "kWh per 100 miles" and the EV Subsidy: as the number of kWh per 100 miles' increases, the appropriate EV Subsidy decreases. This relationship is not as significant as the relationship between the social cost of carbon and the EV Subsidy, or "miles per gallon" and the EV Subsidy, but it is not insignificant.

An ideal EV Subsidy would take the efficiency of the automobile into account, however this may be difficult to implement.

Table 34. Vehicle specific EV subsidy.

Electric Vehicle	kWh per 100 Miles	EV Subsidy ($66.26 SCC)	EV Subsidy ($125 SCC)
2016 BMW i3	27	$2639.15	$5055.08
2017 Chevrolet Bolt	28	$2586.68	$4960.64
2016 Nissan Leaf	30	$2481.72	$4771.77
2016 Tesla Model S 90D	33	$2324.30	$4488.47

Table 34 clearly shows the differences between vehicles that are currently available to purchase. If the social cost of carbon is set at $66.26, this will amount to a $300 difference between a 2016 BMW i3 (the most efficient 2016 automobile) and a Tesla Model S 90D, but this increases to over $500 if the social cost of carbon is set at $125 (U.S. Department of Energy, 2016). Interestingly, the efficiency of an electric vehicle has a diminishing effect on the EV Subsidy as the percentage of renewable energy increases (Figure 27).

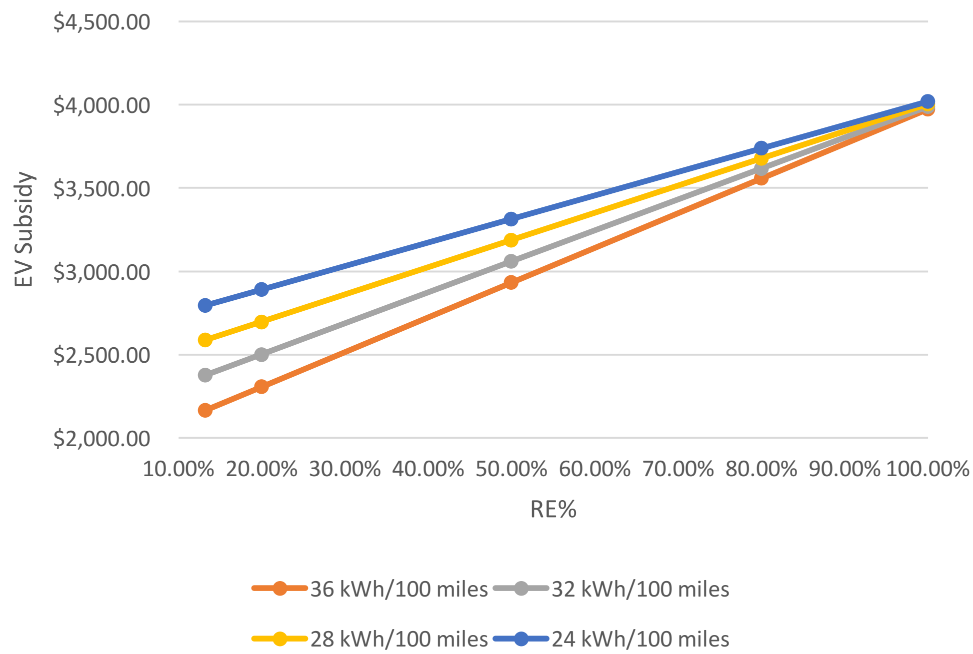


Figure 27. The EV subsidy as a function of RE% and EV efficiency

Electric vehicles in high penetration renewable energy scenarios (50%+ RE) produce very little emissions from the operation of the vehicle. Thus, in these scenarios, the efficiency of the electric vehicles is not nearly as important. This underscores the importance of renewable energy and the impact that it can have on the environmental benefits of an electric vehicle.

Environmental Impact of Batteries

It is common for critics of electric vehicles to focus on the environmental impact of the battery pack. This is a component that is starkly different than its internal combustion engine equivalent. For example, the production of an electric vehicle's components account for 6 tons of carbon dioxide pollution, while the production of an international combustion engine vehicle's components account for 4.5 tons. The electric vehicle is responsible for more emissions, but the difference is not substantial. This is not the case when we look at batteries: an electric vehicle's battery is responsible for approximately 1 ton of carbon dioxide, while a gasoline-powered automobile's battery accounts for just under 0.04 tons of carbon pollution (GREET, 2015).

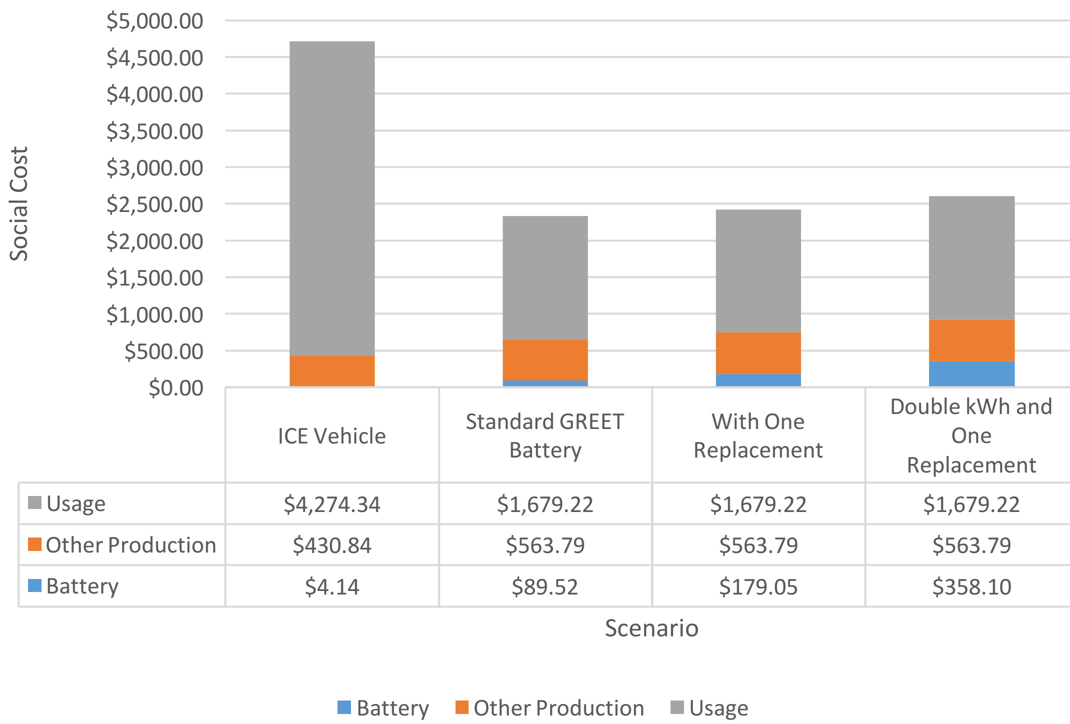


Figure 28. Social cost breakdown: 2016 grid and miles per gallon. This analysis is based on a grid with 13.3% renewable energy and an internal combustion engine vehicle with an efficiency of 25.4 miles per gallon.

The carbon emissions and social costs related to an electric vehicle's battery may be orders of magnitude greater than its gasoline-powered counterpart, however results in Chapter III demonstrated that this disparity does not compensate for the drastic difference in operating emissions. Figure 28 clearly shows how the social costs associated with battery production are minimal compared to usage emissions. This holds true for other battery scenarios where the battery needs to be replaced and where the battery is double the size and needs to be replaced. In Figure 28 we can see that the "Double kWh and One Replacement" scenario is responsible for $2,422 in social costs, while the ICE vehicle is responsible for $4,709 in social costs.

There is no denying that large battery packs and battery replacements are a legitimate environmental concern. It would be ideal to know exactly how long batteries would last and how many batteries will need to be replaced, as this could help to facilitate a more accurate EV Subsidy. However, most modern electric vehicles are less than five years old and there is not enough data to accurately assess the longevity of the batteries. Plug In America conducted one of the only studies on EV battery life; the study looked at Tesla Roadsters as they were the first long range electric vehicles on the road. A sample of 126 cars were analyzed and the conclusion was positive: it is expected that the battery pack will retain 80-85% of its capacity after 100,000 miles (Montavalli, 2013). This indicates that it is entirely possible that an electric vehicle could reach 150,000 miles without needing a replacement battery.

Battery longevity is a function of multiple factors. Overcharging, temperatures, and deep discharges all impact the lifespan of an electric vehicle's battery. Fortunately, these are all variables that can be controlled by smart hardware and software. Modern electric vehicles can use onboard cooling mechanisms to keep the batteries at an acceptable temperature and use software to prevent the batteries from reaching 100% capacity. For example, the Tesla Model S will only charge to 100% if the owner manually asks it to and cars such as the Chevrolet Volt never use full capacity.

Furthermore, a battery's lifespan is strongly correlated to the number of times that is fully discharged. Jim Montavalli (2013) writes:

> After 300 to 500 cycles at 100 percent depth of discharge, a lithium-ion cell's capacity will drop to 70 percent. But partial discharge "reduces stress and prolongs battery life." Drain the batteries consistently to only 50 percent, as is often the case with electric cars that get plugged in frequently, and life expectancy of a healthy battery zooms up to 1,200 to 1,500 cycles. That, of course, translates to 366,000 miles, but don't expect numbers like that on your odometer. Other wild cards such as frequency of fast recharge can also affect battery life. (para. 9)

This furthers the notion that many electric cars will never need a battery replacement, yet it does not change the fact that it is still important to measure the environmental impact of replacement batteries.

There are countless combinations of battery size and battery replacements, however I focused on three specific scenarios (Table 35): the standard battery in the GREET model with no replacements, double the kWh of the GREET model with no replacements, and double the kWh with one replacement (the double kWh scenario is essentially the same as a scenario with the standard kWh and one replacement, due to the fact that the battery emissions data is simply doubled).

Table 35. Battery scenarios and the EV subsidy

	Battery	**Total SC EV**	**Total SC ICE**	**Subsidy**
Standard GREET Battery	\$89.52	\$2,332.54	\$4,709.32	\$2,376.78
With One Replacement	\$179.05	\$2,422.06	\$4,709.32	\$2,287.25
Double kWh and One Replacement	\$358.10	\$2,601.11	\$4,709.32	\$2,108.20

The social cost of an electric vehicle clearly increases (Table 35) if the battery size increases and/or the battery is replaced, and subsequently, leads to a decrease in the EV Subsidy. This decrease is minimal when compared to the overall EV Subsidy, as the detrimental aspects of battery production do not compensate for the externalities related to burning gasoline. In the "double kWh and one battery replacement" scenario, the EV Subsidy continues to grow as the percentage of renewable energy increases (Figure 29).

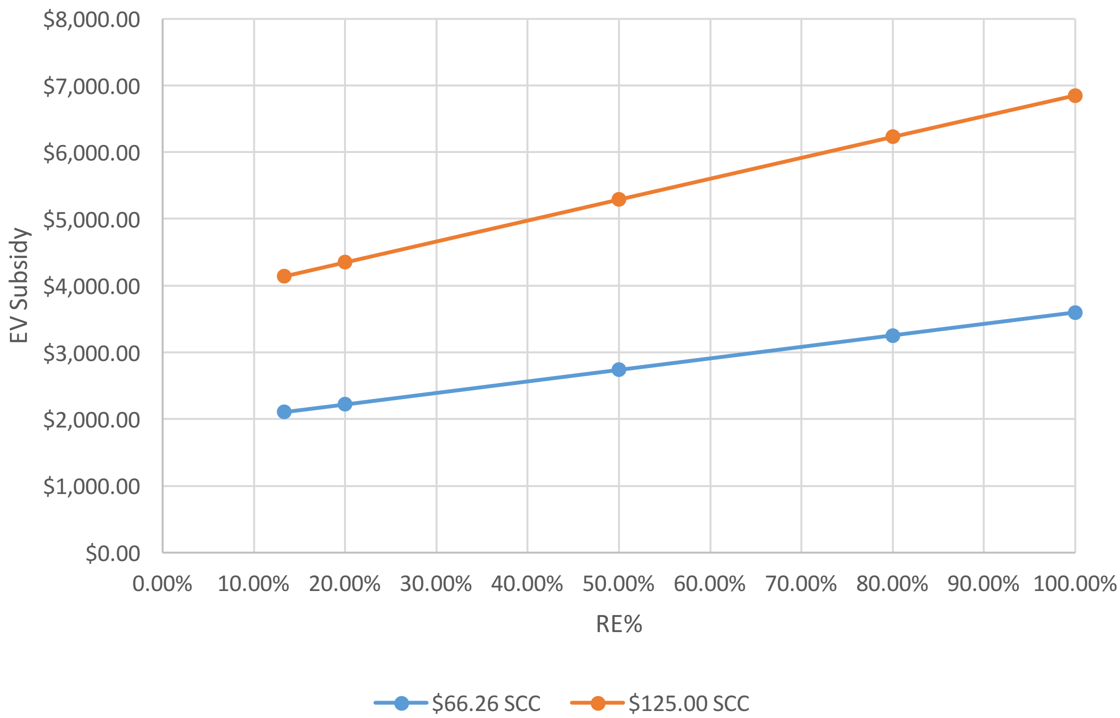


Figure 29. The EV subsidy as a function of RE% (double kWh and battery replacement).

This relationship is consistent with the correlation between RE% and the EV Subsidy I have established throughout this study. The relationship between the social costs of a gasoline-powered vehicle and the EV Subsidy has also been well established. Therefore, it is important to look at the EV Subsidy as a function of both variables.

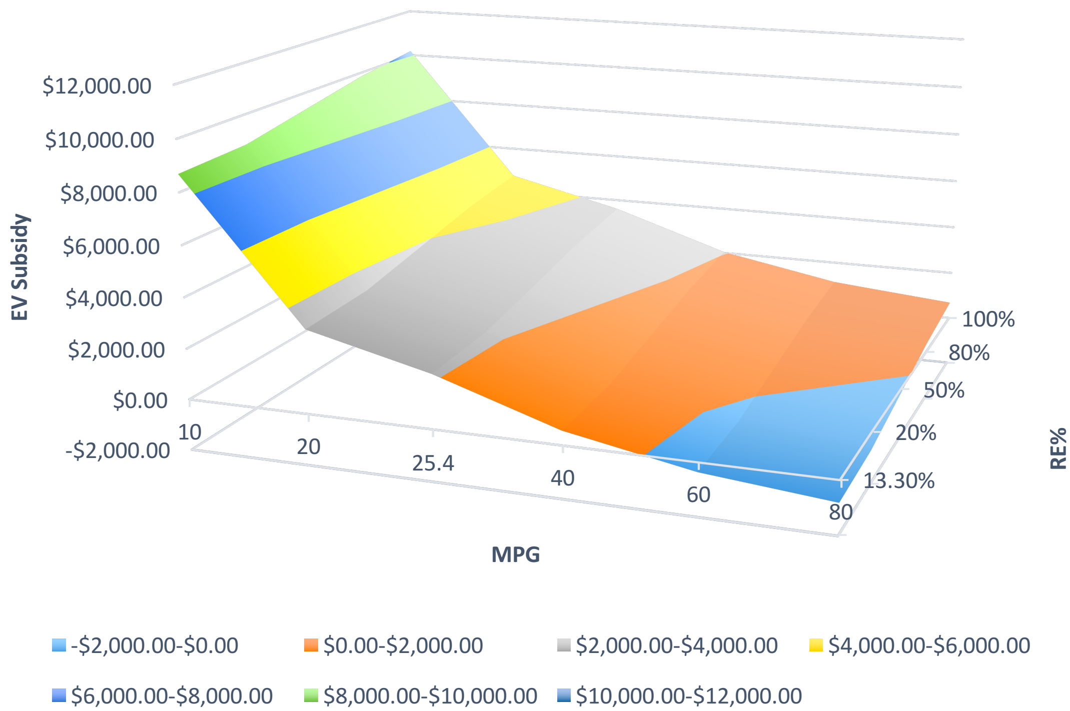
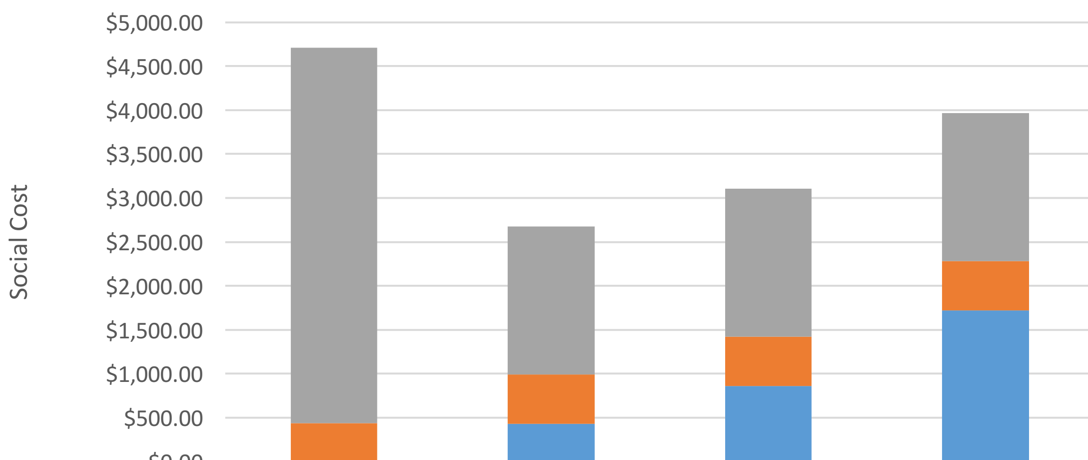


Figure 30. The impact of mpg and RE% on the EV subsidy (double kWh and one replacement).

Figure 30 demonstrates that there are circumstances under which an internal combustion engine vehicle would be environmentally advantageous (the blue portion in the bottom right-hand corner of Figure 30), yet it requires a very limited arrangement of variables to make this happen. A negative EV Subsidy necessitates a combination of high ICE efficiency and a low percentage of renewable energy. It is interesting to note than even in this scenario (double kWh and one battery replacement), the high RE% electric vehicles are still favorable to an 80mpg gasoline vehicle.

The results indicate that electric vehicles can still be extremely beneficial even with larger batteries and battery replacements. Analyzing specific scenarios that penalize the EV (battery replacements, low RE%, large batteries) will refute much of the criticism directed at electric vehicles. Hence, it is also important to analyze battery emissions data that is less favorable for electric vehicles, as there is some variation among the studies that have looked at life-cycle emissions of lithium-ion batteries (Kim et al., 2016). The GREET model was used throughout this study, but its battery-related emissions data is lower than some of the other models. Research by Kim et al. (2016) indicates that the emissions per kWh of battery capacity may be significantly higher than what the GREET model outputs (see Ancillary Appendix 2). I took this data and entered it into the model to determine what the EV Subsidy would look like if battery emissions were significantly increased.



	ICE Vehicle	Kim et al Battery	Kim et al with One Replacement	Double kWh and One Replacement
Usage	$4,274.34	$1,679.22	$1,679.22	$1,679.22
Other Production	$430.84	$563.79	$563.79	$563.79
Battery	$4.14	$429.98	$859.96	$1,719.93

Battery Other Production Usage

Figure 31. Social cost breakdown: 2016 grid and mpg, and Kim et al. emissions data.

The social costs (Figure 31) for electric vehicles are still lower than the costs associated with internal combustion engine vehicles, but the disparity has diminished.

The emissions data from Kim et al. (2016) increases the total social cost of the "Double kWh and One Replacement" EV scenario to $3,962, yet it is still lower than the ICE vehicle's social cost of $4,709. These figures are based on the 2016 grid (13.3% renewable energy) and they do not factor in the benefits of greater renewable energy penetration.

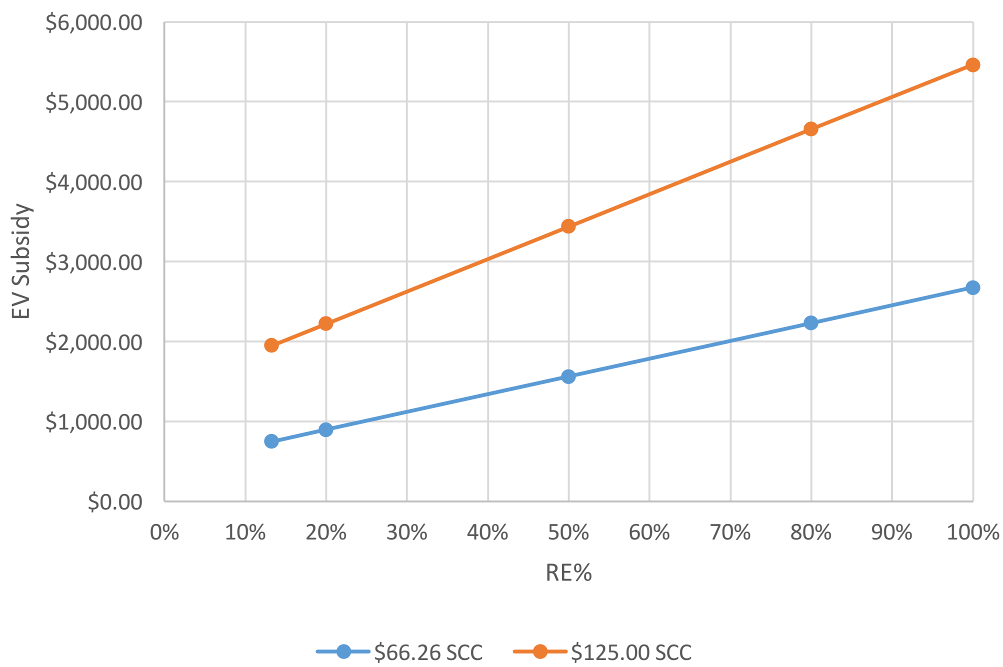


Figure 32. The EV Subsidy as a function of RE% (double kWh and battery replacement, and Kim et al. emissions data).

Again, the EV Subsidy (the difference between the social costs of an EV and ICE) increases in response to an increase in RE% (Figure 32). The benefits of renewable energy are not counteracted by this exceedingly disadvantageous battery scenario (double kWh, one battery replacement, and Kim et al. emissions data). Yet, the environmental advantage of electric vehicles does diminish if the electric vehicle is compared to an extremely efficient internal combustion engine vehicle.

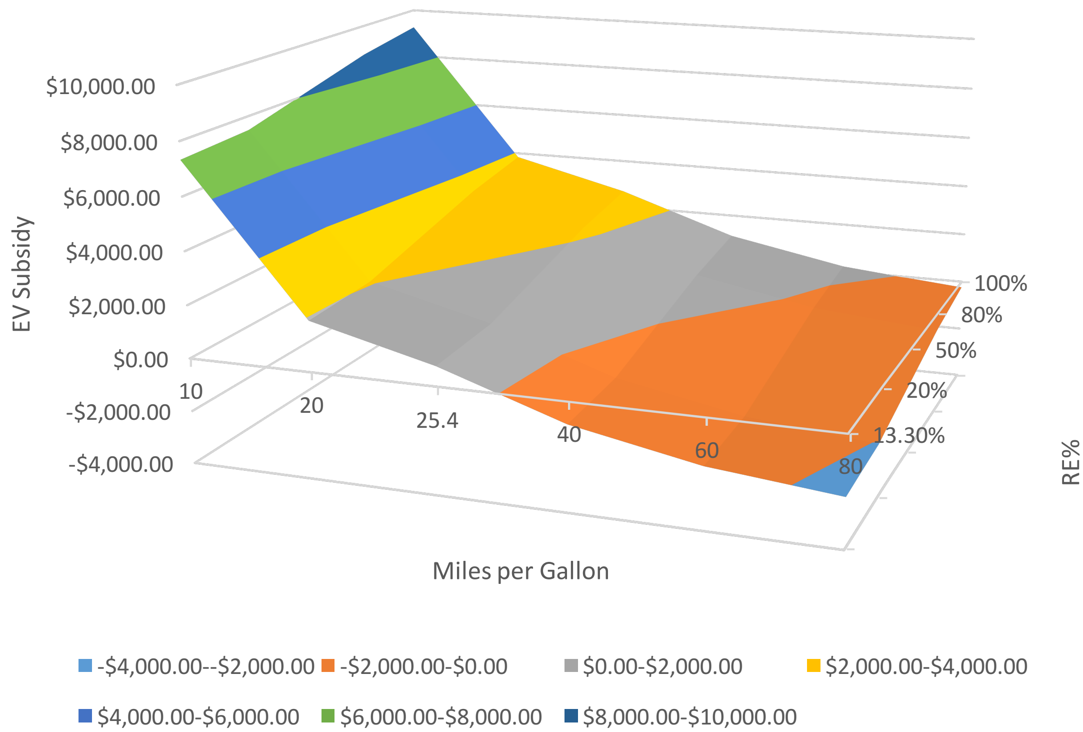


Figure 33. The impact of mpg and RE% on the EV subsidy (double kWh and one replacement).

The combination of high miles per gallon and a disadvantageous battery scenario will move the EV Subsidy into negative territory (indicating that the ICE vehicle would be environmentally advantageous). The orange and blue regions of Figure 33 show the combinations that would result in a negative EV Subsidy, while all other regions would result in a positive EV Subsidy. The data demonstrates that it is possible for an internal combustion engine to have less of an environmental impact than its electric counterpart, but that the majority of scenarios still favor an electric vehicle.

Climate change is the paramount environmental issue of our time, and thus, it is vital to step beyond the EV Subsidy and take a granular look at the greenhouse gas emissions that each battery is responsible for. The Kim et al. data is based on emissions per kWh of battery capacity, which facilitates an analysis of carbon dioxide emissions based on battery pack size.

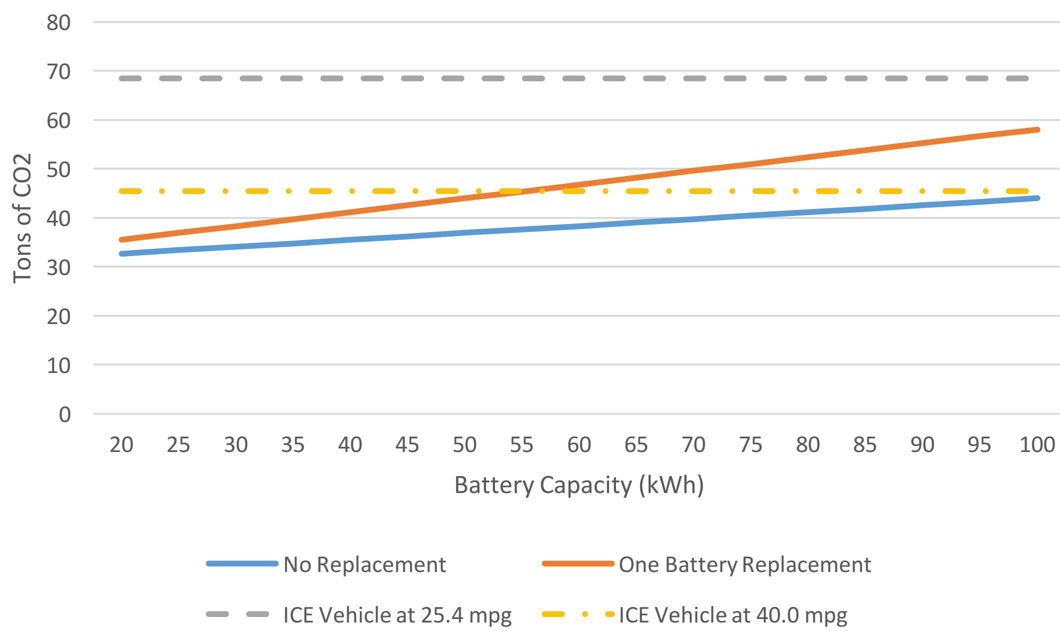


Figure 34. Carbon dioxide emissions per kWh of battery capacity (13.3% RE).

Based on the 2016 grid (13.3% RE) and data from Kim et al. (2016), the carbon emissions for an EV (blue line) would remain less than ICE vehicles with efficiencies of 25.4 miles-per-gallon (orange dashed line) and 40 miles-per gallon (grey dashed line). This changes if the battery needs to be replaced (orange line): the EV would be responsible for fewer carbon emissions than an ICE vehicle with an efficiency of 25.4

mpg, but the carbon emissions for an EV with a battery larger than 55 kWh would exceed those of an ICE with an efficiency of 40 miles-per-gallon.

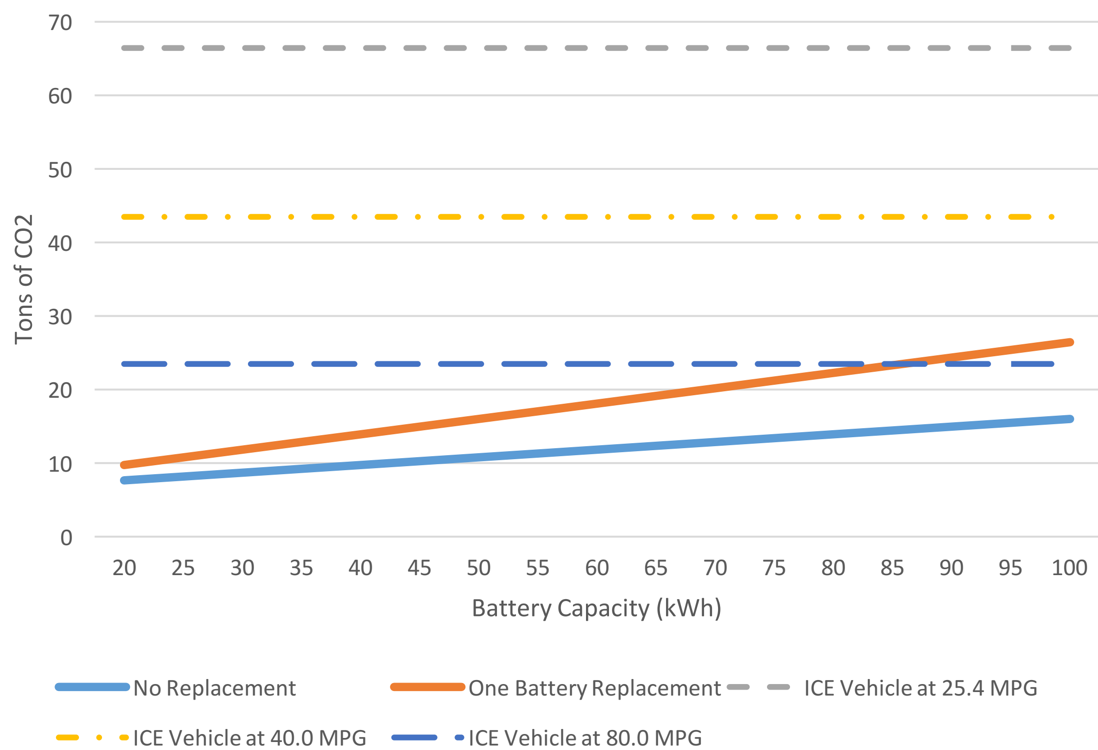


Figure 35. Carbon dioxide emissions per kWh or battery capacity (100% RE).

Once again, the percentage of renewable energy plays a key role in the pollution assigned to an electric vehicle. Based on a 100% renewable energy scenario, the carbon dioxide emissions for an EV with a battery ranging from 20-100 kWh are significantly lower than the carbon emission from an ICE vehicle with an efficiency of 25.4 miles per gallon (grey dashed line in Figure 35) or 40 miles per gallon (orange dashed line). An EV needs to contain a battery pack of at least 85 kWh, and it needs to be replaced at least once, for it to produce more carbon emissions than an ICE with an efficiency of 80 miles per gallon. This clearly demonstrates the extreme efficiency of an EV paired with 100%

renewable energy and highlights the symbiotic ways in which these technologies can be used to mitigate climate change. A detailed analysis of each RE% scenario can be found in Ancillary Appendix 3. Furthermore, an analysis of the carbon impact for currently available individual electric vehicles can be found in Ancillary Appendix 4.

Table 36. Battery carbon emissions and social cost.

RE%	GREET CO2 (tons)	GREET Cost	Kim et al. CO2 (tons)	Kim et al. Cost
13%	0.983	$89.52	4.512	$429.98
20%	0.963	$88.12	4.422	$423.50
50%	0.874	$81.78	4.012	$394.55
80%	0.785	$75.45	3.603	$365.67
100%	0.727	$71.24	3.334	$346.22

Note: This table compares battery-related carbon emissions and the battery social costs from two datasets: GREET 2015 and Kim et al.

The output variables in my study (carbon emissions, social costs, EV Subsidy) are all impacted by the data sets that are entered into the model and the input variables. This results in a range of possible outcomes, but in all scenarios there is one constant that remains true: increased RE% leads to lower battery-based emissions, battery-related social costs, and EV Subsidies. This relationship is displayed in Table 36, as the RE% has a profound impact on the carbon emissions and costs associated with both battery scenarios. My model allows the grid-based emissions from battery production to float with the percentage of renewable energy. An increase in RE% leads to a decrease in battery-related carbon emissions and socials costs, but the model does not reduce non-grid emissions (see Appendix 3). Non-grid emissions will most likely decrease as well, however this is outside the scope of this study. It is noted that the impact that RE% has on production emissions is likely far greater than what is reported in Table 36.

Batteries and their environmental impact will likely remain the most controversial aspect of electric vehicles. The results of this study clearly indicate that the vast majority of RE% and MPG scenarios will result in positive EV Subsidies and lower carbon emissions for the EV. Only a combination of high emissions data (such as Kim et al.), large battery packs, battery replacements, and high ICE efficiency will result in negative EV Subsidies.

Type of Model

There are multiple variables within the EV Subsidy model that deserved extra scrutiny, but the model itself should not be ignored. My research focused on the impacts that renewable energy penetration would have on the social costs of electric vehicles, and thus, it was necessary to accurately predict the distribution of power plants in high penetration renewable energy scenarios. I created three possible models that accomplished this and the “Combined Model” has the most merit (see Chapter II for a detailed explanation of each model). The Combined Model has the best predicative attributes, but an analysis of all models demonstrates that the differences between the models is relatively minor (Figure 36).

The differences between the Proportional Model and the Combined model are so minuscule that they cannot even be picked up by looking at Figure 36. The NREL Model deviates from the other models when the RE% grows from 15% to 70%. This is due to the NREL model’s inclusion of higher levels of coal power in its future scenarios. The problems with the NREL model are outlined in Chapter II. Most importantly, all models show the distinct positive relationship between RE% and the EV Subsidy.

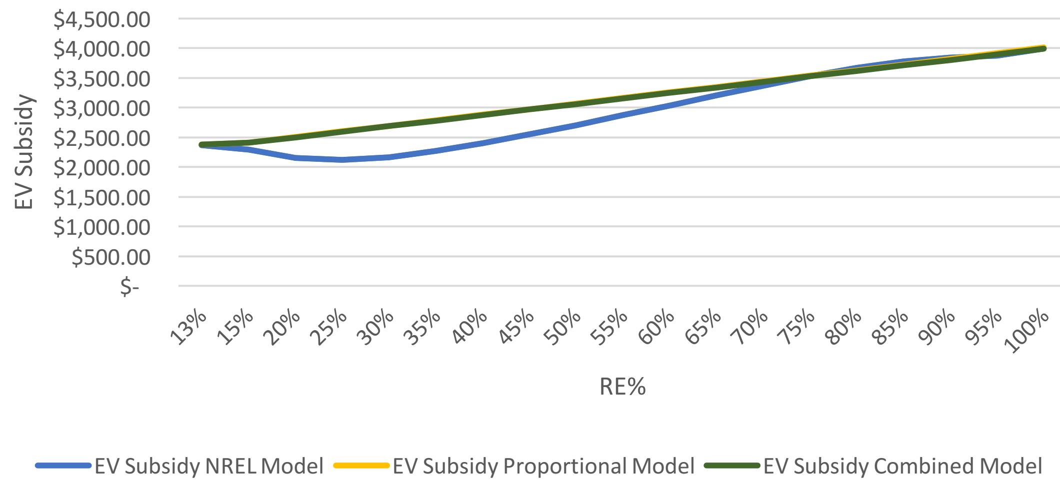


Figure 36. EV subsidy as a function of renewable energy. This graph looks at the EV Subsidy based on three different models for grid prediction.

Policy

The results of my research clearly demonstrate that the benefits of electric vehicles will continue to grow as the percentage of renewable energy increases. The majority of academic research and policy has centered on the current benefits of electric vehicles, but we cannot ignore the true benefits that lie in the future. An EV Subsidy will help to fix the market failure that results from the externalities within our transportation sector. Furthermore, the EV Subsidy can help to spur demand for electric vehicles and promote future growth. A proper EV Subsidy should account for the differences in social costs between supplementary goods (EV and ICE), and ideally, this will lead to an eventual takeover by the environmentally advantageous technology. Unfortunately, the transportation sector is complex and there are other barriers in place, such as: charging infrastructure, EV range, availability of models, and length of ownership. It is unlikely that a subsidy of any amount would initiate an immediate nationwide switch to electric vehicles. Thus, there is an extra benefit to electric vehicles that are bought today: they increase demand for the infrastructure that will facilitate the sales of the progressively cleaner electric vehicles of tomorrow.

The current federal subsidy stands at $7,500 for any electric vehicle with a battery larger than 16 kWh (Berman, 2016). This value is greater than the value I determined for the appropriate EV Subsidy, however it is not recommended that the federal government decrease the current subsidy. Once again, the larger subsidy will help to encourage sales of electric vehicles that will, in turn, break down the barriers to entry for the EV market and facilitate the adoption of future electric vehicles. Furthermore, the Monte Carlo simulation demonstrated that there is significant variability within the system and that the possibility for underestimating the EV Subsidy is far greater than overestimating it. The mean values in the Monte Carlo simulation were significantly greater than the median values, indicating the greater danger for underestimation.

The current federal subsidy diminishes once a car manufacturer sells 200,000 electric vehicles, as it is reduced to 50%, and then 25%, over the year following the milestone being reached (Internal Revenue Service, 2016)). This policy should be changed, as the efficacy of electric vehicles does not change once a certain sales threshold has been met. The opposite effect should actually take place: the subsidy should grow as the percentage of renewable energy grows. An ideal EV Subsidy would be linked to the percentage of renewable energy and would grow over time. It should only be abandoned once the percentage of electric vehicles has reached a critical mass and a nationwide EV infrastructure is put into place.

Increased Subsidy for PV and EV Combination

The EV Subsidy should be a centered around the disparity in externalities between electric vehicles and internal combustion engine vehicles. This is exactly why the EV Subsidy should be tied to the percentage of renewable energy and it is why the subsidy should not be capped at 200,000 vehicles per automaker. It is important to look to the future, but we should not ignore the fact that individuals can currently charge their vehicles with 100% renewable energy if their home has rooftop photovoltaic panels (assuming the car is charged during daylight hours or the home is fitted with batteries).

Table 37. Comparison of EV subsidies.

Scenario	**Subsidy**
EV Subsidy (13.3%RE, 2016 Grid):	$2,376.81
EV Subsidy (100%PV):	$3,903.24
Difference	$1,526.43

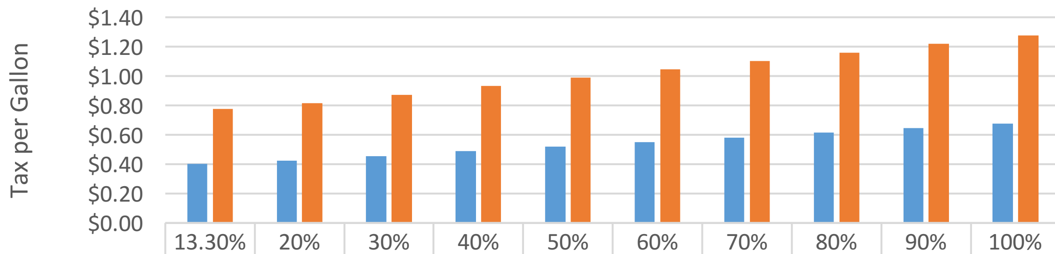
An EV powered by photovoltaics is responsible for a social cost that is $1,526.43 (Figure 37) less than an EV powered by the standard 2016 13.3% RE grid. Thus, the federal EV Subsidy should be increased by $1,500 for individuals that can verify that they will be charging their car with photovoltaics. These technologies have a symbiotic relationship and can be cornerstones of a move toward a carbon neutral world. This additional subsidy would help to encourage the simultaneous adoption of both technologies. A study by the California Air Resources Board revealed that 32% of electric vehicle owners had photovoltaic panels on their roof and 16% were planning to buy panels in the near future (2014). This additional subsidy is empirically justified (see Chapter III) and would reward individuals for adopting both technologies.

Tax on Gasoline

The National Bureau of Economic Research white paper by Holland et al. clarifies that an EV subsidy is actually the second-best policy and that the first-best policy is a Pigovian tax. A Pigovian tax is "a per-unit tax set equal to the external damage caused by an activity, such as a tax per ton of pollution emitted equal to the external damage of a ton of pollution" which, in this context, can be exacted upon the externalities associated with both electric vehicles and internal combustion engine vehicles (Harris & Roach, 2013, p. 1652). Holland et al. support a differentiated tax on mileage for both types of vehicles (2013), but a gasoline tax would be much easier to implement. The appropriate EV Subsidy from this study represents the difference in externalities between electric vehicles and gasoline-powered vehicles. Instead of subsidizing electric vehicles, the value of the EV Subsidy could be used to tax internal combustion engine vehicles. The value could be broken down per gallon, which would allow the tax to be executed as a "gasoline tax." This would serve two key advantages: it would be easy to implement and it would precisely target automobiles that pollute more (i.e. vehicles with poor efficiency).

The EV Subsidy was calculated based on an ICE vehicle with an efficiency of 25.4 miles per gallon (the July 2016 average) and a lifespan of 150,000 miles (University of Michigan, 2016). The total number of gallons is therefore 5905.51 (150,000 miles / 25.4 mpg).

This quantity of gallons can then be divided into the appropriate EV Subsidy (which represents the disparity in externalities) to determine the "EV Subsidy per gallon," which could be implemented as a tax per gallon on ICE vehicles. It is important to point out that this value could be impacted by multiple factors, including the social cost of carbon and the percentage of renewable energy.



	13.30%	20%	30%	40%	50%	60%	70%	80%	90%	100%
$66.26 SCC	$0.40	$0.42	$0.45	$0.49	$0.52	$0.55	$0.58	$0.61	$0.64	$0.68
$125 SCC	$0.78	$0.81	$0.87	$0.93	$0.99	$1.04	$1.10	$1.16	$1.22	$1.27

RE%

$66.26 SCC $125 SCC

Figure 37. Gasoline tax. This graph illustrates the relationship between RE% and the proposed gasoline tax. The blue bars represent the appropriate tax if carbon is priced at $66.26 per ton, while the orange bars represent the appropriate tax if carbon is priced at $125 per ton.

Fortunately, my model can account for the possible variation in these input variables (RE% and SCC), as illustrated in Figure 37. The gasoline tax is clearly a function of both RE% and the social cost of carbon. Once again, this underscores the importance of accurately defining the social cost of carbon, while it also introduces the possibility that a gasoline tax should be tied to the current level of renewable energy. For example, each year a new gasoline tax could be calculated based on the previous year's percentage of renewable energy. This would allow the gasoline tax to more accurately represent the current difference in externalities.

A gasoline tax has many advantages, but it is not a perfect solution. The tax burden would fall disproportionally on those that use a large quantity of gasoline, which is how the tax is intended to work. But, in many cases, the ratio of gasoline expense to vehicle price would be much higher for lower-priced cars. An individual that purchases a $20,000 car might purchase the same number of gallons of gasoline as someone who purchases an $80,000 car. Both owners would pay the same amount in taxes because both cars would be responsible for a similar quantity of gasoline-related externalities, but it is likely that the tax would be far more burdensome for the individual who bought the $20,000 automobile. The tax would be environmentally fair, but regressive: the gasoline tax will account for a larger percentage of income for individuals in the lower income brackets. Furthermore, the impact of the tax will not be uniform throughout all income groups. A study by Tingting Wang and Cynthia Chen (2013) discovered that price elasticities of demand for gasoline vary based on income levels. This is due to the fact that households with greater income account for higher percentages of "discretionary driving," which can be decreased easily if the price of gasoline increases. This is not the case for the lower income brackets, as a much larger percentage of their travel is non-discretionary and cannot be easily reduced. More research needs to be done on the negatives that a gasoline tax could have on lower income groups and the possibility of subsidies to rectify this.

The gasoline tax would initially impact a far greater number of cars than an EV Subsidy. Electric vehicles currently make up a small portion of overall market share and the EV Subsidy is only applied to this small segment of the population. However, the gasoline tax would be applied to all gasoline-powered vehicles. The methodology for the EV Subsidy and the gasoline tax was based on a one-to-one comparison: the social cost of one internal combustion engine vehicle compared to one electric vehicle.

Unfortunately, the market is not split evenly between electric vehicles and internal combustion vehicles. While the gasoline tax and EV Subsidy would be equitable in vehicle-to-vehicle analyses, the total revenue from the gasoline tax would be vastly greater than the total cost of the EV Subsidy. The solution to this problem would be to tax both vehicles based on their social cost. In this scenario we would see a tax on electric vehicles, but an even greater tax on internal combustion vehicles. Thus, there would be no monetary advantage for ICE owners to choose this option.

Gas Tax Revenue

In 2015, Americans used 370 million gallons of gasoline per day for transportation, which amounts to over 138 billion gallons of gasoline (138,335,000,000) a year (U.S. Energy Information Administration, 2016). A gasoline tax of $0.40 to $1.27 can then be multiplied by this quantity of gasoline to determine the yearly revenues from such a tax (Table 38).

Even considering the 2016 renewable energy mix and a social cost of carbon of $66.26, the gasoline tax would generate billions of dollars of revenue. Unsurprisingly, this number increases substantially as the RE% and social cost of carbon increases. But, it is important to note that while the RE% should increase over time, the total revenue from a gasoline tax may not increase simultaneously. A properly implemented gasoline tax should decrease demand for gasoline and gasoline-powered vehicles. This is in addition to the assumption that the market penetration of electric vehicles is expected to increase significantly over the next 25 years. Bloomberg New Energy Finance predicts that electric vehicles will account for 35% of new car sales in 2040 (MacDonald, 2016). The increase in EV sales, in addition to the projected increases in ICE efficiency (U.S. Energy Information Administration, 2016), should lead to a decrease in overall gasoline consumption.

Table 38. Gasoline tax revenue as a function of RE% and SCC.

	Social Cost of Carbon: $66.26		**Social Cost of Carbon: $125**	
RE%	Tax Rate per Gallon	Revenue	Tax Rate per Gallon	Revenue
13.30%	$0.40	$55,675,374,719.34	$0.78	$107,353,344,408.12
20%	$0.42	$58,585,040,973.33	$0.81	$112,640,499,527.55
30%	$0.45	$62,927,108,366.97	$0.87	$120,543,144,422.07
40%	$0.49	$67,299,630,717.22	$0.93	$128,525,208,286.72
50%	$0.52	$71,665,980,091.45	$0.99	$136,504,067,890.09
60%	$0.55	$76,023,230,050.88	$1.04	$144,466,393,351.56
70%	$0.58	$80,374,245,254.63	$1.10	$152,409,207,678.25
80%	$0.61	$84,723,307,661.53	$1.16	$160,331,818,611.02
90%	$0.64	$89,073,662,365.66	$1.22	$168,232,860,171.64
100%	$0.68	$93,426,915,009.48	$1.27	$176,110,734,772.26

The U.S Energy Information Administration (EIA) produces projections for yearly power plant distribution (see Ancillary Appendix 5) and transportation-related gasoline consumption (see Ancillary Appendix 6). These projections do not factor in a large-scale adoption of election vehicles, but they do account for increases in renewable energy and improved efficiency in internal combustion engine automobiles. I was able to use this data to calculate a gasoline tax, and tax revenue, based on the yearly projections.

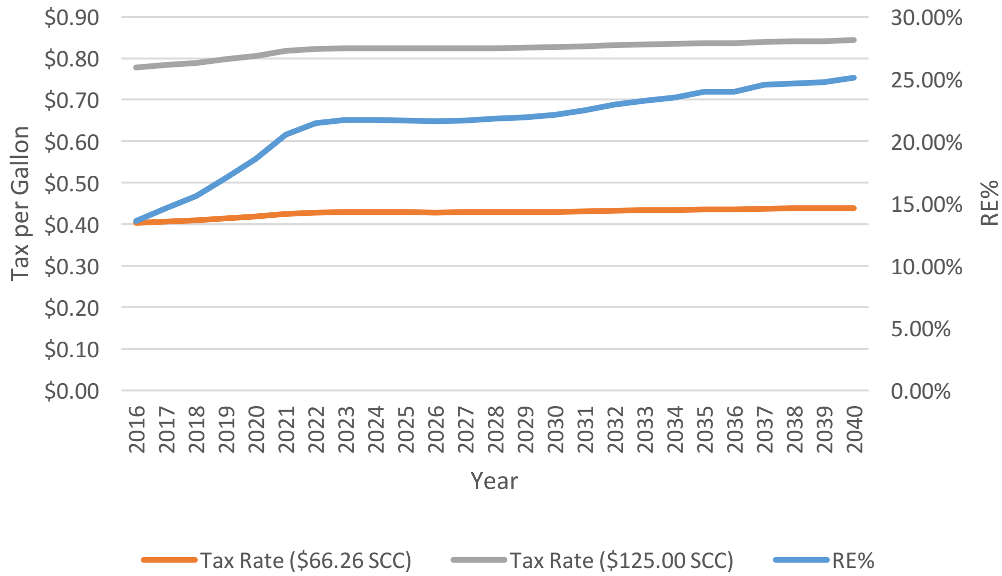


Figure 38. EIA projection-based RE% and tax rates (EIA, 2016).

The EIA projects that the percentage of renewable energy will increase steadily between 2016 and 2040 (Figure 38); this increase causes the per-gallon gasoline tax to increase as well. Yet, this increase in RE% does not supersede the projected decrease in gasoline consumption, and thus, the EIA-based tax revenue projection actually decreases between 2019 and 2040 (Figure 39).

The projected gasoline tax revenue will undoubtedly decrease over time and this will be further exacerbated by any increase in electric vehicle adoption. Furthermore, a gasoline tax would inherently decrease the demand for gasoline, which would lead to an additional reduction in tax revenue (this reduction is not reflected in Figure 38 or Figure 39). This does not take away from the fact that the tax would generate a significant amount of revenue that could be used to promote electric vehicle adoption and reduce carbon emissions.

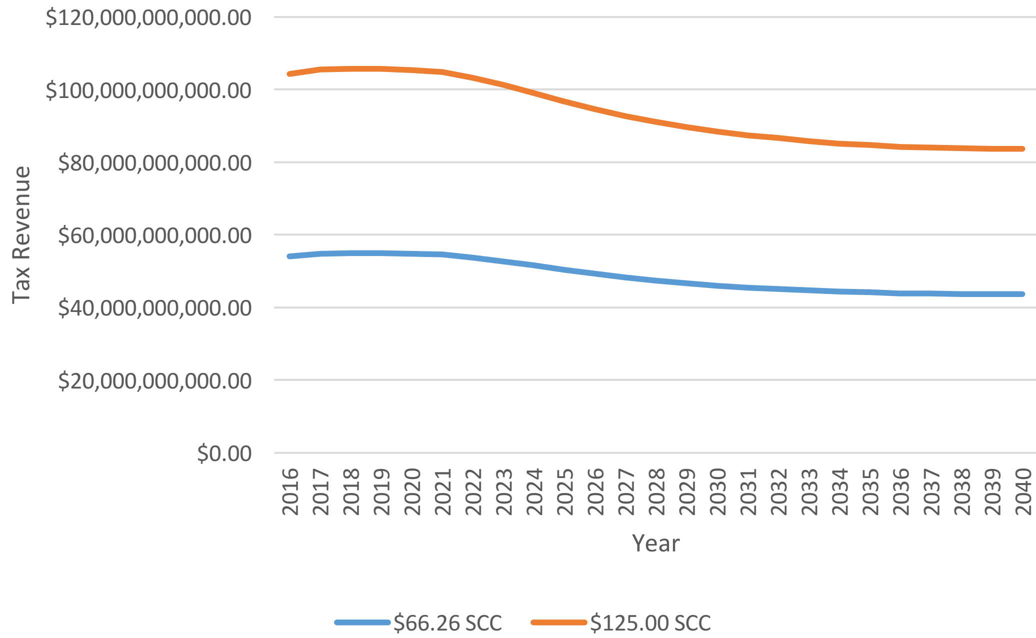


Figure 39. EIA projection-based revenue from gasoline tax.

Renewable Energy Development

The revenue generated from an additional gasoline tax could be used to develop and build new solar and wind farms around the country. This expansion would have a compounding benefit, as the increase in renewable energy would also increase the environmental benefits of electric vehicles. In 2015, the United States invested $56 billion in clean energy, with most of the investment going towards new solar and wind plants (Mills & McCrone, 2015).

The total yearly investment in clean energy (Figure 40) can be compared to the estimated yearly revenue from a new gasoline tax (Figure 39). A gasoline tax based on $66.26 SCC would produce revenue in line with the current total investment, while a gasoline tax based on $125 SCC would generate revenue that is nearly double the current level of investment in clean energy. These revenues could result in a clean energy revolution if the vast majority of the proceeds were directed toward the construction of new renewable energy power plants.

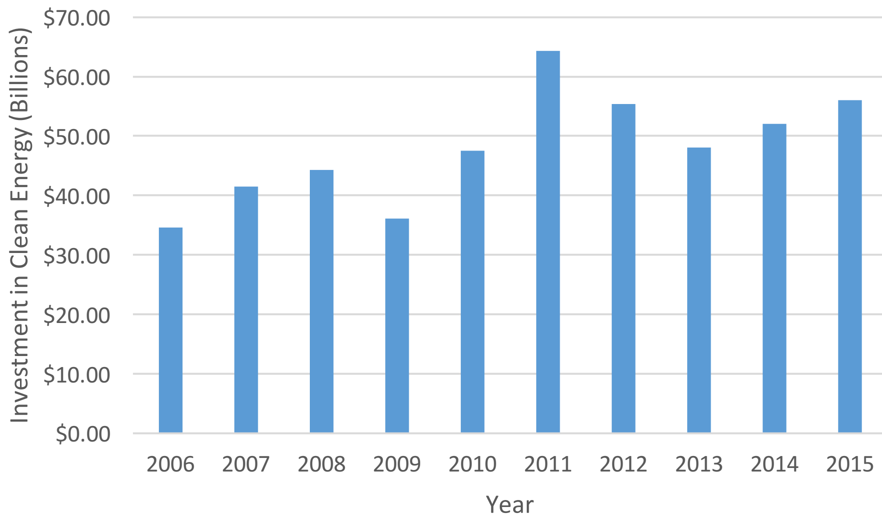


Figure 40. United States investment in clean energy. Data acquired from Bloomberg New Energy Finance.

The capital necessary to install new renewable energy capacity varies based on technology and size (Table 39), but it can be assumed that the tax revenue would be used for large-scale 1MW+ power plants. The capital cost per megawatt-hour can then be divided into the tax revenue to quantify the number megawatts of power that could be installed if all of the revenue was directed toward building that type of renewable energy. In Table 40, this number was multiplied by the "capacity factor" and the number of hours per year to determine the megawatt hours that this new capacity would generate.

Table 39. Installed cost per kWh for renewables.

Technology	Mean Installed Cost (kWh)	Cost per MW
PV <10 kW	$3,897	$3,897,000
PV 10–100 kW	$3,463	$3,463,000
PV 100–1,000 kW	$2,493	$2,493,000
PV 1–10 MW	$2,025	$2,025,000
Wind <10 kW	$7,645	$7,645,000
Wind 10–100 kW	$6,118	$6,118,000
Wind 100–1000 kW	$3,751	$3,751,000
Wind 1–10 MW	$2,346	$2,346,000

Note: Data from the National Renewable Energy Laboratory (2016):
http://www.nrel.gov/analysis/tech_lcoe_re_cost_est.html

Table 40. Possible megawatt hours from tax revenue for photovoltaics and wind.

	Cost per KW	Cost per MW	MW from Tax Revenue	Capacity Factor	MWH per Year
PV 1–10 MW	$2,025	$2,025,000	27494.01	25.8%	62138667.11
Wind 1–10 MW	$2,346	$2,346,000	23732.04	32.2%	66941450.54

A common concern related to electric vehicles is that the increased electricity demand would strain the national power grid. This concern has been debunked (Montavalli, 2011), but a concerted expansion of renewable energy could help to alleviate any lingering fears. In 2016, there were 159,139 electric vehicles sold in the United States (Inside EVs, 2017). Based on the average yearly mileage of 13,476 and an efficiency of 32 kWh per 100 miles, electric vehicles sales increased national electricity demand by 686,258 megawatt hours (Table 41).

Table 41. Electricity necessary to power new EV sales (2016).

	Cars Sold	Average Miles	Average kWh per 100 miles	MWH Necessary	MULTIPLE
2016 EV	159139	13476	32	686258.29	97.55

This electricity demand is a small fraction of the increased renewable energy capacity that a gasoline tax could provide. If 100% of the revenue from a gasoline tax was directed to large-scale wind farms, the expansion in capacity would generate 97.55 times as much power as would be necessary to power every new electric vehicle sold in 2016.

Table 42. Number of cars powered by an expansion in wind power.

	kWh per 100	kWh per Year	MWH per Year	Cars Powered by Tax
2016 BMW i3	27	3638.52	3.63	18,397,988.89
2017 Chevrolet Bolt	28	3773.28	3.77	17,740,917.86
2016 Nissan Leaf	30	4042.8	4.04	16,558,190.00
2016 Tesla Model S 90D	33	4447.08	4.44	15,052,900.00

Note: This table details the number of cars that could be powered by an expansion of wind power funded by a gasoline tax. The number varies based on the efficiency of the electric vehicle.

A gasoline tax (at $66.36 per ton of carbon) would be able to fund enough new wind power to compensate for the additional electricity demand from over 15 million new electric vehicles (Table 41). This number exceeds 18 million if the new electric vehicles are as efficient as BMW's i3 (Table 42). This is a purely hypothetical scenario, as the electricity demand from the new electric vehicles would not perfectly match the supply curve for wind power. But, Table 41 does demonstrate the potential of a gasoline tax and how those kilowatt-hours could be used to power a new fleet of electric vehicles.

If electric vehicles continue to be sold at a rate of 159,139 per year, the increase in power would far exceed the demand from new electric vehicles. Thus, if we focus on the marginal changes to the U.S. fleet of automobiles (159,139 new electric vehicles) and the US power grid (66941450 MWH increase in renewable energy), one can make a case that each marginal electric vehicle will be powered by 100% renewable energy. Based on these assumptions, gasoline should be taxed at the 100% RE rate of $0.68 per gallon (at $66.26 SCC) instead of the 13.3% rate of $0.40 per gallon. This is just one perspective and one can also argue that the we should look at the aggregate as opposed to marginal changes.

Expanded Nationwide Charging Network

The tax revenue would not need to be focused solely on the deployment of renewable energy and a portion of the proceeds could be used to create a nationwide charging network similar to Tesla Motor's supercharging network. The vast majority of driving takes place within cities. An MIT study determined that the current fleet of low-range electric vehicles could meet the demand of 87% of vehicle-days (Needell et al., 2015). Another study by two Colombia doctoral students calculated that 98% of single-trip drives were under 50 miles (Van Haaren, 2012). Thus, the new crop of long-range affordable electric vehicles (Chevrolet Volt, Tesla Model 3) include ranges that go far beyond what is necessary for city driving. The advantage of these vehicles is that their 200+ mile ranges make interstate travel feasible, but this advantage can only be unlocked if the car is paired with an interstate fast-charging network. Tesla has already begun to create such a network, yet a nationwide public network of chargers could help to accelerate the adoption of electric vehicles.

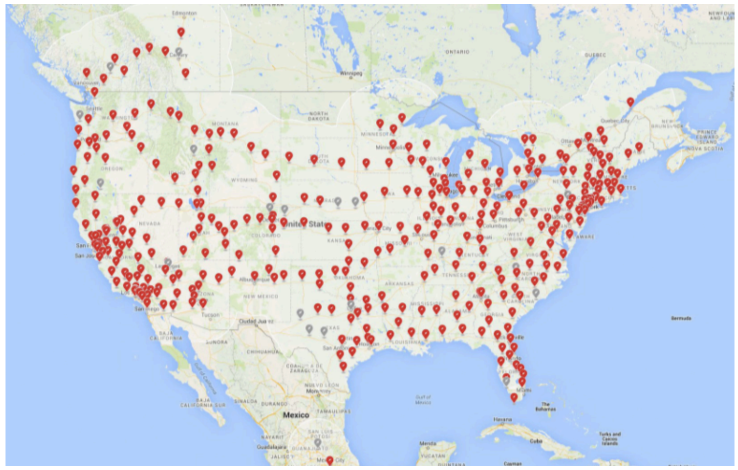


Figure 41. Tesla supercharging network. This map shows the current Tesla Supercharger stations in North America and was taken from: https://www.tesla.com/supercharger

Tesla's Supercharger network allows cars to gain 170 miles of range per half hour of charging (Tesla, 2016). The chargers are strategically placed around the country to facilitate driving between cities and states (Figure 41) and the current (2016) network features 769 stations and 4,876 chargers.

There is some debate about the exact cost to build a Tesla Supercharger, but a 2016 article by the research group Ark Invest indicates that the price hovers around $270,000 per station. Thus, for every billion dollars of tax revenue allotted to charging infrastructure, over 3,700 Supercharger-style charging stations could be built. A small portion of the revenue generated from a gasoline tax could create a charging network that would dwarf the network that Tesla currently has in place. This charging network could grow each year to accommodate the influx of new electric vehicles and would allow electric vehicles to travel around the country without worrying about range anxiety.

The applications for the gasoline tax revenue do not have to end with renewable energy and EV charging infrastructure. Part of the revenue could also be used to establish a "smart" grid and to build grid-scale battery facilities. Each of these technologies will be essential to a carbon neutral grid, as they will help to facilitate the adoption of variable output renewable energy such as wind and solar. The National Renewable Energy Laboratory (NREL) predicts that 100 – 152 GW of battery deployment will be needed for an 80% renewable energy future and this number will need to be even higher if we are to achieve a 100% RE grid (NREL, 2016).

The ideal use for gasoline tax revenue would undoubtedly be a combination of the above-mentioned infrastructure: wind power, solar power, charging stations, grid-scale batteries, and a smart grid. The technologies would be built out incrementally as the revenue comes into the system. This revenue would decrease over time, due to the increased efficiency of ICE vehicles and the greater penetration of electric vehicles. This would not be a cause for concern, as a high RE% smart-grid and EV infrastructure could be in place before the tax dropped to nominal levels. The exact plan for this implementation is outside the scope of my study, but it should be researched extensively before any gasoline tax is put into place.

Conclusion

A variety of factors play a role in defining the disparity in the environmental impacts between electric vehicles and their internal combustion engine counterparts (as quantified by the EV Subsidy). Each of these variables can be manipulated to determine their own role in the EV Subsidy, but one characteristic remains true for all scenarios: an increase in the percentage of renewable energy significantly decreases the social costs assigned to electric vehicles and causes the EV Subsidy to rise.

Table 43. Sensitivity analysis.

		13.30%	**20%**	**50%**	**80%**	**100%**
Cost of Carbon	$20.00 SCC	$639.37	$683.65	$879.56	$1,074.88	$1,208.56
	$66.26 SCC	$2,376.78	$2,500.99	$3,059.42	$3,616.83	$3,988.39
	$125.00 SCC	$4,582.91	$4,808.62	$5,827.35	$6,844.55	$7,518.16
	$200.00 SCC	$7,399.72	$7,755.02	$9,361.48	$10,965.75	$12,025.01
Miles per Gallon	10 MPG	$8,959.26	$9,083.47	$9,641.89	$10,199.31	$10,570.87
	25.4 MPG	$2,376.78	$2,500.99	$3,059.42	$3,616.83	$3,988.39
	40 MPG	$816.65	$940.86	$1,499.28	$2,056.70	$2,428.26
	60 MPG	-$88.09	$36.12	$594.55	$1,151.97	$1,523.52
EV Efficiency	36 kWh/100	$2,166.87	$2,306.08	$2,931.90	$3,556.59	$3,972.99
	32 kWh/100	$2,376.78	$2,500.99	$3,059.42	$3,616.83	$3,988.39
	28 kWh/100	$2,586.68	$2,695.90	$3,186.93	$3,677.07	$4,003.79
	24 kWh/100	$2,796.58	$2,890.81	$3,314.45	$3,737.32	$4,019.18
Battery Scenarios	One Replacement	$2,287.25	$2,399.08	$2,901.81	$3,403.63	$3,738.15
	Double kWh + Replace	$2,108.20	$2,222.85	$2,738.25	$3,252.72	$3,595.68
	Kim et al.	$2,036.32	$2,165.60	$2,746.64	$3,326.61	$3,713.41
	Kim et al. +	$1,606.34	$1,742.10	$2,352.09	$2,960.94	$3,367.19
	Kim et al. + +	$746.38	$895.10	$1,562.98	$2,229.59	$2,674.76
Different Models	Proportional	$2,376.79	$2,503.79	$3,067.22	$3,630.47	$4,008.23
	NREL	$2,364.80	$2,150.69	$2,704.76	$3,665.20	$3,988.39
	Combined	$2,376.78	$2,500.99	$3,059.42	$3,616.83	$3,988.39

Notes: Kim et al. battery data is taken from the paper "Cradle-to-Gate Emissions from a Commercial Electric Vehicle Li-Ion Battery: A Comparative Analysis (2016)." Kim et al. + includes a 64 kWh battery and Kim et al. ++ includes a 64 kWh battery and one replacement.

The sensitivity analysis in Table 43 looks at a variety of scenarios (cost of carbon, mile-per-gallon, EV efficiency, different battery scenarios, and type of model) and how the percentage of renewable energy impacts said scenarios. In each scenario there is a strong correlation between RE% and the EV Subsidy. The efficacy of electric vehicles is undoubtedly linked to the make-up of the grid and the percentage of renewable energy. Thus, it is important to look at electric vehicles not for what they are today, but for what they can become.

Much of the literature has focused on the impact that renewable energy will have on the operating phase of an electric vehicle, but the impact on the production phase should not be ignored. My model is unique in that it disaggregates the "grid-based production emissions" from the "non-grid-based production emissions" and allows the "grid-based emissions" to float with the percentage of renewable energy.

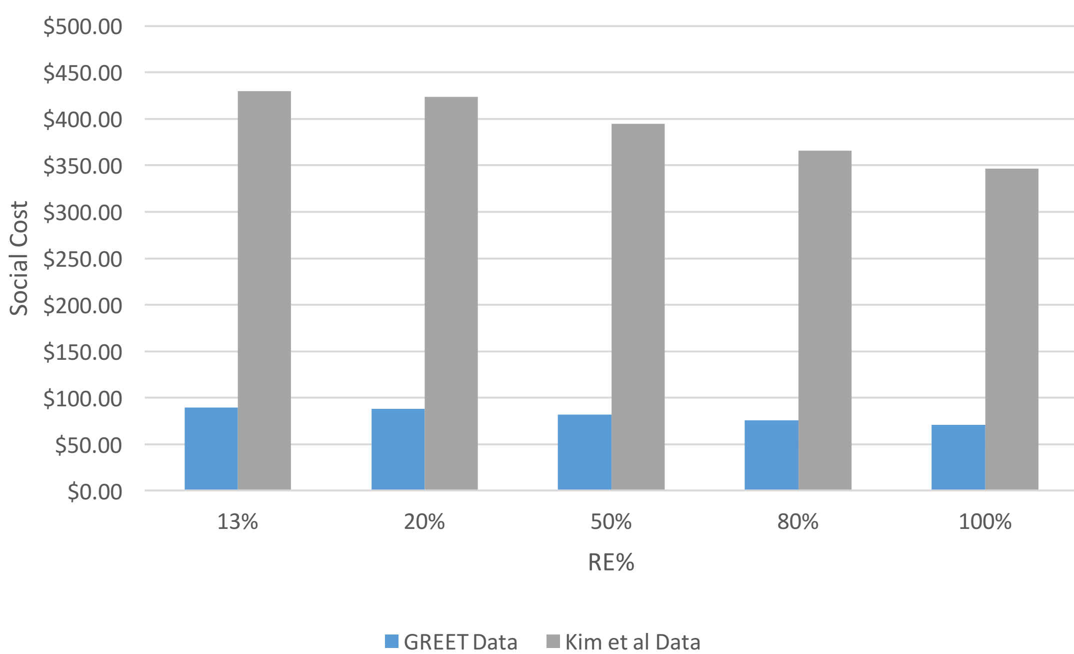


Figure 42. Production-based socials costs for an EV.

Many articles focus on the negative aspects of an electric vehicle's production and center on the faulty assumption that these negatives are fixed in place. The reality is that these production emissions will decrease as the grid becomes cleaner (Figure 42). The full benefits of this reduction are not captured by my model, as it is likely that the non-grid-based production emission's will also decrease over time due to improved efficiencies.

The transportation sector needs to be radically altered if society wants to truly combat the risks of climate change. Renewable energy-powered electric vehicles can be a key component of this revolution: an electric vehicle running on 100% renewable energy would be responsible for 6.30 tons of carbon dioxide over its lifetime, while an internal combustion engine with an efficiency of 25.4 miles-per-gallon would be responsible for 66.40 tons of carbon dioxide (see Table 28 in Chapter III or Appendix 2). This is the direction that our society needs to move in and we have a moral obligation to encourage the technologies that will facilitate this positive change. An appropriate EV Subsidy and/or gasoline tax is but part of the solution.

Recommendations and Summary

The outcomes of my research support the premise that electric vehicles have a positive impact on the environment (relative to internal combustion engine vehicles) and can play an important role in climate change mitigation. The benefits of electric vehicles do not diminish once a specific sales threshold is met and the current cap on electric vehicle subsidies is a perverse incentive that will promote additional market failure. The purpose of the EV Subsidy is to compensate for the externalities that exist within our transportation economy. The number of sales per manufacturer has no bearing on the overall disparity between EV and ICE externalities, and subsequently, it should have no bearing on the number of cars that can take advantage of the EV Subsidy. The cap should be eliminated and the efficacy of the subsidy should be re-evaluated every 5 years. The subsidy should not be eliminated until the number of electric vehicles has reached a critical mass.

My model indicates that the difference in externalities between an electric vehicle and an internal combustion engine vehicle currently resides at $2,376.78 (2016 grid and July 2016 average mile per gallon). This number falls short of the current $7,500 federal tax subsidy, yet I recommend that the current $7,500 subsidy remain in place. My Monte Carlo simulations demonstrated that the variation in pollutant pricing leads to potential variation in outcomes (EV Subsidy). This variation is heavily weighted against the internal combustion engine vehicle: while the bottom 10% of the outputs (EV Subsidy) from the Monte Carlo Simulation fell between -$1,229.89 and $485.26 (2016 grid), the top 10% of the simulations fell between $20,776.32 and $108,978.97. This was a clear indicator that the possibility for underestimating the EV Subsidy is more severe than overestimating it and it is a strong reason for leaving the EV Subsidy at $7,500.

The underlying theme of my research has been the correlation between renewable energy and the EV Subsidy. My model demonstrated the positive relationship between the percentage of renewable energy and the EV Subsidy (Figure 43): an increase in the percentage of renewable energy results in an increase in the EV Subsidy. This correlation is the reason that I also recommend that we link the current EV Subsidy to the percentage of renewable energy. The EV Subsidy should be recalculated at the end of each year and

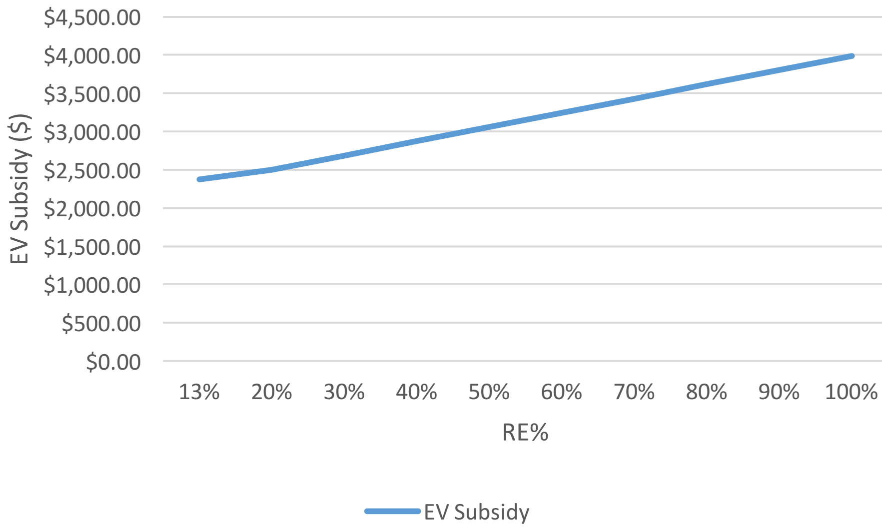


Figure 43. EV subsidy as a function of renewable energy.

should be a function of the national renewable energy percentage and average miles per gallon. This would produce an EV Subsidy that would properly reflect the changing externalities related to electric vehicles and internal combustion engine automobiles.

Appendix 1

Power Generation Regressions

Relationship between Percentage of Wind (Output) and RE % (Input)

Logistic Regression

XLSTAT 2016.04.32523 - Nonlinear regression - Start time: 7/24/16 at 1:30:22 PM / End time: 7/24/16 at 1:30:49 PM
Y / Quantitative: Workbook = Emissions Calculator V3.xlsx / Sheet = General Inputs / Range = 'General Inputs'!$K$39:$K$47 / 8 rows and 1 column
X / Quantitative: Workbook = Emissions Calculator V3.xlsx / Sheet = General Inputs / Range = 'General Inputs'!$B$39:$B$47 / 8 rows and 1 column
Stop conditions: Iterations = 200 / Convergence = 1E-05
Function: Y = pr3/(1+Exp(-pr1-pr2*X1))
Run again:

Summary statistics:

Variable	Observations	Obs. with missing data	without missing	Minimum	Maximum	Mean	Std. deviation
Wind	8	0	8	0.047	0.405	0.247	0.127
Percentage RE	8	0	8	0.133	0.900	0.542	0.259

Nonlinear regression of variable Wind:

Goodness of fit statistics:

Observations	8.000
DF	5.000
R²	0.997
SSE	0.000
MSE	0.000
RMSE	0.008
Iterations	7.000

Model parameters:

Parameter	Value	Standard error
pr1	-2.781	0.145
pr2	5.969	0.418
pr3	0.426	0.013

Equation of the model:

Wind = 0.426458973061796/(1+Exp(+2.78089267684665-5.96863862855643*Percentage RE))

Predictions and residuals:

Observations	Percentage RE	Wind	Pred(Wind)	Residuals
Obs1	0.133	0.047	0.051	-0.004
Obs2	0.300	0.110	0.116	-0.005
Obs3	0.400	0.177	0.172	0.005
Obs4	0.500	0.245	0.235	0.010
Obs5	0.600	0.290	0.294	-0.005
Obs6	0.700	0.335	0.342	-0.007
Obs7	0.800	0.370	0.375	-0.005
Obs8	0.900	0.405	0.397	0.009

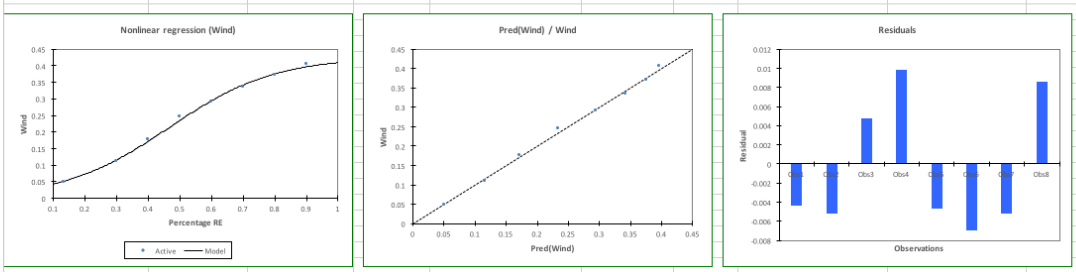


Figure 44. Wind power regression. XLSTAT was used for non-linear regressions for each power generation type. This was done to create an equation that would model the relationship between the percentage of each power generation type and the percentage of renewable energy.

Relationship between Percentage of Solar (Output) and RE % (Input)

Logistic Regression

XLSTAT 2016.04.32523 - Nonlinear regression - Start time: 7/24/16 at 1:35:01 PM / End time: 7/24/16 at 1:35:27 PM
Y / Quantitative: Workbook = Emissions Calculator V3.xlsx / Sheet = General Inputs / Range = 'General Inputs'!$J$39:$J$47 / 8 rows and 1 column
X / Quantitative: Workbook = Emissions Calculator V3.xlsx / Sheet = General Inputs / Range = 'General Inputs'!$B$39:$B$47 / 8 rows and 1 column
Stop conditions: Iterations = 200 / Convergence = 1E-05
Function: Y = pr3/(1+Exp(-pr1-pr2*X1))
Run again:

Summary statistics:

Variable	Observations	Obs. with missing data	without missing	Minimum	Maximum	Mean	Std. deviation
PV	8	0	8	0.005	0.071	0.043	0.022
Percentage RE	8	0	8	0.133	0.900	0.542	0.259

Nonlinear regression of variable PV:

Goodness of fit statistics:

Observations	8.000
DF	5.000
R^2	0.977
SSE	0.000
MSE	0.000
RMSE	0.004
Iterations	8.000

Model parameters:

Parameter	Value	Standard error
pr1	-2.549	0.385
pr2	5.686	1.168
pr3	0.073	0.007

Equation of the model:

PV = 0.0729756822422279/(1+Exp(+2.54903419599158-5.68599511070601*Percentage RE))

Predictions and residuals:

Observations	Percentage RE	PV	Pred(PV)	Residuals
Obs1	0.133	0.005	0.010	-0.005
Obs2	0.300	0.024	0.022	0.002
Obs3	0.400	0.031	0.032	-0.001
Obs4	0.500	0.046	0.042	0.004
Obs5	0.600	0.050	0.051	-0.001
Obs6	0.700	0.054	0.059	-0.005
Obs7	0.800	0.064	0.064	0.000
Obs8	0.900	0.071	0.068	0.003

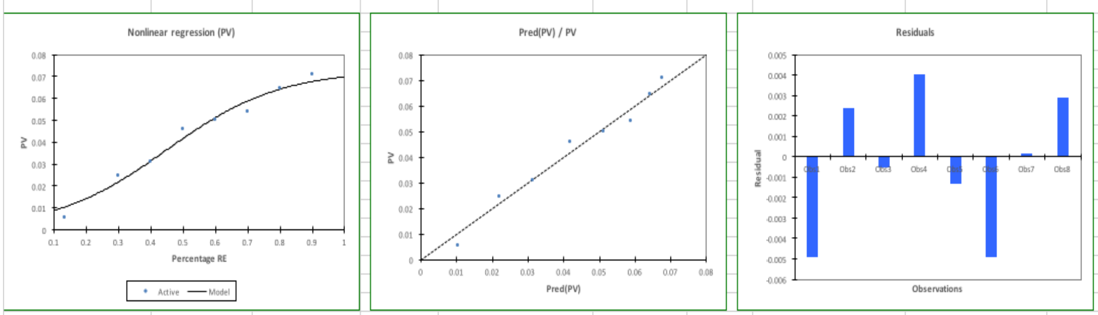


Figure 45. Photovoltaic regression data part 1.

XLSTAT 2016.04.32523 - Nonlinear regression - Start time: 7/24/16 at 1:37:37 PM / End time: 7/24/16 at 1:38:04 PM
Y / Quantitative: Workbook = Emissions Calculator V3.xlsx / Sheet = General Inputs / Range = 'General Inputs'!$J$39:$J$47 / 8 rows and 1 column
X / Quantitative: Workbook = Emissions Calculator V3.xlsx / Sheet = General Inputs / Range = 'General Inputs'!$B$39:$B$47 / 8 rows and 1 column
Stop conditions: Iterations = 200 / Convergence = 1E-05
Function: Y = pr1+(pr4-pr1)/(1+Exp(pr2*(Ln(X1)-pr3)))
Run again:

Summary statistics:

Variable	Observations	Obs. with missing data	without missing	Minimum	Maximum	Mean	Std. deviation
PV	8	0	8	0.005	0.071	0.043	0.022
Percentage RE	8	0	8	0.133	0.900	0.542	0.259

Nonlinear regression of variable PV:

Goodness of fit statistics:

Observations	8.000
DF	4.000
R²	0.987
SSE	0.000
MSE	0.000
RMSE	0.005
Iterations	200.000

Model parameters:

Parameter	Value	Standard error
pr1	1.551	233.111
pr2	0.451	5.811
pr3	5.891	406.233
pr4	-0.035	0.449

Equation of the model:

PV = 1.55051182397255+(-0.0347190120283889-1.55051182397255)/(1+Exp(0.451412698237846*(Ln(Percentage RE)-5.89148138873412)))

Predictions and residuals:

Observations	Percentage RE	PV	Pred(PV)	Residuals
Obs1	0.133	0.005	0.009	-0.003
Obs2	0.300	0.024	0.027	-0.003
Obs3	0.400	0.031	0.035	-0.004
Obs4	0.500	0.046	0.042	0.003
Obs5	0.600	0.050	0.049	0.001
Obs6	0.700	0.054	0.054	0.000
Obs7	0.800	0.064	0.060	0.005
Obs8	0.900	0.071	0.064	0.006

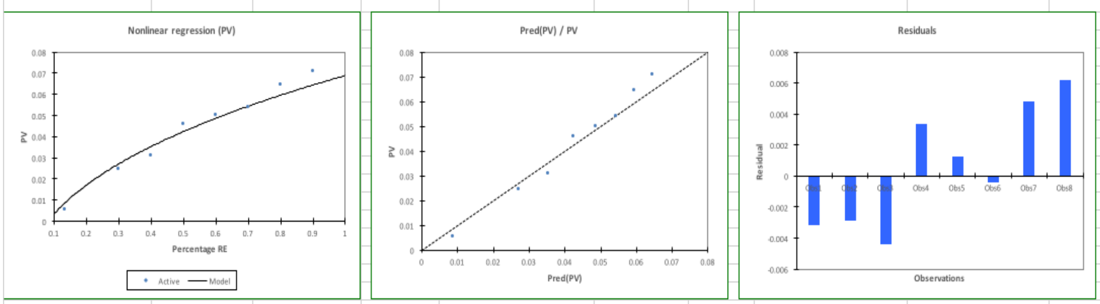


Figure 46. Photovoltaic regression data part 2.

XLSTAT 2016.04.32523 - Nonlinear regression - Start time: 7/24/16 at 1:40:16 PM / End time: 7/24/16 at 1:40:43 PM
Y / Quantitative: Workbook = Emissions Calculator V3.xlsx / Sheet = General Inputs / Range = 'General Inputs'!$J$39:$J$47 / 8 rows and 1 column
X / Quantitative: Workbook = Emissions Calculator V3.xlsx / Sheet = General Inputs / Range = 'General Inputs'!$B$39:$B$47 / 8 rows and 1 column
Stop conditions: Iterations = 200 / Convergence = 1E-05
Function: Y = pr1+(pr4-pr1)/(1+(X1/pr3)^pr2)
Run again:

Summary statistics:

Variable	Observations	Obs. with missing data	without missing	Minimum	Maximum	Mean	Std. deviation
PV	8	0	8	0.005	0.071	0.043	0.022
Percentage RE	8	0	8	0.133	0.900	0.542	0.259

Nonlinear regression of variable PV:

Goodness of fit statistics:

Observations	8.000
DF	4.000
R²	0.990
SSE	0.000
MSE	0.000
RMSE	0.003
Iterations	200.000

Model parameters:

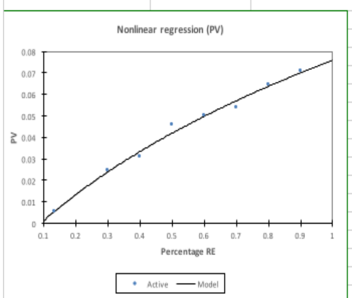
Parameter	Value	Standard error
pr1	0.293	1.251
pr2	0.886	1.394
pr3	2.691	20.187
pr4	-0.015	0.040

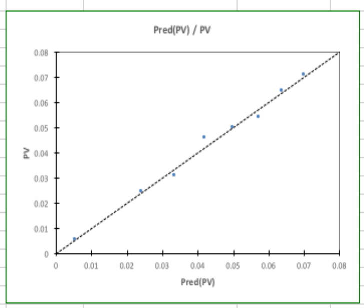
Equation of the model:

PV = 0.293310648675685+(-0.0145702049849519-0.293310648675685)/(1+(Percentage RE/2.69056224476429)^0.885927335514817)

Predictions and residuals:

Observations	Percentage RE	PV	Pred(PV)	Residuals
Obs1	0.133	0.005	0.005	0.000
Obs2	0.300	0.024	0.024	0.000
Obs3	0.400	0.031	0.033	-0.002
Obs4	0.500	0.046	0.042	0.004
Obs5	0.600	0.050	0.050	0.000
Obs6	0.700	0.054	0.057	-0.003
Obs7	0.800	0.064	0.064	0.001
Obs8	0.900	0.071	0.070	0.001





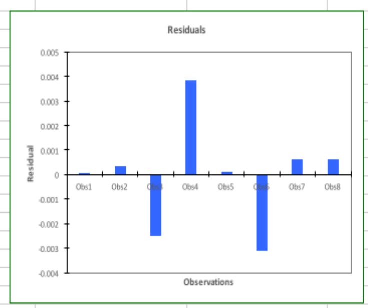


Figure 47. Photovoltaic regression data part 3.

Relationship between Percentage of CSP (Output) and RE % (Input)

Logistic Regression

XLSTAT 2016.04.32523 - Nonlinear regression - Start time: 7/24/16 at 1:47:47 PM / End time: 7/24/16 at 1:48:14 PM
Y / Quantitative: Workbook = Emissions Calculator V3.xlsx / Sheet = General Inputs / Range = 'General Inputs'!$I$39:$I$47 / 8 rows and 1 column
X / Quantitative: Workbook = Emissions Calculator V3.xlsx / Sheet = General Inputs / Range = 'General Inputs'!$B$39:$B$47 / 8 rows and 1 column
Stop conditions: Iterations = 200 / Convergence = 1E-05
Function: Y = pr3/(1+Exp(-pr1-pr2*X1))
Run again:

Summary statistics:

Variable	Observations	Obs. with missing data	without missing	Minimum	Maximum	Mean	Std. deviation
CSP	8	0	8	0.000	0.116	0.030	0.041
Percentage RE	8	0	8	0.133	0.900	0.542	0.259

Nonlinear regression of variable CSP:

Goodness of fit statistics:

Observations	8.000
DF	5.000
R^2	0.996
SSE	0.000
MSE	0.000
RMSE	0.003
Iterations	11.000

Model parameters:

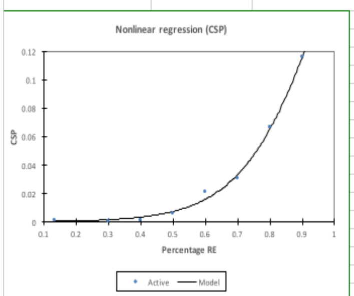
Parameter	Value	Standard error
pr1	-7.720	0.391
pr2	7.999	1.186
pr3	0.311	0.158

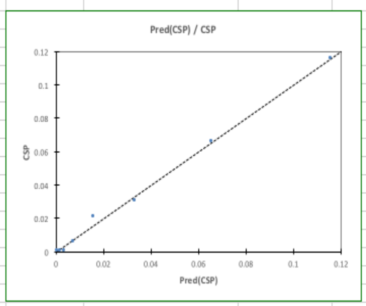
Equation of the model:

CSP = 0.310717664841852/(1+Exp(+7.71976873499381-7.99864249750182*Percentage RE))

Predictions and residuals:

Observations	Percentage RE	CSP	Pred(CSP)	Residuals
Obs1	0.133	0.001	0.000	0.000
Obs2	0.300	0.000	0.002	-0.001
Obs3	0.400	0.000	0.003	-0.003
Obs4	0.500	0.006	0.007	-0.001
Obs5	0.600	0.021	0.016	0.005
Obs6	0.700	0.031	0.033	-0.003
Obs7	0.800	0.066	0.065	0.001
Obs8	0.900	0.116	0.116	0.000





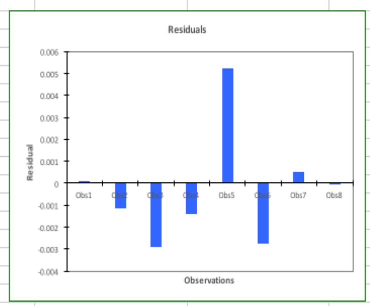


Figure 48. Concentrated solar power regression data part 1.

XLSTAT 2016.04.32523 - Nonlinear regression - Start time: 7/24/16 at 1:49:54 PM / End time: 7/24/16 at 1:50:20 PM
Y / Quantitative: Workbook = Emissions Calculator V3.xlsx / Sheet = General Inputs / Range = 'General Inputs'!$I$39:$I$47 / 8 rows and 1 column
X / Quantitative: Workbook = Emissions Calculator V3.xlsx / Sheet = General Inputs / Range = 'General Inputs'!$B$39:$B$47 / 8 rows and 1 column
Stop conditions: Iterations = 200 / Convergence = 1E-05
Function: Y = pr1+(pr4-pr1)/(1+Exp(pr2*(Ln(X1)-pr3)))
Run again:

Summary statistics:

Variable	Observations	Obs. with missing data	without missing	Minimum	Maximum	Mean	Std. deviation
CSP	8	0	8	0.000	0.116	0.030	0.041
Percentage RE	8	0	8	0.133	0.900	0.542	0.259

Nonlinear regression of variable CSP:

Goodness of fit statistics:

Observations	8.000
DF	4.000
R²	0.745
SSE	0.003
MSE	0.001
RMSE	0.028
Iterations	200.000

Model parameters:

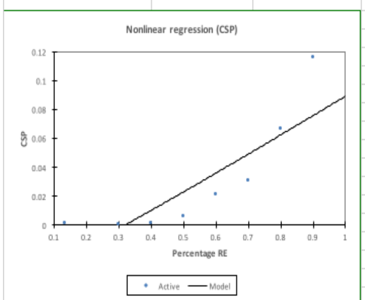
Parameter	Value	Standard error
pr1	3.465	890.815
pr2	1.116	7.826
pr3	2.953	241.246
pr4	-0.036	0.143

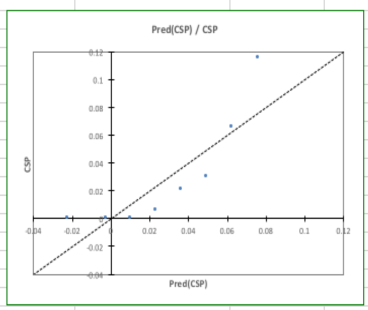
Equation of the model:

CSP = 3.4646561624522+(-0.0359545471383158-3.4646561624522)/(1+Exp(1.11568625014526*(Ln(Percentage RE)-2.95346185834061)))

Predictions and residuals:

Observations	Percentage RE	CSP	Pred(CSP)	Residuals
Obs1	0.133	0.001	-0.022	0.023
Obs2	0.300	0.000	-0.002	0.003
Obs3	0.400	0.000	0.010	-0.010
Obs4	0.500	0.006	0.023	-0.017
Obs5	0.600	0.021	0.036	-0.015
Obs6	0.700	0.031	0.049	-0.019
Obs7	0.800	0.066	0.062	0.004
Obs8	0.900	0.116	0.076	0.040





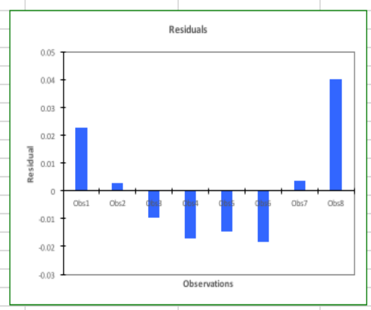


Figure 49. Concentrated solar power regression data part 2.

XLSTAT 2016.04.32523 - Nonlinear regression - Start time: 7/24/16 at 1:51:14 PM / End time: 7/24/16 at 1:51:43 PM
Y / Quantitative: Workbook = Emissions Calculator V3.xlsx / Sheet = General Inputs / Range = 'General Inputs'!$I$39:$I$47 / 8 rows and 1 column
X / Quantitative: Workbook = Emissions Calculator V3.xlsx / Sheet = General Inputs / Range = 'General Inputs'!$B$39:$B$47 / 8 rows and 1 column
Stop conditions: Iterations = 200 / Convergence = 1E-05
Function: Y = pr1+(pr4-pr1)/(1+(X1/pr3)^pr2)
Run again:

Summary statistics:

Variable	Observations	Obs. with missing data	without missing	Minimum	Maximum	Mean	Std. deviation
CSP	8	0	8	0.000	0.116	0.030	0.041
Percentage RE	8	0	8	0.133	0.900	0.542	0.259

Nonlinear regression of variable CSP:

Goodness of fit statistics:

Observations	8.000
DF	4.000
R²	0.996
SSE	0.000
MSE	0.000
RMSE	0.003
Iterations	200.000

Model parameters:

Parameter	Value	Standard error
pr1	4.657	73.719
pr2	4.923	1.279
pr3	1.897	6.603
pr4	0.000	0.002

Equation of the model:

CSP = 4.65719598408802+(6.2001475354576E-06-4.65719598408802)/(1+(Percentage RE/1.89712277430826)^4.92268088517982)

Predictions and residuals:

Observations	Percentage RE	CSP	Pred(CSP)	Residuals
Obs1	0.133	0.001	0.000	0.000
Obs2	0.300	0.000	0.001	0.000
Obs3	0.400	0.000	0.002	-0.002
Obs4	0.500	0.006	0.007	-0.001
Obs5	0.600	0.021	0.016	0.005
Obs6	0.700	0.031	0.034	-0.004
Obs7	0.800	0.066	0.065	0.001
Obs8	0.900	0.116	0.116	0.000

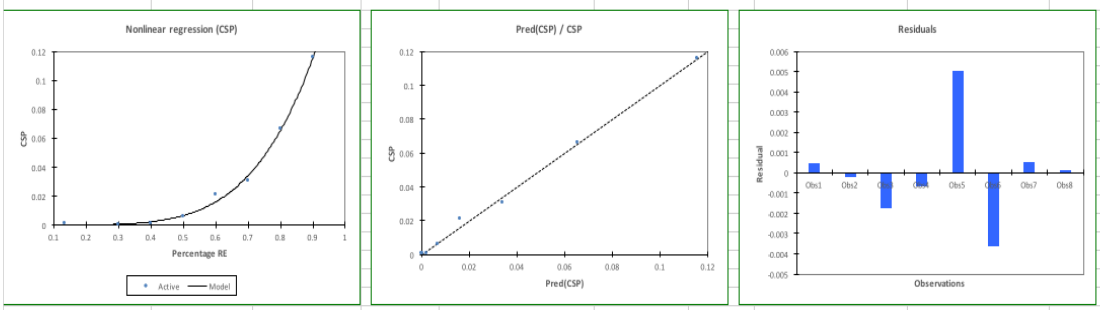


Figure 50. Concentrated solar power regression data part 3.

XLSTAT 2016.04.32523 - Nonlinear regression - Start time: 7/24/16 at 1:55:08 PM / End time: 7/24/16 at 1:55:34 PM
Y / Quantitative: Workbook = Emissions Calculator V3.xlsx / Sheet = General Inputs / Range = 'General Inputs'!$I$39:$I$47 / 8 rows and 1 column
X / Quantitative: Workbook = Emissions Calculator V3.xlsx / Sheet = General Inputs / Range = 'General Inputs'!$B$39:$B$47 / 8 rows and 1 column
Stop conditions: Iterations = 200 / Convergence = 1E-05
Function: Y = pr1*Exp(pr2*X1)
Run again:

Summary statistics:

Variable	Observations	Obs. with missing data	without missing	Minimum	Maximum	Mean	Std. deviation
CSP	8	0	8	0.000	0.116	0.030	0.041
Percentage RE	8	0	8	0.133	0.900	0.542	0.259

Nonlinear regression of variable CSP:

Goodness of fit statistics:

Observations	8.000
DF	6.000
R^2	0.995
SSE	0.000
MSE	0.000
RMSE	0.003
Iterations	41.000

Model parameters:

Parameter	Value	Standard error
pr1	0.000	0.000
pr2	6.346	0.342

Equation of the model:

CSP = 0.000387496078062449*Exp(6.3462902768297*Percentage RE)

Predictions and residuals:

Observations	Percentage RE	CSP	Pred(CSP)	Residuals
Obs1	0.133	0.001	0.001	0.000
Obs2	0.300	0.000	0.003	-0.002
Obs3	0.400	0.000	0.005	-0.004
Obs4	0.500	0.006	0.009	-0.003
Obs5	0.600	0.021	0.017	0.004
Obs6	0.700	0.031	0.033	-0.002
Obs7	0.800	0.066	0.062	0.004
Obs8	0.900	0.116	0.117	-0.001

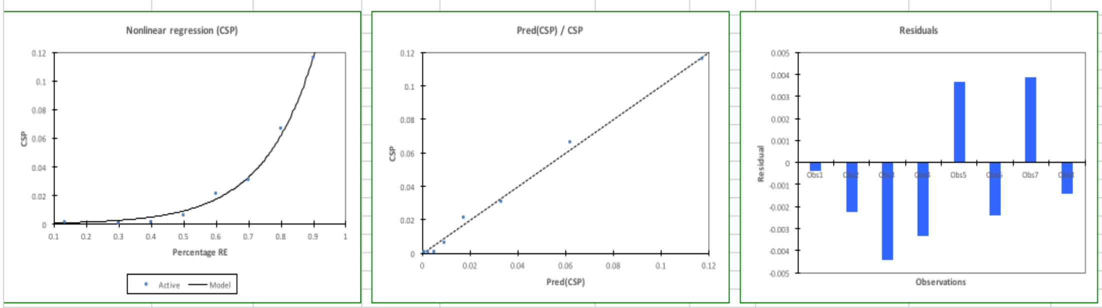


Figure 51. Concentrated solar power regression data part 4.

Relationship between Percentage of Geothermal (Output) and RE % (Input)

Logistic Regression

XLSTAT 2016.04.32523 - Nonlinear regression - Start time: 7/24/16 at 1:58:48 PM / End time: 7/24/16 at 1:59:14 PM
Y / Quantitative: Workbook = Emissions Calculator V3.xlsx / Sheet = General Inputs / Range = 'General Inputs'!$G$39:$G$47 / 8 rows and 1 column
X / Quantitative: Workbook = Emissions Calculator V3.xlsx / Sheet = General Inputs / Range = 'General Inputs'!$B$39:$B$47 / 8 rows and 1 column
Stop conditions: Iterations = 200 / Convergence = 1E-05
Function: Y = pr3/(1+Exp(-pr1-pr2*X1))
Run again:

Summary statistics:

Variable	Observations	Obs. with missing data	without missing	Minimum	Maximum	Mean	Std. deviation
Geothermal	8	0	8	0.004	0.042	0.037	0.013
Percentage RE	8	0	8	0.133	0.900	0.542	0.259

Nonlinear regression of variable Geothermal:

Goodness of fit statistics:

Observations	8.000
DF	5.000
R^2	0.998
SSE	0.000
MSE	0.000
RMSE	0.001
Iterations	7.000

Model parameters:

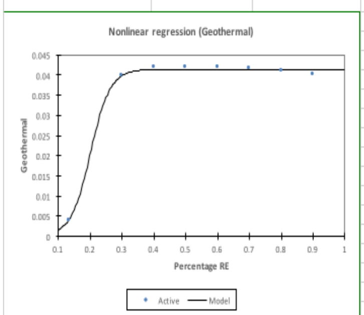
Parameter	Value	Standard error
pr1	-6.559	0.560
pr2	32.616	3.413
pr3	0.041	0.000

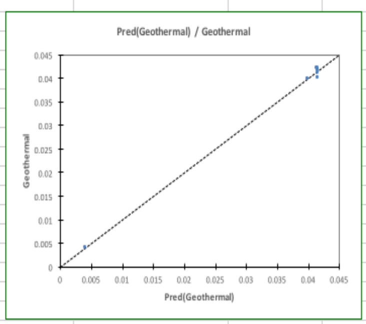
Equation of the model:

Geothermal = 0.0414528945045054/(1+Exp(+6.55949143261789-32.6158734247074*Percentage RE))

Predictions and residuals:

Observations	Percentage RE	Geothermal	red(Geotherma	Residuals
Obs1	0.133	0.004	0.004	0.000
Obs2	0.300	0.040	0.040	0.000
Obs3	0.400	0.042	0.041	0.001
Obs4	0.500	0.042	0.041	0.001
Obs5	0.600	0.042	0.041	0.000
Obs6	0.700	0.042	0.041	0.000
Obs7	0.800	0.041	0.041	0.000
Obs8	0.900	0.040	0.041	-0.001





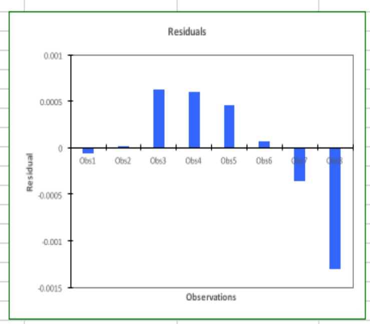


Figure 52. Geothermal regression data part 1.

XLSTAT 2016.04.32523 - Nonlinear regression - Start time: 7/24/16 at 2:02:21 PM / End time: 7/24/16 at 2:02:47 PM
Y / Quantitative: Workbook = Emissions Calculator V3.xlsx / Sheet = General Inputs / Range = 'General Inputs'!$G$39:$G$47 / 8 rows and 1 column
X / Quantitative: Workbook = Emissions Calculator V3.xlsx / Sheet = General Inputs / Range = 'General Inputs'!$B$39:$B$47 / 8 rows and 1 column
Stop conditions: Iterations = 200 / Convergence = 1E-05
Function: Y = pr1+(pr4-pr1)/(1+Exp(pr2*(Ln(X1)-pr3)))
Run again:

Summary statistics:

Variable	Observations	Obs. with missing data	without missing	Minimum	Maximum	Mean	Std. deviation
Geothermal	8	0	8	0.004	0.042	0.037	0.013
Percentage RE	8	0	8	0.133	0.900	0.542	0.259

Nonlinear regression of variable Geothermal:

Goodness of fit statistics:

Observations	8.000
DF	4.000
R²	0.546
SSE	0.001
MSE	0.000
RMSE	0.012
Iterations	200.000

Model parameters:

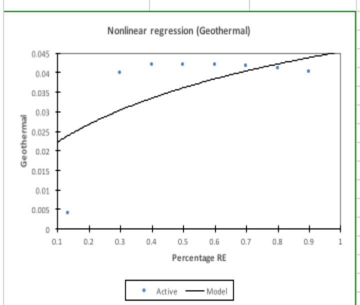
Parameter	Value	Standard error
pr1	0.078	1.718
pr2	0.901	20.127
pr3	0.119	51.451
pr4	0.016	0.233

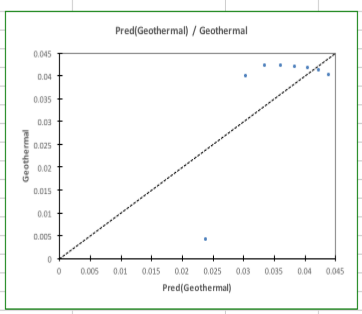
Equation of the model:

Geothermal = 0.0780444155900042+(0.0159916010862455-0.0780444155900042)/(1+Exp(0.900951415890331*(Ln(Percentage RE)-0.119357200025283)))

Predictions and residuals:

Observations	Percentage RE	Geothermal	red(Geotherma	Residuals
Obs1	0.133	0.004	0.024	-0.020
Obs2	0.300	0.040	0.030	0.009
Obs3	0.400	0.042	0.034	0.009
Obs4	0.500	0.042	0.036	0.006
Obs5	0.600	0.042	0.038	0.003
Obs6	0.700	0.042	0.040	0.001
Obs7	0.800	0.041	0.042	-0.001
Obs8	0.900	0.040	0.044	-0.004





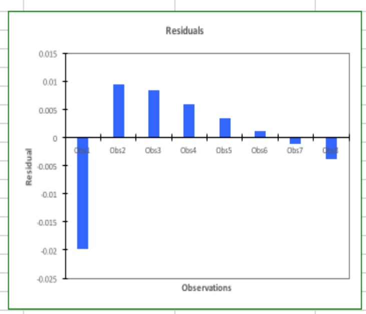


Figure 53. Geothermal regression data part 2.

XLSTAT 2016.04.32523 - Nonlinear regression - Start time: 7/24/16 at 2:03:37 PM / End time: 7/24/16 at 2:04:04 PM
Y / Quantitative: Workbook = Emissions Calculator V3.xlsx / Sheet = General Inputs / Range = 'General Inputs'!$G$39:$G$47 / 8 rows and 1 column
X / Quantitative: Workbook = Emissions Calculator V3.xlsx / Sheet = General Inputs / Range = 'General Inputs'!$B$39:$B$47 / 8 rows and 1 column
Stop conditions: Iterations = 200 / Convergence = 1E-05
Function: Y = pr1+pr2*X1+pr3*X1^2+pr4*X1^3
Run again:

Summary statistics:

Variable	Observations	Obs. with missing data	without missing	Minimum	Maximum	Mean	Std. deviation
Geothermal	8	0	8	0.004	0.042	0.037	0.013
Percentage RE	8	0	8	0.133	0.900	0.542	0.259

Nonlinear regression of variable Geothermal:

Goodness of fit statistics:

Observations	8.000
DF	4.000
R²	0.973
SSE	0.000
MSE	0.000
RMSE	0.003

Model parameters:

Parameter	Value	Standard error
pr1	-0.043	0.008
pr2	0.456	0.064
pr3	-0.759	0.138
pr4	0.397	0.089

Equation of the model:

Geothermal = -0.0430184898916421+0.455624299306463*Percentage RE-0.758813785819626*Percentage RE^2+0.396684113215176*Percentage RE^3

Predictions and residuals:

Observations	Percentage RE	Geothermal	red(Geotherma	Residuals
Obs1	0.133	0.004	0.005	-0.001
Obs2	0.300	0.040	0.036	0.004
Obs3	0.400	0.042	0.043	-0.001
Obs4	0.500	0.042	0.045	-0.003
Obs5	0.600	0.042	0.043	-0.001
Obs6	0.700	0.042	0.040	0.001
Obs7	0.800	0.041	0.039	0.002
Obs8	0.900	0.040	0.042	-0.001

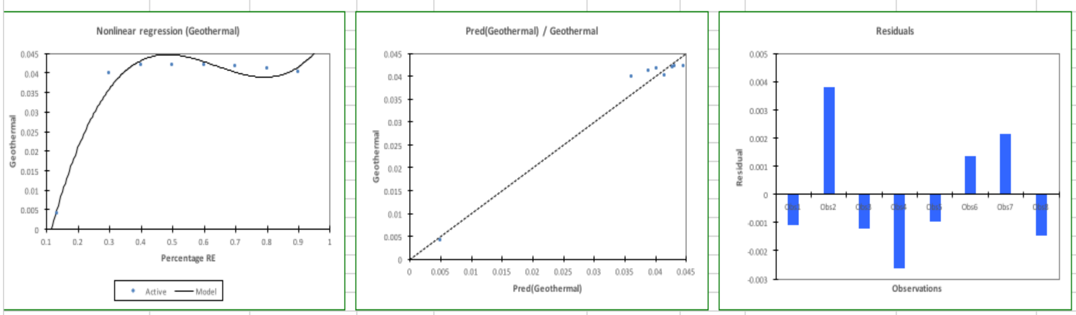


Figure 54. Geothermal regression data part 3.

Relationship between Percentage of Biomass (Output) and RE % (Input)

Logistic Regression

XLSTAT 2016.04.32523 - Nonlinear regression - Start time: 7/24/16 at 2:08:12 PM / End time: 7/24/16 at 2:08:40 PM
Y / Quantitative: Workbook = Emissions Calculator V3.xlsx / Sheet = General Inputs / Range = 'General Inputs'!$F$39:$F$47 / 8 rows and 1 column
X / Quantitative: Workbook = Emissions Calculator V3.xlsx / Sheet = General Inputs / Range = 'General Inputs'!$B$39:$B$47 / 8 rows and 1 column
Stop conditions: Iterations = 200 / Convergence = 1E-05
Function: Y = pr3/(1+Exp(-pr1-pr2*X1))
Run again:

Summary statistics:

Variable	Observations	Obs. with missing data	without missing	Minimum	Maximum	Mean	Std. deviation
Biomass	8	0	8	0.016	0.152	0.092	0.051
Percentage RE	8	0	8	0.133	0.900	0.542	0.259

Nonlinear regression of variable Biomass:

Goodness of fit statistics:

Observations	8.000
DF	5.000
R²	0.979
SSE	0.000
MSE	0.000
RMSE	0.009
Iterations	7.000

Model parameters:

Parameter	Value	Standard error
pr1	-3.007	0.404
pr2	5.850	1.130
pr3	0.173	0.017

Equation of the model:

Biomass = 0.172590151367785/(1+Exp(+3.00734951525838-5.8495508256491*Percentage RE))

Predictions and residuals:

Observations	Percentage RE	Biomass	Pred(Biomass)	Residuals
Obs1	0.133	0.016	0.017	-0.001
Obs2	0.300	0.045	0.038	0.006
Obs3	0.400	0.061	0.059	0.003
Obs4	0.500	0.071	0.083	-0.012
Obs5	0.600	0.105	0.108	-0.003
Obs6	0.700	0.138	0.129	0.009
Obs7	0.800	0.152	0.145	0.007
Obs8	0.900	0.148	0.156	-0.008

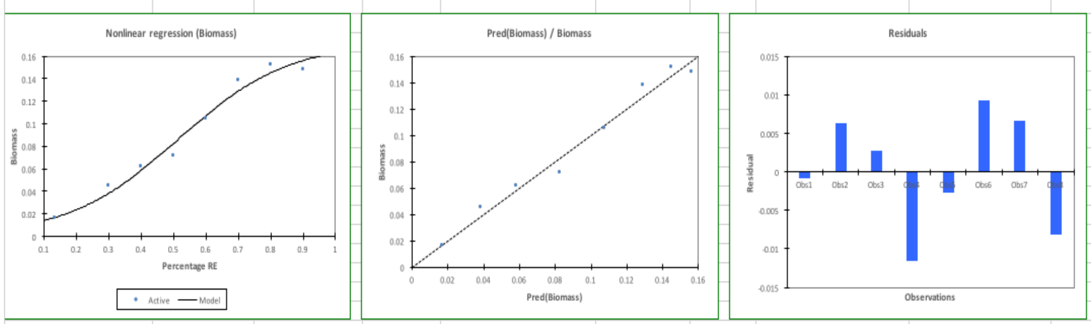


Figure 55. Biomass regression data part 1.

XLSTAT 2016.04.32523 - Nonlinear regression - Start time: 7/24/16 at 2:10:29 PM / End time: 7/24/16 at 2:10:56 PM
Y / Quantitative: Workbook = Emissions Calculator V3.xlsx / Sheet = General Inputs / Range = 'General Inputs'!$F$39:$F$47 / 8 rows and 1 column
X / Quantitative: Workbook = Emissions Calculator V3.xlsx / Sheet = General Inputs / Range = 'General Inputs'!$B$39:$B$47 / 8 rows and 1 column
Stop conditions: Iterations = 200 / Convergence = 1E-05
Function: Y = pr1+(pr4-pr1)/(1+Exp(pr2*(Ln(X1)-pr3)))
Run again:

Summary statistics:

Variable	Observations	Obs. with missing data	without missing	Minimum	Maximum	Mean	Std. deviation
Biomass	8	0	8	0.016	0.152	0.092	0.051
Percentage RE	8	0	8	0.133	0.900	0.542	0.259

Nonlinear regression of variable Biomass:

Goodness of fit statistics:

Observations	8.000
DF	4.000
R²	0.936
SSE	0.001
MSE	0.000
RMSE	0.019
Iterations	200.000

Model parameters:

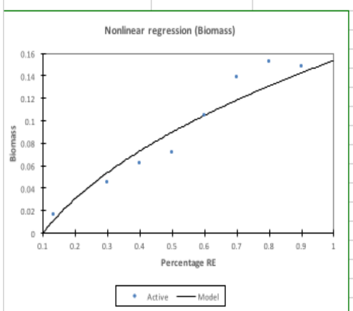
Parameter	Value	Standard error
pr1	4.048	958.806
pr2	0.485	8.228
pr3	5.805	582.666
pr4	-0.079	1.270

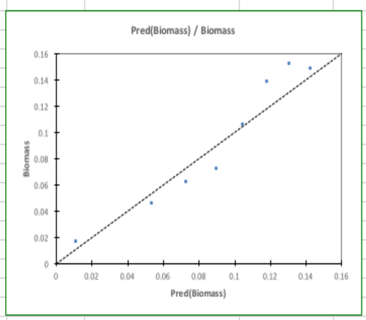
Equation of the model:

Biomass = 4.04759440017249+(-0.0793296759903499-4.04759440017249)/(1+Exp(0.485032877060616*(Ln(Percentage RE)-5.80461854615858)))

Predictions and residuals:

Observations	Percentage RE	Biomass	Pred(Biomass)	Residuals
Obs1	0.133	0.016	0.012	0.004
Obs2	0.300	0.045	0.054	-0.009
Obs3	0.400	0.061	0.073	-0.012
Obs4	0.500	0.071	0.090	-0.019
Obs5	0.600	0.105	0.105	0.000
Obs6	0.700	0.138	0.119	0.020
Obs7	0.800	0.152	0.131	0.021
Obs8	0.900	0.148	0.143	0.005





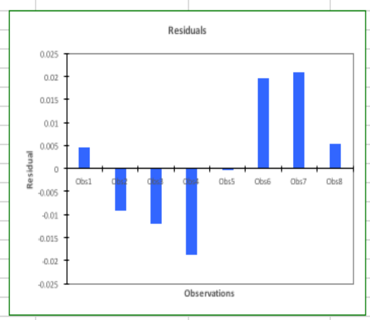


Figure 56. Biomass regression data part 2.

XLSTAT 2016.04.32523 - Nonlinear regression - Start time: 7/24/16 at 2:11:39 PM / End time: 7/24/16 at 2:12:06 PM
Y / Quantitative: Workbook = Emissions Calculator V3.xlsx / Sheet = General Inputs / Range = 'General Inputs'!$F$39:$F$47 / 8 rows and 1 column
X / Quantitative: Workbook = Emissions Calculator V3.xlsx / Sheet = General Inputs / Range = 'General Inputs'!$B$39:$B$47 / 8 rows and 1 column
Stop conditions: Iterations = 200 / Convergence = 1E-05
Function: Y = pr1+(pr4-pr1)/(1+(X1/pr3)^pr2)
Run again:

Summary statistics:

Variable	Observations	Obs. with missing data	without missing	Minimum	Maximum	Mean	Std. deviation
Biomass	8	0	8	0.016	0.152	0.092	0.051
Percentage RE	8	0	8	0.133	0.900	0.542	0.259

Nonlinear regression of variable Biomass:

Goodness of fit statistics:

Observations	8.000
DF	4.000
R²	0.975
SSE	0.000
MSE	0.000
RMSE	0.011
Iterations	8.000

Model parameters:

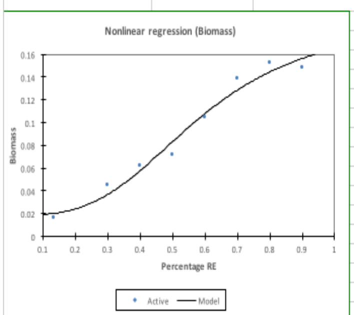
Parameter	Value	Standard error
pr1	0.193	0.053
pr2	3.161	1.393
pr3	0.590	0.124
pr4	0.019	0.012

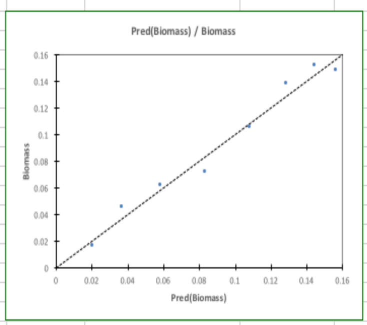
Equation of the model:

Biomass = 0.192804090438518+(0.0186894000647961-0.192804090438518)/(1+(Percentage RE/0.590332047216836)^3.16136909622036)

Predictions and residuals:

Observations	Percentage RE	Biomass	Pred(Biomass)	Residuals
Obs1	0.133	0.016	0.020	-0.004
Obs2	0.300	0.045	0.037	0.008
Obs3	0.400	0.061	0.058	0.003
Obs4	0.500	0.071	0.083	-0.012
Obs5	0.600	0.105	0.108	-0.003
Obs6	0.700	0.138	0.129	0.010
Obs7	0.800	0.152	0.145	0.007
Obs8	0.900	0.148	0.156	-0.008





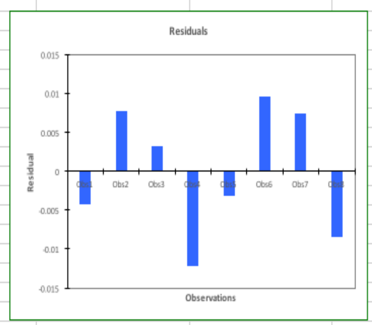


Figure 57. Biomass regression data part 3.

Relationship between Percentage of Hydro (Output) and RE % (Input)

Logistic Regression

XLSTAT 2016.04.32523 - Nonlinear regression - Start time: 7/24/16 at 2:17:41 PM / End time: 7/24/16 at 2:18:07 PM
Y / Quantitative: Workbook = Emissions Calculator V3.xlsx / Sheet = General Inputs / Range = 'General Inputs'!$H$39:$H$47 / 8 rows and 1 column
X / Quantitative: Workbook = Emissions Calculator V3.xlsx / Sheet = General Inputs / Range = 'General Inputs'!$B$39:$B$47 / 8 rows and 1 column
Stop conditions: Iterations = 200 / Convergence = 1E-05
Function: Y = pr3/(1+Exp(-pr1-pr2*X1))
Run again:

Summary statistics:

Variable	Observations	Obs. with missing data	without missing	Minimum	Maximum	Mean	Std. deviation
Hydropower	8	0	8	0.060	0.125	0.099	0.020
Percentage RE	8	0	8	0.133	0.900	0.542	0.259

Nonlinear regression of variable Hydropower:

Goodness of fit statistics:

Observations	8.000
DF	5.000
R²	0.961
SSE	0.000
MSE	0.000
RMSE	0.005
Iterations	3.000

Model parameters:

Parameter	Value	Standard error
pr1	-0.481	0.158
pr2	3.405	0.932
pr3	0.128	0.010

Equation of the model:

Hydropower = 0.128481478956708/(1+Exp(+0.480817461917613-3.40465147841978*Percentage RE))

Predictions and residuals:

Observations	Percentage RE	Hydropower	red(Hydropowe	Residuals
Obs1	0.133	0.060	0.063	-0.003
Obs2	0.300	0.085	0.081	0.004
Obs3	0.400	0.095	0.091	0.004
Obs4	0.500	0.099	0.099	0.000
Obs5	0.600	0.101	0.106	-0.005
Obs6	0.700	0.109	0.112	-0.002
Obs7	0.800	0.114	0.116	-0.003
Obs8	0.900	0.125	0.119	0.005

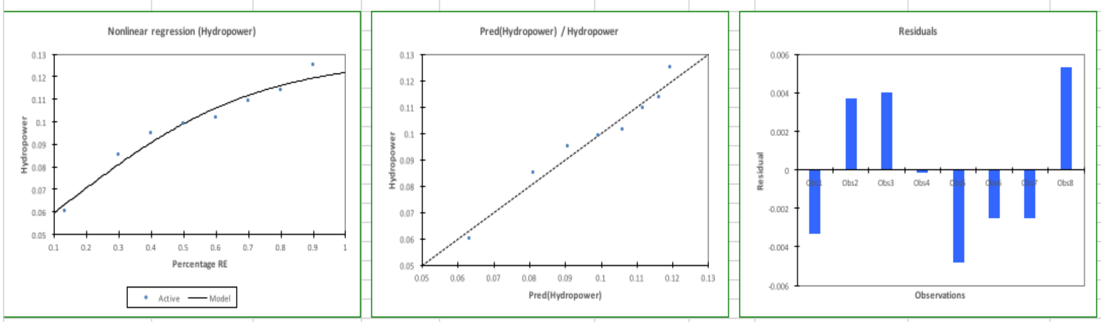


Figure 58. Hydropower regression data part 1.

XLSTAT 2016.04.32523 - Nonlinear regression - Start time: 7/24/16 at 2:18:56 PM / End time: 7/24/16 at 2:19:23 PM
Y / Quantitative: Workbook = Emissions Calculator V3.xlsx / Sheet = General Inputs / Range = 'General Inputs'!$H$39:$H$47 / 8 rows and 1 column
X / Quantitative: Workbook = Emissions Calculator V3.xlsx / Sheet = General Inputs / Range = 'General Inputs'!$B$39:$B$47 / 8 rows and 1 column
Stop conditions: Iterations = 200 / Convergence = 1E-05
Function: Y = pr1+(pr4-pr1)/(1+Exp(pr2*(Ln(X1)-pr3)))
Run again:

Summary statistics:

Variable	Observations	Obs. with missing data	without missing	Minimum	Maximum	Mean	Std. deviation
Hydropower	8	0	8	0.060	0.125	0.099	0.020
Percentage RE	8	0	8	0.133	0.900	0.542	0.259

Nonlinear regression of variable Hydropower:

Goodness of fit statistics:

Observations	8.000
DF	4.000
R²	0.978
SSE	0.000
MSE	0.000
RMSE	0.006
Iterations	200.000

Model parameters:

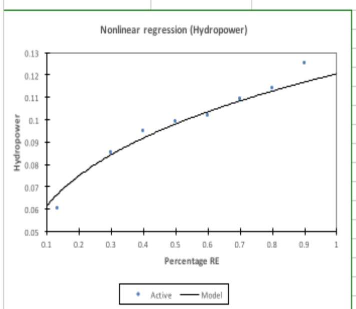
Parameter	Value	Standard error
pr1	0.719	59.624
pr2	0.403	7.696
pr3	4.340	304.681
pr4	0.016	0.765

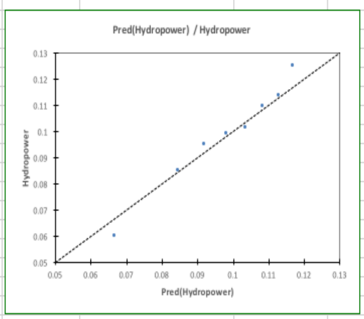
Equation of the model:

Hydropower = 0.718682420028777+(0.0164153011314916-0.718682420028777)/(1+Exp(0.402750787046858*(Ln(Percentage RE)-4.34002241537331)))

Predictions and residuals:

Observations	Percentage RE	Hydropower	red(Hydropowe	Residuals
Obs1	0.133	0.060	0.067	-0.007
Obs2	0.300	0.085	0.084	0.000
Obs3	0.400	0.095	0.092	0.003
Obs4	0.500	0.099	0.098	0.001
Obs5	0.600	0.101	0.104	-0.002
Obs6	0.700	0.109	0.108	0.001
Obs7	0.800	0.114	0.113	0.001
Obs8	0.900	0.125	0.117	0.008





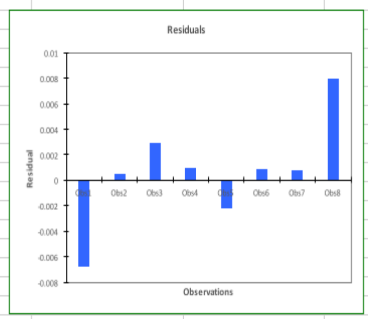


Figure 59. Hydropower regression data part 2.

XLSTAT 2016.04.32523 - Nonlinear regression - Start time: 7/24/16 at 2:20:16 PM / End time: 7/24/16 at 2:20:43 PM
Y / Quantitative: Workbook = Emissions Calculator V3.xlsx / Sheet = General Inputs / Range = 'General Inputs'!$H$39:$H$47 / 8 rows and 1 column
X / Quantitative: Workbook = Emissions Calculator V3.xlsx / Sheet = General Inputs / Range = 'General Inputs'!$B$39:$B$47 / 8 rows and 1 column
Stop conditions: Iterations = 200 / Convergence = 1E-05
Function: Y = pr1+(pr4-pr1)/(1+(X1/pr3)^pr2)
Run again:

Summary statistics:

Variable	Observations	Obs. with missing data	without missing	Minimum	Maximum	Mean	Std. deviation
Hydropower	8	0	8	0.060	0.125	0.099	0.020
Percentage RE	8	0	8	0.133	0.900	0.542	0.259

Nonlinear regression of variable Hydropower:

Goodness of fit statistics:

Observations	8.000
DF	4.000
R²	0.979
SSE	0.000
MSE	0.000
RMSE	0.004
Iterations	200.000

Model parameters:

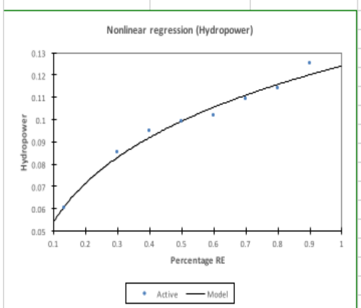
Parameter	Value	Standard error
pr1	0.450	9.594
pr2	0.392	4.710
pr3	8.943	778.377
pr4	-0.014	0.779

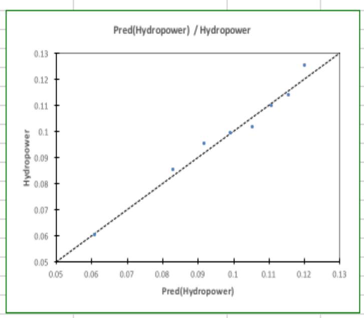
Equation of the model:

Hydropower = 0.449702631274086+(-0.0137785730944266-0.449702631274086)/(1+(Percentage RE/8.94266764011213)^0.391943939092265)

Predictions and residuals:

Observations	Percentage RE	Hydropower	red(Hydropowe	Residuals
Obs1	0.133	0.060	0.061	-0.001
Obs2	0.300	0.085	0.083	0.002
Obs3	0.400	0.095	0.092	0.003
Obs4	0.500	0.099	0.099	0.000
Obs5	0.600	0.101	0.106	-0.004
Obs6	0.700	0.109	0.111	-0.002
Obs7	0.800	0.114	0.116	-0.002
Obs8	0.900	0.125	0.120	0.005





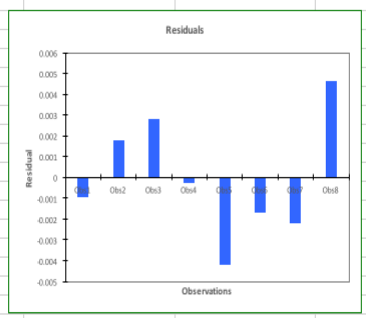


Figure 60. Hydropower regression data part 3.

Relationship between Percentage of Coal (Output) and RE % (Input)

Logistic Regression

XLSTAT 2016.04.32523 - Nonlinear regression - Start time: 7/24/16 at 2:44:40 PM / End time: 7/24/16 at 2:45:08 PM
Y / Quantitative: Workbook = Emissions Calculator V3.xlsx / Sheet = General Inputs / Range = 'General Inputs'!$D$39:$D$47 / 8 rows and 1 column
X / Quantitative: Workbook = Emissions Calculator V3.xlsx / Sheet = General Inputs / Range = 'General Inputs'!$B$39:$B$47 / 8 rows and 1 column
Stop conditions: Iterations = 200 / Convergence = 1E-05
Function: Y = pr3/(1+Exp(-pr1-pr2*X1))
Run again:

Summary statistics:

Variable	Observations	Obs. with missing data	without missing	Minimum	Maximum	Mean	Std. deviation
Coal	8	0	8	0.029	0.492	0.267	0.163
Percentage RE	8	0	8	0.133	0.900	0.542	0.259

Nonlinear regression of variable Coal:

Goodness of fit statistics:

Observations	8.000
DF	5.000
R²	0.914
SSE	0.016
MSE	0.003
RMSE	0.057
Iterations	18.000

Model parameters:

Parameter	Value	Standard error
pr1	7.242	2.944
pr2	-11.006	4.187
pr3	0.420	0.041

Equation of the model:

Coal = 0.42029340924073/(1+Exp(-7.2416257766666+11.0056016767724*Percentage RE))

Predictions and residuals:

Observations	Percentage RE	Coal	Pred(Coal)	Residuals
Obs1	0.133	0.330	0.419	-0.089
Obs2	0.300	0.492	0.412	0.080
Obs3	0.400	0.429	0.397	0.032
Obs4	0.500	0.344	0.357	-0.014
Obs5	0.600	0.257	0.275	-0.018
Obs6	0.700	0.165	0.162	0.003
Obs7	0.800	0.087	0.073	0.014
Obs8	0.900	0.029	0.027	0.002

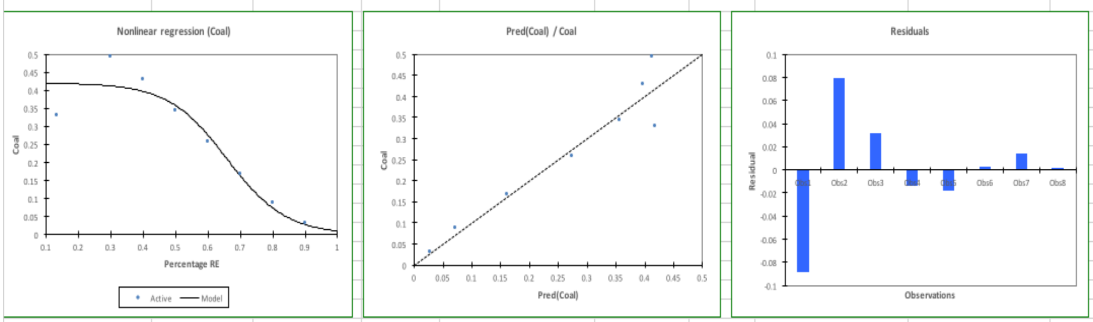


Figure 61. Coal power regression data part 1.

Cubic Regression

XLSTAT 2016.04.32523 - Nonlinear regression - Start time: 7/24/16 at 2:45:56 PM / End time: 7/24/16 at 2:46:23 PM
Y / Quantitative: Workbook = Emissions Calculator V3.xlsx / Sheet = General Inputs / Range = 'General Inputs'!$D$39:$D$47 / 8 rows and 1 column
X / Quantitative: Workbook = Emissions Calculator V3.xlsx / Sheet = General Inputs / Range = 'General Inputs'!$B$39:$B$47 / 8 rows and 1 column
Stop conditions: Iterations = 200 / Convergence = 1E-05
Function: Y = pr1+pr2*X1+pr3*X1^2+pr4*X1^3
Run again:

Summary statistics:

Variable	Observations	Obs. with missing data	Obs. without missing	Minimum	Maximum	Mean	Std. deviation
Coal	8	0	8	0.029	0.492	0.267	0.163
Percentage RE	8	0	8	0.133	0.900	0.542	0.259

Nonlinear regression of variable Coal:

Goodness of fit statistics:

Observations	8.000
DF	4.000
R²	0.992
SSE	0.001
MSE	0.000
RMSE	0.019

Model parameters:

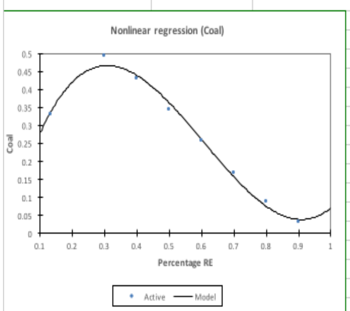
Parameter	Value	Standard error
pr1	0.016	0.056
pr2	3.301	0.426
pr3	-7.189	0.926
pr4	3.942	0.595

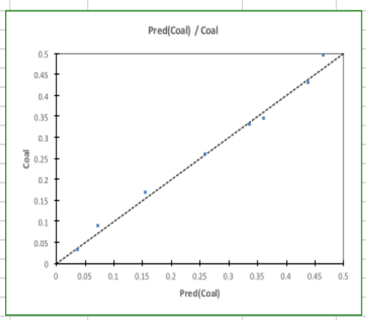
Equation of the model:

Coal = 0.0161878604380196+3.3008113096785*Percentage RE-7.18863871418589*Percentage RE^2+3.94230473265586*Percentage RE^3

Predictions and residuals:

Observations	Percentage RE	Coal	Pred(Coal)	Residuals
Obs1	0.133	0.330	0.337	-0.007
Obs2	0.300	0.492	0.466	0.026
Obs3	0.400	0.429	0.439	-0.010
Obs4	0.500	0.344	0.362	-0.018
Obs5	0.600	0.257	0.260	-0.003
Obs6	0.700	0.165	0.157	0.009
Obs7	0.800	0.087	0.075	0.012
Obs8	0.900	0.029	0.038	-0.009





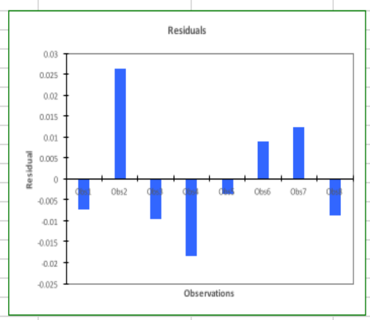


Figure 62. Coal power regression data part 2.

Logistic Regression

XLSTAT 2016.04.32523 - Nonlinear regression - Start time: 7/24/16 at 2:49:43 PM / End time: 7/24/16 at 2:50:10 PM
Y / Quantitative: Workbook = Emissions Calculator V3.xlsx / Sheet = General Inputs / Range = 'General Inputs'!$D$39:$D$47 / 8 rows and 1 column
X / Quantitative: Workbook = Emissions Calculator V3.xlsx / Sheet = General Inputs / Range = 'General Inputs'!$B$39:$B$47 / 8 rows and 1 column
Stop conditions: Iterations = 200 / Convergence = 1E-05
Function: Y = pr1+(pr4-pr1)/(1+(X1/pr3)^pr2)
Run again:

Summary statistics:

Variable	Observations	Obs. with missing data	without missing	Minimum	Maximum	Mean	Std. deviation
Coal	8	0	8	0.029	0.492	0.267	0.163
Percentage RE	8	0	8	0.133	0.900	0.542	0.259

Nonlinear regression of variable Coal:

Goodness of fit statistics:

Observations	8.000
DF	4.000
R²	0.921
SSE	0.015
MSE	0.004
RMSE	0.061
Iterations	13.000

Model parameters:

Parameter	Value	Standard error
pr1	-0.011	0.155
pr2	6.555	4.811
pr3	0.655	0.097
pr4	0.419	0.042

Equation of the model:

Coal = -0.0108314685905944+(0.418641039327069+0.0108314685905944)/(1+(Percentage RE/0.655354229966797)^6.55496950478492)

Predictions and residuals:

Observations	Percentage RE	Coal	Pred(Coal)	Residuals
Obs1	0.133	0.330	0.419	-0.089
Obs2	0.300	0.492	0.416	0.076
Obs3	0.400	0.429	0.402	0.027
Obs4	0.500	0.344	0.356	-0.012
Obs5	0.600	0.257	0.264	-0.008
Obs6	0.700	0.165	0.158	0.007
Obs7	0.800	0.087	0.081	0.006
Obs8	0.900	0.029	0.037	-0.008

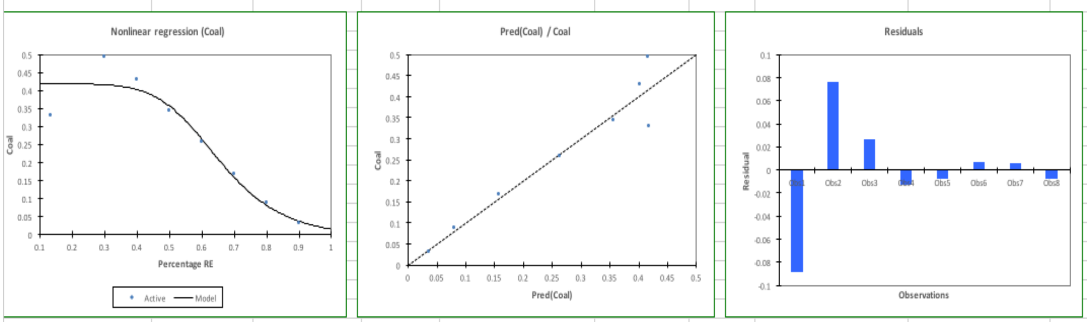


Figure 63. Coal power regression data part 3.

Relationship between Percentage of Natural Gas (Output) and RE % (Input)

Logistic Regression

XLSTAT 2016.04.32523 - Nonlinear regression - Start time: 7/24/16 at 2:56:00 PM / End time: 7/24/16 at 2:56:26 PM
Y / Quantitative: Workbook = Emissions Calculator V3.xlsx / Sheet = General Inputs / Range = 'General Inputs'!$E$39:$E$47 / 8 rows and 1 column
X / Quantitative: Workbook = Emissions Calculator V3.xlsx / Sheet = General Inputs / Range = 'General Inputs'!$B$39:$B$47 / 8 rows and 1 column
Stop conditions: Iterations = 200 / Convergence = 1E-05
Function: Y = pr3/(1+Exp(-pr1-pr2*X1))
Run again:

Summary statistics:

Variable	Observations	Obs. with missing data	without missing	Minimum	Maximum	Mean	Std. deviation
Natural Gas	8	0	8	0.019	0.330	0.079	0.104
Percentage RE	8	0	8	0.133	0.900	0.542	0.259

Nonlinear regression of variable Natural Gas:

Goodness of fit statistics:

Observations	8.000
DF	5.000
R^2	0.986
SSE	0.002
MSE	0.000
RMSE	0.019
Iterations	200.000

Model parameters:

Parameter	Value	Standard error
pr1	-4.077	117.331
pr2	-6.201	2.738
pr3	44.040	5114.057

Equation of the model:

Natural Gas = 44.0402884259064/(1+Exp(+4.07704328469205+6.20072613333372*Percentage RE))

Predictions and residuals:

Observations	Percentage RE	Natural Gas	Pred(Natural Gas)	Residuals
Obs1	0.133	0.330	0.325	0.005
Obs2	0.300	0.097	0.116	-0.019
Obs3	0.400	0.059	0.062	-0.004
Obs4	0.500	0.042	0.034	0.008
Obs5	0.600	0.034	0.018	0.015
Obs6	0.700	0.028	0.010	0.018
Obs7	0.800	0.026	0.005	0.020
Obs8	0.900	0.019	0.003	0.016

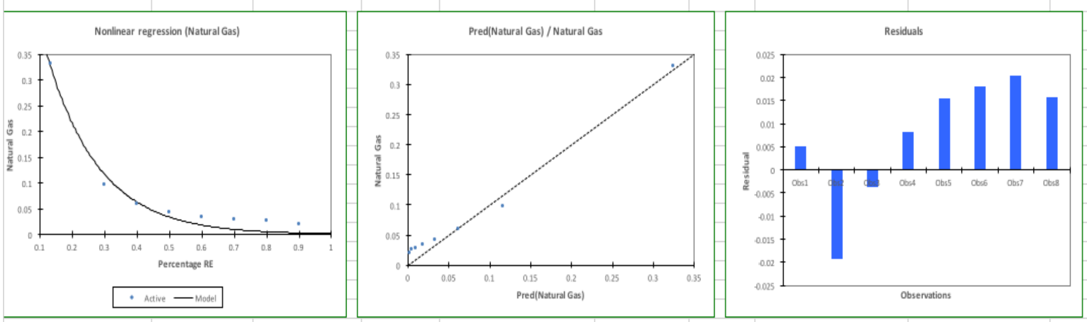


Figure 64. Natural gas regression data part 1.

XLSTAT 2016.04.32523 - Nonlinear regression - Start time: 7/24/16 at 2:57:14 PM / End time: 7/24/16 at 2:57:42 PM
Y / Quantitative: Workbook = Emissions Calculator V3.xlsx / Sheet = General Inputs / Range = 'General Inputs'!$E$39:$E$47 / 8 rows and 1 column
X / Quantitative: Workbook = Emissions Calculator V3.xlsx / Sheet = General Inputs / Range = 'General Inputs'!$B$39:$B$47 / 8 rows and 1 column
Stop conditions: Iterations = 200 / Convergence = 1E-05
Function: Y = pr1+(pr4-pr1)/(1+(X1/pr3)^pr2)
Run again:

Summary statistics:

Variable	Observations	Obs. with missing data	without missing	Minimum	Maximum	Mean	Std. deviation
Natural Gas	8	0	8	0.019	0.330	0.079	0.104
Percentage RE	8	0	8	0.133	0.900	0.542	0.259

Nonlinear regression of variable Natural Gas:

Goodness of fit statistics:

Observations	8.000
DF	4.000
R^2	1.000
SSE	0.000
MSE	0.000
RMSE	0.002
Iterations	34.000

Model parameters:

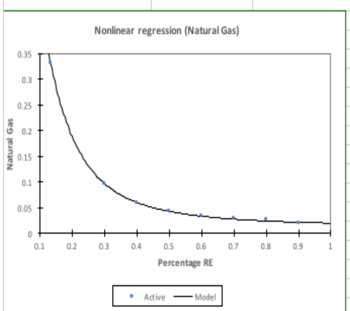
Parameter	Value	Standard error
pr1	0.013	0.004
pr2	2.184	0.287
pr3	0.117	0.034
pr4	0.752	0.257

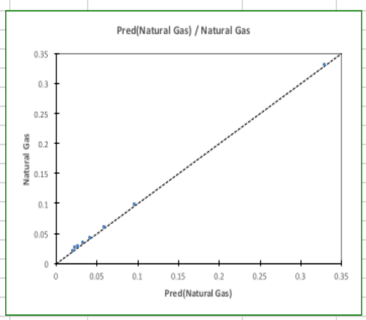
Equation of the model:

Natural Gas = 0.0127145491628474+(0.751880208187016-0.0127145491628474)/(1+(Percentage RE/0.116681098327899)^2.18415321168018)

Predictions and residuals:

Observations	Percentage RE	Natural Gas	Pred(Natural Gas)	Residuals
Obs1	0.133	0.330	0.330	0.000
Obs2	0.300	0.097	0.096	0.000
Obs3	0.400	0.059	0.060	-0.001
Obs4	0.500	0.042	0.042	0.000
Obs5	0.600	0.034	0.033	0.001
Obs6	0.700	0.028	0.027	0.001
Obs7	0.800	0.026	0.024	0.002
Obs8	0.900	0.019	0.021	-0.003





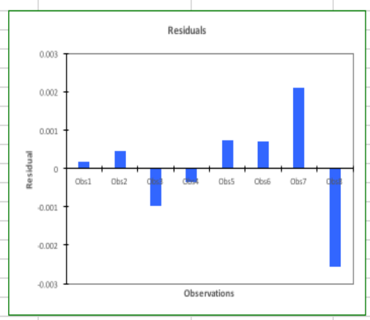


Figure 65. Natural gas regression data part 2.

Exponential Regression

XLSTAT 2016.04.32523 - Nonlinear regression - Start time: 7/24/16 at 2:59:55 PM / End time: 7/24/16 at 3:00:22 PM
Y / Quantitative: Workbook = Emissions Calculator V3.xlsx / Sheet = General Inputs / Range = 'General Inputs'!$E$39:$E$47 / 8 rows and 1 column
X / Quantitative: Workbook = Emissions Calculator V3.xlsx / Sheet = General Inputs / Range = 'General Inputs'!$B$39:$B$47 / 8 rows and 1 column
Stop conditions: Iterations = 200 / Convergence = 1E-05
Function: Y = pr1*Exp(pr2*X1)
Run again:

Summary statistics:

Variable	Observations	Obs. with missing data	without missing	Minimum	Maximum	Mean	Std. deviation
Natural Gas	8	0	8	0.019	0.330	0.079	0.104
Percentage RE	8	0	8	0.133	0.900	0.542	0.259

Nonlinear regression of variable Natural Gas:

Goodness of fit statistics:

Observations	8.000
DF	6.000
R^2	0.986
SSE	0.002
MSE	0.000
RMSE	0.017
Iterations	5.000

Model parameters:

Parameter	Value	Standard error
pr1	0.738	0.080
pr2	-6.164	0.595

Equation of the model:

Natural Gas = 0.737629921633168*Exp(-6.1637881008089*Percentage RE)

Predictions and residuals:

Observations	Percentage RE	Natural Gas	red(Natural Gas	Residuals
Obs1	0.133	0.330	0.325	0.005
Obs2	0.300	0.097	0.116	-0.020
Obs3	0.400	0.059	0.063	-0.004
Obs4	0.500	0.042	0.034	0.008
Obs5	0.600	0.034	0.018	0.015
Obs6	0.700	0.028	0.010	0.018
Obs7	0.800	0.026	0.005	0.020
Obs8	0.900	0.019	0.003	0.016

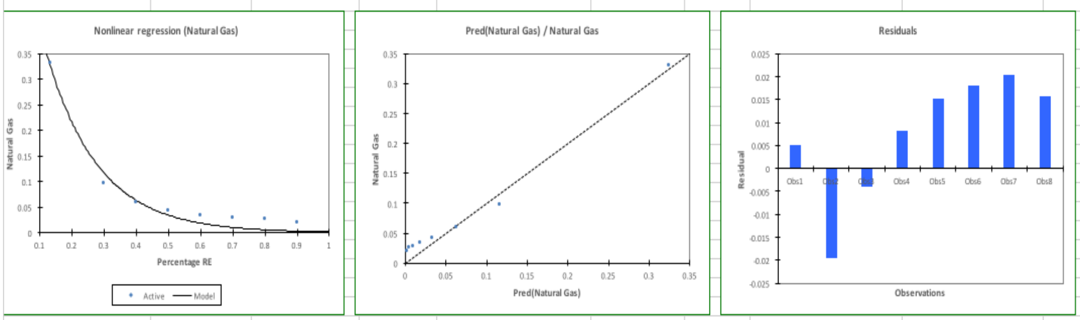


Figure 66. Natural gas regression data part 3.

Relationship between Percentage of Nuclear (Output) and RE % (Input)

Logistic Regression

XLSTAT 2016.04.32523 - Nonlinear regression - Start time: 7/24/16 at 3:02:42 PM / End time: 7/24/16 at 3:03:12 PM
Y / Quantitative: Workbook = Emissions Calculator V3.xlsx / Sheet = General Inputs / Range = 'General Inputs'!$C$39:$C$47 / 8 rows and 1 column
X / Quantitative: Workbook = Emissions Calculator V3.xlsx / Sheet = General Inputs / Range = 'General Inputs'!$B$39:$B$47 / 8 rows and 1 column
Stop conditions: Iterations = 200 / Convergence = 1E-05
Function: Y = pr3/(1+Exp(-pr1-pr2*X1))
Run again:

Summary statistics:

Variable	Observations	Obs. with missing data	without missing	Minimum	Maximum	Mean	Std. deviation
Nuclear	8	0	8	0.047	0.200	0.106	0.043
Percentage RE	8	0	8	0.133	0.900	0.542	0.259

Nonlinear regression of variable Nuclear:

Goodness of fit statistics:

Observations	8.000
DF	5.000
R^2	0.803
SSE	0.003
MSE	0.001
RMSE	0.023
Iterations	200.000

Model parameters:

Parameter	Value	Standard error
pr1	-4.011	147.026
pr2	-1.442	2.079
pr3	12.049	1742.917

Equation of the model:

Nuclear = 12.0487766514759/(1+Exp(+4.01137549791467+1.44200159269809*Percentage RE))

Predictions and residuals:

Observations	Percentage RE	Nuclear	Pred(Nuclear)	Residuals
Obs1	0.133	0.200	0.177	0.023
Obs2	0.300	0.107	0.140	-0.033
Obs3	0.400	0.106	0.121	-0.015
Obs4	0.500	0.105	0.105	0.000
Obs5	0.600	0.101	0.091	0.010
Obs6	0.700	0.098	0.079	0.019
Obs7	0.800	0.080	0.068	0.012
Obs8	0.900	0.047	0.059	-0.012

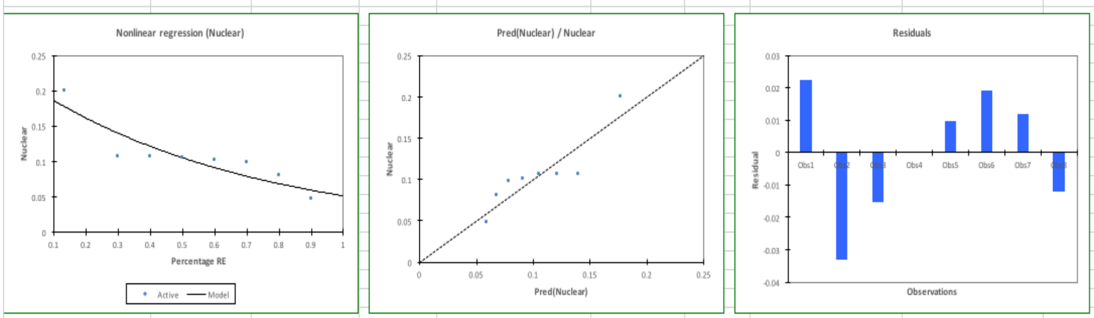


Figure 67. Nuclear power regression data part 1.

XLSTAT 2016.04.32523 - Nonlinear regression - Start time: 7/24/16 at 3:06:53 PM / End time: 7/24/16 at 3:07:19 PM
Y / Quantitative: Workbook = Emissions Calculator V3.xlsx / Sheet = General Inputs / Range = 'General Inputs'!$C$39:$C$47 / 8 rows and 1 column
X / Quantitative: Workbook = Emissions Calculator V3.xlsx / Sheet = General Inputs / Range = 'General Inputs'!$B$39:$B$47 / 8 rows and 1 column
Stop conditions: Iterations = 200 / Convergence = 1E-05
Function: Y = pr1+(pr4-pr1)/(1+(X1/pr3)^pr2)
Run again:

Summary statistics:

Variable	Observations	Obs. with missing data	without missing	Minimum	Maximum	Mean	Std. deviation
Nuclear	8	0	8	0.047	0.200	0.106	0.043
Percentage RE	8	0	8	0.133	0.900	0.542	0.259

Nonlinear regression of variable Nuclear:

Goodness of fit statistics:

Observations	8.000
DF	4.000
R^2	0.882
SSE	0.002
MSE	0.000
RMSE	0.020
Iterations	200.000

Model parameters:

Parameter	Value	Standard error
pr1	0.036	0.437
pr2	0.806	8.717
pr3	0.011	1.410
pr4	1.409	125.108

Equation of the model:

Nuclear = 0.0356485350538057+(1.40850101230925-0.0356485350538057)/(1+(Percentage RE/0.0108972033138383)^0.806137691710666)

Predictions and residuals:

Observations	Percentage RE	Nuclear	Pred(Nuclear)	Residuals
Obs1	0.133	0.200	0.197	0.003
Obs2	0.300	0.107	0.124	-0.018
Obs3	0.400	0.106	0.107	-0.001
Obs4	0.500	0.105	0.096	0.010
Obs5	0.600	0.101	0.088	0.013
Obs6	0.700	0.098	0.082	0.016
Obs7	0.800	0.080	0.077	0.003
Obs8	0.900	0.047	0.074	-0.026

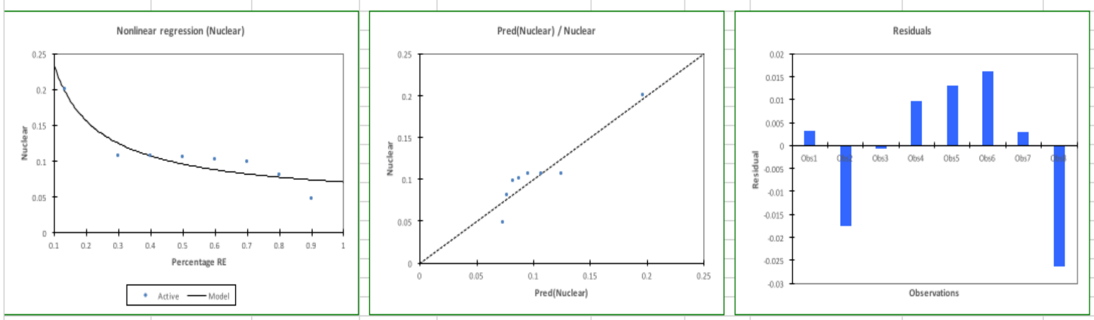


Figure 68. Nuclear power regression data part 2.

XLSTAT 2016.04.32523 - Nonlinear regression - Start time: 7/24/16 at 3:07:51 PM / End time: 7/24/16 at 3:08:20 PM
Y / Quantitative: Workbook = Emissions Calculator V3.xlsx / Sheet = General Inputs / Range = 'General Inputs'!$C$39:$C$47 / 8 rows and 1 column
X / Quantitative: Workbook = Emissions Calculator V3.xlsx / Sheet = General Inputs / Range = 'General Inputs'!$B$39:$B$47 / 8 rows and 1 column
Stop conditions: Iterations = 200 / Convergence = 1E-05
Function: Y = pr1+pr2*X1+pr3*X1^2+pr4*X1^3
Run again:

Summary statistics:

Variable	Observations	Obs. with missing data	Obs. without missing	Minimum	Maximum	Mean	Std. deviation
Nuclear	8	0	8	0.047	0.200	0.106	0.043
Percentage RE	8	0	8	0.133	0.900	0.542	0.259

Nonlinear regression of variable Nuclear:

Goodness of fit statistics:

Observations	8.000
DF	4.000
R^2	0.986
SSE	0.000
MSE	0.000
RMSE	0.007

Model parameters:

Parameter	Value	Standard error
pr1	0.336	0.020
pr2	-1.347	0.151
pr3	2.512	0.329
pr4	-1.527	0.211

Equation of the model:

Nuclear = 0.335852686746938-1.34730290984766*Percentage RE+2.51159664050057*Percentage RE^2-1.52656246330803*Percentage RE^3

Predictions and residuals:

Observations	Percentage RE	Nuclear	Pred(Nuclear)	Residuals
Obs1	0.133	0.200	0.197	0.003
Obs2	0.300	0.107	0.116	-0.010
Obs3	0.400	0.106	0.101	0.005
Obs4	0.500	0.105	0.099	0.006
Obs5	0.600	0.101	0.102	-0.001
Obs6	0.700	0.098	0.100	-0.002
Obs7	0.800	0.080	0.084	-0.004
Obs8	0.900	0.047	0.045	0.003

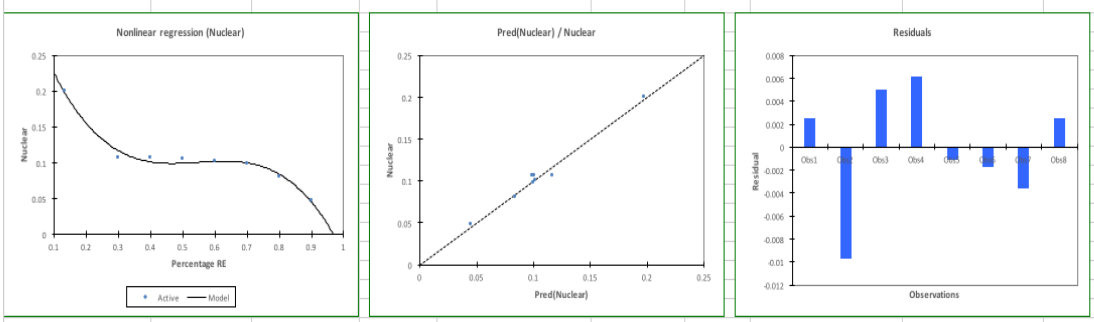


Figure 69. Nuclear power regression data part 3.

XLSTAT 2016.04.32523 - Nonlinear regression - Start time: 7/24/16 at 3:09:15 PM / End time: 7/24/16 at 3:09:42 PM
Y / Quantitative: Workbook = Emissions Calculator V3.xlsx / Sheet = General Inputs / Range = 'General Inputs'!$C$39:$C$47 / 8 rows and 1 column
X / Quantitative: Workbook = Emissions Calculator V3.xlsx / Sheet = General Inputs / Range = 'General Inputs'!$B$39:$B$47 / 8 rows and 1 column
Stop conditions: Iterations = 200 / Convergence = 1E-05
Function: Y = pr1+pr2*X1+pr3*X1^2+pr4*X1^3+pr5*X1^4+pr6*X1^5
Run again:

Summary statistics:

Variable	Observations	Obs. with missing data	without missing	Minimum	Maximum	Mean	Std. deviation
Nuclear	8	0	8	0.047	0.200	0.106	0.043
Percentage RE	8	0	8	0.133	0.900	0.542	0.259

Nonlinear regression of variable Nuclear:

Goodness of fit statistics:

Observations	8.000
DF	2.000
R²	0.999
SSE	0.000
MSE	0.000
RMSE	0.003

Model parameters:

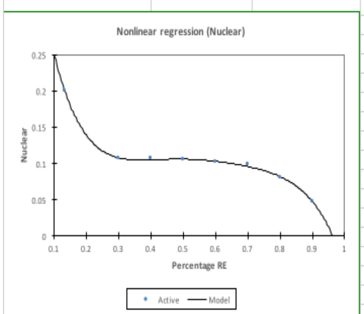
Parameter	Value	Standard error
pr1	0.530	0.054
pr2	-4.046	0.781
pr3	14.904	3.821
pr4	-26.628	8.361
pr5	23.238	8.422
pr6	-8.042	3.181

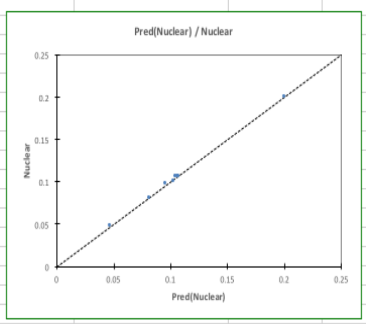
Equation of the model:

Nuclear = 0.530126673055436-4.04606950338409*Percentage RE+14.904390431296*Percentage RE^2-26.6279138799482*Percentage RE^3+23.2378226040966*Percentage RE^4-8.04199095822162*Percentage RE^5

Predictions and residuals:

Observations	Percentage RE	Nuclear	Pred(Nuclear)	Residuals
Obs1	0.133	0.200	0.200	0.000
Obs2	0.300	0.107	0.107	-0.001
Obs3	0.400	0.106	0.105	0.001
Obs4	0.500	0.105	0.106	0.000
Obs5	0.600	0.101	0.103	-0.002
Obs6	0.700	0.098	0.095	0.003
Obs7	0.800	0.080	0.082	-0.001
Obs8	0.900	0.047	0.047	0.000





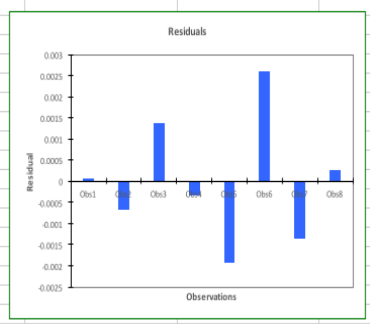


Figure 70. Nuclear power regression data part 4.

Appendix 2

Power Plant Emissions Data by Pollutant

Table 44. Power plant emissions data for carbon dioxide.

		Carbon Dioxide Emissions		
Electricity Generation Type	Percentage	CO2 (g)	CO2 per kWh	CO2 per 150,000
Wind	4.9%	11	0.54	26039.15
Photovoltaic	0.5%	48	0.25	12110.53
Concentrated Solar (CSP)	0.0%	35	0.00	25.60
Hydropower	5.8%	7	0.41	19636.18
Geothermal	0.4%	58	0.23	10828.71
Biomass	1.6%	30.78	0.50	23761.81
Oil	1.0%	942.04	9.39	450619.60
Natural Gas	32.9%	444.40	146.15	7015033.69
Coal	32.9%	962.93	316.67	15200219.10
Nuclear	19.9%	10.48	2.09	100285.36
Total:		2549.64	476.22	22858559.74
			Total tonnes:	**22.86**

Note: The data in the following tables is based on the current 2016 American grid and an electric vehicle with an efficiency of 32 kWh per 100 miles. Pollutant data was collected from GREET 2015, Klein & Whalley (2015), the National Energy Technology Laboratory's "Power Generation Technology Comparison from a Life Cycle Perspective" (Skone, Littefield, Cooney, & Marriott, 2013) and the NEEDS Project's "Final report on technical data, costs and life cycle inventories of PV applications" (Frankl, Menichetti, Raugei, Lombardelli, & Prennushi, 2005).

Table 45. Power plant emissions data for sulfur dioxide.

		Sulfur Dioxide Emissions		
Electricity Generation Type	Percentage	SO2 (mg)	SO2 per kWh	SO2 per 150,000
Wind	4.9%	0.046	0.00	108.89
Photovoltaic	0.5%	0.307	0.00	77.46
Concentrated Solar (CSP)	0.0%	0.042	0.00	0.03
Hydropower	5.8%	0.035	0.00	98.18
Geothermal	0.4%	0.08	0.00	14.94
Biomass	1.6%	0.658	0.01	507.86
Oil	1.0%	3.083	0.03	1474.51
Natural Gas	32.9%	0.095	0.03	1499.84
Coal	32.9%	3.121	1.03	49269.84
Nuclear	19.9%	0.020	0.00	193.19
Total:		7.49	1.11	53244.74
			Total tonnes:	**5.32E-05**

Table 46. Power plant emissions data for nitrous oxide.

	NOX Emissions			
Electricity Generation Type	Percentage	NOX (mg)	NOX per kWh	NOX per 150,000
Wind	4.9%	0.043	0.00	101.79
Photovoltaic	0.5%	0.178	0.00	44.91
Concentrated Solar (CSP)	0.0%	0.107	0.00	0.08
Hydropower	5.8%	0.008	0.00	22.44
Geothermal	0.4%	0.025	0.00	4.67
Biomass	1.6%	1.063	0.02	820.62
Oil	1.0%	4.301	0.04	2057.43
Natural Gas	32.9%	0.413	0.14	6522.01
Coal	32.9%	1.235	0.41	19501.83
Nuclear	19.9%	0.025	0.01	242.05
Total:		7.40	0.61	29317.83
			Total tonnes:	2.93E-05

Table 47. Power plant emissions data for particulate matter 2.5.

	PM2.5 Emissions			
Electricity Generation Type	Percentage	PM2.5 (mg)	PM2.5 per kWh	PM2.5 per 150,000
Wind	4.9%	0.008	0.00	18.94
Photovoltaic	0.5%	0.308	0.00	77.71
Concentrated Solar (CSP)	0.0%	0.017	0.00	0.01
Hydropower	5.8%	0.013	0.00	36.47
Geothermal	0.4%	0.026	0.00	4.85
Biomass	1.6%	0.612	0.01	472.42
Oil	1.0%	0.134	0.00	63.94
Natural Gas	32.9%	0.014	0.00	214.76
Coal	32.9%	0.211	0.07	3327.73
Nuclear	19.9%	0.002	0.00	18.19
Total:		1.34	0.09	4235.02
			Total tonnes:	4.24E-06

Table 48. Power plant emissions data for volatile organic compounds.

	VOC Emissions			
Electricity Generation Type	Percentage	VOCs (mg)	VOCs per kWh	VOCs per 150,000
Wind	4.9%	0.00881	0.00	20.85
Photovoltaic	0.5%	0.08800	0.00	22.20
Concentrated Solar (CSP)	0.0%	0.03760	0.00	0.03
Hydropower	5.8%	0.00002	0.00	0.04
Geothermal	0.4%	0.00044	0.00	0.08
Biomass	1.6%	0.14984	0.00	115.66
Oil	1.0%	0.07418	0.00	35.49
Natural Gas	32.9%	0.07294	0.02	1151.39
Coal	32.9%	0.08682	0.03	1370.43
Nuclear	19.9%	0.00374	0.00	35.75
Total:		0.52239	0.05733	2751.93
			Total tonnes:	2.75E-06

Appendix 3

Vehicle Production-based Emissions

Table 49. Production based emissions for electric vehicles.

EV Components Emissions	2016 Grid WTP	No Carbon Grid WTP	WTP % from Grid
CO2	40028.68995	26654.39259	33%
SO2	224.763812	195.2109832	13%
NOX	52.64059036	36.37567004	31%
PM	10.84568612	8.560861129	21%
VOCs	34.55493882	33.04337142	4%
EV ADR Emissions	**2016 Grid WTP**	**No Carbon Grid WTP**	**WTP % from Grid**
CO2	6537.845746	2317.85766	65%
SO2	9.729011354	0.404216036	96%
NOX	8.006783053	2.874717517	64%
PM	1.059578648	0.338648497	68%
VOCs	11.5966005	11.11965607	4%
EV Battery Emissions	**2016 Grid WTP**	**No Carbon Grid WTP**	**WTP % from Grid**
CO2	6553.95291	4756.561506	27%
SO2	58.11453549	54.14288752	7%
NOX	11.85678056	9.670914141	18%
PM	3.203462814	2.896401836	10%
VOCs	2.266231051	2.063089314	9%

Note: This table displays the total emissions (from a vehicle built using the 2016 grid) and the emissions from a vehicle built using a zero-emissions grid (values were taken from GREET 2015). A comparison of these values was used to determine the percentage of emissions that are actually derived from the grid. Emissions for components, ADR (assembly, disposal, and recycling) and batteries were all looked at.

Table 50. Production based emissions data for internal combustion engine vehicles.

ICE Components Emissions	2016 Grid WTP	No Carbon Grid WTP	WTP % from Grid
CO2	30164.17626	20548.64916	32%
SO2	137.9043955	116.6572212	15%
NOX	39.22690924	27.53315233	30%
PM	8.468783324	6.826095411	19%
VOCs	27.92582149	26.83907152	4%
ICE ADR Emissions	**2016 Grid WTP**	**No Carbon Grid WTP**	**WTP % from Grid**
CO2	6537.845746	2317.85766	65%
SO2	9.729011354	0.404216036	96%
NOX	8.006783053	2.874717517	64%
PM	1.059578648	0.338648497	68%
VOCs	11.5966005	11.11965607	4%
ICE Battery Emissions	**2016 Grid WTP**	**No Carbon Grid WTP**	**WTP % from Grid**
CO2	249.8826829	155.3394028	38%
SO2	4.087483605	3.878573836	5%
NOX	0.401553751	0.286576575	29%
PM	0.17994738	0.163795889	9%
VOCs	0.159229269	0.148543957	7%

Note: This table displays the total emissions (from a vehicle built using the 2016 grid) and the emissions from a vehicle built using a zero-emissions grid (values were taken from GREET 2015). A comparison of these values was used to determine the percentage of emissions that are actually derived from the grid. Emissions for components, ADR (assembly, disposal, and recycling) and batteries were all looked at.

Table 51. Production based emissions comparison data.

Total Emissions	EV Emissions	ICE Emissions
CO2	53120.48861	36951.90469
SO2	292.6073589	151.7208905
NOX	72.50415397	47.63524604
PM	15.10872758	9.708309352
VOCs	48.41777038	39.68165126

References

Anair, D. (2015). USA Today gets it wrong – The benefits of EVs are real. *Union of Concerned Scientists*. Retrieved from: http://blog.ucsusa.org/don-anair/usa-today-gets-it-wrong-the-benefits-of-evs-636

Argonne National Laboratory. (2015). GREET model. *Environmental Protection Agency*. Retrieved from: https://greet.es.anl.gov

Baumhefner, M. (2013). Wall Street Journal op-ed needs a better accountant. Switchboard. *National Resource Defense Council*. Retrieved from: http://switchboard.nrdc.org/blogs/mbaumhefner/wall_street_journal_op-ed_need.html

Berman, B. (2016, September 27). Incentives for plug-in hybrids and electric cars. *PluginCars*. Retrieved from: http://www.plugincars.com/federal-and-local-incentives-plug-hybrids-and-electric-cars.html

Block, B., & Harrison, J. (2014). Electric vehicle sales and future projections. *University of Central Florida: Electric Vehicle Transportation Center*. Retrieved from: http://evtc.fsec.ucf.edu/reports/project5-3-14-14.pdf

Bureau of Labor Statistics. (2016). *CPI inflation calculator*. Retrieved from: http://www.bls.gov/data/inflation_calculator.htm

California Air Resources Board. (2014). *February 2014 Survey Report.* Retrieved from: https://cleanvehiclerebate.org/eng/vehicle-owner-survey/feb-2014-survey

Davies, A. (2016, January 11). The Chevy bolt costs $30k and goes 200 miles on a charge. *Wired*. Retrieved from: http://www.wired.com/2016/01/the-chevy-bolt-costs-30k-and-goes-200-miles-on-a-charge/

DriveClean. (2015). *Plug-in electric vehicle resource center.* Retrieved from: http://www.driveclean.ca.gov/pev/

Edenhofer, O., Pichs-Madruga, R., Sokona, Y., Agrawala, S., Bashmakov, I.A., Blanco, G.,…Broome, J. (2014). Summary for policymakers. *Intergovernmental Panel on Climate Change.* Retrieved from: http://report.mitigation2014.org/spm/ipcc_wg3_ar5_summary-for-policymakers_approved.pdf

Epstein, P. R., Buonocore, J. J., Eckerle, K., Hendryx, M., Stout Iii, B. M., Heinberg, R., . . . Glustrom, L. (2011). Full cost accounting for the life cycle of coal. *Annals of the New York Academy of Sciences, 1219*(1), 73-98.

Fattori, Anglani, & Muliere. (2014). Combining photovoltaic energy with electric vehicles, smart charging and vehicle-to-grid. *Solar Energy, 110*, 438-451.

Frankl, P., Menichetti, E., Raugei, M., Lombardelli, S., & Prennushi, G. (2005). Final report on technical data, costs and life cycle inventories of PV applications. *New Energy Externalities Developments for Sustainability Project*. Retrieved from: http://www.needs-project.org/2009/Deliverables/RS1a%20D11.2%20Final%20report%20on%20PV%20technology.pdf

Habib, Kamran, & Rashid. (2015). Impact analysis of vehicle-to-grid technology and charging strategies of electric vehicles on distribution networks – A review. *Journal of Power Sources*, 277, 205-214.

Harris, J.M. & Roach, B. (2013). Environmental and natural resource economics: A practical approach. *Houghton Mifflin*. Armonk, New York. Third Edition.

Hawkins, T. R., Singh, B., Majeau-Bettez, G. and Strømman, A. H. (2013), Comparative Environmental Life Cycle Assessment of Conventional and Electric Vehicles. *Journal of Industrial Ecology*, 17: 53–64. doi: 10.1111/j.1530-9290.2012.00532.x

Havranek, T., Irsova, Z., Janda, K., & Zilberman, D. (2015). Selective reporting and the social cost of carbon. *Energy Economics, 51*, 394-406.

Holland, S.P., Mansur, E.T., Muller, N.Z., & Yates, A.J. (2015). Environmental benefits of driving electric vehicles? *National Bureau of Economic Research*, Working Paper No. 21291

Inside EVs. (2017, January 5). Monthly plug-in sales scorecard. Retrieved from: http://insideevs.com/monthly-plug-in-sales-scorecard/

Institute for Energy Research. (2011, March 10). *Obama administration pushes for electric vehicles*. Retrieved from: http://instituteforenergyresearch.org/analysis/obama-administration-pushes-electric-vehicles/

Interagency Working Group on Social Cost of Carbon, United States Government. (2013, May). *Technical support document -Technical update on the social cost of carbon for regulatory impact analysis*. Retrieved from https://www.whitehouse.gov/sites/default/files/omb/inforeg/scc-tsd-final-july-2015.pdf

Internal Revenue Service. (2016, February 11). *Plug-in electric drive vehicle credit.* Retrieved from: https://www.irs.gov/Businesses/Plug-In-Electric-Vehicle-Credit-IRC-30-and-IRC-30D

King, D. A. (2004). Climate Change Science: Adapt, Mitigate, or Ignore? *Science, 303*(5655), 176-177.

Kim, H., Wallington, T., Arsenault, R., Bae, C., Ahn, S., & Lee, J. (2016). Cradle-to-Gate Emissions from a Commercial Electric Vehicle Li-Ion Battery: A Comparative Analysis. *Environmental Science & Technology, 50*(14), 7715.

Kintner-Meyer, M., Pratt, R., & Schneider, K. (2006). Impacts assessment of plug-in hybrid vehicles on electric utilities and regional U.S. power grids. *Pacific Northwest National Laboratory*. Retrieved from http://energytech.pnnl.gov/publications/pdf/PHEV_Feasibility_Analysis_Part1.pdf

History of photovoltaics. (2007). *Florida Solar Energy Center*. Retrieved from http://www.fsec.ucf.edu/en/consumer/solar_electricity/basics/history_of_pv.htm

Leiby, P. (2007). Estimating the energy security benefits of reduced U.S. oil imports. *Oakridge National Laboratory*, ORNL-TM-2007-028. Retrieved from http://www.esd.ornl.gov/eess/energy_analysis/files/Leiby2007%20Estimating%20the%20Energy%20Security%20Benefits%20of%20Reduced%20U.S.%20Oil%20Imports%20ornl-tm-2007-028%20rev2007Jul25.pdf

Lopez, A., Robert, B., Heimiller, D., Blair, N,. & Porro, G. (July, 2012) U.S. renewable energy technical potentials: A GIS-based analysis. *National Renewable Energy Laboratory Technical Report*. Retrieved from: http://www.nrel.gov/docs/fy12osti/51946.pdf

MacDonald, J. (2016, February 25). Electric vehicles to be 35% of global new car sales by 2040. *Bloomberg New Energy Finance*. Retrieved from: https://about.bnef.com/blog/electric-vehicles-to-be-35-of-global-new-car-sales-by-2040/

Mai, T.; Sandor, D.; Wiser, R.; Schneider, T (2012). Renewable electricity futures study. NREL/TP-6A20-52409. Golden, CO: *National Renewable Energy Laboratory*. Retrieved from: http://www.nrel.gov/analysis/re_futures/

Michalek, J. J., Chester, M., Jaramillo, P., Samaras, C., Shiau, C.-S. N., & Lave, L. B. (2011). Valuation of plug-in vehicle life-cycle air emissions and oil displacement benefits. *Proceedings of the National Academy of Sciences*, 108(40), 16554-16558

Mills, L., & McCrone, A. (2015, January 13). Clean energy invesment. *Bloomberg New Energy Finance*. Retrieved from: https://www.bnef.com/dataview/clean-energy-investment/index.html

Montavalli, J. (2011). *High voltage*. New York, NY: Rodale Inc.

Montavalli, J. (2013). Tesla roadster battery life study: 85 percent capacity after 100,000 miles. *Plug In Cars*. Retrieved from: http://www.plugincars.com/tesla-roadster-battery-life-study-85-percent-after-100000-miles-127733.html

Moomaw, W., P. Burgherr, G. Heath, M. Lenzen, J. Nyboer, A. Verbruggen, (2011). *Annex II: Methodology. In IPCC Special Report on Renewable Energy Sources and Climate Change Mitigation*, Cambridge University Press, Cambridge, United Kingdom and New York, NY,USA.

Muller, N. (2016). *AP2 data* [Data file]. Retrieved from: https://sites.google.com/site/nickmullershomepage/home/ap2-data/Marginal_Damages_APEEP_V_2002.xls?attredirects=0&d=1

Muller, N., Mendelsohn, R., & Nordhaus, W. (2011). Environmental Accounting for Pollution in the United States Economy. *American Economic Review, 101*(5), 1649-1675.

Needell, Z., Mcnerney, J., Chang, M., & Trancik, J. (2016). Potential for widespread electrification of personal vehicle travel in the United States. *Nature Energy, 1*(9), 16112.

Nordhaus, W. (2007). A review of the Stern Review on the economics of climate change." *Journal of Economic Literature,* 45, 686–702.

Parry, I. (2009). How much should highway fuels be taxed? *Resources for the Future.* Retrieved from http://www.rff.org/RFF/Documents/RFF-DP-09-52.pdf

Parry, I. W. H., Walls, M., & Harrington, W. (2007). Automobile Externalities and Policies. *Journal of Economic Literature, 45*(2), 373-399. doi: 10.1257/jel.45.2.373

Ritte, L., Mischinger, S., Strunz, K., & Eckstein, J. (2012). Modeling photovoltaic optimized charging of electric vehicles. Innovative Smart Grid Technologies (ISGT Europe), 2012 3rd IEEE PES International Conference and Exhibition on, 1-8.

Shahan, Zachary. (2015, August 8). 1 million electric vehicles on the road in September. *Clean Technica.* Retrieved from: http://cleantechnica.com/2015/08/08/1-million-electric-cars-will-be-on-the-road-in-september/

Skone, T. J., Littefield, J., Cooney, G., & Marriott, J. (2013). Power generation technology comparison from a life cycle perspective. *Pittsburgh, PA, USA: National Energy Technology Laboratory*.

Siemer, J. & Knoll, B. (2013) Still more than enough, *Photon International*, 2, 73.

Stern, N. (2007). *The Economics of Climate Change*. Cambridge, U.K: Cambridge University Press.

Tol, R. (2008). The Social Cost of Carbon: Trends, Outliers and Catastrophes. *Economics: The Open-Access, Open-Assessment E-Journal, 2*(2008-25), 1.

United Nations Conference on Climate Change. (2015). *Details of the agreement.* Retrieved from: http://www.cop21.gouv.fr/en/more-details-about-the-agreement/

University of Michigan, Transportation Research Institute. (2016, August 4). *Monthly monitoring of vehicle fuel economy and emissions*. Retrieved from: http://www.umich.edu/%7Eumtriswt/EDI_sales-weighted-mpg.html

U.S. Department of Commerce, United States Census Bureau. (2013). *State totals: Vintage 2013.* Retrieved from http://www.census.gov/popest/data/state/totals/2013/index.html

U.S. Department of Energy. (2013). *eGallon*. Retrieved from http://energy.gov/sites/prod/files/2013/06/f1/eGallon-methodology-final.pdf

U.S. Department of Energy. (2016). *Hybrid and plug-in vehicle emissions data sources and assumptions*. Retrieved from: http://www.afdc.energy.gov/vehicles/electric_emissions_sources.html

U.S. Department of Energy. (2016). *Six charts that will make you optimistic about America's clean energy future*. Retrieved from: https://energy.gov/articles/6-charts-will-make-you-optimistic-about-america-s-clean-energy-future

U.S. Department of Energy, Energy Efficiency and Renewable Energy. (2016). *Compare electric cars side by side.* Retrieved from http://www.fueleconomy.gov/feg/evsbs.shtml

U.S. Department of Energy, National Renewable Energy Laboratory. (2016, February). *Distributed generation renewable energy estimate of costs.* Retrieved from http://www.nrel.gov/analysis/tech_lcoe_re_cost_est.html

U.S. Department of Energy, National Renewable Energy Laboratory. (2016, February). *Energy Storage: Possibilities for expanding grid flexibility.* Retrieved from http://www.nrel.gov/docs/fy16osti/64764.pdf

U.S. Department of Energy, National Renewable Energy Laboratory. (2009). *Solar maps.* Retrieved from http://www.nrel.gov/gis/solar.html

U.S. Department of Transportation, Federal Highway Administration. (2016, July 13). *Average annual miles per driver by age.* Retrieved from https://www.fhwa.dot.gov/ohim/onh00/bar8.htm

U.S. Department of Transportation, Federal Highway Administration. (2012). *Highway statistics 2012: Functional system travel, annual vehicle miles.* Retrieved from http://www.fhwa.dot.gov/policyinformation/statistics/2012/vm2.cfm

U.S. Department of Transportation, Federal Highway Administration. (2012). *Highway statistics 2012: State motor vehicle registrations.* Retrieved from http://www.fhwa.dot.gov/policyinformation/statistics/2012/mv1.cfm

U.S. Department of Transportation, Federal Highway Administration. (2012). *Highway statistics 2012: Motor fuel use.* Retrieved from http://www.fhwa.dot.gov/policyinformation/statistics/2012/mf21.cfm

U.S. Department of Transportation, Federal Highway Administration. (2009). *Summary of travel trends: 2009 National household survey.* Retrieved from http://nhts.ornl.gov/2009/pub/stt.pdf

U.S. Energy Information Administration. (2016). *Annual energy outlook 2016*. Retrieved from retrieved from: http://www.eia.gov/forecasts/aeo/

U.S. Energy Information Administration. (2013). *Arizona state profile and energy estimates*. Retrieved from http://www.eia.gov/state/?sid=AZ

U.S. Energy Information Administration. (2016, October). *Capacity factors for utility scale generators not primarily using fossil fuels.* Retrieved from: https://www.eia.gov/electricity/monthly/epm_table_grapher.cfm?t=epmt_6_07_b

U.S. Energy Information Administration. (2015). *Demand for electricity changes through the day.* Retrieved from: https://www.eia.gov/todayinenergy/detail.cfm?id=830

U.S. Energy Information Administration. (2015). *State carbon dioxide emissions.* Retrieved from: https://www.eia.gov/todayinenergy/detail.cfm?id=830

U.S. Energy Information Administration. (2016). *Use of energy in the United States.* Retrieved from: http://www.eia.gov/energyexplained/?page=us_energy_transportation

U.S. Environmental Protection Agency. (2015). *EPA fact sheet: Social cost of carbon*. Retrieved from https://www3.epa.gov/climatechange/Downloads/EPAactivities/social-cost-carbon.pdf

U.S. Environmental Protection Agency. (2011). *Greenhouse gas emissions from a typical passenger vehicle*. Retrieved from http://www.epa.gov/otaq/climate/documents/420f11041.pdf

U.S. Environmental Protection Agency. (2013). *Greenhouse gas inventory data explorer.* Retrieved from: http://www3.epa.gov/climatechange/ghgemissions/inventoryexplorer/

U.S. Environmental Protection Agency. (2012). *Light-duty automotive technology, carbon dioxide emissions, and fuel economy trends: 1975 through 2012*. Retrieved from http://epa.gov/fueleconomy/fetrends/fetrends-archive.htm

U.S. Environmental Protection Agency. (2016). *Overview of greenhouse gases.* Retrieved from https://www.epa.gov/ghgemissions/overview-greenhouse-gases

U.S. solar market insight 2012 year. (2012). *Solar Energy Industries Association*. Retrieved from http://www.seia.org/research-resources/us-solar-market-insight-2012-year-review

U.S. Environmental Protection Agency. (2013). *Sources of greenhouse gas emissions.* Retrieved from: http://www3.epa.gov/climatechange/ghgemissions/sources/electricity.html

Van Den Bergh, J. C. J. M. & Botzen. W. J. W. (2014). A lower bound to the social cost of CO2 emissions. *Nature Climate Change*, 4(4), 253-258.

Van Haaren, R. (2012). Assessment of electric cars' range requirements and usage patterns based on driving behavior recorded in the national household travel survey of 2009. *Columbia University*. Retrieved from http://www.solarjourneyusa.com/HowFarWeDrive_v1.3.pdf

Wang, T., & Chen, C. (2014). Impact of fuel price on vehicle miles traveled (VMT): Do the poor respond in the same way as the rich? *Transportation*, 41(1), 91-105.

Ancillary Appendix 1

Social Cost of Carbon Meta-Analysis

Table 52. Social cost of carbon meta-analysis data.

Name	*SCC $/ton*		*Median Value*
Nordhaus (1982)	1985.0	Nordhaus (1982)	**1134.3**
Nordhaus (1982)	283.6		
Ayres & Walter (1991)	450.8	Ayres & Walter (1991)	
Nordhaus (1991)	914.6	Nordhaus (1991)	**101.7**
Nordhaus (1991)	457.3		
Nordhaus (1991)	114.3		
Nordhaus (1991)	203.2		
Nordhaus (1991)	101.7		
Nordhaus (1991)	25.4		
Nordhaus (1991)	33.8		
Nordhaus (1991)	16.9		
Nordhaus (1991)	4.3		
Cline (1992)	245.5	Cline (1992)	
Haraden (1992)	72.6	Haraden (1992)	
Hohmeyer & Gaertner (1992)	6383.0		
Penner et al. (1992)	65.0	Penner et al. (1992)	
Haraden (1993)	7.2	Haraden (1993)	**11.6**
Haraden (1993)	11.6		
Haraden (1993)	34.2		
Nordhaus (1993)	18.9	Nordhaus (1993)	
Parry (1993)	0.0	Parry (1993)	**1.5**
Parry (1993)	0.2		
Parry (1993)	0.0		
Parry (1993)	0.2		
Parry (1993)	0.1		
Parry (1993)	0.5		
Parry (1993)	0.1		
Parry (1993)	0.8		
Parry (1993)	0.3		
Parry (1993)	2.0		
Parry (1993)	0.1		
Parry (1993)	0.3		
Parry (1993)	0.1		
Parry (1993)	0.5		
Parry (1993)	0.1		

Parry (1993)	0.8		
Parry (1993)	0.3		
Parry (1993)	1.6		
Parry (1993)	0.7		
Parry (1993)	4.2		
Parry (1993)	0.1		
Parry (1993)	0.4		
Parry (1993)	0.1		
Parry (1993)	0.5		
Parry (1993)	0.2		
Parry (1993)	1.1		
Parry (1993)	0.3		
Parry (1993)	2.0		
Parry (1993)	0.9		
Parry (1993)	5.2		
Parry (1993)	0.3		
Parry (1993)	1.6		
Parry (1993)	0.4		
Parry (1993)	2.3		
Parry (1993)	0.8		
Parry (1993)	4.7		
Parry (1993)	1.5		
Parry (1993)	8.9		
Parry (1993)	3.9		
Parry (1993)	23.4		
Parry (1993)	1.2		
Parry (1993)	7.0		
Parry (1993)	1.8		
Parry (1993)	10.6		
Parry (1993)	3.5		
Parry (1993)	20.9		
Parry (1993)	7.1		
Parry (1993)	39.9		
Parry (1993)	17.3		
Parry (1993)	104.0		
Parry (1993)	115.9		
Parry (1993)	695.8		
Parry (1993)	174.3		
Parry (1993)	1045.4		
Parry (1993)	348.3		
Parry (1993)	2089.3		
Parry (1993)	664.1		
Parry (1993)	3984.3		
Parry (1993)	1732.8		
Parry (1993)	10396.7		
Peck & Teisberg (1993)	11.1	Peck & Teisberg (1993)	**24.5**

Peck & Teisberg (1993)	24.2		
Peck & Teisberg (1993)	24.5		
Peck & Teisberg (1993)	25.4		
Peck & Teisberg (1993)	24.2		
Peck & Teisberg (1993)	24.5		
Peck & Teisberg (1993)	3.8		
Peck & Teisberg (1993)	6.1		
Peck & Teisberg (1993)	13.3		
Peck & Teisberg (1993)	11.9		
Peck & Teisberg (1993)	21.2		
Peck & Teisberg (1993)	21.3		
Peck & Teisberg (1993)	19.3		
Peck & Teisberg (1993)	25.3		
Peck & Teisberg (1993)	24.2		
Peck & Teisberg (1993)	24.8		
Peck & Teisberg (1993)	24.8		
Peck & Teisberg (1993)	24.9		
Peck & Teisberg (1993)	64.0		
Peck & Teisberg (1993)	44.0		
Peck & Teisberg (1993)	36.1		
Peck & Teisberg (1993)	57.6		
Peck & Teisberg (1993)	27.5		
Peck & Teisberg (1993)	27.9		
Peck & Teisberg (1993)	31.4		
Peck & Teisberg (1993)	14.0		
Peck & Teisberg (1993)	49.9		
Reilly & Richards (1993)	51.3	Reilly & Richards (1993)	**71.7**
Reilly & Richards (1993)	76.3		
Reilly & Richards (1993)	184.2		
Reilly & Richards (1993)	157.9		
Reilly & Richards (1993)	29.0		
Reilly & Richards (1993)	50.0		
Reilly & Richards (1993)	67.1		
Reilly & Richards (1993)	80.3		
Azar (1994)	179.4	Azar (1994)	**717.8**
Azar (1994)	717.8		
Azar (1994)	1794.5		
Fankhauser (1994)	46.6	Fankhauser (1994)	
Nordhaus (1994)	17.2	Nordhaus (1994)	
Maddison (1995)	43.0	Maddison (1995)	
Schauer (1995)	6.3	Schauer (1995)	**99.2**
Schauer (1995)	192.1		
Azar & Sterner (1996)	305.1	Azar & Sterner (1996)	**323.01**
Azar & Sterner (1996)	717.8		
Azar & Sterner (1996)	269.2		
Azar & Sterner (1996)	502.5		

Azar & Sterner (1996)	114.8		
Azar & Sterner (1996)	118.4		
Azar & Sterner (1996)	46.7		
Azar & Sterner (1996)	46.7		
Azar & Sterner (1996)	933.1		
Azar & Sterner (1996)	2117.5		
Azar & Sterner (1996)	825.5		
Azar & Sterner (1996)	1471.5		
Azar & Sterner (1996)	341.0		
Azar & Sterner (1996)	351.7		
Azar & Sterner (1996)	140.0		
Azar & Sterner (1996)	140.0		
Downing et al. (1996)	164.6	Downing et al. (1996)	**110.5**
Downing et al. (1996)	56.3		
Hohmeyer (1996)	2463.3	Hohmeyer (1996)	
Hope & Maul (1996)	25.1	Hope & Maul (1996)	**50.2**
Hope & Maul (1996)	86.1		
Hope & Maul (1996)	32.3		
Hope & Maul (1996)	68.2		
Hope & Maul (1996)	17.9		
Hope & Maul (1996)	104.1		
Nordhaus & Yang (1996)	15.0	Nordhaus & Yang (1996)	
Plambeck & Hope (1996)	10.8	Plambeck & Hope (1996)	**52.04**
Plambeck & Hope (1996)	17.9		
Plambeck & Hope (1996)	28.7		
Plambeck & Hope (1996)	28.7		
Plambeck & Hope (1996)	75.4		
Plambeck & Hope (1996)	165.1		
Plambeck & Hope (1996)	1579.2		
Plambeck & Hope (1996)	114.8		
Cline (1997)	231.7	Cline (1997)	
Nordhaus & Popp (1997)	30.8	Nordhaus & Popp (1997)	**21.9**
Nordhaus & Popp (1997)	13.0		
Eyre et al. (1999)	448.9	Eyre et al. (1999)	**308.9**
Eyre et al. (1999)	184.9		
Eyre et al. (1999)	422.5		
Eyre et al. (1999)	195.4		
Roughgarden & Schneider (1999)	70.4		
Tol (1999)	158.6	Tol (1999)	**143.9**
Tol (1999)	140.5		
Tol (1999)	52.1		
Tol (1999)	149.5		
Tol (1999)	147.3		
Tol (1999)	126.9		
Tol (1999)	917.6		
Tol (1999)	550.5		

Tol (1999)	321.7		
Tol (1999)	815.6		
Tol (1999)	788.4		
Tol (1999)	652.5		
Tol (1999)	475.8		
Tol (1999)	389.7		
Tol (1999)	165.4		
Tol (1999)	435.0		
Tol (1999)	423.7		
Tol (1999)	353.4		
Tol (1999)	65.7		
Tol (1999)	58.9		
Tol (1999)	20.4		
Tol (1999)	63.4		
Tol (1999)	63.4		
Tol (1999)	56.6		
Tol (1999)	13.6		
Tol (1999)	13.6		
Tol (1999)	4.5		
Tol (1999)	13.6		
Tol (1999)	13.6		
Tol (1999)	13.6		
Nordhaus & Boyer (2000)	21.2	Nordhaus & Boyer (2000)	
Tol & Downing (2001)	68.9	Tol & Downing (2001)	**39.7**
Tol & Downing (2001)	9.2		
Tol & Downing (2001)	120.9		
Tol & Downing (2001)	10.6		
Clarkson & Deyes (2002)	203.5	Clarkson & Deyes (2002)	
Newell & Pizer (2003)	16.0	Newell & Pizer (2003)	**18.2**
Newell & Pizer (2003)	29.1		
Newell & Pizer (2003)	18.2		
Newell & Pizer (2003)	60.5		
Newell & Pizer (2003)	94.2		
Newell & Pizer (2003)	64.9		
Newell & Pizer (2003)	4.1		
Newell & Pizer (2003)	8.0		
Newell & Pizer (2003)	5.0		
Pearce (2003)	51.8	Pearce (2003)	
Uzawa (2003)	322.2	Uzawa (2003)	
Cline (2004)	394.1	Cline (2004)	**110.5**
Cline (2004)	1019.9		
Cline (2004)	72.5		
Cline (2004)	110.5		
Cline (2004)	55.3		
Cline (2004)	31.9		
Cline (2004)	416.3		

Cline (2004)	170.7		
Cline (2004)	88.4		
Hohmeyer (2004)	114.8	Hohmeyer (2004)	**1116.2**
Hohmeyer (2004)	2117.5		
Link & Tol (2004)	179.0	Link & Tol (2004)	**136.7**
Link & Tol (2004)	385.2		
Link & Tol (2004)	57.1		
Link & Tol (2004)	213.2		
Link & Tol (2004)	11.6		
Link & Tol (2004)	102.2		
Link & Tol (2004)	171.3		
Link & Tol (2004)	380.2		
Link & Tol (2004)	55.3		
Link & Tol (2004)	212.1		
Link & Tol (2004)	11.3		
Link & Tol (2004)	102.0		
Manne (2004)	601.5	Manne (2004)	**312.8**
Manne (2004)	24.1		
Mendelsohn (2004)	4.0	Mendelsohn (2004)	
Mendelsohn (2004)	131.4	Mendelsohn (2004)	**46.4**
Mendelsohn (2004)	24.9		
Mendelsohn (2004)	-5.2		
Mendelsohn (2004)	40.8		
Mendelsohn (2004)	122.3		
Mendelsohn (2004)	24.9		
Mendelsohn (2004)	-5.7		
Mendelsohn (2004)	38.5		
Mendelsohn (2004)	122.3		
Mendelsohn (2004)	29.5		
Mendelsohn (2004)	-0.2		
Mendelsohn (2004)	45.3		
Mendelsohn (2004)	122.3		
Mendelsohn (2004)	22.7		
Mendelsohn (2004)	-5.7		
Mendelsohn (2004)	38.5		
Mendelsohn (2004)	124.6		
Mendelsohn (2004)	24.9		
Mendelsohn (2004)	-5.7		
Mendelsohn (2004)	40.8		
Mendelsohn (2004)	131.4		
Mendelsohn (2004)	27.2		
Mendelsohn (2004)	-5.2		
Mendelsohn (2004)	40.8		
Mendelsohn (2004)	165.4		
Mendelsohn (2004)	36.3		
Mendelsohn (2004)	-3.6		

Mendelsohn (2004)	54.4		
Mendelsohn (2004)	213.0		
Mendelsohn (2004)	47.6		
Mendelsohn (2004)	-1.7		
Mendelsohn (2004)	68.0		
Mendelsohn (2004)	747.7		
Mendelsohn (2004)	201.6		
Mendelsohn (2004)	38.5		
Mendelsohn (2004)	226.6		
Mendelsohn (2004)	3398.5		
Mendelsohn (2004)	815.6		
Mendelsohn (2004)	169.9		
Mendelsohn (2004)	611.7		
Mendelsohn (2004)	5437.5		
Mendelsohn (2004)	1314.1		
Mendelsohn (2004)	271.9		
Mendelsohn (2004)	815.6		
Downing et al. (2005)	101.8	Downing et al. (2005)	
Hope (2005b)	86.2	Hope (2005b)	**72.2**
Hope (2005b)	70.2		
Hope (2005b)	62.2		
Hope (2005b)	92.2		
Hope (2005b)	74.2		
Hope (2005b)	64.2		
Hope (2005a)	42.1	Hope (2005a)	
Tol (2005)	38.7	Tol (2005)	**10.1**
Tol (2005)	31.3		
Tol (2005)	7.4		
Tol (2005)	12.8		
Tol (2005)	-12.8		
Tol (2005)	-1.0		
Guo et al. (2006)	131.4	Guo et al. (2006)	**37.4**
Guo et al. (2006)	24.9		
Guo et al. (2006)	-5.2		
Guo et al. (2006)	40.8		
Guo et al. (2006)	15.0		
Guo et al. (2006)	199.4		
Guo et al. (2006)	4.8		
Guo et al. (2006)	199.4		
Guo et al. (2006)	4.8		
Guo et al. (2006)	419.1		
Guo et al. (2006)	65.7		
Guo et al. (2006)	-2.9		
Guo et al. (2006)	192.6		
Guo et al. (2006)	34.0		
Guo et al. (2006)	-4.8		

Guo et al. (2006)	79.3		
Hope (2006)	38.1	Hope (2006)	
Stern et al. (2006)	629.6	Stern et al. (2006)	
Wahba & Hope (2006)	38.1	Wahba & Hope (2006)	**59.2**
Wahba & Hope (2006)	28.1		
Wahba & Hope (2006)	94.2		
Wahba & Hope (2006)	290.7		
Wahba & Hope (2006)	60.2		
Wahba & Hope (2006)	182.5		
Wahba & Hope (2006)	58.1		
Wahba & Hope (2006)	32.4		
Stern & Taylor (2007)	183.8	Stern & Taylor (2007)	**202.2**
Stern & Taylor (2007)	220.6		
Hope (2008b)	28.1	Hope (2008b)	**26.1**
Hope (2008b)	26.1		
Hope (2008b)	26.1		
Hope (2008b)	26.1		
Hope (2008b)	24.1		
Hope (2008a)	32.1	Hope (2008a)	**134.3**
Hope (2008a)	116.3		
Hope (2008a)	156.4		
Hope (2008a)	130.3		
Hope (2008a)	50.1		
Hope (2008a)	138.4		
Hope (2008a)	124.3		
Hope (2008a)	411.1		
Hope (2008a)	405.0		
Hope (2008a)	1634.2		
Nordhaus (2008)	42.6	Nordhaus (2008)	**44.7**
Nordhaus (2008)	46.8		
Nordhaus (2008)	343.1		
Nordhaus (2008)	42.4		
Anthoff et al. (2009a)	83.9	Anthoff et al. (2009a)	**20.3**
Anthoff et al. (2009a)	14.7		
Anthoff et al. (2009a)	-9.8		
Anthoff et al. (2009a)	123.2		
Anthoff et al. (2009a)	43.9		
Anthoff et al. (2009a)	185.9		
Anthoff et al. (2009a)	21.8		
Anthoff et al. (2009a)	116.4		
Anthoff et al. (2009a)	25.0		
Anthoff et al. (2009a)	5.8		
Anthoff et al. (2009a)	36.4		
Anthoff et al. (2009a)	-2.7		
Anthoff et al. (2009a)	21.2		
Anthoff et al. (2009a)	-4.3		

Anthoff et al. (2009a)	-6.3		
Anthoff et al. (2009a)	-4.0		
Anthoff et al. (2009a)	-8.8		
Anthoff et al. (2009a)	-5.2		
Anthoff et al. (2009a)	122.6		
Anthoff et al. (2009a)	43.7		
Anthoff et al. (2009a)	214.5		
Anthoff et al. (2009a)	20.3		
Anthoff et al. (2009a)	108.2		
Anthoff et al. (2009a)	28.5		
Anthoff et al. (2009a)	5.7		
Anthoff et al. (2009a)	46.0		
Anthoff et al. (2009a)	-3.8		
Anthoff et al. (2009a)	21.2		
Anthoff et al. (2009a)	-4.8		
Anthoff et al. (2009a)	-7.5		
Anthoff et al. (2009a)	-3.2		
Anthoff et al. (2009a)	-11.0		
Anthoff et al. (2009a)	-4.8		
Anthoff et al. (2009b)	-3.1	Anthoff et al. (2009b)	**7.2**
Anthoff et al. (2009b)	-0.6		
Anthoff et al. (2009b)	14.9		
Anthoff et al. (2009b)	74.0		
Anthoff et al. (2009c)	-1.2	Anthoff et al. (2009c)	**99.6**
Anthoff et al. (2009c)	21.0		
Anthoff et al. (2009c)	350.4		
Anthoff et al. (2009c)	102.7		
Anthoff et al. (2009c)	67.9		
Anthoff et al. (2009c)	97.9		
Anthoff et al. (2009c)	379.9		
Anthoff et al. (2009c)	195.8		
Anthoff et al. (2009c)	-0.7		
Anthoff et al. (2009c)	22.0		
Anthoff et al. (2009c)	342.7		
Anthoff et al. (2009c)	101.2		
EPA & NHTSA (2009)	27.0	EPA & NHTSA (2009)	**353.5**
EPA & NHTSA (2009)	50.1		
EPA & NHTSA (2009)	353.5		
EPA & NHTSA (2009)	608.0		
EPA & NHTSA (2009)	1018.0		
Narita et al. (2009)	142.3	Narita et al. (2009)	**11.8**
Narita et al. (2009)	11.8		
Narita et al. (2009)	-3.9		
Anthoff & Tol (2010)	25.9	Anthoff & Tol (2010)	**25.9**
Anthoff & Tol (2010)	46.5		
Anthoff & Tol (2010)	169.3		

Anthoff & Tol (2010)	303.7		
Anthoff & Tol (2010)	1.1		
Anthoff & Tol (2010)	1.9		
Anthoff & Tol (2010)	93.2		
Anthoff & Tol (2010)	119.7		
Anthoff & Tol (2010)	7.8		
Anthoff & Tol (2010)	21.6		
Anthoff & Tol (2010)	2.5		
Anthoff & Tol (2010)	12.1		
Anthoff & Tol (2010)	25.9		
Anthoff & Tol (2010)	32.3		
Anthoff & Tol (2010)	25.9		
Anthoff & Tol (2010)	75.2		
Kemfert & Schill (2010)	70.4	Kemfert & Schill (2010)	**102.8**
Kemfert & Schill (2010)	102.8		
Kemfert & Schill (2010)	248.9		
Narita et al. (2010)	187.4	Narita et al. (2010)	**28.6**
Narita et al. (2010)	28.6		
Narita et al. (2010)	1.3		
Nordhaus (2010)	42.4	Nordhaus (2010)	
Sohngen (2010)	34.5	Sohngen (2010)	
Tol (2010)	3.3	Tol (2010)	
Anthoff et al. (2011)	1.9	Anthoff et al. (2011)	**42.5**
Anthoff et al. (2011)	43.4		
Anthoff et al. (2011)	266.1		
Anthoff et al. (2011)	-3.3		
Anthoff et al. (2011)	2.2		
Anthoff et al. (2011)	11.6		
Anthoff et al. (2011)	65.0		
Anthoff et al. (2011)	83.1		
Anthoff et al. (2011)	2689.9		
Anthoff et al. (2011)	1.0		
Anthoff et al. (2011)	4.2		
Anthoff et al. (2011)	16.5		
Anthoff et al. (2011)	92.3		
Anthoff et al. (2011)	75.5		
Anthoff et al. (2011)	2160.5		
Anthoff et al. (2011)	130.9		
Anthoff et al. (2011)	17.3		
Anthoff et al. (2011)	41.6		
Anthoff et al. (2011)	3.4		
Anthoff et al. (2011)	107.3		
Anthoff et al. (2011)	7.4		
Anthoff et al. (2011)	74.4		
Ceronsky et al. (2011)	644.6	Ceronsky et al. (2011)	**155.02**
Ceronsky et al. (2011)	624.7		

Ceronsky et al. (2011)	673.7
Ceronsky et al. (2011)	828.7
Ceronsky et al. (2011)	1190.0
Ceronsky et al. (2011)	968.6
Ceronsky et al. (2011)	1874.2
Ceronsky et al. (2011)	2190.1
Ceronsky et al. (2011)	418.4
Ceronsky et al. (2011)	397.5
Ceronsky et al. (2011)	427.8
Ceronsky et al. (2011)	493.0
Ceronsky et al. (2011)	679.5
Ceronsky et al. (2011)	841.5
Ceronsky et al. (2011)	1662.1
Ceronsky et al. (2011)	1946.5
Ceronsky et al. (2011)	125.9
Ceronsky et al. (2011)	122.4
Ceronsky et al. (2011)	130.5
Ceronsky et al. (2011)	157.4
Ceronsky et al. (2011)	218.0
Ceronsky et al. (2011)	180.7
Ceronsky et al. (2011)	300.7
Ceronsky et al. (2011)	338.0
Ceronsky et al. (2011)	99.1
Ceronsky et al. (2011)	94.4
Ceronsky et al. (2011)	101.4
Ceronsky et al. (2011)	115.4
Ceronsky et al. (2011)	152.7
Ceronsky et al. (2011)	169.0
Ceronsky et al. (2011)	275.1
Ceronsky et al. (2011)	308.9
Ceronsky et al. (2011)	9.3
Ceronsky et al. (2011)	9.3
Ceronsky et al. (2011)	9.3
Ceronsky et al. (2011)	12.8
Ceronsky et al. (2011)	17.5
Ceronsky et al. (2011)	14.0
Ceronsky et al. (2011)	21.0
Ceronsky et al. (2011)	22.1
Ceronsky et al. (2011)	5.8
Ceronsky et al. (2011)	4.7
Ceronsky et al. (2011)	5.8
Ceronsky et al. (2011)	7.0
Ceronsky et al. (2011)	11.7
Ceronsky et al. (2011)	10.5
Ceronsky et al. (2011)	16.3
Ceronsky et al. (2011)	17.5

Dietz (2011)	2614.7	Dietz (2011)	**2325.2**
Dietz (2011)	2035.8		
Hope (2011)	502.2	Hope (2011)	**381.2**
Hope (2011)	260.2		
Nordhaus (2011)	45.2	Nordhaus (2011)	
Pycroft et al. (2011)	241.1	Pycroft et al. (2011)	**265.7**
Pycroft et al. (2011)	280.4		
Pycroft et al. (2011)	280.4		
Pycroft et al. (2011)	265.7		
Pycroft et al. (2011)	236.2		
Pycroft et al. (2011)	246.0		
Pycroft et al. (2011)	246.0		
Pycroft et al. (2011)	246.0		
Pycroft et al. (2011)	285.4		
Pycroft et al. (2011)	280.4		
Pycroft et al. (2011)	270.6		
Waldhoff et al. (2011)	42.0	Waldhoff et al. (2011)	**41.9**
Waldhoff et al. (2011)	73.4		
Waldhoff et al. (2011)	36.7		
Waldhoff et al. (2011)	15.7		
Waldhoff et al. (2011)	94.4		
Waldhoff et al. (2011)	267.6		
Waldhoff et al. (2011)	1.6		
Waldhoff et al. (2011)	131.2		
Waldhoff et al. (2011)	10.5		
Waldhoff et al. (2011)	15.7		
Waldhoff et al. (2011)	42.0		
Waldhoff et al. (2011)	63.0		
Waldhoff et al. (2011)	42.0		
Ackerman & Munitz (2012)	27.9	Ackerman & Munitz (2012)	**77.34**
Ackerman & Munitz (2012)	77.3		
Ackerman & Munitz (2012)	85.8		
Ackerman & Stanton (2012)	530.4	Ackerman & Stanton (2012)	**480.9**
Ackerman & Stanton (2012)	125.8		
Ackerman & Stanton (2012)	1083.2		
Ackerman & Stanton (2012)	278.7		
Ackerman & Stanton (2012)	1847.3		
Ackerman & Stanton (2012)	346.1		
Ackerman & Stanton (2012)	2000.1		
Ackerman & Stanton (2012)	431.5		
Botzen & van den Bergh (2012)	46.8	47.1 47.3	
Botzen & van den Bergh (2012)	47.3		
Cai et al. (2012)	35.7	Cai et al. (2012)	**40.8**
Cai et al. (2012)	45.8		
Espagne et al. (2012)	87.5	Espagne et al. (2012)	**437.4**
Espagne et al. (2012)	787.3		

Gerlagh & Liski (2012)	46.7	Gerlagh & Liski (2012)	**163.3**
Gerlagh & Liski (2012)	163.3		
Gerlagh & Liski (2012)	183.3		
Johnson & Hope (2012)	1195.6	Johnson & Hope (2012)	**202.2**
Johnson & Hope (2012)	548.3		
Johnson & Hope (2012)	278.7		
Johnson & Hope (2012)	157.3		
Johnson & Hope (2012)	94.4		
Johnson & Hope (2012)	22.5		
Johnson & Hope (2012)	247.2		
Johnson & Hope (2012)	786.5		
Johnson & Hope (2012)	62.9		
Johnson & Hope (2012)	27.0		
Johnson & Hope (2012)	-6.3		
Johnson & Hope (2012)	651.7		
Johnson & Hope (2012)	314.6		
Johnson & Hope (2012)	4.5		
Kopp et al. (2012)	495.4	Kopp et al. (2012)	**450.3**
Kopp et al. (2012)	525.4		
Kopp et al. (2012)	480.4		
Kopp et al. (2012)	690.5		
Kopp et al. (2012)	360.3		
Kopp et al. (2012)	705.5		
Kopp et al. (2012)	405.3		
Kopp et al. (2012)	525.4		
Kopp et al. (2012)	495.4		
Kopp et al. (2012)	675.5		
Kopp et al. (2012)	225.2		
Kopp et al. (2012)	165.1		
Kopp et al. (2012)	300.2		
Kopp et al. (2012)	120.1		
Kopp et al. (2012)	120.1		
Kopp et al. (2012)	105.1		
Kopp et al. (2012)	135.1		
Kopp et al. (2012)	90.1		
Kopp et al. (2012)	585.4		
Kopp et al. (2012)	615.4		
Kopp et al. (2012)	555.4		
Kopp et al. (2012)	930.7		
Kopp et al. (2012)	585.4		
Kopp et al. (2012)	1155.8		
Kopp et al. (2012)	450.3		
Kopp et al. (2012)	615.4		
Kopp et al. (2012)	585.4		
Kopp et al. (2012)	855.6		
Kopp et al. (2012)	270.2		

Kopp et al. (2012)	195.1
Kopp et al. (2012)	390.3
Kopp et al. (2012)	210.2
Kopp et al. (2012)	135.1
Kopp et al. (2012)	105.1
Kopp et al. (2012)	150.1
Kopp et al. (2012)	120.1
Kopp et al. (2012)	660.5
Kopp et al. (2012)	690.5
Kopp et al. (2012)	600.4
Kopp et al. (2012)	1140.8
Kopp et al. (2012)	810.6
Kopp et al. (2012)	1666.2
Kopp et al. (2012)	480.4
Kopp et al. (2012)	690.5
Kopp et al. (2012)	660.5
Kopp et al. (2012)	1005.7
Kopp et al. (2012)	300.2
Kopp et al. (2012)	210.2
Kopp et al. (2012)	450.3
Kopp et al. (2012)	285.2
Kopp et al. (2012)	150.1
Kopp et al. (2012)	120.1
Kopp et al. (2012)	150.1
Kopp et al. (2012)	150.1
Kopp et al. (2012)	855.6
Kopp et al. (2012)	915.7
Kopp et al. (2012)	750.5
Kopp et al. (2012)	1921.4
Kopp et al. (2012)	1921.4
Kopp et al. (2012)	4143.0
Kopp et al. (2012)	540.4
Kopp et al. (2012)	900.7
Kopp et al. (2012)	855.6
Kopp et al. (2012)	1411.0
Kopp et al. (2012)	390.3
Kopp et al. (2012)	240.2
Kopp et al. (2012)	630.5
Kopp et al. (2012)	630.5
Kopp et al. (2012)	195.1
Kopp et al. (2012)	135.1
Kopp et al. (2012)	180.1
Kopp et al. (2012)	225.2
Kopp et al. (2012)	450.3
Kopp et al. (2012)	465.3
Kopp et al. (2012)	420.3

Kopp et al. (2012)	690.5
Kopp et al. (2012)	330.2
Kopp et al. (2012)	870.6
Kopp et al. (2012)	360.3
Kopp et al. (2012)	450.3
Kopp et al. (2012)	450.3
Kopp et al. (2012)	510.4
Kopp et al. (2012)	165.1
Kopp et al. (2012)	135.1
Kopp et al. (2012)	225.2
Kopp et al. (2012)	105.1
Kopp et al. (2012)	90.1
Kopp et al. (2012)	75.1
Kopp et al. (2012)	105.1
Kopp et al. (2012)	75.1
Kopp et al. (2012)	525.4
Kopp et al. (2012)	540.4
Kopp et al. (2012)	480.4
Kopp et al. (2012)	915.7
Kopp et al. (2012)	525.4
Kopp et al. (2012)	1366.0
Kopp et al. (2012)	390.3
Kopp et al. (2012)	525.4
Kopp et al. (2012)	525.4
Kopp et al. (2012)	585.4
Kopp et al. (2012)	195.1
Kopp et al. (2012)	135.1
Kopp et al. (2012)	270.2
Kopp et al. (2012)	150.1
Kopp et al. (2012)	105.1
Kopp et al. (2012)	90.1
Kopp et al. (2012)	105.1
Kopp et al. (2012)	90.1
Kopp et al. (2012)	585.4
Kopp et al. (2012)	585.4
Kopp et al. (2012)	525.4
Kopp et al. (2012)	1080.8
Kopp et al. (2012)	720.5
Kopp et al. (2012)	1831.3
Kopp et al. (2012)	420.3
Kopp et al. (2012)	585.4
Kopp et al. (2012)	585.4
Kopp et al. (2012)	660.5
Kopp et al. (2012)	210.2
Kopp et al. (2012)	150.1
Kopp et al. (2012)	300.2

Kopp et al. (2012)	195.1		
Kopp et al. (2012)	120.1		
Kopp et al. (2012)	90.1		
Kopp et al. (2012)	120.1		
Kopp et al. (2012)	120.1		
Kopp et al. (2012)	720.5		
Kopp et al. (2012)	735.5		
Kopp et al. (2012)	630.5		
Kopp et al. (2012)	1621.2		
Kopp et al. (2012)	1621.2		
Kopp et al. (2012)	3422.5		
Kopp et al. (2012)	480.4		
Kopp et al. (2012)	720.5		
Kopp et al. (2012)	720.5		
Kopp et al. (2012)	825.6		
Kopp et al. (2012)	255.2		
Kopp et al. (2012)	165.1		
Kopp et al. (2012)	390.3		
Kopp et al. (2012)	390.3		
Kopp et al. (2012)	150.1		
Kopp et al. (2012)	105.1		
Kopp et al. (2012)	135.1		
Kopp et al. (2012)	180.1		
Marten & Newbold (2012)	42.4	Marten & Newbold (2012)	**142.6769813**
Marten & Newbold (2012)	142.7		
Marten & Newbold (2012)	223.7		
Perrissin-Fabert et al. (2012)	51.3		
Tol (2012)	48.4	Tol (2012)	
Anthoff & Tol (2013)	535.2	Anthoff & Tol (2013)	**73.54382152**
Anthoff & Tol (2013)	209.7		
Anthoff & Tol (2013)	88.8		
Anthoff & Tol (2013)	147.6		
Anthoff & Tol (2013)	64.6		
Anthoff & Tol (2013)	73.5		
Anthoff & Tol (2013)	470.6		
Anthoff & Tol (2013)	29.0		
Anthoff & Tol (2013)	14.3		
Anthoff & Tol (2013)	5.5		
Anthoff & Tol (2013)	1.0		
van den Bijgaart et al. (2013)	233.6	van den Bijgaart et al. (2013)	**28.4**
van den Bijgaart et al. (2013)	38.8		
van den Bijgaart et al. (2013)	18.2		
van den Bijgaart et al. (2013)	10.9		
Cai et al. (2013)	171.9	Cai et al. (2013)	**286.5**
Cai et al. (2013)	286.6		
Cai et al. (2013)	552.7		

Dennig (2013)	126.2	Dennig (2013)	
Foley et al. (2013)	246.3	Foley et al. (2013)	
Greenstone et al. (2013)	48.5	Greenstone et al. (2013)	**86.7**
Greenstone et al. (2013)	33.7		
Greenstone et al. (2013)	44.0		
Greenstone et al. (2013)	38.7		
Greenstone et al. (2013)	36.9		
Greenstone et al. (2013)	37.3		
Greenstone et al. (2013)	23.4		
Greenstone et al. (2013)	32.4		
Greenstone et al. (2013)	28.8		
Greenstone et al. (2013)	24.7		
Greenstone et al. (2013)	-5.8		
Greenstone et al. (2013)	-1.3		
Greenstone et al. (2013)	-8.5		
Greenstone et al. (2013)	-2.7		
Greenstone et al. (2013)	-12.1		
Greenstone et al. (2013)	160.9		
Greenstone et al. (2013)	98.9		
Greenstone et al. (2013)	133.9		
Greenstone et al. (2013)	129.4		
Greenstone et al. (2013)	111.9		
Greenstone et al. (2013)	177.5		
Greenstone et al. (2013)	100.2		
Greenstone et al. (2013)	136.2		
Greenstone et al. (2013)	142.9		
Greenstone et al. (2013)	114.2		
Greenstone et al. (2013)	36.9		
Greenstone et al. (2013)	36.0		
Greenstone et al. (2013)	16.2		
Greenstone et al. (2013)	45.8		
Greenstone et al. (2013)	-0.9		
Greenstone et al. (2013)	243.6		
Greenstone et al. (2013)	142.0		
Greenstone et al. (2013)	195.5		
Greenstone et al. (2013)	199.6		
Greenstone et al. (2013)	168.1		
Greenstone et al. (2013)	294.4		
Greenstone et al. (2013)	155.5		
Greenstone et al. (2013)	221.1		
Greenstone et al. (2013)	245.9		
Greenstone et al. (2013)	192.8		
Greenstone et al. (2013)	86.7		
Greenstone et al. (2013)	66.5		
Greenstone et al. (2013)	39.6		
Greenstone et al. (2013)	99.8		

Greenstone et al. (2013)	22.0		
Greenstone et al. (2013)	91.8		
Greenstone et al. (2013)	148.1		
Hwang et al. (2013)	48.5	Hwang et al. (2013)	**71.3**
Hwang et al. (2013)	51.6		
Hwang et al. (2013)	63.7		
Hwang et al. (2013)	81.9		
Hwang et al. (2013)	479.3		
Hwang et al. (2013)	215.4		
Hwang et al. (2013)	122.9		
Hwang et al. (2013)	78.9		
Hwang et al. (2013)	109.2		
Hwang et al. (2013)	48.5		
Hwang et al. (2013)	28.8		
Hwang et al. (2013)	21.2		
Jensen & Traeger (2014b)	46.0	Jensen & Traeger (2014b)	
Lintunen & Vilmi (2013)	116.6	Lintunen & Vilmi (2013)	
Moyer et al. (2013)	71.9	Moyer et al. (2013)	**507.9**
Moyer et al. (2013)	943.9		
Newbold et al. (2013)	61.4	Newbold et al. (2013)	**61.2**
Newbold et al. (2013)	17.4		
Newbold et al. (2013)	61.2		
Nordhaus & Sztorc (2014)	80.2	Nordhaus & Sztorc (2014)	
Tol (2013)	0.1	Tol (2013)	**0.9**
Tol (2013)	0.0		
Tol (2013)	0.7		
Tol (2013)	-0.5		
Tol (2013)	0.4		
Tol (2013)	-0.2		
Tol (2013)	1.1		
Tol (2013)	21.4		
Tol (2013)	4.8		
Tol (2013)	95.8		
Tol (2013)	1.3		
Tol (2013)	203.0		
Tol (2013)	0.2		
Tol (2013)	250.0		
Weitzman (2013)	4.5	Weitzman (2013)	**346.1**
Weitzman (2013)	22.5		
Weitzman (2013)	94.4		
Weitzman (2013)	157.3		
Weitzman (2013)	278.7		
Weitzman (2013)	548.3		
Weitzman (2013)	1195.6		
Weitzman (2013)	1195.6		
Weitzman (2013)	1024.8		

Weitzman (2013)	822.5		
Weitzman (2013)	629.2		
Weitzman (2013)	413.5		
Weitzman (2013)	202.3		
Weitzman (2013)	4.5		
Golosov et al. (2014)	58.6	Golosov et al. (2014)	**227.8**
Golosov et al. (2014)	511.2		
Golosov et al. (2014)	26.1		
Golosov et al. (2014)	504.0		
Golosov et al. (2014)	227.8		
Golosov et al. (2014)	4393.7		
Golosov et al. (2014)	33.0		
Howarth et al. (2014)	47.7	Howarth et al. (2014)	**128.8**
Howarth et al. (2014)	210.0		
Jensen & Traeger (2014a)	37.2	Jensen & Traeger (2014a)	**53.7**
Jensen & Traeger (2014a)	45.7		
Jensen & Traeger (2014a)	47.8		
Jensen & Traeger (2014a)	90.3		
Jensen & Traeger (2014a)	75.5		
Jensen & Traeger (2014a)	59.5		
Lemoine & Traeger (2014)	40.9	Lemoine & Traeger (2014)	**49.1**
Lemoine & Traeger (2014)	49.1		
Lemoine & Traeger (2014)	49.1		
Lemoine & Traeger (2014)	61.4		
Lemoine & Traeger (2014)	57.3		
Newbold & Marten (2014)	49.1	Newbold & Marten (2014)	
Pycroft et al. (2014)	236.2	Pycroft et al. (2014)	**292.8**
Pycroft et al. (2014)	285.4		
Pycroft et al. (2014)	280.4		
Pycroft et al. (2014)	270.6		
Pycroft et al. (2014)	300.1		
Pycroft et al. (2014)	339.5		
Pycroft et al. (2014)	334.6		
Pycroft et al. (2014)	324.7		
Rezai & van der Ploeg (2014)	87.4	99.07284383 110.7	
Rezai & van der Ploeg (2014)	110.7		

Note: The data for the following table was taken from the meta-analysis by Havranek et al. (2015) The median value from each study was the only value that was used, as I did not want to give extra weight to studies that included a greater number of estimates. Each median value was multiplied by the Bureau of Labor Statistics' value of 1.11 to convert the 2010 dollars into 2016 dollars.

Ancillary Appendix 2

Alternate Battery Production Data

Table 53. Cradle to gate emissions data for an electric vehicle's battery.

Table S1: Detailed Cradle-to-gate emissions from Focus BEV battery

Functional unit	1 kWh battery						1 kg battery					
Pollutant	GHG (kg CO_2- eq.)	VOC (g)	CO (g)	NO_x (g)	PM (g)	SO_x (g)	GHG (kg CO_2- eq.)	VOC (g)	CO (g)	NO_x (g)	PM (g)	SO_x (g)
Cell materials	27	43	102	96	62	845	2.2	3.4	8.2	7.7	4.9	67.6
Cell manufacturing	63	10	17	182	12	185	5.0	0.8	1.3	14.6	1.0	14.8
Enclosure	25	24	185	57	80	86	2.0	1.9	14.8	4.5	6.4	6.8
Thermal Management	5.9	1.5	39	11	11	22	0.5	0.1	3.2	0.9	0.9	1.7
Electrical System	0.5	1.2	2.1	5.9	6.0	27	0.04	0.1	0.2	0.5	0.5	2.2
BMS	13	1.6	5.3	15	5.0	25	1.0	0.1	0.4	1.2	0.4	2.0
Pack manufacturing	1.7	0.2	0.7	3.2	1.5	8.8	0.1	0.02	0.1	0.3	0.1	0.7
Transportation	4.1	6.5	9.2	34	3.3	18	0.3	0.5	0.7	2.7	0.3	1.5
Total	141	87	360	404	181	1282	11.3	7.0	28.8	32.3	14.5	97.4

Note: The following table was taken from the supporting information for the paper "Cradle-to-Gate Emissions from a Commercial Electric Vehicle Li-Ion Battery: A Comparative Analysis," by Kim et al. These tables detail the cradle-to-gate emissions for lithium ion batteries.

Table 54. Greenhouse gas emissions meta-analysis for an electric vehicle's battery.

Table S2: Comparison of GHG emissions estimates across studies

Reference	Battery type	Mass (kg)		Total energy (kWh)	Specific energy (kWh/kg)		GHG emissions (primary energy) from cradle-to-gate of battery				GHG emissions from cradle-to-gate of cell			
							kg CO_2-eq./kg battery (MJ_p/kg battery)		kg CO_2-eq./kWh battery		kg CO_2-eq./kg cell		kg CO_2-eq./kWh cell	
		Battery	Cell		Battery	Cell	Materials /parts	Cell /pack mfg.	Materials /parts	Cell /pack mfg.	Materials /parts	Cell mfg.	Materials /parts	Cell mfg.
Notter et al. (2010)[1]	LMO	300	240	34.2	0.114	0.14	5.8	0.16 (2.4)	51	1.4	5.5	0.13	39	0.88
Dunn et al. (2012)[2]; GREET (2015)[3]	LMO	210	190[a]	28	0.13	0.15	4.9	0.27 (3.9)	37	2.1	4.8	0.3	33	2.0
EPA (2013)[4]	LMO	na	80%[b] of battery	na	0.08-0.1	0.1-0.125	6.2	0.18 (2.9)	62	1.8	6.3	0.22	50	1.8
Majeau-Bettez et al. (2011)[5]; Hawkins et al. (2013)[6]	NCM	214	171	24	0.112	0.14	16.0	6.0 (80-105)[c]	143	54	15.1	7.5	108	54
EPA (2013)[4]	NCM	na	80%[b] of battery	na	0.08-0.1	0.1-0.125	8.7	3.4 (62.1)	87	34	9.4	0	76	0
Ellingsen et al. (2014)[7]	NCM	253	152	26.6	0.11	0.17	6.9	[d]11.3 (180); [e]18.5 (300); [f]44.5 (730)	65	108; 176; 425	5.7	18.7; 30.6; 73.9	33	107; 175; 424
This study	LMO /NCM	303	168	24	0.08	0.14	6.1	5.2 (120)	76	65	4.0	9.1	28	64

[a] estimated based on materials breakdown; [b] average value of the range in EPA (2013); [c] estimated from the direct energy inputs in Ellingsen et al. (2014)[7], 371-473 MJ/kWh, based on an electric and fossil energy share of 51.7% and 48.3% respectively and a primary energy to electricity conversion factor of 0.35 as in Majeau-Bettez et al. (2011)[5]; [d] lower bound value; [e] asymptotic value; [f] average value[7]

Note: The following table was taken from the supporting information for the paper "Cradle-to-Gate Emissions from a Commercial Electric Vehicle Li-Ion Battery: A Comparative Analysis," by Kim et al. These tables detail the cradle-to-gate emissions for lithium ion batteries

Ancillary Appendix 3

Carbon Emissions and Battery Capacity

The data in the following figures describe the relationship between an electric vehicle's battery capacity (in kWh) and the total tons of CO2 that can be assigned to the vehicle. The blue line describes the CO2 emissions from an electric vehicle with a standard life-cycle, while the red line is used to depict the CO2 emissions for an electric vehicle that needs one battery replacement. These scenarios are then compared to an ICE vehicle with an efficiency of 25.4 miles per gallon (purple dashed line) and 20 miles per gallon (green dashed line). In total, there are five figures, each detailing a different RE% scenario: 13.3% (2016 grid), 20%, 50%, 80%, and 100% RE. The battery emissions data for these figures was taken from Kim et al. and entered into my model.

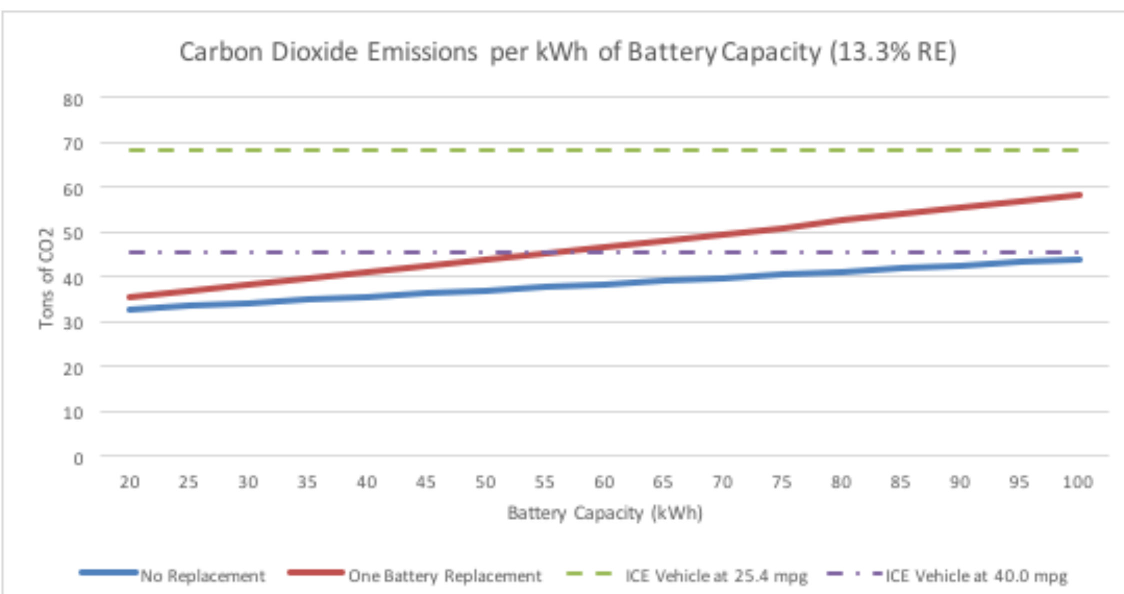


Figure 71. Carbon dioxide emission per kWh for a grid with 13.3% renewable energy.

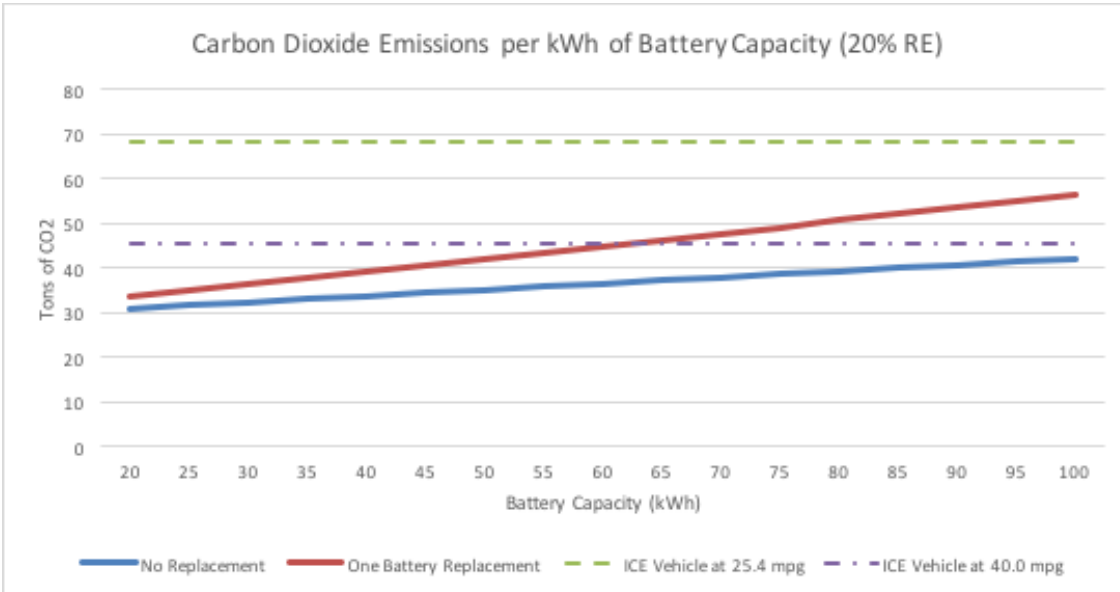


Figure 72. Carbon dioxide emission per kWh for a grid with 20% renewable energy.

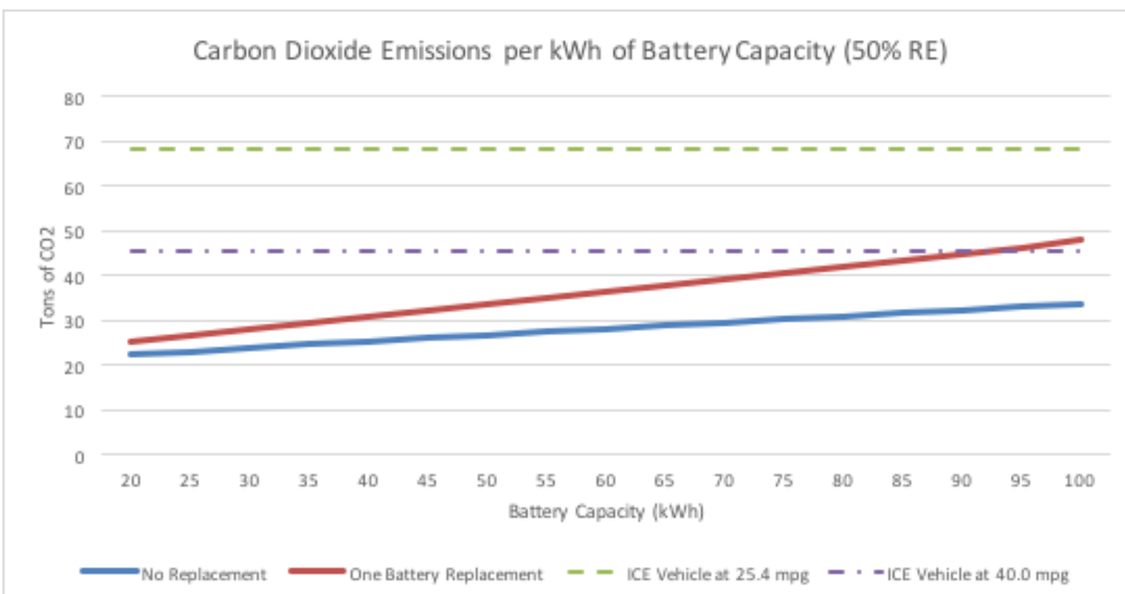


Figure 73. Carbon dioxide emission per kWh for a grid with 50% renewable energy.

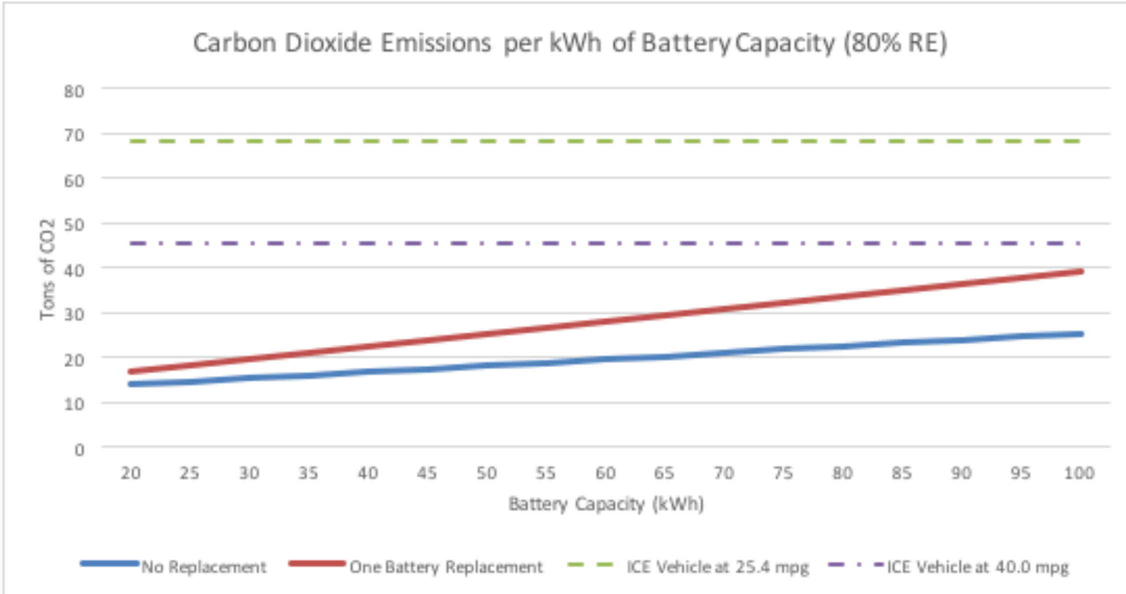


Figure 74. Carbon dioxide emission per kWh for a grid with 80% renewable energy.

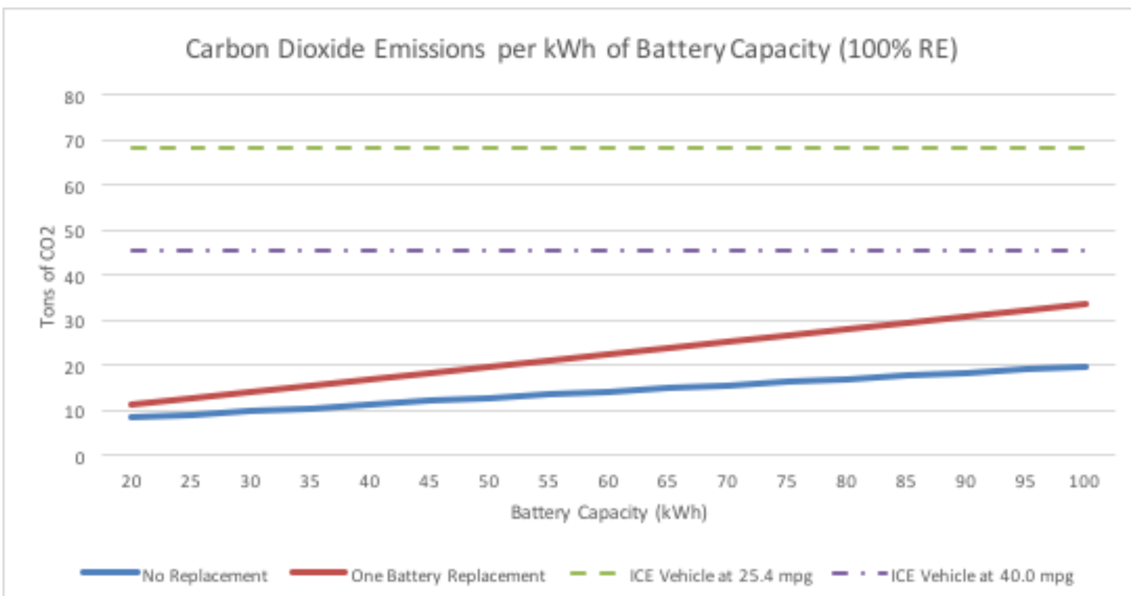


Figure 75. Carbon dioxide emission per kWh for a grid with 100% renewable energy.

Ancillary Appendix 4

Sample EV Emissions Data

It is possible to use the per kWh battery emissions data from Kim et al. to model the life-cycle CO2 emissions for electric vehicles that are currently on the market. This data is displayed in the figure and table below.

Table 54. Carbon emissions data by electric vehicle.

Car Model	*kWh per 100 mi*	*Operating CO2*	*kWh Battery*	*Production CO2*	*Total CO2*	*Total Co2 with Replacement*
2016 BMW i3	27	19.29	23	10.23	29.51	32.76
2017 Chevrolet Bolt	28	20.00	60	15.44	35.45	43.91
2016 Nissan Leaf	30	21.43	30	11.21	32.64	36.87
2016 Tesla Model S 90D	32	22.86	90	19.67	42.53	55.22

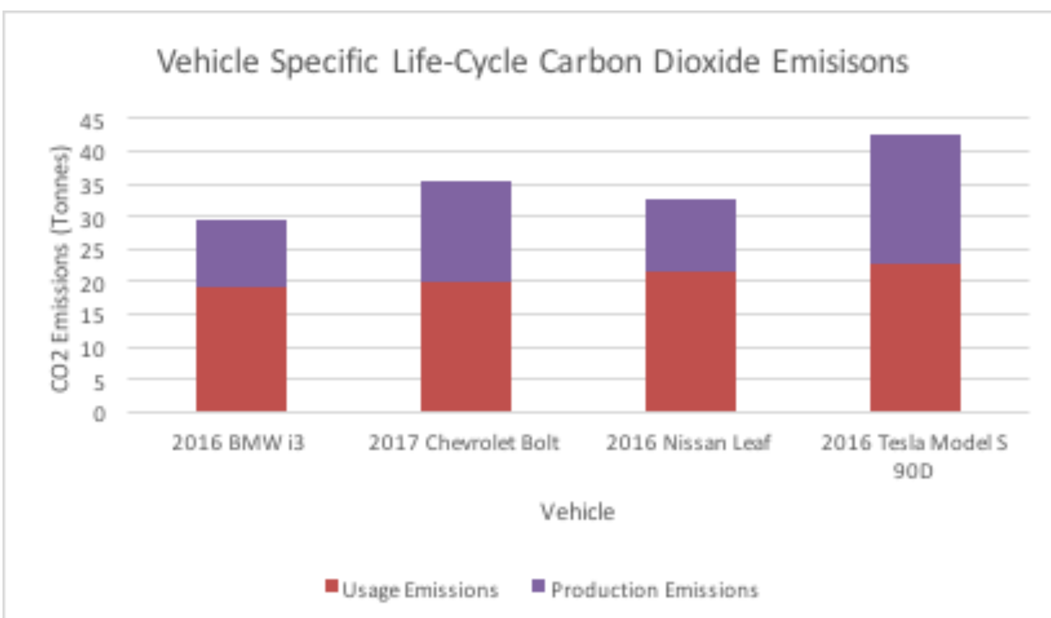


Figure 76. Carbon emissions data by electric vehicle.

Ancillary Appendix 5

EIA Power Plant Projections

Table 55. EIA power plant projections.

Year	Coal	Natural Gas	Oil	Nuclear GW	Hydropower	Geothermal	Biomass	Solar Thermal	Solar PV	Wind	Total	Percentage Renewable
2014	1581.546509	1128.669922	30.069641	797.067993	262.254181	15.877	47.734681	2.521398	14.992	180.889008	4061.622333	0.129078537
2015	1354.901123	1348.267334	25.836992	797.686523	245.48114	16.675781	31.730382	3.309412	18.81949	187.539871	4030.248048	0.12494419
2016	1356.836426	1330.272583	24.28495	781.334595	254.966125	17.164848	32.141332	3.486698	28.081173	213.301514	4041.870244	0.135863265
2017	1365.220581	1322.622559	21.897411	786.220337	271.444641	17.248056	30.249152	4.221064	44.224918	231.140839	4094.489558	0.146179069
2018	1386.101318	1288.804688	21.240395	771.425903	280.694794	16.967447	38.713007	4.434896	47.578037	251.332031	4107.292516	0.155752289
2019	1387.015137	1265.559937	15.100471	770.34552	292.973572	18.884289	39.173755	4.457641	47.791279	303.931396	4145.232997	0.170608488
2020	1388.029053	1201.190063	14.876619	777.491516	292.73172	21.482309	39.730753	4.487856	47.806011	364.458893	4152.284793	0.185608064
2021	1346.798218	1163.623413	14.560392	787.106323	292.747528	23.868671	39.31923	4.503494	64.461746	430.679474	4167.668489	0.205289875
2022	1296.130493	1196.445068	14.221413	789.090454	292.764923	26.277197	40.242681	4.516656	88.071999	448.536346	4196.29723	0.214572456
2023	1272.746704	1244.237793	13.968439	789.090454	292.785095	28.620718	42.350971	4.530266	102.323143	449.760498	4240.414081	0.217047362
2024	1222.292114	1326.68103	13.628058	789.090454	293.459045	30.774544	45.095275	4.540166	105.242027	449.859985	4280.662698	0.217015707
2025	1179.269043	1396.410889	13.192623	789.090454	293.719299	32.61681	46.922649	4.551432	107.46994	449.928375	4313.171514	0.21682618
2026	1143.134033	1463.67395	12.66371	789.090454	293.859314	34.38554	47.58144	4.56585	109.309067	450.167755	4348.431113	0.216139785
2027	1093.101929	1536.867065	12.266976	789.090454	293.880432	36.709202	47.676696	4.580266	115.82357	450.740631	4380.737221	0.216723978
2028	1049.640015	1597.873535	11.933494	789.091431	293.90097	38.899796	48.98263	4.592618	125.040329	451.618347	4411.573165	0.218297341
2029	1004.679504	1661.86377	11.643885	789.090454	294.217957	40.742054	49.624468	4.613462	132.658829	452.564117	4441.6985	0.219380241
2030	972.48999	1702.086548	11.35686	789.090454	294.236572	42.269356	50.442216	4.627594	143.463638	453.10318	4463.166408	0.221399443
2031	973.923401	1703.99646	11.016072	789.090454	294.391022	44.209431	48.60225	4.642364	162.731125	453.558563	4486.161142	0.224721031
2032	978.402283	1704.794067	10.898203	789.090454	294.410767	47.037842	48.529019	4.660393	188.673279	454.177734	4520.674041	0.229498748
2033	971.556274	1726.824951	10.728304	789.090454	294.514801	48.296776	50.578746	4.677608	207.922226	454.651611	4558.841751	0.232655974
2034	965.124817	1753.181885	10.573342	789.090454	294.539429	50.512138	48.703025	4.689234	226.932312	455.149536	4598.496172	0.234973703
2035	962.432373	1768.43335	10.436224	789.090454	294.7948	51.375534	49.236108	4.708985	256.249695	455.968994	4642.726517	0.239586396
2036	951.586792	1812.692749	10.243569	789.090454	295.122955	52.351337	49.044749	4.717055	265.94751	456.421478	4687.218648	0.239716806
2037	949.224548	1823.958008	10.067904	789.090454	295.735413	53.133995	51.417056	4.738864	296.229828	461.250183	4734.846253	0.245521243
2038	937.9198	1868.339355	9.696714	789.090454	295.932159	54.188412	52.951507	4.76489	308.647034	463.073059	4784.603384	0.246531837
2039	927.567566	1909.734497	9.508823	789.090454	295.960907	54.971622	53.426047	4.783664	322.676575	464.245239	4831.965394	0.247531585
2040	918.786255	1942.257446	9.347122	789.090454	296.25235	55.526024	57.171818	4.800538	345.027222	468.31781	4886.577039	0.251115608

Note: Data was taken from: http://www.eia.gov/forecasts/aeo/

Table 56. Renewable energy projected percentages.

Year	RE%
2014	12.91%
2015	12.49%
2016	13.59%
2017	14.62%
2018	15.58%
2019	17.06%
2020	18.56%
2021	20.53%
2022	21.46%
2023	21.70%
2024	21.70%
2025	21.68%
2026	21.61%
2027	21.67%
2028	21.83%
2029	21.94%
2030	22.14%
2031	22.47%
2032	22.95%
2033	23.27%
2034	23.50%
2035	23.96%
2036	23.97%
2037	24.55%
2038	24.65%
2039	24.75%
2040	25.11%

Note: I summed the EIA projection data for each source of renewable energy, which facilitated the creation of the per-year renewable energy percentage table above.

Ancillary Appendix 6

EIA Projections for Gasoline Consumption

Table 57. EIA transportation projection data.

Year	*Gallons (Millions)*
2016	134092.5984
2017	134684.5051
2018	133949.5849
2019	132504.0272
2020	130635.8521
2021	128144.5124
2022	125547.3498
2023	122818.8858
2024	120151.2512
2025	117419.0312
2026	114836.8001
2027	112470.6452
2028	110418.3875
2029	108563.8254
2030	106933.2193
2031	105460.2056
2032	104153.8903
2033	102983.966
2034	101999.8873
2035	101192.1189
2036	100555.8166
2037	100050.3712
2038	99650.27352
2039	99413.0571
2040	99261.12147

Note: Data was taken from: http://www.eia.gov/forecasts/aeo/