The Impact of Hybrid Electric Vehicles Incentives on Demand and the Determinants of Hybrid-Vehicle Adoption

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The Impact of Hybrid Electric Vehicles Incentives on
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This dissertation is dedicated to my daughter Rachel, who provided an ever present source of motivation to persevere.
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Upon entering graduate school, an insightful professor explained that early adulthood can be a tumultuous time, and that therefore we new students must not get derailed by life events but rather accept them as part of the process. Although at that point I was still mesmerized by youthful arrogance and optimism and didn’t think that these bumps would happen, it turns out that I’m not an outlier. Thankfully, when these events did in fact occur, it was my friends, family, colleagues, and professors that provided me with the strength I needed to continue.

Therefore, first I would like to thank my parents who instilled the importance of education in me at an early age and also a sense of responsibility to do something meaningful with this education. In addition to this commitment to education, they taught me that I was not allowed to quit any commitment I made, no matter how small. This one lesson drilled into me throughout childhood provided me the necessary dedication to complete this dissertation. In addition to my parents, I would like to thank Jackson Yordon, my ever present partner and champion, who listened to countless ramblings...
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SUMMARY

According to the Energy Information Administration, transportation currently accounts for over 60% of U.S. oil demand (E.I.A. 2010). Improving automobile energy efficiency could therefore reduce oil consumption and the negative environmental effects of automobile use. Subsidies for energy-efficient technologies such as hybrid-electric vehicles have gained political popularity since their introduction into the market and therefore have been implemented with increasing frequency. After the introduction of hybrid-electric vehicles into the U.S. market, the federal government initially implemented a $2000 federal tax deduction for these vehicles (later increased to a $3500 credit). Many states followed, offering various exemptions, such as high-occupancy vehicle (HOV) lane use, and excise-tax, sales-tax, and income-tax exemptions. Because not all states have implemented these subsidies, this policy topic is an ideal candidate for an outcome evaluation using an observational study postulation.

States adopt incentives for different reasons based on factors that make adoption more attractive, however, so it is first necessary to identify these differences that predict policy adoption. This allows for the evaluative work to control for self selection bias. Three classes of internal determinants of policy adoption, political context, problem severity, and institutional support, and one type of external diffusion factor, are tested using logistic regression. Results suggest that the number of neighboring states that have already adopted incentives are consistently a determinant of diffusion for all three types of incentives test, HOV lane exemptions, sales-tax exemptions, and income-tax
exemptions. In terms of internal factors, constituent support, a type of political context, predicts, sale-tax, income-tax, and HOV lane exemptions, but that the other two classes of determinants, problem severity and institutional support, were not universally significant across types of incentives. Overall, these results suggest automobile manufacturing did not impact whether these policies were implemented, nor were they implemented to address air quality issues or gas price increases. Rather these policies were responses to popular support for hybrid vehicles.

In addition, this dissertation identifies the average treatment effect of these incentives on state-level demand for hybrid vehicles. These effects are estimated using traditional parametric techniques, difference-in-difference regression, and fixed effects on two comparison groups: (1) the natural control group, states that did not adopt subsidies, and (2) a constructed control group, states that proposed subsidies during this same time period but did not adopt them. In addition to these parametric models, propensity score matching was used to construct a third comparison group using the models that identified determinants of the policy adoption.

These findings were supplemented by exploratory analyses using the individual-level National Household Travel Survey. This multitude of evaluative analyses shows that overall, monetary hybrid incentives are not overwhelming effective in promoting the diffusion of this technology, but that HOV lane exemptions, however, if implemented in places with high traffic congestion, were found to impact aggregate demand and an individual’s propensity to adopt a hybrid. The other two types of incentives, sales tax exemptions and income tax credits, were not found to be effective at the aggregate or the individual level.
In addition, travel behavior was found to strongly predict adoption, more so than socioeconomic variables, stated attitudes, or characteristics of the built environment. The number of walking trips per month and the number of times a person used public transportation were found to be significant predictors of hybrid adoption, implying the decision to adopt a hybrid includes factors other than purely economic ones, such as environmental attitudes.

These analyses provide insight into why states adopt certain policies and the circumstances in which these incentives are effective. Since people may be motivated by factors other than economic factors, creating effective incentives for energy efficiency technologies may be more challenging than just offsetting the price differential. Instead, customization to the local community’s characteristics could help increase the efficacy of such policies.
CHAPTER 1: INTRODUCTION

Overview

The impact of the personal automobile in the United States is far-reaching. The average automobile emits 5.48 metric tons of CO2 equivalent into the atmosphere and consumes over 500 gallons of gasoline annually (based on 12,000 miles of driving) (E.P.A. 2005). These emissions and oil consumption contribute to the degradation of the environment and U.S. dependence on foreign oil. Because coercive transportation policies, such as regulations and taxes, have little political support in the United States, market-based, noncoercive policies have been implemented with the hope that a patchwork of incentives and public-awareness campaigns will encourage substantial change in Americans’ use of their personal vehicle. Examples of these market-based noncoercive policies include monetary incentives for the purchase of hybrid-electric vehicles; expanding high-occupancy vehicle (HOV) lanes in urban settings; and through information campaigns and financial incentives, promoting alternative commuting options, such as public transportation, telecommuting, and carpooling.

This dissertation examines a noncoercive, market-based policy implemented by the states and attempts to identify the determinants of hybrid adoption. Specifically, this dissertation addresses the following research question:

1. Which states adopt subsidies for hybrid-electric vehicles?
2. What is the effect of incentives on consumer demand for hybrid-electric vehicles?
3. Do attitudes predict the adoption of hybrid vehicles?
When hybrid-electric vehicles were introduced into the U.S. market, the federal government implemented a $2000 tax deduction toward the purchase of a qualifying vehicle. Individual states passed their own sets of subsidies, through mechanisms such as excise- and sales-tax exemption and income-tax credits. State and local governments have also begun experimenting with more creative incentives, such as exemptions for HOV lane requirements and free or reduced parking rates. Although the federal government increased the incentive’s value in 2005 and more states have passed incentives, little evaluative research has been completed to determine if these efforts have increased demand for hybrid vehicles, and what research that has been completed does not put the question of effectiveness to rest (Diamond 2009; Gallagher and Muehlegger 2011). This dissertation will close this gap in the evaluation literature and attempt to identify the treatment effect of state-level hybrid-vehicle incentives.

This dissertation will also identify the determinants of adoption. Previous research has identified socioeconomic variable to be correlated with adoption behavior, although a comprehensive causal model of technology adoption has never been developed. The consumer-choice model of hybrid-electric vehicle adoption will be expanded by incorporating attitudes, transportation behavior, and other socio-economic and demographic variables into a causal model of adoption.

Fortunately, data from the National Household Transportation Survey, complemented by unique data collected for this dissertation, allows for comprehensive evaluation of these research questions. Because of the rich data and the possibility of selection bias, this dissertation utilizes a number of statistical analyses, including panel-data analysis and propensity-score matching. The goal of this research is to provide empirical analyses that will inform transportation analysts.
The results of this dissertation: (1) provide further understanding into the adoption patterns of state level HEV incentives, (2) provide a comprehensive study on the impact of state-level incentives for hybrid-electric vehicles on demand and (3) identify how consumer heterogeneity impacts their propensity to adopt this technology.

**Background on Hybrid–Electric Vehicle Technology and Policy**

Incentives for technology adoption are typically focused on mature technologies, not those where there is a possibility that the standards or dominant technology will change in future years. Hybrid-electric vehicles represent a mature technology, and therefore provided the government with an ideal technology to support through monetary incentives to consumers. Hybrid technology employs utilizes both gasoline and an electric battery for operation. The two sources may operate in parallel to power the vehicle, or the vehicle may be driven primarily by one source, with the other source supporting the operation. The Toyota Prius, the most popular hybrid on the market, is considered to be series-parallel hybrid—the gas and electric motors may operate in parallel or the car may be driven using either electricity or gasoline. The energy source is chosen to maximize energy efficiency based on the instantaneous characteristics of the drive. Because the battery is charged internally, the automobile does not need to be plugged in but still obtains higher fuel efficiency than traditional internal-combustion engines. This technology therefore requires little change in the consumer’s behavior after the purchase, making a hybrid-electric vehicle a more attractive choice than older purely electric cars for the consumer who is concerned about maintaining battery charge and resistant to engaging in significant lifestyle changes (e.g., the need to find alternative transportation when the vehicle is being charged).
Electric and hybrid-electric technology, although never previously commercially dominant in automobiles, has been feasible for many decades. Before internal-combustion engines became the standard energy-conversion method in automobiles, they competed with electric and hybrid vehicles and other external-combustion engines powered by steam or electricity to win market dominance. A number of electric and hybrid manufacturers flourished in the United States and Europe before and during the World War I, but a combination of events combined to end the commercial production of hybrid vehicles. Among these were the development of a starter motor for internal-combustion engines and the Great Depression (Høyer 2008). Although support for these alternative engines remained because of their reduced energy requirements and emissions, because of major technological disadvantages, no mainstream production of hybrid-electric vehicles existed after World War II. Still, some of the major car manufacturers continued to produce concept hybrid cars, such as the Volkswagen Taxi and the GM 512. In 1976, Congress passed legislation for the research, development, and demonstration of hybrid and electric vehicles, recognizing their viability as a potential alternative capable of large production levels (Pub. L. No. 94-413). This long-term research-and-development trajectory led to creation of a mature and reliable technology released into the automobile market.

In 1999, hybrid vehicles made a significant push into the U.S. automobile market with the introduction of the Honda Insight. Toyota’s Prius followed the next year. Once these vehicles were on the market, the federal government implemented incentives for consumers to adopt these vehicles. Since then, all major car companies have invested in this technology and brought
hybrid cars to market. As of 2007, over 18 models of hybrid vehicles have been sold in the U.S. automobile market and approved for the federal tax credit.\footnote{For more information see: http://www.irs.ustreas.gov/newsroom/article/0,,id=157632,00.html. Last Accessed March 13, 2011}

In terms of federal incentives, the U.S. government instituted a tax deduction of $2000 for most hybrid-electric vehicles in 2002. After the Energy Policy Act of 2005, the tax deduction was changed to a tax credit of $3500, thereby increasing the value of the subsidy. At this time, the IRS set a horizon on these tax credits, which suggests a policy goal of technology diffusion. After the second quarter in which over 60,000 units of a specific hybrid-electric model are sold, the tax credit for that specific model begins to decline and is eventually reduced to zero. In 2006, Toyota announced that sales of Prius exceeded the subsidy limit and as a result, the credit was to be phased out by October of 2007. The Toyota Prius is the most popular hybrid automobile currently on the market, with worldwide sales passing 1 million in 2008 (Toyota 2008).

When hybrid vehicles were introduced into the U.S. market in 1999, only one state, Virginia, offered incentives for adoption of alternative-fuel vehicles. By 2005, 13 states enacted one of two types of incentives to promote the diffusion of hybrid vehicles and alternative-fuel vehicles into the market. The first type is a strict pecuniary subsidy implemented through either a tax credit or deduction or through a fee exemption. The second type provides consumers with a convenience incentive, such as exemptions from passenger rules governing HOV lane use, which results in shorter commute times. This type of subsidy can be calculated monetarily based on a person’s wage and time saved, but because there is no monetary transfer, this subsidy is categorized differently in this research. Table 1 summarizes state subsidies.

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Table 1: State Level Hybrid Electric Vehicles Incentives, 2001-2005.

<table>
<thead>
<tr>
<th>Type of Incentive</th>
<th>2001</th>
<th>2002</th>
<th>2003</th>
<th>2004</th>
<th>2005</th>
</tr>
</thead>
<tbody>
<tr>
<td>HOV exemption</td>
<td>VA</td>
<td>VA, UT</td>
<td>VA, UT, FL</td>
<td>VA, FL, UT</td>
<td>VA, FL, UT, CA</td>
</tr>
<tr>
<td>Income-tax credit</td>
<td>CO, WV</td>
<td>CO, WV</td>
<td>CO, WV, NY</td>
<td>CO, WV, NY, OR</td>
<td>CO, WV, NY, OR</td>
</tr>
<tr>
<td>Excise-tax exemption</td>
<td>MD</td>
<td>MD</td>
<td>MD</td>
<td>MD, NM</td>
<td>NM, DC</td>
</tr>
<tr>
<td>Sales-tax exemption</td>
<td>ME</td>
<td>ME</td>
<td>ME</td>
<td>ME, CT</td>
<td>ME, CT, WA</td>
</tr>
</tbody>
</table>

Beginning in 1993, Virginia established special license plates for these alternative-fuel vehicles, including hydrogen, natural gas, and full-electric vehicles. The following year, Virginia passed legislation that allowed these vehicles to use HOV lanes, regardless of the number of people in the vehicle. In 2000, the year after the first hybrid vehicle was introduced in the market, Virginia added hybrid vehicles to the list of vehicles eligible for these special license plates. At that time, Virginia was the only state that offered such incentives for hybrid vehicles. These license plates allowed access to the HOV lanes in two major areas—Washington, D.C. metro area, including I-395/95, I-295, and I-66, and the area around Virginia Beach (Morrison and Counts 2005; Diamond 2008). In 2007, 2008, 2009, and 2010 the law was extended only on an annual basis.²

Because the legislation differs by state, the tax-credit values also differ between states. For example, Colorado’s tax credit equates to half the difference between the cost of the hybrid and the cost of the same or most similar vehicle that uses a traditional fuel, so that the credit

²For information see: Virginia Department of Motor Vehicles. http://www.dmv.virginia.gov/
differs by model.3 Using manufacturers’ suggested retail prices to identify average purchase price, the Colorado tax credit in 2006 for the Honda Insight was valued at between $1300 and $2600; for the Toyota Prius it was valued between $1300 and $1750. Combined with the federal tax deduction of $3500, the total value of government subsidies for an individual vehicle in Colorado would be approximately $4500. Alternatively, both Connecticut and Washington offer a sales-tax rebate. These state’s sales-tax rates are 6% and 6.5%, respectively, which would mean a savings of between $1000 and $1500.

Because of the variation between incentive values, it is not clear if the incentives will affect the demand for these vehicles or if the treatment effect is homogenous between states. Estimates from Consumer Affairs and Edmunds.com suggest that hybrids are priced $3000 to $5000 more than similar non-hybrid automobiles. Although these additional costs may be recouped through reduced gasoline consumption, these savings are realized over as many as 10 years and depend on variables such as miles driven, fuel prices, and inflation rates. Therefore, if the incentive does not reduce the price of the hybrids so that they are comparable to non-hybrid equivalents on the market, the subsidies could have little or no effect. This dissertation attempts to identify the impact of these incentives on demand for hybrids and on how incentives affect an individual’s propensity to adopt a hybrid vehicle.

The Field of Policy Evaluation Research

One primary goal of this dissertation is to evaluate a state-level policy. Policy evaluation, one of the last steps in the policy process, has in the last half century become a more established
discipline due to the increase in federal social programs and subsequent concerns about
government waste (Haveman 1987). After a policy is implemented, evaluators work to quantify
expected and unexpected outcomes. Policy evaluation is a field of applied research whose goal is
to identify how changes in policies affect certain populations and environmental conditions. It is
inherently different from many other methods used in public policy, particularly in
environmental policy, such as cost-benefit analysis, risk assessment, and cost-effectiveness
analysis. This is an important distinction—these other methods are prospective and aid the policy
analyst in implementation, whereas policy evaluation is perspective in nature in that it takes
place after implementation (Bennear and Coglianese 2005).

Since governments often do not operate in the marketplace, but instead provide a service
that the market may not do efficiently, making a profit, a standard measure of success in private
industry, cannot be used as an appropriate metric of success for most public policies. Without
this standard measure of effectiveness, the discipline of policy evaluation has grown in
popularity as a means of helping program managers to identify program effectiveness. Program
evaluations do this by helping to rank indicators of programmatic effectiveness and quantifying
and classifying these indicators to make conclusions about the policy in question. Policy
evaluation can not only identify the impact of intended outcomes, but also identify and measure
the impacts of unintended consequences, as well as provide in-depth conclusions about other
measures, such as the distribution of costs and benefits, transparency, equity, and public
acceptance of a program (Bennear and Coglianese 2005). Evaluations can then be utilized by
analysts to refine policies or to create new legislation in other jurisdictions. Ideally, evaluations
provide a mechanism to feedback into the policy analysis process and will impact the
implementation and development of future policies.
In policy evaluation, two categories of evaluations can be performed: process evaluations and outcome evaluations (Rossi 1993). Process evaluations answer questions about how the program was designed, how it was implemented, and whether the program’s goals are fully defined. For instance, in cases such as grant or funding programs, process evaluations can identify whether review committees use consistent criteria in determining awardees or whether program-management styles have created inefficient distribution of funds.

On the other hand, outcome evaluations look at outputs and outcomes to determine the impact of the program on the participants. Output measures used in evaluations of environmental policies can include short-term measures of facility pollutants, energy usage, and number of people enrolled in a home-energy audit. Outcomes are medium to long term and tend to be less tangible or harder to measure. Examples include human health impacts such as mortality or cancer rates, changes in ambient air quality, or changes in environmental attitudes after a policy.

As Rossi et al. (1993) identify, the use and perceived value of evaluations varies, depending on the political climate. In times of fiscal conservatism, there is increased focus on evaluations for assessing the efficiency of a program, demonstrating fiscal responsibility, or showing adept management (Rossi 1993). In recent years, evidence-based policy (also known as empirically based policy) has become popular within the U.S. government, as demonstrated through legislation, executive branch memos, and institutional support. In 1993, The Government Performance and Results Act (GPRA) was passed because “waste and inefficiency in Federal programs undermine the confidence of the American people in the Government and reduces the Federal Government’s ability to address adequately vital public needs” and because “congressional policymaking, spending decisions and program oversight are seriously handicapped by insufficient attention to program performance and results” (C.F.R. 1993).
purpose of this act is to “systematically [hold] Federal agencies accountable for achieving program results.” This act required agencies to create performance plans that articulate goals that are “objective” and “measureable.” To achieve the goals of the GPRA, the Office of Management and Budget (OMB) introduced the Program Assessment Rating Tool (PART) to assist agencies in their efforts to evaluate programs and as a way to assess value of future funding. Statements from this Office suggest that program evaluation should even impact fiscal budget decisions (Orzag 2009). These pieces together demonstrate the federal government’s commitment during the 1990’s and 2000’s to evidence-based policies and ultimately evaluations.

As the federal government committed to the goals of the GPRA, applied practitioners began more and more to use methods to better identify accurate estimates of treatment effects. A significant amount of methodological progress and theoretical advances has appeared in the literature in the past 20 years. These have expanded the evaluator’s ability to estimate the impact of a policy even if the policy was not randomly assigned (Rossi 1993; Dehejia and Wahba 1999; List, Millimet et al. 2003; Greenstone 2004). Known as quasi-experimental methods, these tests attempt to construct, through statistical methods, the counterfactual condition—that is, what would have happened to the subject under conditions contrary to actual conditions (Shafer 2002).

Random assignment of the treatment represents the best method of identifying the counterfactual because it combats the possibility of confoundedness—spurious relationships—between treatment and outcome. Confoundedness can result from nonrandom placement of subjects into the treatment and control groups and creates biased estimates of the treatment effect. Unfortunately, in environmental policy, random assignment is usually not economically practical or politically feasible (Greenstone and Gayer 2009). Without a randomized controlled trial, selection bias (or nonrandom placement into treatment groups) could preclude identifying
program impact if the characteristics that predict which individuals select into treatment are correlated with the outcome variable. Quasi-experimental methods make up nonrandom assignment of control and treatment groups when random assignment fails (Rossi 1993).

Quasi-experimental methods are those that can be employed to take natural experiment data, where the assignment has been made by nature, such as a weather event, or observational data collected after the policy implementation, and reconstruct the characteristics of a randomized control trial. Quasi-experimental methods include parametric regression techniques such as fixed effects, difference-in-difference regression, but also includes other applications such as instrumental variables, regression discontinuity, and propensity-score analysis (Greenstone and Gayer 2009). Although these methods were initially used primarily by wage and labor economists, environmental policy has embraced more quantitative methods (List, Millimet et al. 2003; Greenstone 2004; Bennear and Coglianese 2005; Greenstone and Gayer 2009). Their use in environmental policy is less common than in other fields, such as education policy. This dissertation will use fixed effects, difference-in-difference regression, and propensity-score analysis. Although these tools represent the most advanced efforts to accurately identify treatment effects, limitations do still exist. A further discussion on their strengths and limitations will be discussed in Chapter 5.

Evaluation of environmental policies can help alter policies that are ineffective or create unplanned impacts. As Norton (2005) posits, an iterative approach in which evaluations are used to inform future policies or to alter existing policies are is important because environmental problems are wicked problems: problems that are never solved—or only resolved for a short time. These wicked problems thus require constant review and alteration (Rittel and Webber
1973; Norton 2005), as well as monitoring to see if characteristics, such as pollution levels have changed.

This iterative approach is part of a framework known as adaptive management. Adaptive management is both an ex-ante and an ex-post evaluation technique in that the analyst uses the evaluative techniques to look at previously implemented policies, as well as to determine and predict impacts to future policies. Adaptive management, which promotes experimentalism, multiscalar analysis, and place sensitivity, applies this iterative approach to ecosystem management, although it can be extended to other areas of environmental policy.

Experimentalism reduces future uncertainty because outcomes are better known and understood; multiscalar analysis and place sensitivity allow managers to apply policies to varying levels of space and time (Norton 2005). This variation may mean policies customized to a community’s environmental needs or a pilot implementation for a predetermined time period. Results from this dissertation point towards customization and place sensitivity. Adaptive management relies on teams of scientists, managers, and policy-makers to identify and bound the problems into quantifiable terms and develop a model that explains different relationships and identifies the most effective policy options. Simultaneous testing, monitoring, and evaluation allow policy analysts to learn more about the problem; increase knowledge, information sharing, and stakeholder consensus; and ultimately improve on the implemented policy (McLain and Lee 1996). Adaptive management therefore includes evaluation as a key step.

Criticisms of adaptive management include the high costs required to implement the monitoring and its failure to create a shared understanding within stakeholders (McLain and Lee 1996). Even with these criticisms, however, adaptive management’s key characteristics, in particular experimentalism, remain attractive for policy analysts because relatively little work
that has been completed within the environmental policy field and so therefore there is often not consensus about project policy impacts (McLain and Lee 1996).

The remainder of this dissertation proceeds as follows. The second chapter will review the relevant fields of literature and present the analytical framework and hypotheses to be tested. The third chapter, “Data and Methodology,” will review the two data sets used to test these hypothesis, as well as the methodologies used. The fourth chapter will present the results of this analysis. The fifth chapter will discuss the implications of the results as they relate to evaluative research and its application in the environmental policy field, as well as the impact of these results on future initiatives.
CHAPTER 2: LITERATURE REVIEW

Demand for goods is often manipulated by policy-makers through subsidies and taxes. This dissertation examines the impact of a policy aimed at accelerating the technology-diffusion process by coercing the automobile purchaser. Because states nonrandomly adopt these policies, direct comparison of the average change in hybrid purchases between the treatment group and the control group is not possible unless additional statistical techniques are performed. One such method, propensity score matching (thoroughly reviewed in section 3.2), requires the development of a model to predict states’ adoption of these incentives. Therefore, this chapter will review policy diffusion studies literature. Second, literature on technology-diffusion theory and applied research with an emphasis on energy-efficiency technologies is presented, followed by a discussion on the role that demographics and attitudes play in the adoption of hybrid-electric vehicles. Finally, the literature on these disparate topics will be synthesized into one conceptual model that will guide the analysis section.

Determinants of State-Level Environmental Policy Adoption

Within the realm of environmental policy, understanding policy diffusion patterns at the state level can help to understand the causal model describing policy innovation. Academics long posited that weak federal environmental regulation and leadership could lead to “a race to the bottom,” where states relax their environmental laws to attract businesses because the costs of more lenient clean-air standards are not internalized—beyond state borders, neighboring and non-neighboring states will experience economic or social costs from the pollution—while the
state reaps the benefits of lenient standards that attract business. Recent research, however, has disputed this hypothesis (Potoski 2001; List, Millimet et al. 2003). In fact, in the absence of strong federal regulation, states often pass and enact laws and regulations that surpass federal standards. Therefore, the reasons and factors which act as catalysts for policy innovation are not well understood.

One such example of state leadership is automobile fuel efficiency standards. Although the Federal efficiency standards originated in 1975 by the Energy Policy Conservation Act, it was in response to the 1973–74 Arab Oil Embargo and high gasoline prices, not environmental concerns (Leone and Bradley 1982). This act aimed to double new-car fuel economy by model year 1985 in an effort to decrease U.S. dependence on foreign oil. To meet this goal, Congress set fuel-economy standards for many of intervening years between 1975 and 1985, starting with an 18 mpg standard for passenger cars in 1978, and increasing until the target fuel economy of 27.5 mpg would be met for the 1985 model year. The incremental increases between 1980 and 1985 were to be set by the National Highway Traffic Safety Administration (NHTSA). For the post-1985 period, Congress mandated continued application of the 27.5 mpg standard for passenger cars but allowed NHTSA to increase the standards. Based on this policy, the average U.S. fleet efficiency grew from 13.1 mpg in 1975 to 26.2 mpg by 1987. This achievement was short-lived, however, as fuel efficiency dropped back to 20.1 mpg in the next decade because of a loophole that excluded some automobiles, such as sport-utility vehicles (SUVs), from the standards (E.P.A. 2010) All three major U.S. producers initially exceeded the standards to avoid heavy fines, but as early as 1983 the big three automobile manufacturers began to petition the

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Department of Transportation for a temporary relaxation of the standard; this was implemented for five years until 1990 (Leone and Bradley 1982). At that point, the standard was brought back up to 27.5 mpg, although modest mandated increases for light trucks and SUVs did occur, even though analysts have posited that technology advances have made large increases in efficiency feasible for modest costs. The United States fuel efficiency standards thus remained untouched for almost 20 years.

In the wake of weak federal regulation, states instead became leaders in clean-air policy. For example, California and many northeastern states have enacted policies that exceed federal regulations in multiple applications, which causes uncertainly for business interests and manufacturers. In 2002 California passed legislation to reduce greenhouse gases specifically from passenger vehicles in beginning in 2009; nine other states eventually passed similar bills. Because this state legislation would exceed federal requirements, however, this law became mired in the legal system since the states needed a waiver from the EPA to exceed the federal laws (Engel). In 2006 the California legislature also approved the reduction of emissions from greenhouse gases generated in California at both point sources such as utility plants and by mobile sources such as cars. The emission-reduction targets were set at 25% by the year 2020 to bring California’s total emissions down to 1990 levels (Eilperin 2006).

This lack of federal leadership finally changed, however, in May 2009. The Executive Branch announced support for a joint Environmental Protection Agency (EPA) and the National Highway Traffic Safety Administration (NHTSA) program that would require 5% annual increased efficiency from 2012 through 2016 and requires that by 2016 automakers must achieve a 40% improvement over current efficiency standards—rising to 39 mpg for cars and 30 mpg for light trucks and SUVs, and averaging 35 mpg overall (The White House, 2009). This proposal
was supported by many car companies because federal standards would allow the automobile companies to perform long term product design. The joint EPA NHTSA effort is aligned with California’s efficiency standards (and with the regulations in nine other states), in part to avoid multiple entities mandating efficiency standards for automobiles. Therefore, it appears as if diffusion can go bottom up, from the state-level to the federal level as wells as top down.

States are therefore important players in environmental policy and regulation, often serving as early innovators in pioneering new policies that are eventually adopted by the federal government. Research into why certain states are leaders while others are laggards or non-players has led to a field within policy studies that focuses on the determinants of state policy diffusion and innovation. This field of research grew from a seminal article from the 1960s that looked at innovation in public agencies. L. B. Mohr conducted interviews with health departments to identify the determinants of innovative policy-making in local departments of public health. Mohr hypothesized that “innovation is directly related to the motivation to innovate, inversely related to the strength of obstacles to innovation, and directly related to the availability of resources for overcoming such obstacles” (Mohr 1969). Mohr then went on to more specifically define these three conditions of innovation. Environmental demands, material and status interests and capabilities, and wealth were postulated as motivation and resources to innovate; community norms, attitudes, and lack of information were categorized as obstacles to innovation (Mohr 1969).

Berry and Berry (1990) used these foundations to move from innovative public agencies to state-level policy adoption, using lottery policy as a case in which to study this phenomenon. Their research furthered this field for multiple reasons and contributed to a movement in policy studies that aims to identify determinants in numerous policy settings. First, it analyzed pooled
longitudinal data using event-history analysis, meaning that the when there was not adoption, the state was treated as truncated instead of a negative event. This better took account for the possibility that states adopted a policy outside of the time frame studied. In addition, Berry and Berry integrated two previously disparate topics: external determinants and internal determinants and found that both external and internal factors influence the probability that a state will adopt a policy. External factors are pressures from outside the state to innovate and can come from the federal government (vertical diffusion) or other states (also known as horizontal or regional diffusion). Internal factors help states innovate, as states respond to the domestic pressures and experiences; (Berry and Berry 1990).

External factors of diffusion finds its roots in sociology, where the pathways of policy diffusion are explained largely through individual actors and their relationships, which form policy networks. A policy network consists of a group of actors who share an interest in some policy area and who are linked by their direct and indirect contacts with one another (Mintrom and Vergari 1998). Policy studies scholars have applied this framework in policy diffusion studies research by looking at the phenomenon of horizontal diffusion, the impact of other states policies impacting another state. The difficulty with exploring not just how the policy diffusions, but why the policy diffusion is that it requires not a state level analysis, but rather an individual level analysis to explore the causal pathways between these actors. Therefore, much of the research on this subject was conducted as case studies (Kirst, Meister et al. 1984).

Mintrom and Vergari, however, attempted to understand the impact horizontal diffusion using surveys to collect data on a large number of actors. They looked at both the impact of conversations and interactions with members of interstate or external policy networks as well as intrastate or internal policy networks (Mintrom and Vergari 1998). Their findings suggest that
policy networks are important for an entrepreneur within a policy setting and the effectiveness of a network can impacts whether the policy is implemented. Mintrom and Vergari’s findings support Berry and Berry’s assertion that policy diffusion is neither a purely internal or external process. External factors are posited to be important factors because states pay attention to and are influenced by the actions of both the federal government and other state governments.

At the aggregate level, empirical studies suggest that the relationship is positive; states will succumb to the pressure to innovate when there is more pressure, although some scholars have argued that this theory may not hold for all policy issues (Daley and Garand 2005). Although external factors have been shown to empirically impact adoption, the causal mechanism behind such results have not been clearly articulated (Mooney 2001). There are two theories for why horizontal diffusion occurs. First is interstate learning, and the other is competition. Horizontal diffusion of ideas occurs because states learn about different policies from other states or because states worry that inaction could lead to relocation of businesses to other states (Berry and Berry 1990; Mintrom and Vergari 1998; Daley and Garand 2005). These hypotheses in terms of the casual model have not been settled in the literature, however.

Another limitation of horizontal diffusion theories is that the regional diffusion postulation assumes that there is a geographical factor of knowledge; in other words, states have additional access to information for states that are geographically neighbors versus states on the other side of the county (Mooney 2001). Recent research, however, suggests that diffusion pressures may be more complex than previously thought (Boehmke & Witmer, 2004; Mooney, 2001). Mooney (2001) argues that the impact of diffusion need not be uniformly positive, and he suggests that scholars and researchers need to understand more fully the learning process behind diffusion pressures.
Theories on external, as well as internal determinants of policy adoption have helped guide a diverse series of studies focusing on determinants of policy adoption in a number of policy settings, such as children’s health insurance (Volden 2006), bottom-up policy diffusion from cities to states (Shipan and Volden 2006), and post-secondary education regulations (McLendon, Heller et al. 2005). The remaining of the literature review will focus on internal determinants, specifically applied to environmental policies, since the ability of each determinant to explain state variation in policies often depends on the nature of the policy in question (Potoski and Woods 2002). The next section will review the main categories of determinants of state-level policy diffusion and is categorized similarly to Stafford (2006): political context, problem severity, and institutional capability. Political context refers to the characteristics of the state and the government that attempt to explain the distribution of power between major stakeholders, under the theory that policy is often determined by political and economic self-interest (Schneider and Volkert 1999). Problem severity attempts to reflect the current state of the environmental under the hypothesis that the more severe a problem, the more likely a state is to address that problem. Finally, institutional capacity reflects the resources, both fiscal and political, available to the state to implement this policy (Bacot and Dawes 1997).

**Political Context**

Political context refers to how government and its constituents’ characteristics affect policy adoption. Multiple frameworks, such as public-choice theory, the iron triangle, and issue networks, put forth theories that would predict the impact of these players on policy adoption. Public-choice theory hypothesizes that a government will pursue a policy that increases the likelihood it will become reelected because politicians are self-interested utility maximizers
(Schneider and Volkert 1999). This assumption is implicit in the framework of the iron triangle, where centralized players influence public policy. The iron triangle consists of business, government, and the military, which have consolidated power so that individuals do not have comparable power in the political realm (Helco 1978). These restricted sets of stakeholders therefore gain utility through influence and deal-making. Issue networks, on the other hand, posit that within a policy issue, a large number of participants and policy activists, including individuals and interest groups, compete to implement policy. In issue networks power is unconsolidated; no one is in control of the policies or issues (Mills 2002). Networks encompass a range of affected interests, and although a measure of agreement exists, there are always disagreements within the issue network.

These theories predict how power is consolidated within a policy issue and therefore what the determinants of policy adoption will be, but measuring and operationalizing these indicators of power structure has been a struggle in applied research. In policy-diffusion applied research, many components of the political context have been presented, including (1) interest-group pressure, (2) public opinions, and (3) government control. Public-choice theory, the iron triangle, and issue networks all place particular importance on interest groups in public policy because the firms they represent can overcome collective-action problems more easily than grass roots movements (Buchanan and Tulloch 1975). Indicators of business lobbying therefore has been included in many works of applied research, but finding accurate measures of interest-group strength remains a challenge. The most common indicator used is the sector presence of the related industry, but the construct validity of this indicator is often question (Ringquist 1993; Potoski and Woods 2002). One reason for this is that the size of an is not a direct measurement of their strength (Daley and Garand 2005); industries with a large presence in a state may not or
may not have an effective lobbying effort in that state.

Although the size of an organization or industry does not reflect its strength, it remains the standard in the literature under the assumption that the economic importance of an industry will be correlated with their ability to effectively lobby state legislatures for policies that they find beneficial. In addition, it is asserted that the size of an industry represents a state’s commitment to and dependence on such industries (Bacot and Dawes 1997; Stafford 2006). This variable has also been used to examine local policy diffusion. At the city level, research has also used manufacturing presence to examine the diffusion of gun laws (Godwin and Schroedel 2000).

Alternative variables have been used as interest group, but the construct validity of these variables is not strong either. In an examination of welfare policy, three variables were posited as proxies of interest group strength. First, percent minority was used, as welfare being a minority focused issue, as well as percent high school graduates and median income, under the assumption that higher educated and wealthier individuals would be able to lobby more effectively (Volden 2002). Federal funding to state EPA offices (Ando and Polasub 2009) has also been used as a proxy for interest-group strength, although this measure seems to more accurately reflect the impact of vertical diffusion strength—the impact of federal government on state policies—as opposed to that of interest groups (Stafford 2006).

Using the standard measurement of interest group strength, the size of the manufacturing sector is often found to be an important determinant in environmental-policy-diffusion studies. In terms of how the indicator is measured, it can be done a number of ways. This has been used in research as the percentage of population employed by related industries (Ando and Polasub 2009) or the value added from manufacturing by those industries (Ringquist 1993; Potoski
2001), although questions persist whether this variable captures interest-group strength or public opinion in the state.

The second category of political context, public opinion, depicts the population’s commitment to certain issues and overall political sentiment. In environmental-policy-diffusion studies, a common proxy of public opinion is environmental group memberships. Groups used include Sierra Club, Greenpeace, and National Wildlife Federation (Berry and Berry 1990; Ringquist 1993). This determinant has been asserted to represent public commitment to the environment as pointing to the existence of an issue network, as these environmental groups often embody many of the characteristics of one, such as a large number of decentralized players with a lack of consensus.

Polling indicators that attempt to depict general trends in public opinions related to environmental attitudes have also been used. Some researchers have used results from a large survey, such as the General Social Survey, to identify state-level public attitudes toward their environment (Jones and Dunlap 1992). Other measures include the percentage of people who voted for George Bush as an indicator of pro-business attitudes (Stafford 2006) and the fraction of appellate court judges appointed by Democratic presidents as capturing antibusiness attitudes in a state (Ando and Polasub 2009). Per-capita income and education have been used in models, because they are often correlated with a higher degree of environmental commitment (Daley and Garand 2005), but using these demographic variables in place of additional indicators is questionable since these variables are merely correlated with, and not indicators of, public opinion.

Finally, government control refers to the political powers that control the legislative and executive branches of the state government, how unified they are, and the ideologies of the
players. Government control affects policy diffusion because the degree to which a single political party controls the institutions of state government can reflect consolidated power and thus be positively correlated with the state’s probability of innovating (Berry and Berry 1990). Similarly, research has found that split governments (states whose legislative and executive offices were not held by the same party) are more likely to adopt less controversial policies, such as a lottery (rather than a tax increase) because divided governments lack the political resources to increase taxes, whereas unified governments may have the political capital to achieve a substantial tax increase (Berry and Berry 1990).

To capture the ideologies of the political powers, researchers have used the League of Conservation Voters voting index for the Senate, which catalogs the voting records of the U.S. Senators for each state and provides an index of their voting history based on conservation issues (Bacot and Dawes 1997; Potoski 2001; Daley and Garand 2005; Ando and Polasub 2009). Some researchers have included a dummy variable for whether the state is in the south, based on the position that southern states function differently in the environmental arena, particularly on the political and economic fronts (Bacot and Dawes 1997).

**Problem Severity**

Although the power structure of a state determines its propensity to adopt a policy, conditions outside the political environment also affect policy adoption. In particular, problem severity has been found to be positively correlated with a state’s propensity to adopt a policy to correct the issue: the more severe the issue, the more likely a state will address it. Unlike political context, environmental conditions tend to be very policy specific. Daley and Garand (2005) investigated the determinants of variation in the strength of state hazardous-waste
programs by looking at internal determinants and external determinants from other states, as well as the federal government, and using density of Superfund sites in a state as a measure of problem severity. Other research gives other predictions of adoption of natural resource damage-mitigation programs: the number of oil spills (Ando and Polasub 2009); the per capita of TRI (Toxics Release Inventory) chemicals released to air, surface water, and land (Bacot and Dawes 1997; Stafford 2006); and the sum of each state’s criteria-pollutant emissions (in tons) in 1995 as reported by the U.S. Environmental Protection Agency (Potoski 2001).

**Institutional Capacity**

Institutional capacity has been defined as both the commitment to, and ability of, a state to implement a policy. Capacity is resource related—the financial capacity of a state to carry out specific legislative requirements—and administrative—a state’s ability to manage environmental programs (Bacot and Dawes 1997). If a state does not have the resources to carry out legislation, it will most likely not be passed by the legislature. Institutional capacity as it relates to fiscal commitment has been put into practice as state expenditures dedicated to a specific use (Ringquist 1993; Bacot and Dawes 1997; Stafford 2006). In this case, it refers to the value of state expenditures related to air, traffic, or energy policy. State commitment to a policy issue from a legislative perspective has been used as an index of a state’s “greenness.” Since collective interest in environmental issues is fairly modern, these indices are limited in number and thus their use has been limited in applied research (Potoski 2001; Daley and Garand 2005).

In empirical work, prior research has included measures of previous environmental programs and policies as an indicator of institutional capacity. Finally, some research has used indicators of political weakness in a particular area as a sign of institutional incapability. For
example, voluntary pollution-prevention programs have been included as an indicator of weak environmental agencies (Stafford 2006).

Because state governments cannot create or implement policies without allocated funds, research into the determinants of policy adoption almost uniformly include an indicator of overall fiscal health. Most commonly, the indicator used is borrowed from Berry and Berry’s seminal article: the ratio of total state revenue minus total state spending to total state spending (Berry and Berry 1990).

Appendix A summarizes the three categories of indicators, political context, problem severity, and institutional capacity and indicators of each category used in environmental policy adoption. These three categories of policy diffusion determinants will be operationalized and applied to build a model of electric vehicle incentive policy adoption.

Technology Diffusion

Technology diffusion is a demand-side model of technology change; subsidies for energy-efficient technologies such as hybrid-electric vehicles intend to alter the diffusion trajectory of the technology by increasing demand. Diffusion is the last step in the invention-innovation-diffusion process (Schumpeter 1962) with a large body of research that spans numerous disciplines. Although many determinants of technology diffusion have been identified, no overarching theory accepted by all disciplines adequately predicts technology-diffusion patterns. Further refinement is of particular importance to policy scholars, because technology fuels economic growth and increases productivity (Hall and Khan 2003).

Modern diffusion research originated with work in the 1940s, 1950s, and 1960s that provided a foundation for the S-shaped diffusion curves (Rogers 1962). These curves, which are
popular frameworks in current research, provided researchers with preliminary predictors of technological change. Giriliches’s seminal work identified the S-shaped curve, now common in diffusion studies, by researching hybrid corn adoption-rate variation between regions. In the 1940s, other researchers used sociological frameworks to explain the diffusion of hybrid corn. By identifying a temporal lag between the introduction to the technology and adoption of the technology, they found that communication between previous and potential adopters led to diffusion (Ryan and Gross 1943). Giriliches’s important contribution was to posit that observations are not points of equilibrium, which may or may not change over time, but points on an adjustment path, moving toward a new equilibrium position; Giriliches thereby framed the work into a movement, rate of movement, and a destination model (Griliches 1957). Griliches’s research focused on the rate and level of acceptance, the slope, and the ceiling, with a concentration in economic predictors of adoption, particularly profitability. These points have been reiterated in more recent work, such as Hall and Kahn (2003), who posit that adoption is not a binary choice of adopt or do not adopt, but rather a timing issue of when to adopt. In the 1940s, researchers used sociological frameworks to explain the diffusion of hybrid corn. By identifying a temporal lag between the introduction to the technology and adoption of the technology, they found that communication between previous and potential adopters led to diffusion.

Since these early studies, other researchers have enhanced diffusion theory, but there are still shortcomings, one of the major ones is that no models of diffusion include failure as a possible outcome (Geroski 2000). This is problematic in that most innovations fail, so technology diffusion has only been looked at as an outcome and not as a possibility in the technology-transfer process. Therefore, conditions have been identified that change diffusion
trajectories, but not that predict diffusion in and of itself.

The following sections will review current research in the areas of technology diffusion, encompassing multiple disciplines. For purposes of this research, two main technology-diffusion models will be reviewed, the epidemic and consumer-choice models, because of their frequent applications in empirical work and because of their applicability to this research.

**Epidemic Models**

The most common diffusion model in the literature is the epidemic model. The epidemic model assumes an S-shaped curve that describes the cumulative distribution of the adoption, with the logistic function describing the most simplified version of the S-curve, although other models do exist. (For example, the Bass model also produces an S-curve, but it is appropriate when the distribution of the data is not normal.)\(^5\) The modified logistic growth model, that incorporates parameters that describe the characteristics of the function, presented by Griliches (Griliches 1957) is:

\[ P(t) = \frac{K}{1 + e^{-(a+bt)}} \]  

where \( P \) is the percentage of consumers who have adopted; \( K \) is the ceiling or equilibrium value; \( t \) is the time variable; \( b \) is the rate-of-growth coefficient; and \( a \) is the constant of integration, which positions the curve on the time scale (Griliches 1957). In the epidemic models, the rate of adoption is defined as the derivative of this cumulative distribution function.

The epidemic model can look at the change in the number of adopters in a given time period, given by \( \frac{dP}{dt} \), where \( P_t \) is the number of individuals or firms that adopted the innovation at time \( t \). The epidemic model focuses on explaining the fraction of firms or consumers who have adopted the new technology at any point in time. The epidemic model primarily focuses on the effect of information on the diffusion rate, particularly technology spillovers, which are flows of information between rivals in the same industry (Geroski 2000, 607). The premise of the epidemic model is that information and “endogenous process(es) of learning and taste information through personal contact or observation” drives technology diffusion (Kemp 1997). Other researchers include more types of information, specifically R&D and learning by doing, for possible determinants of technological change (Clarke, Weyant et al. 2008). In epidemic models, new adoptions are a function therefore of how many firms or individuals have adopted the technology. An epidemic model considers information to be the key to diffusion; once people know about it, they will adopt it.

The strengths of the epidemic model are that it has been applied extensively and is relatively easy to do empirically. Because it has strict assumptions, it has been possible to reduce a case to a certain set of variables to be examined. On the other hand, there are limitations to this model because of these assumptions and because the model is an aggregate model; the level of analysis is the population, not the individual. In addition, the ability to adopt and the infectiousness of the technology, defined in the models as \( \beta \), are modeled as constant (Geroski 2000). Also, the population of adopters is constant. As Kemp (1997) and other have noted, one of the biggest weaknesses of this model is the lack of causality and therefore generalizability.
**Consumer Choice Models**

Another framework to model technology adoption is consumer-choice models. These models use economic theory to explain individual-level decisions. Where the epidemic models are aggregated diffusion rates, consumer-choice models look at individual adoptions as the level of observation. Consumer choice models come from a class of models, known as discrete choice models that are derived under an assumption of utility maximizing behavior by the decision maker. Random utility models assert that the decision maker, $n$, facing $j$ alternatives will obtain a certain level of utility, $U_{nj}$, for each alternative and will choose the alternative that maximizes his or her utility. The probability that a person will adopt a technology is therefore written as:

$$P_{ni} = P(U_{ni} > U_{nj}) \forall j \neq i$$

(2)

Meaning that a person will choose choice $i$ only if the utility that person would experience from that alternative is higher that the utility derived from choice $j$. In cases where there are only two choices, as can be the case in technology adoption, modeled as choice “adoption,” and “no adoption,” discrete choice models can be written as a logistic choice probability:

$$P_{ni} = \frac{e^{(X_{ni}\beta)}}{\sum_j e^{x_{nj}\beta}}$$

(3)

Where $X_{nj}$ is a vector of observed variables relating to alternative $j$ (Train 2009). If the observed part of utility is considered to be a linear function of the observed factors, the utility can be written up as:

$$U_{nj} = X_{nj}\beta + \epsilon_{nj}$$

(4)

which asserts that individuals differ in characteristics $X_n$ which affect their utility and
thus the probability of adopting the new technology. By doing so, the model can incorporate heterogeneity of the adopter and of the adoption environment. Since these models are rooted in economic theory, the probability of adopting is determined primarily by pecuniary variables, such as uncertainty and price. From this point, a threshold level of adoption is presented, above which a firm or consumer will adopt the technology, but will not otherwise (Geroski 2000). Using this model, pecuniary variables such as learning, search costs, opportunity costs, switching costs, and income of the firm or the consumer have been tested in the literature (Geroski 2000).

One drawback of this framework is that it does not focus on external factors that may impact adoption, but rather internal characteristics of the firm or individuals. Although internal factors are important, they do not encapsulate the entire adoption decision. The diffusion process may be driven by external changes. Discrete choice models do allow for socioeconomic variables to be included in the model if they affect the utility over the alternatives. For example, for energy-efficiency cases, changes in energy prices and technology cost as are also determinants of technology adoption. In addition, income could be included in a choice model of hybrid adoption, as there may be a differential effect of income on the utility of a person’s choice to adopt a hybrid (Train 2009).

Another limitation of the consumer choice model is that this framework assumes unrealistic conditions, such as complete information and complete rationality on the part of the consumer (Train 2009). Particularly in times of new technology, where information is also being diffused through the population, complete information is a highly unlikely assumption. The individual-choice model asserts that individual rational actors weigh costs and benefits of the technology to decide whether or not to adopt. Previous research, however, has shown that individuals experience difficulties in calculating net present value of future savings or have
irrational discount rates (Thompson, 2002).

Technology Diffusion Policies for Environmental Technologies

Subsidies such as those enacted for hybrid-electric vehicles, also called environmental-technology policies, are instruments that foster technology diffusion. They are one part of an environmental-policy portfolio to address climate change that also includes emissions standards and regulation, as well as pollution taxes. Environmental-technology policies have been identified as policies that address two sets of market failures—technological innovation, such as incomplete information and knowledge spillovers, and environmental externalities—common in environmental pollution problems. Together, these failures result in more pollution than desired and underinvestment in new technology and research and development (Jaffe, Newell et al. 2005). Underinvestment in new technology is particularly likely if the cost of pollution from the production and use of the good is not factored into the private marginal cost. A firm that invests in or implements new technology typically creates benefits for others while incurring all the costs. The firm therefore lacks incentive to increase those benefits by investing in technology. Applying this idea to transportation, consider that the cost of the automobile is lower than the theoretically efficient price because it does not include the cost of air pollution accrued by others during the production and running of the automobile.

Besides these market failures, other barriers exist that result in a slower than socially optimal diffusion rate for many energy-efficiency technologies. Researchers have examined uncertainty and risk and their relationship to energy-efficiency technology purchases, as well as to consumers’ internal discount rates of energy investments. In an economic simulation using a discrete-choice model, Thompson tested for the existence of the efficiency gap—a discount of
future savings of energy-efficiency investments at rates in excess of market rates for borrowing or saving that results in a lower than expected investment in energy efficiency if predicted assuming complete rationality (Thompson 2002). His simulation points to the existence of the energy-efficiency gap, originally posited to exist due to structural and market barriers (Hirst and Brown 1990). Although some researchers dispute the existence of this gap, claiming instead diverging definitions of rationality, most researchers do support the idea that uncertainty has a damping effect on energy-efficiency investments (Hassett and Metcalf 1995).

Finally, additional conditions are present that make energy-efficiency technology diffusion less likely to occur organically. For example, these technologies often have higher initial costs compared with a substitute. In addition, the savings from the upgrade are seen over the lifetime of the unit, making upgrade less desirable, especially if long-term ownership is uncertain, which is often the case for automobiles and houses. Incentives attempt to immediately recover some of the cost differences.

To combat these barriers to adoption, market-based government incentives, such as subsidies for hybrid-electric vehicles, have become popular within both the academic community and government policy-makers. Support for these policies exists because they help to reduce the additional costs to consumers of adopting these technologies. In addition, as opposed to technology-mandating policies that may lock consumers into subpar technologies, these market-based environmental technology policies are flexible, encourage innovation, and are therefore powerful in helping to diffuse environmental technology (Norberg-Bohm 2000).

Empirical evidence of the impact of market-based approaches on diffusing environmental technology is limited. In a well cited paper, Jaffe and Stavins use consumer-choice diffusion models to examine residential builders’ decisions to use energy-efficiency materials and products
in the construction of new houses. They determine an efficiency level by assuming that builders will equate the marginal benefits to the marginal costs of energy efficiency. Using data they collected, they examined a number of variables expected to be significant, namely energy price and technology cost. Surprisingly, however, they found that energy price was barely significant, one-third that of technology costs (Jaffe 1995). These findings support the existence of an efficiency gap and reaffirm that research in this field has not identified how future energy prices are discounted and whether consumers decide rationally.

Hassett and Metcalf (1995) found that tax credits for residential home improvements have a significant impact on consumer behavior. An earlier study (Walsh 1989) on the same subject, however, found that energy-conservation improvement activity was not affected by tax credits, although public knowledge and attitudes of energy efficiency since then might have shifted enough so the results may not be generalizable to other time periods. The small number of studies in this area is limited because of the requirement for large individual-level data sets and data on utility usage, which are often not available to researchers.

Due to the lack of available data, some researchers have conducted experiments to look at consumers’ willingness to support green-energy programs (Rose, Clark et al. 2002). Rose found high participation and relatively little free-riding and concluded that individuals did place a value on the public good, defined as green-pricing programs, even though the consumers might not experience savings from participation. This research supports the theory of irrational behavior related to energy decisions. Although experimental economics approaches have been limited, there is potential for this methodology.

In studies that examine consumer preferences of automobiles, energy prices have consistently been shown to affect purchase decisions. Applied research has found gasoline price
to be positively significant when exploring the demand for fuel-efficient vehicles (Greenlees 1980; McCarthy and Tay 1998). In addition, using hedonic price models of fuel efficiency, two studies found that consumers have a marginal valuation of fuel efficiency (Atkinson and Halvorsen 1984; Espey and Nair 2005). Although this dissertation is not attempting to identify cross-price elasticity of gasoline prices, these studies do support the idea that energy prices will have an impact on the diffusion of hybrid-electric vehicles.

Finally, three recent papers have reviewed hybrid-electric-vehicle policy incentives, in an attempt to evaluate the impact of these subsidies. The first study used registration data to conduct a cross-sectional analysis examining whether a larger incentive value resulted in a higher treatment effect. Cross-sectional analysis was chosen because the author claimed that he could not control for time-dependent variables and using a panel data analysis would result in inconsistent results (Diamond 2009) and did not find the incentives to be significant.

A second publication addresses this issue, using similar data from J.D. Power and Associates. Using quarterly sales data from car dealers, the analysis was aggregated to state-level data. The authors found that other than in Virginia, HOV incentives have no impact on hybrid-electric-vehicle sales, but that sales tax, although smaller in value, has a larger impact than income-tax deductions and credits. In addition, gasoline prices and consumer preferences for environmental quality or energy security were found to be significant indicators of hybrid-vehicle adoption (Gallagher and Muehlegger 2011). While the authors do mention the possibility of endogeneity affecting their results, they do not try to correct for the time invariant bias by using fixed effects.

The third paper examining hybrid-vehicle incentives restricts its evaluation to allowances for HOV lane usage in Virginia. Using a case-study methodology, this analysis found that HOV
incentives for hybrid-vehicle purchases were effective in certain counties, specifically those counties with two characteristics: (1) proximity to Interstate 395, which has had an HOV-3 law in effect since 2006 and has high congestion and (2) a high number of commuters into the Washington, D.C. area (Diamond 2008). These findings point to the need for targeted, experimental transportation policy that can respond to a specific community’s needs.

Research has also been conducted to determine whether a rebound effect—adopting a larger hybrid vehicle to compensate for lower gasoline costs—occurred when hybrid vehicles came to market. A survey of Swiss automobile consumers found that Prius owners were less likely to increase their car sizes than consumers who purchased similar internal-combustion-engine automobiles, such as the Toyota Corolla and Toyota Avensis. This study also found tax rebates increased sales by 25%, although given the difference in tax structures between the Swiss and U.S. systems, as well as the difference in consumer preferences, lifestyles, and public transportation availability, these results should not be generalized to American consumers (de Haan, Peters et al. 2007).

Other research using a discrete-choice experiment, or contingent valuation, on Canadian consumers found that they were willing to purchase clean-fuel vehicles, but were sensitive to other automobile attributes, such as cost and power (Ewing and Sarigollu 2000). Ewing and Sarigollu then used their results to simulate the effects of government intervention on the purchase of clean-fuel vehicles. They found that the impact of commuting time changes (such as those brought by allowing hybrid vehicles in the HOV lanes) would only increase their market share by 1%; they explained this small increase as based on short Canadian commuting times. Overall, Ewing and Sarigollu found government intervention, such as increasing gasoline prices, subsidizing electricity, and reducing commuting time, insufficient to create a market for electric
vehicles, and therefore they speculated that industry subsidies may be more effective. Because this simulation originated from a contingent valuation, consumer-stated preferences may differ from their revealed preferences.

**Understanding the Characteristics of HEV Adopters**

Research evaluating hybrid subsidies has also identified demographic predictors of hybrid-vehicle purchase. For instance, Diamond (2009) and Gallagher and Muehlegger (2008) found income as well as age to be positively correlated with hybrid purchases as well as age; younger people have been found more likely to buy hybrids than older people. In addition to these variables, both these studies also attempted to account for attitudes, by using proxies. Attitudes have been defined in a variety of ways, but attitudes are commonly viewed as summary evaluations of objects along a continuum ranging from positive to negative with a magnitude, or attitude strength. (Petty, Wegener et al. 1997) Attitudes are important because they are a latent or underlying variable that is assumed to guide or influence behavior. Preferences or attitudes, especially toward new objects, are constructed—either by individuals, but can be influenced by others (Sorrentino 1996). Therefore, the accurate measurement of attitudes is of great concern since they are assumed to influence decisions. Beliefs, on the other hand, represent the information he has about the object (Fishbein and Ajzen 1975). For instance, a belief would be that eating too many calories causes weight gain. The connection between these two concepts is that a person’s attitude toward some object is determined by his beliefs related to that the object (Fishbein and Ajzen 1975). Given this connection with beliefs and the influence by others, and therefore unstable characteristic of attitudes, measurement in applied settings has remained a
challenge.

In terms of state level incentives for hybrid vehicles, Gallagher and Muehlegger included state-level Sierra Club memberships as a measure of state level environmental attitudes. Although this variable was found not significant, by itself, this may not imply that attitudes, such as environmentalism, do not predict the adoption of hybrid-vehicle subsidies. Rather, this proxy may suffer from construct validity issues. Similarly, Diamond included as a measure of state environmentalism the Research Renewal Institute’s “Green Planning Capacity index,” an aggregate of four variables measuring each state’s environmental management framework. In his analysis, this variable was found to be significant. In addition, Kahn (2007) found that census tracts with a higher percentage of environmentalists who are more likely to have higher percentages of people who commute by public transit, purchase hybrid vehicles, and consume less gasoline. Similarly to Gallagher and Muehlegger, Kahn used membership in the Green Party as a proxy for environmental attitudes.

If hybrid adoption is examined at the individual level using a discrete choice model, inclusion of these attitudinal variables is important, since these attitudes may be correlated with many demographic variables that have also been found to have an impact on hybrid adoption. In a stated-preference study, Ewing and Sarigollu (2000) found that individuals self-identified as environmentally concerned were approximately three times more likely to purchase an alternative or electric vehicle than individuals not concerned with the environment. In addition, Ewing and Sarigollu found four environmental factors correlated with both age and income, providing evidence that income and age are correlated with attitudes and attitudes. Although Ewing and Sarigollu relied on stated preferences instead of revealed preference, it provides evidence that attitudes may be predictors of hybrid-vehicle adoption.
Although few unaggregated analyses looking at hybrid adoption have been completed, individual-level studies looking at the effect of attitudes on vehicle adoption in general have found that attitudes do have an impact on vehicle choice. Prior research has identified several psychological factors, such as attitudes and lifestyle, risk perception, and self-image that influence the car-purchasing decision (Choo and Mokhtarian 2004; Lane and Potter 2007). Choo and Mokhtarian (2006), using a mail survey in San Francisco and choice model, found that travel attitudes and lifestyle are important predictors of vehicle type chosen. Specifically, they found that people who enjoyed high-density living preferred compact cars, as well as luxury cars.

Further contributing to confounding factors, previous research has found that residents with certain attitudes self-select into different neighborhoods (Cao, Mokhtarian et al. 2006). Although studies have shown that residents of neighborhoods with higher levels of density, land-use mix, transit accessibility, and pedestrian friendliness drive less than residents of more suburban neighborhoods, the researchers posit that these differences exist in part because residents self-select into these neighborhoods. Using a longitudinal analysis, Handy et al. found that differences in travel behavior between suburban and traditional neighborhoods are largely explained by attitudes (Handy, Cao et al. 2005). This caveat is significant, because residential information that may be correlated with hybrid-electric-vehicle adoption, such as density and traffic congestion, may also be correlated because of self-selection. That is, residents with attitudes that make them more likely to purchase a hybrid vehicle may self-select into these areas, accounting for any differences in observed purchase behavior. Unfortunately, little research has been completed to determine the relationship between density and traffic congestion and hybrid-vehicle adoption, partly because large-scale, individual-level data sets required for this type of analysis are not readily available.
When examining the impact of consumer heterogeneity on automobile purchase decision, disentangling the individual level purchase from the household is difficult and it is not clear how to incorporate attitudes into a household level decision model. Traditionally, vehicle choice models are done at the household level (Lave and Train 1979; Manski and Sherman 1980; Mannering and Mahmassani 1985) since consumer purchase decision research revealed that many purchase decisions are done at the household level (Davis 1976). Even within hybrid research, some applied work is done at the household level (Turrentine and Kurani 2007). Recent efforts have attempted to incorporate household and individuals' level characteristics as to allow the examination of attitude variables on adoption, and include individual level variables such as gender, age, education and employment information, as well as household information such as number of people in the household, their age group, and personal and household income (Ewing and Sarigollu 2000; Choo and Mokhtarian 2004).

In sum, research has found demographic and lifestyle variables, such as income, age, and education to be correlated with hybrid-vehicle adoption, but this correlation may be the result of a confounding variable, attitudes, that was not appropriately included in the models. In addition, other individual-level variables, such as areas of high density or traffic congestion, may predict hybrid-vehicle purchase, but they may do so because of residents self-selecting into those neighborhoods.

**Discussion and Hypotheses**

This literature review has spanned many topical areas: policy diffusion, technology diffusion, and determinants of technology adoption within the energy-efficiency technology policy arena in an effort to cover all the literature relevant to these research questions. This
literature review encompassed multiple disciplines and policy topics in an effort to build causal models and extract hypotheses regarding (1) determinants of policy adoption, (2) the efficacy of hybrid-electric-vehicle purchase incentives and the predictors of hybrid-vehicle adoption. A discussion of the hypotheses and the models built from the literature follows.

**State Determinants of Hybrid–Electric–Vehicle Policy Adoption**

In this chapter, three categories of policy diffusion determinants have been identified: political context, problem severity, and institutional capacity. Research suggests that in the absence of federal policies, states do not in fact engage in a “race to the bottom.” Instead, certain states become leaders while others become laggards. This dissertation will attempt to identify the characteristics of leader states. In addition, the results of this analysis will be used to help reduce the potential bias introduced from nonrandom placement of states into the treatment and control groups, which may inhibit the research’s ability to identify the impact of incentives on the demand for hybrid vehicles.

Therefore, this dissertation tests four hypotheses related to internal determinants, shown below as 1.1, 1.2, 1.3, and 1.4, and one hypothesis related to external determinants, hypothesis 1.5, to identify how stakeholder relationships and governmental conditions affect a state’s propensity to adopt hybrid-vehicle incentives.

**State Adoption of Hybrid–Electric–Vehicle Subsidies**

<table>
<thead>
<tr>
<th>Hypothesis</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hypothesis 1.1</td>
<td>State with higher level of public support for hybrid-electric vehicles will be more likely to adopt hybrid-vehicle subsidies.</td>
</tr>
<tr>
<td>Hypothesis 1.2</td>
<td>Interest-group strength affects a state’s propensity to adopt hybrid-vehicle incentives.</td>
</tr>
</tbody>
</table>
subsidies. Specifically, the presence of automotive manufacturing (conventional vehicles) in a state will decrease the likelihood of that state adopting hybrid-vehicle subsidies.

Hypothesis 1.3 A higher problem severity affects a state’s propensity to adopt hybrid-vehicle subsidies.

Hypothesis 1.4 Institutional capacity affects a state’s propensity to adopt hybrid-vehicle subsidies—states with surpluses are more likely to adopt subsidies for hybrid-vehicle purchases than those without.

Hypothesis 1.5 The number of neighboring states that have previously adopted any type of HEV incentive impacts a state’s propensity to adopt an incentive.

Although this section spells out the general determinant categories, Chapter 3 will more thoroughly discuss the operationalization of these predictors. The first hypothesis looks at the impact of constituent support. The issue network framework posits that large numbers of players can use their collective power to affect a policy issue. Elected officials that serve constituencies with more support for this hybrid-electric-vehicle technology will be more likely to support these policies than those in states where their constituencies do not collectively support this technology. Indicators of public support will be further discussed in the data section, but three measures will be used: (1) purchase rate of hybrid vehicles within a state, (2) environmental club memberships, and (3) state-level-utility spending on energy-efficiency programs. Although utility company spending on energy-efficiency programs does not intuitively reflect constituent support, it can be argued that the spending levels for these programs—particularly for cooperative utility companies—reflect a broader demand for them. Therefore, higher spending is assumed to be a proxy for higher constituent support for energy efficiency.

The second hypothesis tests whether one form of consolidated power, interest-group strength, has an impact on a state’s propensity to adopt an incentive. The hybrid-electric-vehicle
supply during this time period was manufactured primarily by two companies, Honda and Toyota. It is posited that states with automobile manufacturers will resist these incentives, and so a negative relationship is hypothesized: the presence of automobile manufacturing will decrease a state’s propensity to adopt hybrid subsidies.

Components of the other classes of predictors—problem severity and institutional capacity—are also tested. Problem severity has consistently been found to affect state policies. Because this policy topic is the intersection of three policy issues—transportation policy, environmental policy, and energy policy—three different indicators, each capturing a different policy issue, will be used. These indicators will be further discussed in Chapter 3.

Finally, institutional capacity, in terms of fiscal measures, will be tested. Prior research has found that revenue generating policies are implemented by states with a budget deficit (Berry and Berry 1990). Since hybrid-electric vehicle incentives are revenue draining, it is hypothesized that states with budget surpluses would be more likely to adopt subsidies.

Efficacy of Hybrid–Electric–Vehicle Incentives and Predictors of Adoption

The second aspect of this dissertation is a policy evaluation. This dissertation also attempts to answer how hybrid-vehicle purchase incentives affected demand and what other factors influence an individual’s decision to buy a hybrid. Therefore, the following hypotheses will also be tested.

**Impact of Hybrid-Electric-Vehicle Incentives on Demand**

Hypothesis 2.1a: State-level hybrid subsidies increase the aggregate demand for hybrid-electric vehicles.

Hypothesis 2.1b: State-level hybrid subsidies increase the probability that an individual will purchase a hybrid.

**Consumer Attitudes and Attitudes Affecting the Probability of Adoption**
Hypothesis 2.2  
Attitudes toward the built environment and travel behavior impact an individual’s likelihood of purchasing a hybrid.

The two technology models presented in the literature review, the epidemic and consumer-choice models, approach the theory from different perspectives. The epidemic model treats the population as homogeneous, while the consumer-choice model treats the population as heterogeneous and treats these differences as predictors to adoption. Together, these two models will be used to discover whether hybrid-electric-vehicle incentives alter demand by examining (1) whether the slope of the cumulative diffusion curve is altered by changes in price from the incentives (communicated in hypothesis 2.1a) and (2) if differences between consumers, specifically attitudes, as well as incentives for hybrid vehicles, are predictors of the adoption of these vehicles (communicated in hypothesis 2.1b and hypothesis 2.2).

Figure 1 incorporates the different individual level predictors of hybrid adoption, trying to incorporate both attitude and economic variables into one model of discrete choice. Income and age have been found to affect the propensity to adopt a hybrid vehicle, but this dissertation will attempt to identify whether these variables are in fact predictors of adoption or proxies for attitudes. Hypothesis 2.1 will therefore examine consumer heterogeneity in terms of place of residence, socioeconomic correlation, and attitudes to see which variables predict adoption.
Although previous research points to attitudes as largely explaining adoption behavior, little research has utilized such a large scale survey to explore the interaction between attitudes, demographic variables, and travel behavior on adoption of this technology.

Figure 1: Hypothesized Causal Model of Hybrid Adoption.
CHAPTER 3: DATA AND METHODOLOGY

This chapter reviews the data used in this dissertation and the methodology used to test the hypotheses given in the previous chapter. Two distinct data sets will be used—the “Aggregate Data Set” and the 2008 National Household Travel Survey. Data from multiple sources have been identified and collected, allowing for a rich analysis using multiple econometric methods.

Data

The Aggregate Data Set

The Aggregate Data Set is a unique data set built from a variety of sources summarized in Table 2. This data set will be used to test hypotheses 1.1–1.4 and hypothesis 2.1, which aim to identify the determinants of state-level environmental policy adoption, and evaluate the impact of these subsidies on hybrid-vehicle demand. Analyses performed to test each hypothesis may use different portions of the ADS. Data were restricted to 2000–2005. Some data are not for this entire period—subsidies for these vehicles were not adopted until 2001, and nonattainment status data were not available for 2005—but this was not expected to present problems. Because there is little between-year variation for this nonattainment status variable, it was lagged during the analysis.

Policy data, both proposed and enacted subsidies, were collected from the Department of Energy’s Energy Efficiency and Renewable Energy Alternative Fuels and Advanced Vehicles Data Center. Four types of subsidies have been identified and coded in the data set: (1) HOV lane exemption, (2) excise-tax exemption, (3) sales-tax exemption, and (4) income-tax
exemption. HOV lane exemptions allows hybrid-vehicle owners to purchase a special license plate that lets them use the HOV lane, regardless of how many passengers are in the vehicle.

### Table 2: Aggregate Data Set.

<table>
<thead>
<tr>
<th>Category</th>
<th>Variable</th>
<th>Source</th>
<th>2000</th>
<th>2001</th>
<th>2002</th>
<th>2003</th>
<th>2004</th>
<th>2005</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Policy</strong></td>
<td>States that proposed legislation but did not pass (HOV exemptions, tax credits, excise tax exemption, and sales tax exemption)</td>
<td>Department of Energy's Energy Efficiency and Renewable Energy Alternative Fuels and Advanced Vehicles Data Center</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>X</td>
</tr>
<tr>
<td></td>
<td>Passed and enacted legislation (HOV exemptions, tax credits, excise tax exemption, and sales tax exemption)</td>
<td>Department of Energy's Energy Efficiency and Renewable Energy Alternative Fuels and Advanced Vehicles Data Center</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>X</td>
</tr>
<tr>
<td><strong>Political Context</strong></td>
<td>Public Opinion: Sierra Club membership</td>
<td>Sierra Club</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td></td>
<td>Aggregate number of hybrids sold in the U.S. for each state</td>
<td>R.L. Polk</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td></td>
<td>Interest group pressure: percentage of manufacturing that comes from automobile manufacturing</td>
<td>Bureau of Economic Analysis</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td></td>
<td>Party of Governor</td>
<td>National Governors' Association</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td></td>
<td>Constituent Support: State-level spending on utilities energy efficiency (thousand-dollar units)</td>
<td>Energy Information Administration</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td><strong>Problem Severity</strong></td>
<td>Air Quality Measures</td>
<td>Average number of non-attainment status per county from the U.S. EPA</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Gasoline Prices</td>
<td>Energy Information Administration</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td></td>
<td>Roadway Congestion Index</td>
<td>Texas Traffic Institute</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td><strong>Institutional Capacity</strong></td>
<td>(Revenue – Expenditure)/Expenditure</td>
<td>Natl. assn. of state budget officers</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td></td>
<td>Population</td>
<td>U.S. Census</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td><strong>Control Variable</strong></td>
<td>Density</td>
<td>U.S. Census</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td></td>
<td>Per Capita Income</td>
<td>U.S. Census</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td></td>
<td>Aggregate number of new car registrations for each state</td>
<td>R.L. Polk</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
</tbody>
</table>

Hybrid demand, which can be used as an indicator of public opinion related to hybrid vehicles or as an outcome of the policy, and total car demand were obtained from R.L. Polk. The data were new car registrations at the state level, for every car model on the market. These data
were aggregated to total new car registrations and total new hybrid registrations for each state for the years 2001–2005. Coding hybrids did present difficulties because they can be identified in various ways. As of 2007, there were 18 hybrid options for consumers. Some of these models have been marketed as hybrids with distinct names, such as the Honda Insight or the Toyota Prius, but other models have been designed so that hybrid technology is an available option like an automatic transmission or sunroof. Toyota Camry, Honda Accord, and Ford Escape all offer hybrid alternatives of their traditional counterparts. These data limitations have restricted the coding of hybrid vehicles to those with unique model names, the Honda Insight and the Toyota Prius. Although this variable therefore suffers from measurement error, the bias should be downward because the dependent-variable count is lower than the actual amount of hybrid sales. In addition, it is assumed that because these two models were the most prominent during this time period, they represent a significant portion of the total hybrid market share.

Previous literature examining comparable policy problems was used to guide the data collection for variables that explain environmental policy adoption. As identified in the literature review, factors that affect the adoption of environmental policies fall into a number of categories: political context, problem severity, and institutional capacity. Interest-group pressure and government control were all identified in the literature as various facets of political context. Similar to previous research, state-level Sierra Club membership data were collected as a measure of public opinion (Ando and Polasub 2009). An indicator of interest group pressure used in the literature, the percentage of state gross domestic product that was attributed to manufacturing, was collected (Daley and Garand 2005). These data were collected from the Bureau of Economic Analysis. Finally, political party of the governor was included as an additional measure of political context. This information was collected from the National
Governors’ Association.

Finally, an additional measure of constituent support, or public opinion was collected. Data for demand-side efficiency programs for utilities, reported as annual energy-efficiency electricity program spending by the utility companies, have been compiled by the Energy Information Administration for the years 1990–2009. These numbers are self-reported by both private and public utility companies, so although they capture state-level institutional support for subsidies for energy-efficiency technologies, this variable is susceptible to measurement error.

Identifying measurements for the problem-severity category of predictors posed challenges, since transportation policies can be seen as the intersection of environmental, energy, and smart-growth policies. For this reason, multiple measures were chosen to capture problem severity from these three points of view. To look at the impact of smart-growth issues on the adoption of hybrid-electric vehicle subsidies, including HOV lane exemptions and pecuniary subsidies, the Texas Transportation’s Institute Roadway Congestion Index (RCI) measure of congestion was used. It is a compilation of congestion indexes for 85 large metropolitan areas in the United States. If a metropolitan area was identified as being in multiple states, the congestion was counted in both states. For example, New York City congestion was coded for Connecticut, New Jersey, and New York. The RCI is a measure of both intensity and duration of congestion, with anything higher than 1.0 representing a higher than desirable amount of congestion. Further explanations of this index can be found on the Texas Transportation Institute website.⁶ Since each state may have multiple metropolitan areas, the average index for all metropolitan areas in the state has been used for this analysis.

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⁶For more information, please see: http://mobility.tamu.edu/ums/report/appendix_a.pdf.
To capture problem severity from an environmental perspective, the number of counties in nonattainment status has been collected. As part of the 1990 Clean Air Act, a county can receive a nonattainment status for each of the following criteria pollutants: 1 hour ozone, 8 hour ozone, carbon monoxide, nitrogen dioxide, sulfur dioxide, particulate matter PM-10, particulate matter PM-2.5, and lead, based on air samples.⁷ According to the Sec. 107.(a):

Each State shall have the primary responsibility for assuring air quality within the entire geographic area comprising such State by submitting an implementation plan for such State which will specify the manner in which national primary and secondary ambient air quality standards will be achieved and maintained within each air quality control region in such State.⁸

Once nonattainment status is reached, a state must form a plan, accepted by the EPA, that creates incentives to correct the problem. Part of the plan could be to reduce automobile usage in the area, because automobiles are significant sources of most of the criteria pollutants, except for sulfur dioxide and lead.⁹ For example, they are considered one of the primary sources of carbon monoxide, and NO₂.¹⁰ NO₂ reacts with volatile-organic compounds to form ozone and fine particulate pollution, two additional criteria pollution. In terms of the operationalization of this variable during this analysis, the variable was computed to be the total number of nonattainment status in the state, divided by the number of counties. Since one county can hypothetically have nonattainment status for up to eight criteria pollutants, the variable’s maximum is 8, with a minimum of 0.

Finally, to capture problem severity in terms of energy policy, gasoline price data have

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⁷ For more information, please see: http://www.epa.gov/oar/caa/title1.html#id. Last accessed June 10, 2011
⁸ For more information, see: http://www.epa.gov/oar/caa/title1.html#id. Last accessed June 10, 2011
⁹ For more information, see http://www.epa.gov/air/peg/cleanup.html. Last accessed June 10, 2011
¹⁰ For more information, see http://www.epa.gov/ttn/naaqs/so2/index.html. Last accessed June 10, 2011
been collected. Because gasoline prices mimic crude-oil prices, they represent problem severity from a macro level (Borenstein, Cameron et al. 1997; Bachmeier and Griffin 2003). More important, however, increases in gasoline prices may constrain individuals’ budgets so that they prefer to consume less. With an inelastic demand, however, consumers would have to change their behavior or purchase an alternative car. Gasoline prices and fuel efficiency are found to be substitutes, so that the cross-price elasticity is positive: when gas prices increase, the demand for fuel efficiency increases (Espey and Nair 2005). In this case, the price differential of the hybrid vehicle becomes less significant because the operating cost savings are greater.

Obtaining proxies for institutional capacity in terms of environmental policy or energy efficiency remained a difficult challenge, because data on a state’s monetary commitment to energy efficiency are not collected in a consistent manner. In the 1990s, a comprehensive review of state’s environmental efforts, the Green Book, was compiled, but it was only published once, for the years 1991–92. In 2004, the American Council for an Energy-Efficiency Economy (ACEEE) has begun publishing an annual State Energy Efficiency Scorecard based on the accumulation of both qualitative and quantitative data. Unfortunately, because the first publication is in the middle of the time period studied, using data taken directly from this publication is infeasible.

In addition, the development of institutional capacity for transportation-policy was impossible. ACEEE’s score card included several indicators of transportation policy: compliance with California’s tailpipe emissions standards, exemplary land-use policies, transit funding, and state fleet requirements. The first indicator, California’s tailpipe emissions

standards, was not collected until the policy began in 2004, making it infeasible to be used. Exemplary land-use policies and fleet requirements are qualitative in nature. Finally, transit funding, collected by the Bureau of Transportation Statistics, are collected longitudinally for multiple years. Unfortunately, these data are only collected every 5 years: 1995, 2000, and 2005. Therefore, no adequate measures of institutional support for transportation policies were identified for this analysis. The only measure of institutional capacity is one used in multiple studies is one of fiscal health. This analysis borrows from Berry and Berry (1990), using the ratio of total state revenue minus total state spending, to total state spending. This ratio allows controlling for difference sizes across states.

Several limitations of the Aggregate Data Set have been identified. First, there is only one measure of institutional capacity. In addition, as previously mentioned, variables such as state spending on energy efficiency and hybrid purchases may suffer from measurement error. Because these data are aggregated to the state level, based on this analysis alone, conclusions about the impact of subsidies cannot be made at the individual level. These results will not speak to whether individuals exposed to subsidies will be more likely to purchase a hybrid-electric vehicle. Conclusions are restricted to state-level demand. Therefore, to test hypothesis 2.1b and hypothesis 2.2, additional analysis at the individual level is required.

The National Household Travel Survey

Data from the 2008 National Household Travel Survey provides such individual-level data regarding travel behavior not publicly available anywhere else. These data will therefore be used to test hypotheses 2.1b and 2.2. This survey is conducted every 7 years by the U.S. Department of Transportation, with the last previous survey being completed in 2001. In 2008, 150,000 households were surveyed, and weights were computed for multiple levels of
observations: households, vehicles, and person level. To make these data appropriate for analysis at these multiple levels, nonresponse weights were created for all three levels to compensate for the low-response rates of hard-to-reach population groups. The analysis for this dissertation is at the individual level; the person weight was based on the 2008 American Community Survey so that the sample could be expanded to the nation. These data are from a household-level survey, with each household member being surveyed, so there are multiple levels of observation in the survey. The data collected consist of individual-level travel behavior, household vehicle ownership, and individual uses of the vehicles, as well as common socioeconomic variables common in large-scale surveys. In prior years, the National Household Travel Survey collected data on every individual within a household, along with vehicle characteristics and uses, but did so without assigning vehicles to individuals, only to households. This structure restricted research on individual travel behavior as it relates to vehicle usages, since no ownership was assigned. Since the 2001 survey, the structure of the database has changed, so that vehicles are now linked to a primary driver. Although this is not identical to individual purchase data, these are the only publicly available data that include car make and model at an individual-level survey. This format will still be susceptible to measurement error if the primary driver did not purchase the vehicle.

The survey also collected data on attitudes, allowing research to identify the impact of attitudes on an individual’s propensity to adopt hybrid vehicles. The attitude questions attempt to capture attitudes related to transportation issues, such as traffic congestion and driving conditions. Table 3 provides the variables of interest from the National Household Travel

12 More information on the American Community Survey can be found at: http://www.census.gov/acs/www/
Table 3: Selected National Household Travel Survey Variables.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>Summary</th>
</tr>
</thead>
</table>
| Education          | Highest level of education completed             | 01= less than high school
                   |                                                                  | 02= high school graduate
                   |                                                                  | 03= some college
                   |                                                                  | 04= bachelor’s degree
                   |                                                                  | 05= graduate or professional degree                                  |
| Age                | Respondent’s age                                 | 5-88                                                                    |
| Public transportation used | How often individual used public transit in past month | 1-180                                                                  |
| Household income   | Household income                                 | 1-18, with each increase representing 5,000; i.e. 1 is 0 < income < 4,999; 2 is 5000< income < 9999 |
| Number of walking trips | How many estimated walking trips the individual took in one Month | 1-155                                                                  |
| Black              | Stated ethnicity of the individual               | 1=Black; 0 otherwise                                                   |
| Asian              | Stated ethnicity of the individual               | 1= Asian; 0 otherwise                                                  |
| Other              | Stated ethnicity of the individual               |                                                                        |
| Hybrid             | Whether the respondent states that the car linked to the person is a hybrid vehicle | 1= yes; 0 otherwise                                                   |
| Urban Size         | What is the size of the MSA of the household     | 01= not in an urbanized area
                   |                                                                  | 02= 50,000-199,999
                   |                                                                  | 03= 200,000-499,999
                   |                                                                  | 04= 500,000-999,999
                   |                                                                  | 05= > 1 million without rail
                   |                                                                  | 06= > 1 million with rail                                           |
| Detached Home      | Whether the individual lives in an detached home | 1= yes; 0 otherwise                                                   |
| Congestion         | Highway congestion is the most important transportation issue | Most important issue=1, 0 otherwise                                   |
| Transit            | Access to availability of public transit         | Most important issue=1, 0 otherwise                                   |
| Cost               | Price of travel                                  | Most important issue=1, 0 otherwise                                   |
| Aggressive         | Aggressive or distracted drivers                 | Most important issue=1, 0 otherwise                                   |
| Safety             | Safety concerns                                  | Most important issue=1, 0 otherwise                                   |
| Walkways           | Having a walkway available                      | Most important issue=1, 0 otherwise                                   |

Note: more Information on this survey can be found at: nhts.ornl.gov

To supplement this data set, multiple additional variables are merged. For instance, state incentive data will be merged with the National Household Travel Survey data, as well as traffic-
congestion data collected from the Texas Traffic Institute. As previously discussed, data from the Roadway Congestion Index from the Texas Transportation Institute are used as measures of traffic severity.

Methodology

The three research questions that are examined in this dissertation use multiple econometric methods to test the hypotheses. These methods have been chosen based on the structure of the variables and the data sets. This section reviews the methods chosen to examine each research question.

To identify predictors of incentive adoption, this dissertation uses the aggregate data set data for years 2001 to 2005. Longitudinal data traditionally utilize fixed effects, random effects, difference-in-difference estimation, or pooled time-series regression analysis. For multiple reasons, pooled times-series regression has been identified as the most useful method for these analyses. First, pooled cross-section analysis is useful when the number of cases being studied is small, such that the researcher is limited in the number of explanatory variables that can be used. For instance, using all states in a panel-data analysis leaves the researcher with only 50 observations, severely limiting the number of independent variables that can be included. Pooling panel data also allows time-invariant data to be explored as possible determinants, whereas fixed effects time-demean the data. With fixed effects, variables are transformed by subtracting the mean from values, so only variables with variation are left. Fixed effects therefore estimate the impact of internal changes over time on the propensity to adopt. Because this research is more interested in the variation between states, pooled times-series regression is a more appropriate method. This is particularly helpful for variables such as nonattainment status,
which has minimal availability.

Although pooled time-series regression is a commonly used method for data such as the Aggregate Data Set, disadvantages do exist. For example, heteroskedasticity is often mentioned as a source of concern for pooled time-series regression when the dependent variable is a continuous variable (Beck, Katz et al. 1998). Heteroskedasticity is when variables may have inconsistent variances between units. For instance, the variance of a variable, such as income, may differ between Texas and Wyoming, because inputs into the Texas system are larger than the homogenous population of Wyoming. But because this research uses a binary dependent variable, heteroskedasticity is not an issue.

Logistic regression, the parametric technique appropriate when the dependent variable is binary, does require that the errors be uncorrelated. Although logistic regression does not require the error terms to be normally distributed, the assumption that the errors are uncorrelated is important, and if not met can produce biased estimates. In time series data in this subject area, errors tend to be correlated in two ways. First, they tend to be contemporaneously correlated, so that errors in state \( i \) at time \( t \) are correlated with errors in country \( j \) at time \( t \). For example, errors in New York might look like errors in New Jersey because the data for New York and New Jersey are not independent. Second, errors tend not to be independent from time \( t \) to time \( t + 1 \), for example, variables such as political ideology or population. If observations are not independent of one another, called serial correlation, they could result in invalid statistical inferences. Regardless, multiple research projects in the policy-adoption discipline have used this method, although statistical tests should evaluate the severity of contemporaneously correlated errors, known as autocorrelation (Potoski 2001; Daley and Garand 2005; Ando and Polasub 2009).
Therefore, although there are some limitations in this method, pooled cross-section analysis will be used, and the econometric model used to answer this research question is the following:

\[
P(y_{i,t} = 1) = f(x_{i,t}, y_{i,(t-1)}, \ldots x_{i,(t-1)}),
\]

where \( P \) is the probability of \( Y \) equaling 1 and \( f \) a vector of suitable covariates. In this case, \( Y \) is a binary variable, with 1 being an incentive and 0 being no incentive in a state. There are four types of subsidies, so multiple models are estimated. To deal with serial correlation, Beck, Katz et al. (1998) posit adding a series of dummy variables that mark the number of periods since either the start of the sample period or the previous occurrence of the event. Although this strategy has been widely employed by international relations and conflict researchers who have data on multiple countries for a large amount of periods \( T \), because the data available for this research cover only 5 years, it is not an appropriate mechanism for dealing with serial correlation when \( T \) is small, say less than 10 (Beck 2001).

Because hybrids subsidy adoption remain a “rare event,” with estimates of hybrid-electric-vehicle adoption below 10% of all observations, methodologies used in disciplines such as epidemiology that deal with rare events data will be used (King and Zeng 2001). When the dependent variable is unbalanced in terms of how often an event is observed, logistic regression can produce biased estimators that underestimate event probabilities. To address this issue, it is possible to bootstrap the results, to repeatedly select a subset of events \( Y \) and use that subset to run the regression on the restricted number of events. This sampling will be repeated a high number of times so that the stability of the results can be tested. The robustness can be evaluated through histograms of the regression coefficients so that the histograms can be compared to the
original regression results. Random selection is desirable because without a selection rule, the sampling is independent of all other variables and so cannot cause bias. Alternatively, stratified sampling allows observations to be randomly selected within certain categories of independent variables, but will not be used in this analysis.

To determine the impact of subsidies on the demand for hybrid-electric vehicles, this study uses two distinct data sets, the Aggregate Data Set and the National Household Travel Survey data set. Both data sets suffer from the same issue common in most public-policy evaluation. The ideal method to test whether subsidies influence demand for hybrid vehicles would be a randomized experiment within the population. Randomization guarantees that self-selection does not affect an evaluator’s ability to yield unbiased estimators of the treatment effect. Self-selection means that individuals select into treatment groups in nonrandom patterns. Such self-sorting has a negative impact if the characteristics that predict which individuals select into treatment are correlated with the outcome variable, in which case the evaluation will produce biased estimators. Unfortunately, a randomized control trial in this area is neither financially nor politically feasible. To identify how subsidies have affected the demand for hybrid-electric vehicles, this study replicates an experimental design with a random treatment using data available, commonly referred to as observational or quasi-experimental methods.

Using the Aggregate Data Set, this study attempts to estimate treatment effects using traditional panel-data methods: fixed effects and difference-in-difference estimation. Fixed-effects panel data regression has been previously been employed in relevant literature as a policy-evaluation method (Diamond 2009; Gallagher and Muehlegger 2011). This analysis uses the following model:

\[ y_{it} = \alpha + \beta x_{it} + \beta D_{it} + v_i + \epsilon_{it}, \]  

(6)
where \( v_i \) are time-independent state-level characteristics, \( y_{it} \) is the outcome variable for each year and each state. The vector \( x_{it} \) contains other control variables that may be correlated with the policy. These variables have been chosen from the literature reviewed. Fixed-effects controls are used for the average differences across states in any observable or unobservable predictors that remain constant across time, identified as \( v_i \). Examples of unobservables include state-level political outlook. If all state-level unobservable characteristics remain constant during the time period, then the coefficients will be less biased, because the error term’s state-level component is accounted for. The policy evaluated is \( D_{it} \), and in this particular research it is a binary variable; there are four treatments: (1) HOV lane exemption, (2) excise-tax exemption, (3) sales-tax exemption, and (4) income-tax credits.

This fixed-effects method is supplemented with a difference-in-difference estimator for comparison. Difference-in-difference estimation assumes that the outcome paths between the treated and the non-treated groups would not be systematically different in the absence of intervention. The model is represented as:

\[
Y_{it} = \beta_0 + \beta_1 T_{it} + \beta_2 D_{it=0} + \beta_3 T_{it}D_{it=1} + \epsilon_{it},
\]

where \( Y_{it} \) denotes the outcome of every unit for every time period, \( T \) is a time variable, \( D_{it} \) is an indicator variable coded 1 if unit is in treatment group and 0 if it is in the control group. For purposes of this research, \( D_{it} \) is an indicator variable for whether the state implemented a subsidy, and \( Y \) is the percentage of total sales that are hybrid. Although difference-in-difference and fixed effects are empirically similar, difference-in-difference allows for time-specific intercepts, shown as \( T \), whereas fixed effects does not. Both intercept and slope of the treatment and control group can be shifted.

An additional control group will be constructed in an effort to reduce selection bias based
on theoretical understanding of the population will be performed. As done in similar observational studies (Pion and Cordray 2008; Youtie, Shapira et al. 2010), a comparison group can also be identified using theory-based knowledge of the population. This comparison group design is known as a constructed control design (Rossi 1993). As of 2005, 27 states had proposed subsidies for hybrid-electric vehicles. Some spent a substantial amount of time in the legislature being debated. HOV lane exemptions contrast with federal laws regarding HOV lanes, so multiple states, including Georgia, have passed legislation allowing hybrid cars to be driven in HOV lanes, but federal approval is pending. Since it is possible to posit that states that propose such legislation are more similar in nature to the treatment group than the general population is, the final analysis will restrict the control group to states that have proposed legislation. Fixed effects and difference-in-difference estimation will then be run using this restricted sample.

Because these data come from an observational study, the results from both the fixed-effects analysis and difference-in-difference estimation may not be consistent if selection bias exists, but the results are a starting point for any additional analyses that need to be done. To correct the probable selection bias, additional analysis will be performed. Propensity-score matching is a commonly used method that attempts to remove selection bias by imitating an experimental design (Rosenbaum and Rubin 1983; Heckman, Ichimura et al. 1997; Dehejia and Wahba 1999; List, Millimet et al. 2003; Pion and Cordray 2008). This is achieved by identifying observed variables that differ between the treatment and control groups.

The propensity score \( e_i \) is defined as the probability that the \( i \)th unit is treated given that its vector of covariates is \( X_i \):

\[
e_i = e(X_i) = \Pr(W_i = 1/X_i) \tag{8}
\]
when the treatment variable is $W_i$, a dichotomous variable, with 1 for being treated (a state having incentives) and 0 for having no incentives. Empirically, the treatment variable becomes a dependent variable in a logistic regression to identify the probability of a person receiving treatment. Once the propensity score is calculated, it can be used for one of three methods: matching, subclassification, and weighting. Matching pairs each observation in the treatment group with an observation in the control group with a similar propensity score. There are multiple matching algorithms, but the most common is one-to-one matching with or without replacement. Unmatched units are discarded. Subclassification on the propensity score ranks all units by their propensity score and then uses boundaries to create subclasses of treated and control units with similar values of the propensity score. Five or six subclasses are typically used, with approximately the same total number of units within each subclass. Weighting methods use the inverse of the propensity score as a weight to apply to each treated unit and the inverse of one minus the propensity score as the weight to apply to each control unit (Rubin 2001). For this research, a one-to-one matching with replacement will be used.

Although propensity-score matching has been widely applied in recent evaluation and observational study literature, many restrictions to this method still exist. If treatment and control groups have the same distribution of propensity scores, then they have the same distribution of all observed covariates just as in a randomized experiment. This means that the only further calculation required after matching is performed is determining the difference in the means of the average treatment effect between the treatment and the control groups. Since we do not condition on all covariates except on the propensity score, we have to check whether the matching procedure is able to balance the distribution of the relevant variables in both the control and treatment groups. If the matching procedure does not produce balanced distribution, then
propensity-score matching may not estimate an unbiased estimate of the average treatment effect.

The implication of this method is that if a group of treated units and control units have the same value of the propensity score $e_i$, then they have the same distribution of multivariate $X_i$, which removes selection bias issues. Thus, having these groups of treated and control units with matching propensity scores controls for all the observed covariates that affect the probability of a unit selecting into treatment. If treatment and control groups have the same distribution of propensity scores, they have the same distribution of all observed covariates, and thus mimic a randomized controlled experiment (Rubin 2001). This is referred to as a balanced panel.

Multiple criteria have been provided in the literature to determine if propensity score matching produces balanced groups. Of noted importance is the requirement that the covariate distributions are similar in nature. Rubin provides easy-to-understand guidelines to identify when propensity score matching produce balanced groups (Rubin 2001). First, the difference in the means of the propensity scores in the two groups being compared must be small, for example less than half a standard deviation apart, unless the distributions of the covariates in both groups are nearly symmetric or the distributions of the covariates in both groups have nearly the same variances, and the sample sizes are approximately the same. Second, the ratio of the variances of the propensity score in the two groups must be close to one and third, the ratio of the variances of the residuals, of the covariates after adjusting for the propensity score must be close to one.

Multiple applied research efforts have found that propensity-score matching does not produce balance on the covariates (Pion and Cordray 2008; Youtie, Shapira et al. 2010). Further, propensity-score matching may not eliminate differences between the two groups, meaning that
selection bias is still a significant threat to internal validity. Although this possibility is real, propensity-score matching is currently the best tool researchers have to deal with selection bias.

The hypotheses addressing the impact of subsidies on an individual’s propensity to adopt a hybrid will be addressed using the National Household Travel Survey. Since the data are cross-sectional, the panel data methods described above are not appropriate for this data set. Instead, the model being estimated is a consumer-choice model, not an epidemic model. A cross-sectional logistic regression will test hypotheses 2.1b and 2.2 using the following model:

\[
\log\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 T_i + \beta_2 X_i + \epsilon_i, \tag{9}
\]

where Y is equal to log(p/1-p), and p is the probability of Y equaling 1. The dependent variable for this hypothesis is “an individual owning a hybrid or alternative vehicle.” The explanatory variable \(T_i\) is the existence of an incentive where the person resides. Additional covariates that address attitudes and traffic congestion are included in this model, as well as other demographic variables explained in Table 3. Since the National Household Travel Survey data set is weighted to adjust for nonresponses, models will be estimated using the weighted sample.
CHAPTER 4: ANALYSIS

This chapter presents the results from analyses that test the hypotheses under each research question identified in Chapter two in an effort to address to following three research questions:

1. Which states adopt subsidies for hybrid-electric vehicles?
2. What is the effect of incentives on consumer demand for hybrid-electric vehicles?
3. Do attitudes predict the adoption of hybrid vehicles?

The first section of the chapter presents the analyses performed to answer the first research question, specifically addressing two categories of determinants, internal determinants (political context, institutional capacity, and problem severity), and external determinants, the impact of neighboring states HEV incentives adoption. The second section looks at the impact of these subsidies on demand by applying aggregate data to both parametric and nonparametric methods. This allows the construction of multiple comparison groups. Finally, using the National Household Travel Survey, tests are performed to better understand how subsidies, consumer attitudes, and travel behavior affects an individual’s propensity to adopt hybrid-vehicle technology.

Identifying Predictors of Policy Adoption

During 2001–2005, the study period for this research, states’ implementation of incentives to promote the diffusion of hybrid-electric vehicles increased. As Figure 2 shows, the number of states with enacted incentives increased from 5 in 2001 to 12 states, plus the District
of Columbia, in 2005. In 2001, only Virginia (HOV lane exemption), Maryland (excise-tax deduction), Maine (sales-tax exemption), Colorado (income-tax credit), and West Virginia (income-tax credit) had active incentives. By 2005, four states offered HOV lane exemption, four states offered a tax credit, three states offered sales-tax exemptions, and two states offered excise-tax exemptions. This trend continued in the following years; in 2005 alone, over 30 states proposed new legislation to support diffusion of this technology, with an additional two states enacting HOV lane exemptions at the beginning of 2006.

![Figure 2. Number of States that Offered HEV Incentives, 2001-2005.](image)

This trend demonstrates that some states have become leaders in the use of these incentives, while others have become laggards. This section of the analysis attempts to understand why some states take a leadership role in environmental policies while others do not.
As identified in the literature, one possible explanation of diffusion is the pressure by neighboring states to adopt, known as horizontal diffusion. Figure 3 presents the diffusion pattern from a geographical perspective. Looking at the geographical distribution, it appears as though geographical clusters of incentives do exist, with both coasts comprising of the majority of the incentives. This clustering mimics the leadership trends in other environmental areas, such as air quality.
Table 4: Summary Statistics of ADS.

<table>
<thead>
<tr>
<th></th>
<th>With Subsidies (Treatment)</th>
<th>Natural Control Group Without Subsidies</th>
<th>Constructed Control Group Proposals</th>
<th>Population</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td># of Obs.</td>
<td>Mean</td>
<td>Standard Deviation</td>
<td># of Obs.</td>
</tr>
<tr>
<td>Traffic Congestion Index</td>
<td>80</td>
<td>0.95</td>
<td>0.37</td>
<td>175</td>
</tr>
<tr>
<td>Spending on energy efficiency (million's)</td>
<td>80</td>
<td>57.29</td>
<td>10.16</td>
<td>175</td>
</tr>
<tr>
<td>Hybrid registrations</td>
<td>80</td>
<td>1620.0</td>
<td>3672.07</td>
<td>175</td>
</tr>
<tr>
<td>Total registrations (1000s)</td>
<td>80</td>
<td>284.0</td>
<td>337.48</td>
<td>175</td>
</tr>
<tr>
<td>Republican governor</td>
<td>75</td>
<td>0.475</td>
<td>0.502</td>
<td>175</td>
</tr>
<tr>
<td>gasoline (cents per gallon)</td>
<td>80</td>
<td>129.2</td>
<td>33.03</td>
<td>175</td>
</tr>
<tr>
<td>Income ($1000)</td>
<td>80</td>
<td>45.53</td>
<td>7.17</td>
<td>175</td>
</tr>
<tr>
<td>Population (millions)</td>
<td>80</td>
<td>7.116</td>
<td>8.827</td>
<td>175</td>
</tr>
<tr>
<td>Density(pp/sq. mile)</td>
<td>80</td>
<td>699.5</td>
<td>1976.11</td>
<td>175</td>
</tr>
<tr>
<td>Sierra club memberships (1000s)</td>
<td>80</td>
<td>27.96</td>
<td>44.27</td>
<td>175</td>
</tr>
<tr>
<td>Percentage of manufacturing from automobile</td>
<td>70</td>
<td>0.321</td>
<td>0.231</td>
<td>160</td>
</tr>
<tr>
<td>State Fiscal Health</td>
<td>70</td>
<td>0.1547</td>
<td>0.962</td>
<td>174</td>
</tr>
<tr>
<td>% of new automobiles that are hybrids</td>
<td>80</td>
<td>0.522</td>
<td>0.468</td>
<td>175</td>
</tr>
<tr>
<td>Percentage of counties in nonattainment status</td>
<td>80</td>
<td>12.07</td>
<td>15.61</td>
<td>175</td>
</tr>
</tbody>
</table>
Table 4 presents state-level summary statistics of the ADS data. The ADS data in this table will be used to both identify the determinants of HEV incentive adoption and to understand the impact of these incentives. The impact analysis will be performed using three different control groups, the natural control group (states that did not adopt incentives), a constructed control group (states that proposed incentives but did not adopt them), and a control group constructed using propensity scores. Therefore, table 4 divides the statistics into the treatment group, the natural control group, the constructed control group, and the population. As stated in Chapter 3, “State fiscal health” has been defined as revenue minus spending, divided by revenue. Therefore, observations under 0 are those states/years in which there was a budget deficit; anything above a zero signifies a budget surplus. In addition, since data for nonattainment status were not available for 2005, the data were lagged to increase usable observations.

Because table 4 does not highlight the differences in the variable distribution, kernel density plots, presented in Appendix D, were created for states by treatment condition (incentive or no incentive) as supplemental information. Reviewing the summary statistics and the kernel density plots reveals several key points. For example, states with subsidies had similar distributions to states without subsidies, but higher means for both nonattainment status density and income. In addition, the means for gasoline prices, population, and density do not vary between the two groups. Finally, note that although gasoline price data have been adjusted into 2001 constant dollars, gas prices rose dramatically during the 2000–2005 time period, explaining the large standard deviation in that variable.

The kernel density plots also reveal that although the distribution of automobile manufacturing in the lower half of the probability distribution function is similar between states that implemented incentives and those that did not, there are a cluster of states with high
percentages of manufacturing that did not adopt subsidies. This provides support that manufacturing may reduce the likelihood that a state will adopt incentives for hybrids; the hypothesis will be formally tested further using regression.

Finally, the variation of hybrid registrations between states is large. The mean of new car hybrid-vehicle registrations per state is 800, but the maximum, in California is over 29,000. To control for total car demand in each state, the percentage of new car registrations for each year that are hybrid-electric vehicles has been calculated. Even after controlling for this cause of variation in demand, significant differences do exist. The mean percentage is less than 1% of all new registrations, although the maximum is 2.15% (Washington).

Examining summary statistics reveals that states that adopt incentives look differently than states that do not adopt. In order to better understand why states adopt incentives, this section tests the following five hypotheses:

Hypothesis 1.1 State with higher level of constituent support for hybrid-electric vehicles will be more likely to adopt hybrid-vehicle subsidies.

Hypothesis 1.2 Interest-group strength affects a state’s propensity to adopt hybrid-vehicle subsidies. Specifically, the presence of automotive manufacturing (conventional vehicles) in a state will decrease the likelihood of that state adopting hybrid-vehicle subsidies.

Hypothesis 1.3 A higher problem severity affects a state’s propensity to adopt hybrid-vehicle subsidies.

Hypothesis 1.4 Institutional capacity affects a state’s propensity to adopt hybrid-vehicle subsidies—states with surpluses are more likely to adopt subsidies for hybrid-vehicle purchases than those without.

Hypothesis 1.5 The number of neighboring states that have previously adopted any type of HEV incentive impacts a state’s propensity to adopt an incentive.

These hypothesis will be tested using a logistic regression. As discussed in Chapter 3, issue networks, large networks of unconsolidated actors, often self-sort into groups to align with
similarly interested individuals to influence policy; in other situations, consolidated power in business and government drive policy. This research compares the impact of these organized groups on the implementation of hybrid-vehicle incentives. In addition, institutional capacity and problem severity, considered from the perspective of energy policy (gasoline prices), environmental policy (nonattainment status), and transportation policy (traffic congestion), will be tested to determine their impact on hybrid-vehicle adoption.

Table 5 shows the results of an initial logistic-regression analysis to identify how differences in states affect their propensity to adopt hybrid-vehicle incentives. Alaska and DC were removed due to missing data. Because the data are pooled, states are coded as 1 when they implement the policy and for all years that the policy is enacted. Although this does cause some concern regarding construct validity, multiple states, such as Virginia, require annual legislative amendments to continue the incentives. Model A shows that the percentage of state gross domestic product (GDP) attributed to manufacturing has an impact on a state’s propensity to adopt a policy; the coefficient is strong in terms of strength and significance. For every additional percentage of state GDP that comes from automobile manufacturing, a state is 0.40 times less likely to adopt it. The diffusion rate of hybrid cars is also significant; for every 1% of cars sold that are hybrids, a state is 467 times more likely to adopt an incentive. Gasoline cost is also significant, but in the opposite direction than hypothesized. Although no explanation can be given at this time, higher gasoline prices could reduce a state’s likelihood that it implements incentives because the political capital needed to pass such a policy is being utilized elsewhere.
### Table 5: Determinants of Policy Adoption Using a Pooled Dependent Variable.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Policy Adoption</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Intercept)</td>
<td>2.27 (0.92)</td>
</tr>
<tr>
<td>State Fiscal health</td>
<td>0.96 (-0.17)</td>
</tr>
<tr>
<td>Population</td>
<td>1.00 (1.73)</td>
</tr>
<tr>
<td>% of new autos that are Hybrids</td>
<td>467 (3.52)**</td>
</tr>
<tr>
<td>Republican governor</td>
<td>0.87 (0.75)</td>
</tr>
<tr>
<td>Traffic congestion</td>
<td>0.32 (-1.86)</td>
</tr>
<tr>
<td>Energy efficiency spending (1000's)</td>
<td>1.00 (0.52)</td>
</tr>
<tr>
<td>Density (pp/ sq. mile)</td>
<td>0.99 (0.2)</td>
</tr>
<tr>
<td>Gasoline (cents per gallon)</td>
<td>0.96 (-2.68)**</td>
</tr>
<tr>
<td>Sierra club memberships (per 1000)</td>
<td>0.98 (-1.18)</td>
</tr>
<tr>
<td>SGDP attributed to manufacturing (%)</td>
<td>0.340 (-1.74)</td>
</tr>
<tr>
<td>County nonattainment density</td>
<td>0.97 (-1.35)</td>
</tr>
<tr>
<td>Per capita income</td>
<td>1.00 (0.27)</td>
</tr>
<tr>
<td>Number of bordering states with any incentive</td>
<td>2.37 (3.31)**</td>
</tr>
<tr>
<td>Observations</td>
<td>245</td>
</tr>
<tr>
<td>AIC</td>
<td>174.55</td>
</tr>
<tr>
<td>Count R-Squared</td>
<td>0.85</td>
</tr>
<tr>
<td>Adj. Count R Squared</td>
<td>0.14</td>
</tr>
</tbody>
</table>

Signif. codes: *** 0.001  ** 0.01  * 0.05  . 0.1

In addition, traffic congestion negatively impacts a state’s propensity to adopt an incentive. This does not come as a surprise, as states with traffic congestion may focus on alternatively policies, such as public transportation projects.
Hypothesis 1.5 tests whether the number of neighboring states is a significant factor of diffusion. Previous research has demonstrated that this factor is significant and the results of this analysis support the previous research (Berry and Berry 1990; Mintrom and Vergari 1998; Daley and Garand 2005; Ando and Polasub 2009). Although it is not clear if this variable is significant because of competition or learning, one could conjecture that the external diffusion significant is not likely due to from interstate competition because individuals and companies would not likely be influence to relocate to another state due to these policies.

Because some of the observed variables have huge variation over time, it could be assumed that unobserved time-dependent variables create biased estimates when the data for all five years are pooled. Evidence that this bias is possible exists in the increased number of adoptions and proposals during this time period, as well as the huge variation in gasoline prices over time. Unobserved reasons for rising gas prices may also have an impact on a state’s probability to adopt an incentive. To account for this possibility, year dummy variables were added to Model A, but none of the year dummies were found to be significant. The model in Table 5 did not pass the Durbin-Watson test for autocorrelation, meaning that time dependent correlations may produce biased estimates due understating standard error variability (Beck, Katz et al. 1998). Although the literature does provide some solutions to autocorrelation threats, the solutions only apply when the time period is large, such as twenty time periods or higher (Beck, Katz et al. 1998). Chapter 5 contains further discussion regarding interpretation in light of autocorrelation concerns.

To determine the quality of a model from a logistic regression, multiple diagnostic analyses are required, since common indicators of model fit, such as R-squared, cannot be calculated. All diagnostics performed for each logistic model are presented in Appendix B, but
only the diagnostics performed for Table 5 are reviewed in the body of this dissertation. For this regression model, a likelihood-ratio test was used to test the hypothesis that the relationships proposed in the model provide a plausible explanation for those that exist in the data. The null hypothesis for that test was rejected, meaning that Model A as a whole fits significantly better than an empty model (Hosmer and Lemeshow 2000). In addition, the Hosmer & Lemeshow test was performed, although caution is suggested when using this test in sample sizes less than 400. This test (1) partitions the observations into 10 equal-sized groups according to their predicted values and (2) runs an F-test for equality of mean residuals of the 10 groups. If null hypothesis is rejected, the model does not fit the data well (Hosmer and Lemeshow 2000). The model did pass this test.

To get a better idea of how well the model predicts the data, additional descriptive statistics can be calculated that describe how well the model predicts negative and positive events. The specificity score for Model A is 0.97, and the sensitivity for the model is 0.28. The specificity score is the true negatives divided by the total negatives, and the sensitivity is the true positives divided by the total positives. Table 6 presents this information in a cross tabulation of predicted adoptions. Although no traditional R-squared can be calculated in a logistic regression, alternative indicators of have been developed. The two most commonly used alternative R-squares are the count R-square and the adjusted R-square. The count R-square is calculated by the ratio of the the correctly predicted ones and zeros are added over the total observations as a measure for how well the model predicts the outcome. The limitation of count R-square is that it does not account for models that are unbalanced in terms of the distribution of the dependent variable, which is a characteristic of this data set. The adjusted R-squared, however, accounts for this issue. The adjusted count R-squared measures the proportion of correct predictions beyond
this baseline. The count R-squared is 0.85, and the adjusted count R-squared is 0.14.

Table 6: Cross Tabulation of Predicted Adoptions (Model A).

<table>
<thead>
<tr>
<th>Actual</th>
<th>Fitted</th>
<th>+</th>
<th>-</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>+</td>
<td>12</td>
<td>6</td>
<td>18</td>
<td></td>
</tr>
<tr>
<td>-</td>
<td>30</td>
<td>197</td>
<td>227</td>
<td></td>
</tr>
<tr>
<td></td>
<td>42</td>
<td>203</td>
<td>245</td>
<td></td>
</tr>
</tbody>
</table>

These diagnostic show that although these models do perform moderately well, further refinement could be beneficial. Additional analyses are required because both these models do not account for the hypothesis that state heterogeneity will cause heterogeneous outcomes (i.e., state $i$ with characteristic $y$ may choose to adopt a different policy than state $j$ with characteristic $z$). It is possible that states adopt policies for different reasons; characteristics that predict HOV lanes may differ from the other subsidies. For this reason, increased model specificity is needed. To do this, the dependent variable—whether a state has adopted an incentive—is separated out to distinguish between the different types of subsidies (HOV lane exemption, tax credit, and sales-tax exemption).

Table 7 shows the results of these analyses. Excise-tax exemption was not evaluated because only five positive events occurred during the five year time period, too few positive events to model determinants using a logistic regression. Based on likelihood ratio tests, three of the variables, state fiscal health, operationalized as the revenue to spending ratio, whether the governor was republican, and the percentage of manufacturing in a state that comes from automobile manufacturing were not included in any of the models because they were not found to be significant in any of the models.
First, income was found to be significant in the HOV lane exemption model, but again the magnitude is so small that interpretation of the significance is not feasible. In addition, the number of neighboring states that enacted incentives was also included in the analysis to identify the impact of external diffusion factors. This variable was positive in direction and significant in all three models, indicating that intra-state learning has a significant impact on state level policies.

Although institutional capacity was not found to be a predictor of state policy diffusion, the other two categories of variables, political context and problem severity was found to prediction policy adoption. The first set of indicators of political context, public opinion, was
operationalized as the purchase rate of hybrid purchases, environmental club memberships, and state-level utility spending on energy-efficiency programs. The first indicator, hybrid-diffusion rate, is significant and in the direction hypothesized, positive, in all three models. In states that enact HOV lane exemptions, hybrid-vehicle owners may support the enactment of such a law because of personal gain. Thus, the political institutions may be responding to constituent pressure for a policy that directly affects the hybrid-vehicle owners. In states where a tax credit or sales-tax exemption was enacted, however, hybrid owners do not stand to gain anything from the law, since their purchases have already been made. This significance instead may be a measure of constituent support for environmental and energy-efficiency policies.

The second indicator of public opinion, Sierra Club membership, is also a significant in models describing HOV lane exemptions and tax credits, but not for sales tax exemptions, which is in line with their position of hybrid-electric vehicles (Hybridcars.com 2008). On the other hand, Sierra Club memberships seem to decrease the odds that a state will pass HOV lane exemptions. Further investigation into Sierra Club efforts and public statements suggests that this finding may be in line with its mission. Since HOV lane exemptions may increase state fleet energy efficiency but do so with tradeoff—increased congestion in HOV lanes—the Sierra Club typically has come out against these policies. In Houston, a region that considered HOV lane exemptions for hybrid-electric vehicles, the Sierra Club officially declared opposition to alternative-fuel vehicles in HOV lanes if they were single-occupancy vehicles (Mannchen 2008). In other places where urban development is a heated topic, such as Seattle, coalitions that include the Sierra Club support the development of transit and bus lanes, instead of expanding the highway infrastructure. This position is in line with one of the Sierra Club’s stated goals to reduce the individual’s dependence on the personal vehicle (Van Kleeck 2005).
The final indicator of public opinion or constituent support, state utility spending on energy-efficiency programs, was significant in both HOV lane exemption and tax credits. Increased utility spending on energy efficiency increases the odds that a state will enact HOV lane exemptions, but decreases the odds that it will adopt a tax credit. Although the positive relationship is significant, the magnitude is relatively small, making interpretation of this variable even more difficult.

The second category of variables tests was problem severity, was also operationalized several ways. The first variable used, nonattainment density, was not found to be significant in any of the models and was therefore not included. Surprisingly, traffic congestion did not impact a state’s propensity to adopt HOV lane exemptions, but it is a significant predictor of sales-tax deductions; states with sales-tax exemptions tend to be states with little traffic. Finally, gasoline prices were found to be significant in both HOV lane exemptions and sales tax exemptions, but not in the model describing tax credit adoption. The significant is also in the opposite direction than hypothesized. This result could be because as gasoline prices rise, the political capital has focused attention on other policies that may limit the ability to adopt hybrid-vehicle incentives.

Because the positive events are not common, occurring in only 37 out of 255 events, bootstrapping the logistic regression results provided further insight into the reliability of the fitted logistic models. This can be useful, since rare-event data has been shown to underpredict positive events when using logistic regression (King and Zeng 2001). This was done for two of the three models, HOV lane exemption adoptions and tax-credit incentives, for exploratory and confirmation purposes. A sample of states that did not adopt incentives was taken and then combined with observations in which an incentive occurred so that a logistic regression could be performed on a new subsample. The size of the random sample was 10 times the number of
positive events, so that enough observations were included to run the model. The sampling and regression were repeated 1000 times so that histograms could be created for these 1000 odd ratios.

The histograms, presented in Appendix C, show that the logistic regression produces consistent estimators. Figure 4 presents the distribution of the odd-ratios from bootstrapping for two covariates, Sierra Club memberships and gasoline, from HOV lane exemptions determinants for illustrative purposes. In the logistic model using the full data set, the odds ratio for Sierra Club membership is 0.999; for gasoline it is 0.966. The means of the bootstrapped odds ratios were very close to the fitted model, providing evidence that the model produced accurate estimates of the predictors.

In sum, these results show that constituent support, or public opinion, operationalized as the percentage of vehicles purchases that were hybrids, and sierra club memberships as significant. In addition, external factors seem to be impact policy diffusions. Overall, it does not appear that HEV incentives are adopted as a solution to a traffic, environmental, or energy issue.
The Impact of Hybrid–Electric–Vehicle Incentives on Demand

Based on the previous section’s analysis, states do appear to adopt incentives for hybrid-electric vehicles primarily in response to constituent support and external diffusion pressures, and to a lesser extent problem severity. It is not clear, however, if this policies result in higher demand for these vehicles. To further understand this research question, this section of the dissertation tests the following hypothesis:

Hypothesis 2.1a: State-level hybrid subsidies increase the aggregate demand for hybrid-electric vehicles.

As another illustrative tool, Figure 5 presents the percentage of cars sold that were hybrids during the years of 2001-2005 for some selected states. The graph shows, the diffusion trajectory for all the states follows the traditional S-curve used in epidemic models. Therefore, part of the increase over time is attributable to normal diffusion patterns of new
technologies.

Figure 5: The Diffusion Trajectory of Selected States, 2001-2005.

As stated in the methods section, this hypothesis will be tested using three control groups: (1) the natural control group, (2) a constructed control group, and (3) a group derived using propensity scores. Table 3 presents summary statistics for the data set, split by these control groups: states that have adopted incentives, and states that have proposed incentives. In addition, table 5 presents summary statistics for both the population and the treated group (states that have adopted incentives). As discussed earlier, summary statistics show that states that have adopted incentives differ in some ways from states that have not enacted incentives. For instance,
automobile manufacturing activity is lower for states that have adopted subsidies than for those
states that have not, and the hybrid-vehicle registration level in states with incentives is higher
than in states without subsidies. Because the summary statistics are pooled for all years,
however, it is not clear how the difference in hybrid-vehicle registrations between the two groups
changes over time and if these two groups differ when the incentives were enacted. To illustrate
this aspect of the panel data, figure 6 shows the distribution of states’ annual aggregate number
of hybrid car registrations as a percentage of all registrations for years 2001 to 2005. As the
density plots show, the mean rate of hybrid purchases differed during the first time period. In
2001, states with incentives have a higher mean diffusion rate than those without for each year of
the period covered, while the difference appears to have increased slightly over the time period.
In 2001, the difference in the mean hybrid-diffusion rate between states with subsidies and those
without was 0.1%; the difference grew to 0.5% in 2005.

These graphs point out that the treatment and the control group substantially differs
before treatment with respect to the outcome. In addition, these charts illustrate that the
difference in the changes of the outcome during this time period is larger for states with
incentives than those without incentives. Although these graphs point to a larger increase in
diffusion for states with incentives, because the states differ before treatment, self selection is a
concern and a threat to the results. Therefore, a constructed control group may reduce
differences in both the baseline characteristics as well as unobserved, uncontrolled, time variant
variables.
Figure 6: Hybrid Diffusion Rate for States with Subsidies and States Without Subsidies, 2001-2005.
This methodology allows for an alternative to propensity-score matching and to account for both observed and unobserved differences between the treatment and control groups; propensity score matching can only account for observed differences. Because unobserved differences between the original control group and states that adopted incentives could impact the demand, using a constructed control design allows for exploratory analysis to see if restriction of the group alters the model, although a theoretical argument must be made which explains why the constructed control group may be more similar than the natural control group. In this case, one such possible theoretical argument is unobserved indicators of the political environment which precipitated the proposal in the legislature. For instance, although Sierra Club memberships may pick up the environmentalism of the state, it may not capture all of the impact of environmental attitudes that impact both policy and outcome. Restricting the control group to states that proposed incentives could create a group more similar to the treatment group with respect to these unobserved covariates.

In addition to these unobserved characteristics, a comparison of the covariates between the treatment group and the constructed control group verifies that the groups look more similar in observed ways. Summary statistics show that the difference in means between the treatment and control groups has decreased by restricting the control to states that proposed subsidies, in covariates such as income and population, as well as for determinants of adoption, such as manufacturing and energy-efficiency spending.

The constructed control group, states that proposed incentives during this time period, was used to develop a model of treatment of effect. In 2005, the number of states that proposed, but did not enact, subsidies rose dramatically. Figure 7 shows that in 2005, 35 proposals were in state legislatures. Over the five years, 27 states had at least one proposal in legislatures, but some
states, such as Connecticut, had active proposals for multiple years and more than one type of proposal. Both excise-tax exemptions and sales-tax exemptions proposals increased from 0 in 2004 to 10 in 2005. Constructed control groups have been used in other applied evaluative research (Dale and Krueger 2002; Youtie, Shapira et al. 2010). Twelve states were eliminated, bringing the sample down to 34.

![Figure 7: Number of Proposals in Legislative Bodies, 2001–2005.](image)

When comparing the constructed control group to the natural control group, comparing the distribution of the covariates using the two populations can reveal whether restriction increases bias or reduces bias. Appendix D presents kernel density plots for all independent variables for states that have adopted subsidies and those that have not and compares those kernel density plots with states that proposed incentives. Using this constructed control design does not significantly change the distribution of any of the covariates, but rather takes out some of the outliers in covariates such as automobile manufacturing as a percentage of all manufacturing, gasoline prices, and population. It looks like restricting the sample to the
constructed control group may increase the differences in the distributions for the traffic congestion index, although not substantially.

Table 9 shows the results of analyses estimating the impact of state incentives using parametric estimations techniques for panel data, fixed effects (Model A), and difference-in-difference regression (Model B) for both the natural control group and the constructed control group. As explained in the methodology section, fixed effects time-demean the data; variables are transformed by subtracting the mean from values and therefore estimate the impact of within state changes over time on the aggregate demand. Similarly, in difference-in-difference regression, the average gain in the control group is subtracted from the average gain in treatment group; this differencing accounts for some biases between the treatment and control groups that could result from time-constant differences between those groups, as well as biases from comparisons over time in the treatment group that could be the result of trends. The dependent variable for these models is the percentage of new car registrations that were hybrids. This transformation captures the choice aspect of this issue by controlling for total car demand and also standardizes the data points for easier comparison.

Note that HOV lane exemptions seem to have a negative impact on aggregate demand, although because an interaction term has been included (HOV\*congestion index), this impact is for states where there is not traffic congestion. This interaction term reveals heterogeneous treatment effects. When there is not an incentive, congestion does not affect hybrid-electric vehicle demand; the existence of an incentive coupled with congestion, however, turns out to be a significant predictor of demand. This is true in all four models. This means that the incentive alone does not increase demand, but if the incentive is enacted in a state where the congestion problem is severe, demand increases. The sales-tax exemption was also found to be significant in
all four models, while the income tax credit was not found to be significant in all of the models, only the fixed effects estimation. This is surprising because the value of the incentive is probably smaller than the income tax credit. In Maine, where the sales tax is 5%, the savings on the purchase of a new Prius would be approximately $1250. This is less than the estimated premium paid over an equivalent conventional automobile.

In addition to testing incentives, additional variables were included. Gasoline prices was found to increase aggregate demand, and in the direction expected. A $1 increase in gasoline

<table>
<thead>
<tr>
<th>Table 9: Fixed Effects and Difference-in-Difference Regression Results.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model A Fixed Effects</td>
</tr>
<tr>
<td>Intercept</td>
</tr>
<tr>
<td>HOV lane exemption</td>
</tr>
<tr>
<td>Income tax credit</td>
</tr>
<tr>
<td>Sales tax exemption</td>
</tr>
<tr>
<td>Density (pp/ sq. mile)</td>
</tr>
<tr>
<td>gasoline price (cents per gallon)</td>
</tr>
<tr>
<td>Per capita income</td>
</tr>
<tr>
<td>Population</td>
</tr>
<tr>
<td>Total registrations</td>
</tr>
<tr>
<td>Traffic Congestion</td>
</tr>
<tr>
<td>HOV*(Traffic Congestion)</td>
</tr>
<tr>
<td>R-Squared</td>
</tr>
<tr>
<td>Adj. R-Squared</td>
</tr>
<tr>
<td>Observations</td>
</tr>
</tbody>
</table>

Dependent variable is (# of hybrid registrations)/(total registrations)

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
price results in over .5% increase in demand. This finding supports similar research that hypothesizes complementary cross-price elasticity between gasoline prices and energy efficiency (Espey and Nair 2005). Although gasoline price was found to negatively influence a state’s propensity to adopt an incentive, it did affect a state’s aggregate demand.

The consistency between the four models is high, indicating that the results are robust. Although restricting the analysis to states that proposed incentives did not alter the fitted model significantly, it is still possible that self-selection produces biased estimates of the policy’s impact. To alleviate this concern, propensity-score matching will be also performed in an attempt to construct a more ideal comparison group and serve as an alternative analysis. Together, these three comparison groups provide a thorough understanding of the true average treatment effect of hybrid-electric-vehicle incentives.

**Propensity–Score Matching**

Table 10 showed that states that adopt subsidies look different from states that do not in ways that affect both placement into treatment and the outcome. Therefore, propensity score matching can help to identify the true average treatment effect by reducing self-selection bias. To create a propensity score which is then used to construct a new comparison group, a logistic model describing the predictors of adoption must be developed. Then, states that adopted incentives are match to states that did not adopt incentives with similar propensity scores, and the average treatment effect is calculated. Therefore, the logistic models developed to test hypotheses 1.1-1.4 are used in this section. Because only confounding covariates should be included in the model, external diffusion factors and the hybrid diffusion rate, which is essentially the outcome variable are removed from these logistic models. The average treatment
The effect was calculated for each of the three incentives for which a fitted model was created, HOV lane exemptions, tax credits, and sales-tax exemptions. It is important to note, that the outcome variable used for this analysis is the change in the percentages of hybrid purchases between the time \( t \) and time \( (t-1) \), the number of observations has been reduced to 205 and 196. This allows to capture the increase in sales after implantation.

Table 10 shows that after matching, the treatment effect remains significant for HOV lane exemptions. It is important to note, however, that in the parametric regression, an interaction term was used to identify treatment heterogeneity based on traffic congestion, which was found to be significant. This treatment heterogeneity cannot be tested using propensity scores. In addition, the impact of income-tax credits was found to be significant using propensity score matching, while a sales tax exemption was not found to be significant. These estimates, however, are only unbiased if the covariates used achieve balance between the treatment and the new comparison group. Therefore, balance statistics are reviewed.

<table>
<thead>
<tr>
<th></th>
<th>HOV exemptions</th>
<th>Tax Credit</th>
<th>Sales Tax</th>
</tr>
</thead>
<tbody>
<tr>
<td>Estimate</td>
<td>0.22</td>
<td>0.21</td>
<td>0.02</td>
</tr>
<tr>
<td>Standard Error</td>
<td>0.08</td>
<td>0.11</td>
<td>0.13</td>
</tr>
<tr>
<td>T-statistic</td>
<td>2.76</td>
<td>2.05</td>
<td>0.19</td>
</tr>
<tr>
<td>P-Value</td>
<td>0.005</td>
<td>0.04</td>
<td>0.86</td>
</tr>
<tr>
<td>Original number of observations</td>
<td>205</td>
<td>196</td>
<td>196</td>
</tr>
<tr>
<td>Original number of treated observations</td>
<td>12</td>
<td>13</td>
<td>7</td>
</tr>
<tr>
<td>Matched number of observations</td>
<td>12</td>
<td>13</td>
<td>7</td>
</tr>
</tbody>
</table>

The balance statistics for income-tax credits and sales-tax exemptions are provided in the Appendix F and Appendix G, respectively, while the results of the HOV incentive are in
presented in the body of this dissertation, in table 10. In the table 10, the first three statistics are
descriptive statistics for each variables used to create the propensity score. The means of each
variable are presented for the treatment and control groups both before and after matching. For
HOV lane exemptions, matching reduced the difference in the means of all of the variables
except for gasoline: population, sierra club memberships, Sierra Club memberships, and
spending on energy-efficiency programs. In addition, the t-test p-value tests whether the
difference was statistically different. Although matching did reduce the differences in the means
for most of the covariates, the difference in the average gasoline price in states with incentives
and states without is still significant at the 1 percent level after matching.

The second section of outputs provides a series of statistical tests that test differences
between the two distributions of the analysis variable. The first statistic, the variance ratio,
calculates the ratio between the variances for the treatment and control groups. This statistic is
designed to measure how close the variances are to each other. A balanced sample will have
similar variances in the covariates; this ratio should equal 1 if there is perfect balance. Matching
only decreased the variance ratio for some of the variables, such as energy efficiency spending
by utility companies. As Rubin stated, ideal ratios would be between 0.5 and 1.5 (Rubin 2001)
Table 10: Covariate Balance Statistics for HOV Lane Exemptions.

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Population (persons)</th>
<th>Gasoline (cents per gallon)</th>
<th>Sierra Club Memberships (persons)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Before Matching</td>
<td>After Matching</td>
<td>Before Matching</td>
</tr>
<tr>
<td>Treatment mean</td>
<td>10,630,218</td>
<td>10,630,218</td>
<td>140.59</td>
</tr>
<tr>
<td>control mean</td>
<td>54,52,522</td>
<td>11,362,358</td>
<td>134.34</td>
</tr>
<tr>
<td>std mean diff</td>
<td>52.05</td>
<td>-7.32</td>
<td>16.89</td>
</tr>
<tr>
<td>T-test p-value</td>
<td>0.10</td>
<td>0.80</td>
<td>0.58</td>
</tr>
<tr>
<td>Variance ratio (Tr/Co)</td>
<td>2.50</td>
<td>3.16</td>
<td>1.18</td>
</tr>
<tr>
<td>KS Bootstrap p-value</td>
<td>0.008</td>
<td>0.27</td>
<td>0.80</td>
</tr>
<tr>
<td>KS Statistic</td>
<td>0.45</td>
<td>0.35</td>
<td>0.17</td>
</tr>
</tbody>
</table>

The second section of outputs provides a series of statistical tests that test differences between the two distributions of the analysis variable. The first statistic, the variance ratio, calculates the ratio between the variances for the treatment and control groups. This statistic is designed to measure how close the variances are to each other. A balanced sample will have similar variances in the covariates; this ratio should equal 1 if there is perfect balance. Matching only decreased the variance ratio for some of the variables, such as energy efficiency spending by utility companies. As Rubin stated, ideal ratios would be between 0.5 and 1.5 (Rubin 2001).

Kolmogorov Smirnoff (K-S) bootstrap p-value is used to detect a difference in the distribution between two groups by comparing the maximum difference between the empirical cumulative distribution functions of the two groups. This maximum difference then constitutes the test statistic for the K-S test, and its associated p-value is provided. All of the covariates, except for population, had significant differences in distribution after matching.
Additional diagnostic tools are used to understand the distribution, although they are not statistical tests. In Appendix E, QQ plots are presented for each variable in the fitted model regarding HOV lane exemptions, before and after matching. QQ plots detect distribution differences between two data sets by plotting their quantiles against each other. If they data sets are equivalent, then the QQ plot falls along a straight line through the origin at a 45-degree angle. For the two variables that continued to have statistically different distributions, these QQ plots show a cluster of observations kept far from the y=x line. These QQ plots show that the distribution between the two groups is less similar after matching.

Overall, matching did not balance the two groups with respect to HOV lane exemption analysis. Although it did decrease the differences in the means for all of the variables except for gasoline, the differences in the distributions for all the variables except for population increased.

Propensity-score matching for tax credits and sales-tax exemptions are provided in Appendix F and Appendix G, respectively. In terms of matching for estimating the impact of tax credits, matching made did not create two groups with similar means for all covariates; the difference in income between the two groups remained significant. More importantly, however, is that matching increased the difference in the distribution between the two groups, so that the differences became significant for all covariates except for population. Matching performed slightly better for the sales-tax exemption analysis; it reduced the differences in means for all variables, but the distribution between the two groups remained significant for both gasoline prices and the traffic congestion index. Therefore, it appears that balance was not achieved by matching for any of the incentives, although the matching did not significantly reduce balance for the two groups with respect to the sales tax exemption analysis. The findings from the propensity score analysis, however, do come with a caveat. Because data is constructed in such
a way so that each year that a state has an incentive counts as one variable (so that Virginia has been counted for four years), the analysis is in some ways cross sectional. It does not look at the change in one state’s demand over the time period. This means that the states with incentives are in some ways over counted.

Overall, propensity-score matching shows that improving balance of the covariates is a challenging task. Although in this analysis, balance was only marginally achieved in one of the three cases, the findings are somewhat consistent with the parametric results. It seems that HOV lane exemptions do seem to impact demand, while evidence pointing to the effectiveness of tax credits and sales tax exemptions is somewhat less compelling. The final section of the analysis will complement these aggregate analyses with individual level data to better understand the impact of incentives on individual level behavior.

**Impact of Attitudes and Incentives on Individual’s Propensity to Adopt Hybrids**

The last section of this analysis chapter will use data from the National Household Travel Survey to identify how consumer heterogeneity affects hybrid-vehicle adoption. This analysis is only exploratory and serves as a starting point for future analyses. In particular, this section looks at the impact of attitudes, transportation behavior, and other socioeconomic variables to test the hypothesis:

Hypothesis 2.2 Attitudes toward the built environment and travel affect an individual’s likelihood of purchasing a hybrid.
In 2008, the number of states that had adopted HEV incentives had state relatively the same since 2005, although the composition of state level incentives change dramatically. As Figure 8 shows, HOV lane exemptions continued to grow in popularity up to 7 states in 2008 from 4 states in 2005. Income tax credits states roughly consistent, although some states, such as West Virginia, did not extend their tax credits when they expired. Sales tax exemptions, on the other hand, became less popular by 2008.

One challenge with respect to the analysis in this section is capturing the temporal aspect of the purchase data and the implementation date while the data is only cross sectional. To combat this issue, the incentives identified as being implemented during the time period of 2001-2007 were also included for this analysis, regardless of whether or not the states stopped the incentive.
Therefore, the assumption is made that if a person lived in a state with an incentive during the time period of 2001-2008, he purchased the automobile while the incentive was active. An additional limitation resulting from the time dimension not captured in this analysis is that a person may have purchased a hybrid in a state without an incentive and moved to a state with an incentive between the purchase date and the survey date. This case would be captured as having purchased a hybrid when having received an incentive even though it did not occur.

Since the National Household Travel Survey is a household-level survey, with analytical applications at the house, individual, and vehicle level, the survey contains weights for all three variables to estimate the U.S. population. Table 11 gives summary statistics of the weighted data for selected variables. Detailed Explanations of each variable is provided in .
Table 11: Summary Statistics of National Household Travel Survey Variables.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Standard Error</th>
<th>95% Confidence Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hybrid Cars</td>
<td>0.056</td>
<td>0.003</td>
<td>0.05 - 0.06</td>
</tr>
<tr>
<td><strong>State Incentives</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sales Tax</td>
<td>0.012</td>
<td>0.002</td>
<td>0.001 - 0.02</td>
</tr>
<tr>
<td>HOV lane exemptions</td>
<td>0.37</td>
<td>0.005</td>
<td>0.36 - 0.38</td>
</tr>
<tr>
<td>Excise tax exemptions</td>
<td>0.008</td>
<td>0.001</td>
<td>0.006 - 0.01</td>
</tr>
<tr>
<td>Income tax credit</td>
<td>0.08</td>
<td>0.003</td>
<td>0.07 - 0.09</td>
</tr>
<tr>
<td><strong>State Attitudes</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cost</td>
<td>0.35</td>
<td>0.006</td>
<td>0.34 - 0.36</td>
</tr>
<tr>
<td>Transit</td>
<td>0.049</td>
<td>0.002</td>
<td>0.04 - 0.05</td>
</tr>
<tr>
<td>Congestion</td>
<td>0.14</td>
<td>0.001</td>
<td>0.14 - 0.15</td>
</tr>
<tr>
<td>Walkways</td>
<td>0.025</td>
<td>0.002</td>
<td>0.02 - 0.03</td>
</tr>
<tr>
<td>Aggressive</td>
<td>0.19</td>
<td>0.004</td>
<td>0.18 - 0.20</td>
</tr>
<tr>
<td><strong>Transportation Behavior</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of walking trips (per month)</td>
<td>4.31</td>
<td>0.07</td>
<td>4.18 - 4.45</td>
</tr>
<tr>
<td>Household income</td>
<td>13.5</td>
<td>0.06</td>
<td>13.4 - 13.6</td>
</tr>
<tr>
<td><strong>Demographic Variables</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Education</td>
<td>3.37</td>
<td>0.01</td>
<td>3.35 - 3.40</td>
</tr>
<tr>
<td>Black</td>
<td>0.102</td>
<td>0.005</td>
<td>0.09 - 0.11</td>
</tr>
<tr>
<td>Asian</td>
<td>0.03</td>
<td>0.002</td>
<td>0.03 - 0.03</td>
</tr>
<tr>
<td>Other</td>
<td>0.07</td>
<td>0.003</td>
<td>0.06 - 0.07</td>
</tr>
<tr>
<td>Respondent age (years)</td>
<td>47.3</td>
<td>0.16</td>
<td>46.9 - 47.6</td>
</tr>
<tr>
<td><strong>Built Environment</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Urban Size</td>
<td>2.3</td>
<td>0.001</td>
<td>2.2 - 2.3</td>
</tr>
<tr>
<td>Traffic congestion</td>
<td>1.01</td>
<td>0.002</td>
<td>1.007 - 1.01</td>
</tr>
<tr>
<td>Number of times public transportation used (per month)</td>
<td>1.61</td>
<td>0.12</td>
<td>1.40 - 1.82</td>
</tr>
<tr>
<td>Detached home</td>
<td>0.76</td>
<td>0.01</td>
<td>0.74 - 0.77</td>
</tr>
</tbody>
</table>

Number of observations =67,407; Population size = 52,707,671
The summary statistics shows that 75 percent of the nation live in detached homes and have an average age of 47.3 years. In addition, 5.6% of automobiles on the road at the time of the survey were hybrids. In terms of attitudes, thirty five percent of individuals stated that transportation costs were the most important transportation issue to them while only approximately 5 percent of think that access to transit is most important. In terms of incentives, approximately 37 percent of individuals in 2008 lived in states that offer HOV lane incentives during the time period of 2001-2008, compared with only one percent of people were exposed to sales tax exemptions. In terms of education, the mean educational level was some level of college.

The National Household Travel Survey allows examination of an individual’s travel behavior and attitudes across various communities. As stated in the literature review, the built environment where people live has been found to be correlated with their attitudes (Cao, Mokhtarian et al. 2007). Consistent with the literature, Figure 9 shows that respondents’ attitudes differ by the size with their locality. It is important to note, however, that these findings are for all respondents of the survey, not just for individuals linked to a vehicle. Living in a non-urbanized area increases the rate of which transportation costs were reported as the important issue. Although cost remained the most highly cited transportation issue even in areas with a population greater than 1 million and with subway or rail, the percentage of respondents that reported other issues as the most important did increase; the most significant increases was congestion, followed by transit.
To explore this relationship further, Table 12 identifies whether this difference is statistically significant. Model A tests whether the mean size of respondents’ metropolitan statistical area is statistically different, based on their attitudes. The results show that all the attitude variables are significant except for walkways. But note that this analysis is not meant to establish causation—instead, it demonstrates that attitudes are significantly different based on the population size of the respondent’s community. The second model, also exploratory, looks at how differences in attitudes affect an individual’s propensity to own a hybrid vehicle while controlling for whether the person lives in a state where there is an incentive. To perform this analysis, National Household Travel Survey data were merged with data used in previous analyses, specifically state-level incentive data and the Congestion Index from the Texas Transportation Institute. Model B shows that congestion still affects the probability of a person driving a hybrid, and even controlling for attitude, the presence of an HOV lane exemption...
incentive increases an individual’s propensity to adopt a hybrid. The reduction in sample size between the two models is due to the restriction in the second model to individuals linked to a vehicle.

**Table 12: Preliminary Regression Results from National Household Travel Survey.**

<table>
<thead>
<tr>
<th></th>
<th>Model A</th>
<th>Model B</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Urban Size</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>2.071</td>
<td>0.796</td>
</tr>
<tr>
<td></td>
<td>(67.79)**</td>
<td>(2.00)*</td>
</tr>
<tr>
<td>Congestion</td>
<td>-0.284</td>
<td>0.983</td>
</tr>
<tr>
<td></td>
<td>(7.30)**</td>
<td>-0.14</td>
</tr>
<tr>
<td>Transit</td>
<td>0.587</td>
<td>1.185</td>
</tr>
<tr>
<td></td>
<td>(10.46)**</td>
<td>-1.18</td>
</tr>
<tr>
<td>Walkways</td>
<td>0.038</td>
<td>1.027</td>
</tr>
<tr>
<td></td>
<td>-0.45</td>
<td>-0.14</td>
</tr>
<tr>
<td>Aggressive</td>
<td>0.131</td>
<td>0.851</td>
</tr>
<tr>
<td></td>
<td>(3.10)**</td>
<td>-1.46</td>
</tr>
<tr>
<td><strong>Traffic Congestion Index</strong></td>
<td>1.025</td>
<td>-1.1</td>
</tr>
<tr>
<td>Sales Tax</td>
<td>0.597</td>
<td>-1.46</td>
</tr>
<tr>
<td>HOV Lane Exemption</td>
<td>0.332</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.84)**</td>
<td></td>
</tr>
<tr>
<td>Excise Tax Credit</td>
<td>0.789</td>
<td>-0.57</td>
</tr>
<tr>
<td>Income Tax Credit</td>
<td>0.898</td>
<td>-0.76</td>
</tr>
<tr>
<td>HOV*(Congestion Index)</td>
<td>2.471</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.50)*</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>219,472</td>
<td>120,332</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.03</td>
<td></td>
</tr>
</tbody>
</table>

* significant at 5%; ** significant at 1%
To fully understand the casual relationship between behaviors, attitudes, and incentives on purchase decision, additional variables should be included. As stated in the methods section, hypothesis 2.2 is tested using discrete choice model. Table 13 includes variables that measure travel behavior, as well as attitudes and socioeconomic variables. It should be noted, that several additional variables, such as home ownership, the number of children, and marital status were tested, but were not included in the final model because they were not found to be significant or increase the quality of the model. In terms of the quality of the model, it passed the likelihood ratio test, but since the model is derived from weighted survey data, is impossible to calculate most of the indicators of how well the model predicts positive and negative events.

The results of table 13 show that behaviors, rather than attitudinal variables, are found to be highly significant predictors of hybrid-electric-vehicle adoption. Respondent age and whether the person lives in a detached home, although tested to see if they impacted a person’s propensity to adopt an incentive, were removed based on likelihood ratio tests. Although in previous research, lifestyle variables have been found to have an impact on travel demand, vehicle miles traveled, and travel mode choice, the relationship of these lifestyle variables associated with the built environment to the type of automobile owned is not well understood. Cao et al. (2007) and Handy et al. (2005) showed that changes in the built environment influence changes in auto ownership, but only in whether an individual owns a car at all, not in characteristics of the car that a person adopts. Additional research using the 2001 National Household Travel Survey showed that respondents living in zip codes with higher Green Party members had a higher propensity to adopt a Prius (Kahn 2007), but little research has been completed to see how the built environment and its associated behaviors affect the choice of vehicles.
In addition, the results of this analysis support the evidence from the previous section regarding the impact of HEV incentives. The interaction term of HOV and the congestion index is still significant, but the number of public transportation and walking trips increased the probability of a person owning a hybrid. Previously, the auto ownership decision has been viewed as a function of factors such as employment location and residential location. But most studies of this connection assume that auto ownership is exogenous to individuals’ activity and travel decisions, thereby inadvertently leaving out the role auto ownership plays in land use or transportation decisions or the way that land use interacts with automobile ownership (Cao, Mokhtarian et al. 2007).

The results of this model support the results from the previous section using aggregate data. HOV lane requirement exemptions alone seem to decrease an individual’s propensity to adopt a hybrid vehicle, but if the incentive is located in areas of high congestion, the two conditions combined do result in a significant effect. In states with HOV lane exemptions, a one-unit increase in the congestion variable increases an individual’s propensity to own a hybrid by 2.59 times. These results reflect that hybrid adoption alone does not solve a person’s experience with traffic, but that well placed incentives can increase a person’s utility through decreased experiences with traffic and time spent in congestion.
<table>
<thead>
<tr>
<th>Factor</th>
<th>Coefficient</th>
<th>T-statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sales Tax Exemptions</td>
<td>0.469</td>
<td></td>
</tr>
<tr>
<td>HOV Lane Exemptions</td>
<td>0.316</td>
<td>(2.02)*</td>
</tr>
<tr>
<td>Excise Tax Exemptions</td>
<td>0.839</td>
<td></td>
</tr>
<tr>
<td>Income Tax Credit</td>
<td>0.946</td>
<td>-0.3</td>
</tr>
<tr>
<td>Traffic Congestion</td>
<td>1.299</td>
<td>-1.01</td>
</tr>
<tr>
<td>HOV*(Congestion)</td>
<td>2.592</td>
<td>(1.86)</td>
</tr>
<tr>
<td>Cost</td>
<td>1.118</td>
<td>-0.84</td>
</tr>
<tr>
<td>Transit</td>
<td>1.308</td>
<td>-1.57</td>
</tr>
<tr>
<td>Walkways</td>
<td>0.976</td>
<td>-0.11</td>
</tr>
<tr>
<td>Aggressive</td>
<td>0.845</td>
<td>-1.42</td>
</tr>
<tr>
<td>Number of times public transportation used (per month)</td>
<td>1.02</td>
<td>(3.22)**</td>
</tr>
<tr>
<td>Number of walking trips (per month)</td>
<td>1.013</td>
<td>(2.57)*</td>
</tr>
<tr>
<td>Household income</td>
<td>0.981</td>
<td>-1.47</td>
</tr>
<tr>
<td>Education</td>
<td>1.074</td>
<td>-1.66</td>
</tr>
<tr>
<td>Black</td>
<td>1.588</td>
<td>(2.18)*</td>
</tr>
<tr>
<td>Asian</td>
<td>0.869</td>
<td>-0.76</td>
</tr>
<tr>
<td>Other</td>
<td>1.24</td>
<td>-1.24</td>
</tr>
<tr>
<td>Urban Size</td>
<td>1.009</td>
<td>-0.28</td>
</tr>
<tr>
<td>Observations</td>
<td>67407</td>
<td></td>
</tr>
</tbody>
</table>
CHAPTER 5: DISCUSSION AND CONCLUSIONS

Over the last decade, states have implemented a patchwork of monetary and non-monetary incentives for hybrid-electric vehicles. This dissertation examined this issue using multiple data sources to study both policy adoption and impact. First, leadership in this area was studied by examining various categories of internal factors of adoption, including problem severity, institutional support, and political context, as well as external diffusion factors operationalized as the number of neighboring states that had already adopted an incentive. Second, parametric and nonparametric techniques were used to estimate the average state-level treatment effects of these incentives and estimate the individual-level characteristics that contribute to the propensity to adopt this technology.

This chapter therefore begins with a brief review and discussion of these analyses. Because this dissertation used econometric techniques somewhat novel to the environmental policy community, the second section of this chapter discusses the challenges and opportunities for further use of these methods in applied settings. This chapter concludes with a discussion of the implications of this research and directions for future study of this topic.

Summary of key Findings and Discussion

This dissertation reviews the impact of hybrid-electric-vehicle policies at both the aggregate and individual level using two technology models presented in the literature review, the epidemic and consumer-choice models. Using the epidemic model and treating the population as homogeneous, fixed effects and difference-in-difference estimation were used to identify whether the slope of the cumulative diffusion curve is altered by changes in the price of
the good. Estimates were made using two control groups, the entire population of states that did
not adopt incentives and a constructed control design of states that proposed incentives but did
not adopt them during the sample time period. Restricting the sample to states that proposed
incentives was one of two techniques used to correct for self-selection bias. The second method
was propensity-score matching, which used the fitted logistic models identifying determinants of
policy adoption to create composite propensity scores. These scores were used to construct
comparison groups by matching states that adopted incentives with states that have similar
propensities to adopt but did not.

To complement this aggregate analysis, individual-level data from the National
Household Travel Survey were used. Using a consumer-choice model to treat the population as
heterogeneous allowed further identification of the impact of these state incentives, as well as
exploratory analyses into consumer adoption of this new technology.

These analyses tested both the efficacy of state incentives and the determinants of hybrid
adoption. Specifically, the following hypotheses were tested:

Hypothesis 2.1a: State-level hybrid subsidies increase the aggregate demand for hybrid
electric vehicles.

Hypothesis 2.1b: State-level hybrid subsidies increase the probability that an individual will
purchase a hybrid.

Hypothesis 2.2 Attitudes toward the built environment and travel behavior impact an
individual’s likelihood of purchasing a hybrid.

In the five parametric models, HOV lane exemptions—when there is little traffic
congestion—were found to have a negative impact on adoption, but a highly strong positive
impact when traffic congestion is high. The impact of income tax credits was inconclusive, as it
was only found to be significant in the fixed effects model, and not in the difference in difference
model nor in the NHTS analysis. Sales tax exemptions were found to increase the demand of hybrid automobiles in all four models using aggregated data, but was not found to be significant using NHTS data.

Using propensity scores was found to create a balanced comparison group for one class of incentives, HOV lanes exemptions. The results from the propensity score showed an insignificant treatment effect for this policy, but because propensity-score matching does not allow for heterogeneous treatment impacts, it could not be used to test how the impact of HOV lane exemptions varies with respect to differences in traffic congestion.

These results are in line with previous research. Diamond, in an analysis of Virginia, a state that has implemented HOV lane exemptions for hybrids, found that counties near HOV lanes had a higher hybrid diffusion rate than counties further away from interstates. In other research looking at all states, Diamond did not find HOV lane exemptions to impact adoption. This heterogeneous treatment effect demonstrated between these two papers parallels the findings in this dissertation; states with high traffic congestion (Virginia has one of the highest congestion in the nation) may have exploited the uniqueness of their state to increase technology adoption whereas states that had little traffic, such as Utah, may not be able to impact demand through this mechanism. Alternatively, Gallagher and Muehlegger (2011) assert that sales-tax exemptions did account for a modest increase in hybrid purchases and that tax credits did not have an impact. They assert that the smaller valued incentive is more effective because the buyer receives it instantaneously upon purchase (Gallagher and Muehlegger 2011).

Hypothesis 2.1b and 2.2 were testing using a discrete choice model, in which the probability of technology adoption was modeled to be a function of how variables impact the decision maker’s utility (Train 2009). This model assumes rationality of the actor therefore, and
only variables that will impact utility should be included in the model. Surprisingly, travel behavior variables are significant, indicating that this behavior impacts the overall utility of a person who purchases a hybrid. Although a full explanation of how travel behavior affects utility cannot be extrapolated from these results, some possible explanations exist. These results seem to be in line with previous research that has found people’s attitudes can change after moving into a different community and that people’s transportation behavior is influenced by the built environment (Choo and Mokhtarian 2004; Cao, Handy et al. 2006; Cao, Mokhtarian et al. 2007). Similarly, this dissertation research showed that people who act on their attitudes somehow influence purchase behavior. The most likely explanation is that people who engage in this type of behavior have more environmental tendencies than those that do not, so that these behaviors capture attitudes that are not included in this model. Although some transportation behaviors were included in this model, because the survey did not capture environmental attitudes or attitudes regarding energy because the attitude questions were restricted to transportation issues, they may not accurately capture all attitudes relevant to vehicle choice. Previous research has found that attitudes do affect vehicle choice (Choo and Mokhtarian 2004), and even that hybrid adoption is in part determined by environmental attitudes (Rose, Clark et al. 2002; Kahn 2007; Gallagher and Muehlegger 2011).

When looking at how little significance the monetary incentives had, insight can be gained by examining the true monetary value of each of these incentives and determining whether these state incentives, when added to the federal tax credit, diminished the premium paid for the hybrid. The value of each incentive, even between comparable types of incentives, does differ between each state, based on the structure of the incentive, the purchase price of the automobile, and the differential price between the hybrid vehicle and a comparable traditional
car. Colorado, West Virginia, New York, and Oregon all provided tax credits or deductions during the time period studied. The values for these incentives, for 2005, are estimated to be between $1500 and $3750. The federal government’s subsidy, which has been available since 2002 and therefore was available during the time period studied, was a $2000 tax credit. These state tax credits, combined with the $2000 federal tax credit, may more than compensate for the estimated increased cost of the Prius. Oregon’s tax credit does not push the combined value of the federal and state tax credits above the price differential estimated by Colorado ($4040), but West Virginia’s does by over $1000. Even if the price differential is eliminated, other barriers of adoption do exist. For example, public awareness of these incentives varied. In addition, New York’s tax credit was claimed over three years, so that the consumer recouped the additional cost over that time, which could be an additional barrier to adoption.

By itself, the sales-tax deduction value during this time period of 2001–2005 was not enough in any state to offset the premium paid to purchase a hybrid vehicle. Connecticut and Washington’s state sales-tax rates are 6% and 6.5%, respectively, which would mean a savings of between $1000 and $1500, based on the 2005 Manufacturer’s Suggested Retail Price of the Toyota Prius, although the actual value depended on the purchase price of the vehicle. Maine’s

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13 In New York, the credit is for 50% of the incremental cost of any vehicle, with a maximum of $5,000 per vehicle. In West Virginia, the credit value is 100% of the difference between the hybrid and a comparable vehicle, but the maximum value is $3750. Colorado has established an incremental price difference of $4040 for the 2005 Prius, and this amount was approved for West Virginia. A West Virginia resident in 2005 would therefore be eligible for the full $3750 available. Colorado’s tax credit is also for the difference between the cost of the vehicle and the cost of the same or most similar vehicle that uses a traditional fuel. According to information from the Colorado Department of Revenue, the value of Colorado’s tax credit for the Honda Insight was between $2600 and $3100, and the tax credit for the Toyota Prius was between $2600 and $3500. Finally, Oregon’s tax credit is structured differently. The tax credit is for 50% of the difference between the hybrid and traditional vehicle, and the tax credit is capped at $1500. Although this amount is smaller, the value, combined with the federal tax credit, considerably offsets the increased cost of the hybrid. For more information on these state’s tax credits, see http://www.tax.ny.gov/pdf/2002/inc/it253i_2002.pdf; http://www.state.wv.us/taxrev/uploads/wvafmv%2D1.pdf; http://www.state.wv.us/taxdiv/; http://www.colorado.gov/cs/Satellite/Revenue/REVX/1184834145957.
sales-tax credit amounted to approximately $500 for hybrid cars for which there is no comparable model powered by gasoline, such as the Toyota Prius and Honda Insight. Maine’s credit is only $300 for vehicles that have a comparable gasoline-powered model, such as the Honda Civic Hybrid, although these vehicles were not captured in this analysis. Adding the maximum value of exemption and adding it to the federal tax credit of $2000 does not eliminate the increased purchase cost, but does reduce it to just 12.3% of the original increased cost.

Finally, excise-tax exemptions were also not large enough to offset the higher purchase price of the hybrid. According to the New Mexico’s Department of Energy and Conservation and Management Division, the excise-tax exemption for hybrid vehicles results in consumer savings of between $600 and $1000. This is less than one-third the lower end of the premium to purchase a hybrid. Even adding the excise-tax exemption to the federal government’s tax credit—a total tax savings of between $2600 and $3000—does not cancel out the increased cost of purchasing a hybrid compared with a traditional automobile. In addition, Maryland’s excise-tax credit, valued at $250 to $1,000, was also not large enough to offset the additional costs of a hybrid.

Overall, part of the insignificance of these incentives may be explained by the fact that they did not off-set the increased initial price of purchasing a hybrid. In addition, the little impact of the monetary incentives may also be due to an efficiency gap, a higher than rational discount of future savings related to operating costs (Hirst and Brown 1990). This may mean,

14http://www.state.me.us/revenue/forms/sales/str46a.pdf
16http://go.ucsusa.org/hybridcenter/incentives.cfm#MD The Maryland Clean Energy Incentive Act, effective 07/01/00 through 07/01/04, provided tax credits against the 5% vehicle excise tax, up to $2,000 for electric vehicles and up to $1,000 for qualifying hybrid-electric vehicles for model year 2000 and later.
then, that policy analysts may want to explore alternative incentive structures for promoting the diffusion of other types of energy efficiency technologies.

In addition to policy evaluation, this dissertation explores which states adopt these incentives. Specifically, five hypotheses were tested:

Hypothesis 1.1 State with higher level of constituent support for hybrid-electric vehicles will be more likely to adopt hybrid-vehicle subsidies

Hypothesis 1.2 Interest-group strength affects a state’s propensity to adopt hybrid-vehicle subsidies. Specifically, the presence of automotive manufacturing in a state will decrease the likelihood of that state adopting hybrid-vehicle subsidies.

Hypothesis 1.3 A higher problem severity affects a state’s propensity to adopt hybrid-vehicle subsidies.

Hypothesis 1.4 Institutional capacity affects a state’s propensity to adopt hybrid-vehicle subsidies—states with surpluses are more likely to adopt subsidies for hybrid-vehicle purchases than those without.

Hypothesis 1.5 The number of neighboring states that have previously adopted any type of HEV incentive impacts a state’s propensity to adopt an incentive.

This analysis examined why certain states led in incentives for hybrid electric vehicles while others were laggards. Berry and Berry hypothesize that both internal and external determinants impact a state’s decision to adopt a policy. External factors were found to be significant. Two reasons for this significance is given in the literature, competition and learning. Because the data is aggregate at the state level, the reason for the influence cannot be determined based on the data, although some hypotheses can be asserted. Because HEV incentives are not likely to cause relocation of manufacturing or constituents, it is unlikely that competition causes the diffusion. Rather, learning is likely to be the mechanism that promotes horizontal diffusion.
The internal factors tested point to public opinion and constituent support, as opposed interest groups and other indicators of consolidated strength, impacting policy adoption. Although the pooled models hinted at strong opposition to hybrid-electric-vehicle incentives by manufacturing interests, creating models that predict individual incentives revealed that the presence of manufacturing interests is a less important predictor than originally thought. Instead, public opinion, or constituent support predicted policy adoption of state incentives. For instance, Sierra Club membership had a negative impact on adoption of HOV incentives but a positive impact on tax credits. These findings, which may not seem intuitive, are in line with the Sierra Club’s public statements regarding these policies. Since HOV lane exemptions are contentious within the environmental community, states with significant support for environmental issues may not have the political capital to enact policies such as these. This opposition to HOV lane exemptions by environmental groups may lie in the fact that they are not an efficient method for increasing air quality, do not lower dependence on the personal automobile, do not increase carpooling rates, and may disproportionately be exploited by some demographic groups such as high-income commuters that can afford to by a brand new car.

Surprisingly, problem severity did not significantly impact a state’s propensity to adopt incentives. Nonattainment status was not significant in any of the models, while traffic congestion was found to impact sales tax exemptions. Surprisingly, gasoline price, a proxy for problem severity from an energy perspective, was found to be significant in all models, but in the opposite direction hypothesized. This result could be because as gasoline prices rise, there is little political capital to enact policies that do not directly address them (as opposed to incentives to purchase hybrid vehicles).
Policy Implications

Tailoring a Policy to the Community

Both these technology-adoption models support the assertion that incentives may have an impact on hybrid-electric-vehicle adoption if customized to the community. Most important, it appears that incentives must be well designed policies that respond to the needs of the community to be effective. Non-pecuniary incentives, when they provide alternative benefits to an individual, such as time savings, may have a greater impact than traditional monetary transfers. Even tax credits worth significant sums of money may not change demand, if not implemented towards a targeted population.

As discussed in the introduction, some concepts within natural resource management prescribe to this iterative and customized approach to policy implementation and evaluation. Adaptive management uses evaluation both ex-ante and ex-post to look at previously implemented policies, as well as impacts to future policies, before suggesting modifications to the evaluated policy. Its three basic tenets: experimentalism, multiscalar analysis, and place sensitivity, applies this iterative approach to ecosystem management, although it can be extended to other areas of environmental policy. Experimentalism reduces future uncertainty because outcomes are better known and understood; multiscalar analysis and place sensitivity allow managers to apply policies to varying levels of space and time (Norton 2005). This variation may mean policies customized to a community’s environmental needs or a pilot implementation for a predetermined time period. Adaptive management relies on teams of scientists, managers, and policy-makers to identify and bound the problems into quantifiable terms and develop a model that explains different relationships and identifies the most effective policy options.
Simultaneous testing, monitoring, and evaluation allow policy analysts to learn more about the problem; increase knowledge, information sharing, and stakeholder consensus; and ultimately improve on the implemented policy (McLain and Lee 1996). Adaptive management therefore includes evaluation as a key step.

This caveat of customization is evidenced by the inconsistent estimated treatment effect for tax credits even though they have the largest monetary value of the three pecuniary hybrid-vehicle incentives. Although Sales-tax exemptions were found significant in all four parametric models, they were not found to be significant in the individual level analysis using National Household Travel Survey data. Therefore, although the some of the parametric models demonstrate a possible significant impact on demand, additional models contradict that finding, bringing in a certain level of uncertainty regarding the true effect of this incentive.

Hybrid incentives are not the first time governments have attempted to promote change in the characteristics of the national automobile fleet through legislation, although over the past decade state governments have taken more of a leadership role in regulatory issues related to automobiles. In addition, in 2007 the United States Supreme Court ruled that the Environmental Protection Agency has the authority to regulate tail-pipe emissions from automobiles. This ruling means that the ownership of automobile fuel-efficiency standards may be within EPA’s jurisdiction. This ruling is likely to change the political landscape, but at present, coercive policies, such as technology-forcing standards addressing fuel efficiency, are unlikely to be a major consideration due a lack of political support. Although the adopted fuel-efficiency standards will increase the minimum to 35 miles per gallon, current technology is already available to reach these standards using traditional internal-combustion engines. Plug-in hybrids and 100% electric vehicles are now on the market, but they have yet to substantially diffuse into
the marketplace. Therefore, correct implementation of incentives for alternative vehicles is important because incentives are currently the largest legislative effort to diffuse any alternative vehicles into the U.S. automobile market. This research will help to direct the development of future subsidies and incentives for technology adoption.

Evaluating these subsidies is also relevant since the number of stakeholders in this policy arena is significant, and the effects of subsidies may be felt on U.S. culture, physical landscape, and environmental quality. Hybrid subsidies in particular affect numerous stakeholders, among them automobile manufacturers and consumers, and, through alternative incentives such as HOV lane exemptions, other commuters in the community. Because HOV lane exemptions change the purpose of HOV lanes from increasing vehicle occupancy rates to accommodating alternative vehicles, the design of these lanes may need to be revisited.

Since most states are considering the implementation of hybrid-vehicle subsidies, and many states, such as Michigan, Massachusetts, Minnesota, Hawaii, and Georgia, are considering HOV lane exemptions, this evaluation can inform policy analysts about the effectiveness of these policies—and may help them to better design policies toward appropriate populations. This research shows that creative or less conventional types of incentives, in the sense that they are not a monetary transfer (HOV requirement exemptions), could be offered in more places. The important caveat of the impact of these incentives, however, is that they implementation must be made with respect to local characteristics, as if the policy does not fit the community, it will not be effect. In addition, further consideration should be given to the secondary effects of policies such as these, such as increased congestion in HOV lanes and marginal changes in air pollution.
**Causal Inference in Environmental Policy**

These results also point to the need to establish causal inference in policy evaluation and for further development of methods in which to do so. Program evaluation at its best intends to move away from correlation and toward establishing a causal relationship between the treatment and the outcome. Causal inference is the ultimate goal in using statistical methods, although it is not always clear how to achieve inference (Holland 1986). The use of observational data in environmental policy evaluations allows researchers to ex post assess policies to specify this causal relationship, while attempting to identify causal inference. As discussed in Chapter 1, observational data are collected after the implementation, meaning that no attempts to control the placement into treatment and control groups were made, making it an attractive, inexpensive alternative for evaluators that can be done long after policy implementation. This advantage comes with tradeoffs; most notably, results from observational data are susceptible to confounding factors and selection biases that lead to incorrect estimates of the treatment effect. Observational studies that do not take into account the possibility of biases, such as selection bias and bias resulting from spurious relationships, may incorrectly attribute changes in the environment to policies.

In recent years, many articles have begun to posit the use of quasi-experimental or even experimental methods in environmental policy as a way to establish this causal relationship while accounting for these biases (Frondel and Schmidt 2005; Ferraro 2009; Greenstone and Gayer 2009). As the researchers point out, experiments are ideal for a variety of reasons. First, they are the best defense against confounding factors. Second, experimentalism, a primary feature of adaptive management, allow policy analysts to test the effectiveness of a policy before
widespread implementation or when expanding to different communities. This characteristic is particularly important because of the possibility of unintended consequences—such as economic harm or environmental damage (Greenstone and Gayer 2009). Experiments, however, are not easy to perform because of fiscal and political constraints, making quasi-experimental methods the more common class of evaluative tool. True random experimental designs are rare, if not entirely nonexistent, in environmental policy.

Selecting quasi-experimental methods, however, is not straightforward and can be based on a multitude of factors such as evaluator knowledge or data availability. For instance, independent longitudinal data sets do not always exist for environmental program evaluation. A researcher who wants to evaluate facility performance in the face of regulation may not have data available for the control group, unregulated facilities (List, Millimet et al. 2003). Similarly, the impact of a home-energy audit for customers who participate in a voluntary program cannot be compared since no data are collected from individuals who are not enrolled. If data do exist, Greenstone and Gayer (2009) put forth three preferred quasi-experimental approaches: fixed effects or difference-in-difference, instrumental variables, and regression discontinuity. Each has limitations. For example, instrumental variables are only appropriate when there are endogeneity issues that require the researcher to find an instrumental variable Z that is correlated with the treatment, but independent of potential outcomes. The availability of such data is often questionable, and proving that correlation between Z and Y is zero often relies on logical argument instead of statistics.

Ferraro (2009) categorizes quasi-experimental methods instead as (1) either assuming that treatment assignments are affected only by observable variables (matching and cross-sectional regression) or (2) assuming that treatment assignments are affected by both observable
and unobservable variables (panel data methods). Both Gayer and Greenstone and Ferraro do not discuss the idea that combining methods provides the most protection against biases. Most researchers applying propensity-score matching do not automatically assume that the treatment assignments are affected only by observed variables, especially because matching on a propensity score requires the researcher to first run a logistic regression to identify the significant variables that predict treatment. In doing so, the researcher is exposed to various pseudo R-squared calculations and prediction models such as ROC (receiver operating characteristic) curves that reveal residual variation of the dependent variable that is unaccounted for. This unaccounted variation, if correlated with the outcome, will prevent accurate treatment-effect estimation. Neither Greenstone and Gayer nor Ferraro suggest combining propensity-score matching with parametric methods in order to test the robustness of the results by comparison. Comparing the results, as well as strengths and weaknesses, of the methods allows researchers to make assessments about the validity of the methods for both observed selection bias and unobserved time-invariant biases (albeit not simultaneously), resulting in the most promising methods currently in the environmental evaluators’ methods portfolio.

As researchers begin to include propensity-score matching in their methodological toolbox, concern remains that these methods can fail to reduce bias, or even increase it because of unobserved confounding factors. One reason for this concern is that if balance is not achieved, this limitation is often not acknowledged. In addition, as previously noted, propensity-score matching requires the creation of a balanced panel so that the restricted control and treatment groups have similar means and distributions of all observed covariates that are identified to predict the placement into treatment. Even if balance is achieved, bias can still exist because this selection is only on the observables and not the unobserved covariates that may affect outcome.
To use the example of hybrid subsidies, if there remains an uncollected covariate that helps to describe the prediction of who adopts hybrid subsidies (e.g., the proxy for environmentalism is incomplete), then the estimates of the average treatment effect (the impact of having an incentive on demand) will be inconsistent and biased. When there are unobservable confounders, standard regression and matching estimators will fail to provide a fully valid estimate of the causal effect of the treatment.

Contrary to the concerns about selection on observables by Ferraro and Greenstone and Gayer, however, research using propensity-score analysis has been successfully conducted in the environmental policy arena (List, Millimet et al. 2003). List et al. examined the effects of air-quality regulation on economic activity to test the “race to the bottom” hypothesis that localized environmental regulation will affect capital investment. List et al. chose multiple matching methods to compare estimates in an effort to thoroughly account for possible section-bias issues. First, they altered the nearest neighbor matching algorithm to include a cutoff point so that significantly different observations were not matched. Second, because they had panel data with many observations, they were able to perform a matching exercise in an attempt to remove time-region or county-specific unobservables not controlled for by the propensity score. To do this, they restricted the matching pairs to be from the same year. Then they restricted the matching pairs to be from the same region and the same state. Finally, they restricted the matched pairs to be from the same county from a different year. After that, they computed the mean difference in the birth of clean plants across the matched treatment and control groups. This work is an exemplar of how propensity-score matching can be used effectively, although it was the richness of the data allowed such analysis.
In terms of the work completed for this thesis, however, propensity-score matching was less effective. It was relatively successful in reducing selection bias in HOV lane exemptions, but it did not achieve balance between the treatment and control groups for this policy or for the other two policies. Using the propensity score to identify the average treatment effect of hybrid-vehicle incentives on state-level demand revealed that increasing the balance between the treatment and control groups of HOV lane exemptions eliminated the measured treatment effect, although it did not account for treatment heterogeneity. In addition, matching did not improve balance for the sample that was chosen to calculate the average treatment effect of tax credits. In his study of the Clean Air Act, Greenstone also used matching on the propensity score to assess the effect on nonattainment designations of changes in sulfur dioxide concentrations. Although the treatment effect remained significant when he applied this method, the distributions of the covariates were not similar, although the differences were reduced by matching. The quality of the results from propensity-score matching largely depends on the quality and size of the data structure used in the evaluation. Although researchers have posited using multivariate analysis after propensity-score matching, combining the parametric and nonparametric techniques is not common, possibly because of the data requirements. The sample size must be large enough and the model must be rich (Baser 2006).

If propensity-score matching fails to reduce bias, little published literature provides direction on the importance of interaction terms, sensitivity analysis, and alternative matching algorithms for selection of the control group. This may be why the quality of propensity-score matching applied research varies so greatly. A review of applied-research efforts using propensity-score analysis reveals that reporting the nuanced results of propensity-score matching is inconsistent (Weitzen, Lapane et al. 2004). In terms of the model used to calculate the
propensity score, over half the research efforts did not provide information about what method was used to select variables, over half were unclear about whether interaction terms were incorporated into the propensity score, and most did not report goodness of fit of the propensity score or the ability of the model to predict events. More important, almost half the studies included no information about propensity-score balance (Weitzen, Lapane et al. 2004). This is alarming because failing to check for balance could introduce additional bias, referred to as *choice bias* (Baser 2006).

In addition to the guidelines offered by Rubin (2001) that help evaluators assess the quality of the matching results, Baser also provides assessment guidelines. Where Rubin categorizes assessment into three categories—the difference in the means, the difference in the variances, and the ratio of the variances of the residuals—Baser also suggests that the difference in the means be small, but recommends that the difference be statistically insignificant and that the mean differences as a percentage of the average standard deviation be low. Baser also recommends that 100% reduction bias in the means of explanatory variables be achieved, although that is not very likely. Rubin does not explicitly discuss the differences in the distributions of the covariates, even though he does discuss covariate variance. Baser prescribes a comparison of the covariate distributions by looking for differences in the density estimates of the treatment and control groups. But questions remain as to “how” balanced the groups must be to be considered adequate.

As previously stated, there are steps to be taken if the first attempts at propensity-score matching do not fix bias issues. Multiple matching methods to construct a control group exist, with the main methods being kernel matching, Mahalanobis matching, and nearest neighbor. Comparing results from various matching techniques can provide insight. For instance, the
matching technique helps to understand the severity of choice bias; different propensity-score-matching techniques may produce different results and balance. If there is nontrivial variation in the estimated treatment effect between matching methods, then bias is probable. Sensitivity analysis was not completed for this dissertation, in part because the data are not as rich as required. None of the proposed propensity-score-matching techniques in the literature is a priori superior to the others, and some may create subpar control groups. The general tendency in the literature is to choose matching with replacement when the control data set is small, which is what was chosen for this research (Baser 2006). Some published works exist to help guide the analyst in specifying the propensity models, but additional research in this area is warranted before matching algorithm recommendations can be made conclusively (Johnson, Crown et al. 2009).

**Future research**

The results from this study reveal interesting implications about which states became leaders in hybrid vehicle incentives and which incentives were effective. There are several remaining issues, however, that require further analysis.

First, several difficulties with modeling the predictors of state-level hybrid-electric-vehicle incentives were pervasive in the analysis. These issues include only moderate specification, or goodness of model fit, and issues with autocorrelation. Although the models passed overall goodness-of-fit tests, the final fitted models did not predict positive events very well. The fitted model for HOV lane exemptions predicted 0 out of 13 events, the tax-credit model predicted 1 of 15 positive events, and the sales-tax exemption model predicted 1 out of 8 events. This low
predictability could be because positive events are not common (they occur in only 37 out of 255 events). Rare-event data have been shown to underpredict positive events when there is a binary dependent variable (King and Zeng 2001). To deal with this potential issue, bootstrapped odds ratio estimates were calculated for each of the covariates for two of the models, HOV lane exemptions and tax credits. Although these results were comparable to the fitted model, additional issues persist; statistical tests identified autocorrelation as a significant issue. Autocorrelation can overestimate the impacts of the covariates on the dependent variable (Beck, Katz et al. 1998).

Solutions to autocorrelation would be to create dummy variables that indicate the time from either the beginning of the sample time or from a positive event, although the population size should be bigger than the data used in this dissertation (Beck, Katz et al. 1998). In addition, a duration model, or event history model, will address this issue of autocorrelation as well as address the fact that this data is truncated. After this time period studied of 2001-2005, additional states did adopt incentives, so it may be beneficial to treat the data this way, since some adoptions were not captured in this dataset. Event-history analysis has been used extensively to look at policy adoption and other political economy research. This methodology was not chosen for this dissertation because a logistic model needed to be fitted for use in propensity-score matching and because pooled time series cross sectional analysis is also an accepted method in policy-adoption models, even with its limitations in terms of correcting for autocorrelation. Further research, however, could utilize duration models and compare the determinants between the two models.

In addition, because the National Household Travel Survey data are rich and timely, additional research can be done to better understand the causal relationship between attitudes,
transportation behavior, and hybrid-vehicle purchase. The present analysis was limited in the fact that it did not capture the purchase date. If that was captured, then further understanding would exist as to whether the person experienced the incentive when the automobile was purchased. Solutions to this limitation do exist, however, and will be performed in future analyses. For instance, the age of the vehicle could be used as a proxy for purchase date to incorporate time information into the analysis. Using the model year as a proxy for purchase date requires the assumption that all hybrids were adopted new, but would allow the analysis to explore the adoption rate over time. This information could be used to assign the vehicles and their owners into both a treatment group (living in a state with a subsidy at the time of purchase) and a control group (living in a state without an incentive). This type of design is known as a regression discontinuity design. In addition, to account for the possibility of interstate relocating affect the results of the analysis using the NHTS, the analysis can be restricted to certain years, particularly those closer to the survey to account for the possibility that a person moved states between the time of adoption of the hybrid and the time they responded to the survey. This restriction will also be done in future efforts. Besides implementing new econometric methods and strategies to account for limitations of this data, it is possible to include additional variables to test further variables of interest: these include gas prices, and finer variables of the built environment data such as zip code density. These new variables would allow further model refinement to better understand the determinants of hybrid adoption.
APPENDIX A: SUMMARY OF VARIABLES USED IN ENVIRONMENTAL POLICY ADOPTION LITERATURE

<table>
<thead>
<tr>
<th>Category</th>
<th>Variable</th>
<th>Proxy</th>
<th>Reference</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Environmental Condition</td>
<td>Problem Severity</td>
<td>Density of superfund sites</td>
<td>(Daley and Garand 2005)</td>
<td>Collected by the author</td>
</tr>
<tr>
<td>Political Context</td>
<td>Environmental Political strength</td>
<td>Environmental membership</td>
<td>(Potoski 2001; Daley and Garand 2005)</td>
<td>Sierra Club, Greenpeace, and National Wildlife Federation (Index created by the Green Index)</td>
</tr>
<tr>
<td>Environmental Attitudes</td>
<td>Survey questions</td>
<td>Survey questions</td>
<td>(Jones and Dunlap)</td>
<td>General Social Survey</td>
</tr>
<tr>
<td>Interest Group Strength</td>
<td>Per capita manufacturing of GSP</td>
<td>Per capita manufacturing of GSP</td>
<td>(Daley and Garand 2005)</td>
<td>Not identified</td>
</tr>
<tr>
<td>Interest Group Strength</td>
<td>Percentage of population employed by oil industry, that stand opposed to NRD enforcement</td>
<td>Percentage of population employed by oil industry, that stand opposed to NRD enforcement</td>
<td>(Potoski 2001; Ando and Polasub 2009)</td>
<td>(U.S. Census Bureau) Employment in crude petroleum, natural gas extraction and basic chemical manufacturing</td>
</tr>
<tr>
<td>Interest Group Strength</td>
<td>Value added by manufacturing by those industries most responsible for air pollution as a percentage of a</td>
<td>Value added by manufacturing by those industries most responsible for air pollution as a percentage of a</td>
<td>(Potoski 2001) (Ringquist 1993)</td>
<td>1992 economic census</td>
</tr>
<tr>
<td><strong>Federal Support</strong></td>
<td>Federal funding of state EPA</td>
<td>(Daley and Garand 2005; Ando and Polasub 2009)</td>
<td>Consolidated Federal Funds Report and are publicly available from the Census Bureau (<a href="http://www.census.gov/govs/www/cffr.html">www.census.gov/govs/www/cffr.html</a>)</td>
<td></td>
</tr>
<tr>
<td>---------------------</td>
<td>------------------------------</td>
<td>-----------------------------------------------</td>
<td>--------------------------------------------------------------------------------------------------</td>
<td></td>
</tr>
<tr>
<td><strong>Political Ideology</strong></td>
<td>Fraction of appellate court judges appointed by Democratic Presidents</td>
<td>(Ando and Polasub 2009)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Institutional Capacity</strong></td>
<td>Administrative resources</td>
<td>State spending on air pollution</td>
<td>State spending on air pollution</td>
<td></td>
</tr>
<tr>
<td><strong>State level Environmental Ideology</strong></td>
<td>Green Index’s assessment of state level environmental policies</td>
<td>(Daley and Garand 2005)</td>
<td>The Green Index</td>
<td></td>
</tr>
<tr>
<td><strong>Political Ideology</strong></td>
<td>Survey of state-level clean air policies (used as dependent variable in study, but can be used as independent variable for purposes of this study)</td>
<td>(Potoski 2001)</td>
<td>State Air Pollution Control Survey (SAPCS) conducted in 1998 by the Council of State Governments.</td>
<td></td>
</tr>
<tr>
<td><strong>Resources</strong></td>
<td>State deficit</td>
<td>(Berry and Berry 1990)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
APPENDIX B: LOGISTIC DIAGNOSTIC TESTS FOR POLICY

ADOPTION ANALYSIS

<table>
<thead>
<tr>
<th>Test</th>
<th>HOV lanes</th>
<th>Tax Credit</th>
<th>Sales Tax</th>
</tr>
</thead>
<tbody>
<tr>
<td>Likehood Ratio Test</td>
<td>0.0001</td>
<td>0.0058</td>
<td>7.56e-05</td>
</tr>
<tr>
<td>Modified Hosmer-Lemeshow Test</td>
<td>0.24</td>
<td>0.45</td>
<td>0.60</td>
</tr>
<tr>
<td>Specificity</td>
<td>0.98</td>
<td>0.99</td>
<td>0.96</td>
</tr>
<tr>
<td>Sensitivity</td>
<td>0/13</td>
<td>0.07</td>
<td>0.125</td>
</tr>
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</table>

Cross-Tabulation of Predicted Adoptions for HOV Lane Exemptions

<table>
<thead>
<tr>
<th>Actual</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Fitted</td>
<td>+</td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td>+</td>
<td>0</td>
</tr>
<tr>
<td>-</td>
<td>13</td>
</tr>
<tr>
<td></td>
<td>13</td>
</tr>
</tbody>
</table>

Cross-Tabulation of Predicted Adoptions for Tax Credits

<table>
<thead>
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</tr>
</thead>
<tbody>
<tr>
<td>Fitted</td>
<td>+</td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td>+</td>
<td>1</td>
</tr>
<tr>
<td>-</td>
<td>14</td>
</tr>
<tr>
<td></td>
<td>15</td>
</tr>
</tbody>
</table>

Cross-Tabulation of Predicted Adoptions for Sales Tax

<table>
<thead>
<tr>
<th>Actual</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Fitted</td>
<td>+</td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td>+</td>
<td>1</td>
</tr>
<tr>
<td>-</td>
<td>7</td>
</tr>
<tr>
<td></td>
<td>8</td>
</tr>
</tbody>
</table>
APPENDIX C: DISTRIBUTION OF BOOTSTRAPPED ODDS-RATIOS

Bootstrapping the coefficients provides insight into the reliability of the regression results because the number of positive events in the population is not high (as a percentage of total events). For this population, the total number of positive events is 37 out of 255, or 14.5%. The bootstrapping procedure involved sampling 100 states out of the larger population of states that did not adopt incentives. This sample was matched to the states that adopted the incentive. This sample was then fitted using a logistic regression model. This process was repeated 1000 times, with the regression results compiled into one matrix. The distribution of the coefficients is presented in histograms in this appendix. These histograms are compared to the regression coefficients on page 76 to see if the regression coefficients align with the results. Alternatively, the 95% confidence intervals can overlaid onto the histograms to see how many times the regression model from the bootstrapped sample fell outside of the interval. This process was not needed, because the variation in the bootstrapped coefficients was not large. The results of both HOV lane exemptions and of tax credit are presented on the following pages. The histograms illustrate the reliability of the regression coefficients presented on page 76.

Because the numbers of positive events are not high, some of the bootstrapped regression fitted models did not converge. For HOV lane exemptions, 46 iterations did not converge, resulting in 954 regression coefficients for each histogram. For income tax credits, 80 of the fitted models did not converge, leaving this analysis with 920 points. When bootstrapping sales tax exemption model, the models did not converge enough to use this method.
HOV Lane Exemptions
Percent of new car registrations that are hybrids

Population

Percent of Total

Percent of Total
Note: The minimum regression coefficient for the bootstrapped sample is not obvious for population and hybrid adoptions; the minimum for population is 1, while for “percent of new car registrations that are hybrids,” the minimum bootstrapped coefficient is 1.5.
Tax Credit Adoption Variables

Graphs showing distribution of income, Sierra Club memberships, spending on energy efficiency, and percent of hybrids.
SGDP attributed to automobile manufacturing.
APPENDIX D: KERNEL DENSITY PLOTS OF STATES BY INCENTIVE STATUS

The kernel density plot is a nonparametric method for estimating the probability density function of a variable, using a kernel weighting function. Kernel density plots are useful in comparing the distribution of several variables. The kernel density plots in this appendix allow an assessment of the constructed control group used in the analysis. These plots provide a metric, the distribution of each covariate, to compare the new constructed comparison group, states that adopted subsidies, with the natural comparison group, states that did not adopt incentives. Using the first pair of kernel density plots as an example, the left hand graph presents the distribution of congestion in states with subsidies and state without subsidies. The right hand side presents the distribution of traffic congestion in states with subsidies and states that proposed subsidies. Comparing these two graphs is a method, without a statistical test, to evaluate whether creating the constructed comparison group reduced the differences in the two distributions.
For traffic congestion, reducing the two groups did not reduce the differences in the distribution, although the differences in the distribution did not increase.

For gasoline, states that did not adopt subsidies but that experienced high gasoline prices were removed from the natural comparison group (shown on the left) for the constructed control group (shown on the right), thereby increasing the similarity of treatment and control groups’ distributions.
Reducing the comparison groups to states that proposed subsidies (shown on the right) did remove some high population states that did not adopt subsidies, thereby increasing the similarity of the distribution between the two groups.
On the right hand side, the constructed control group is compared with the treatment group. On the left hand side, the treatment group is compared with the natural control group. Reducing the comparison group did not change the distribution significantly.

Reducing the comparison group removed some of the outliers with higher percentages of automobile manufacturing, thereby increasing the similarity of the distribution between the two
groups.

The graph on the right shows that reducing the comparison group to those states that proposed subsidies removed some of the observations in the right hand tale, but did not dramatically increase the similarity between the two groups.

The constructed control group did not increase the difference in the distribution of density between the two groups; observations that were removed were mainly from around the mean.
For hybrid registrations, the constructed control group did not increase the difference in the
distribution of density between the two groups.
Reducing the control group decreased the similarity of the energy efficiency programs distributions, because it reduced states with lower levels of investment in energy efficiency programs.

Reducing the comparison group to states that proposed incentives increased the similarity by moving some states that had a low level of nonattainment status in the comparison group.
APPENDIX E: Q-Q PLOTS FOR PROPENSITY–SCORE MATCHING OF HOV SUBSIDIES

QQ-plots are used to compare the distributions of two samples. In this case, the two QQ-plots for each covariate together provide a picture about the impact of propensity score matching. Specifically, these diagnostics help to determine whether the distribution of the two groups was made more similar. If the dots follow the line, then the distributions are similar; therefore, matching would ideally make the plots on the right more linear than they were before (the QQ plots on the left).

These QQ plots are an additional method to evaluate whether the distributions of two samples are similar; these plots are supplemental to the K-S statistics presented on in the results section. QQ plots can be used to interpret the differences in the distribution. If Q-Q plot slope is less than the $y=x$ line, the sample plotted on the horizontal axis is has a more dispersed distribution than the sample plotted on the vertical axis. If the slope of the QQ-plot is steeper than the $y=x$ line, then the converse is true. Finally, an S-shape indicates that a difference in skewness or heavy tails between the two samples.
Distribution of Sierra Club Memberships Before and After Matching

Old Treatment Group vs. Old Control Group

New Treatment Group vs. New Control Group
Distribution of Nonattainment Status Density Before and After Matching
Distribution of Energy Efficiency Spending Before and After Matching
Distribution of Gasoline Before and After Matching
### APPENDIX F: PROPENSITY SCORE BALANCE STATISTICS, RESULTS

#### FOR INCOME TAX INCENTIVES

<table>
<thead>
<tr>
<th></th>
<th>Energy-Efficiency Spending (millions)</th>
<th>Sierra Club Memberships</th>
<th>Income</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Before Matching</td>
<td>After Matching</td>
<td>Before Matching</td>
</tr>
<tr>
<td>Treatment mean</td>
<td>24,586</td>
<td>24,586</td>
<td>24,842</td>
</tr>
<tr>
<td>Control mean</td>
<td>33,638</td>
<td>15,556</td>
<td>14,675</td>
</tr>
<tr>
<td>Std mean diff</td>
<td>-37.54</td>
<td>37.45</td>
<td>88.28</td>
</tr>
<tr>
<td>T-test p-value</td>
<td>0.29</td>
<td>0.57</td>
<td>0.01</td>
</tr>
<tr>
<td>Variance ratio (Tr/Co)</td>
<td>0.12</td>
<td>0.19</td>
<td>0.15</td>
</tr>
<tr>
<td>K-S Bootstrap p-value</td>
<td>0.22</td>
<td>0.01</td>
<td>0.00</td>
</tr>
<tr>
<td>K-S Statistic</td>
<td>0.29</td>
<td>0.45</td>
<td>0.37</td>
</tr>
<tr>
<td><strong>Population</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Treatment mean</td>
<td>6,970,709</td>
<td>6,970,709</td>
<td></td>
</tr>
<tr>
<td>Control mean</td>
<td>5,866,086</td>
<td>5,086,633</td>
<td></td>
</tr>
<tr>
<td>Std mean diff</td>
<td>15.53</td>
<td>26.50</td>
<td></td>
</tr>
<tr>
<td>T-test p-value</td>
<td>0.59</td>
<td>0.47</td>
<td></td>
</tr>
<tr>
<td>Variance ratio (Tr/Co)</td>
<td>1.22</td>
<td>1.34</td>
<td></td>
</tr>
<tr>
<td>K-S Bootstrap p-value</td>
<td>0.3</td>
<td>0.10</td>
<td></td>
</tr>
<tr>
<td>K-S Statistic</td>
<td>0.26</td>
<td>0.38</td>
<td></td>
</tr>
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</table>
APPENDIX F: PROPENSITY SCORE MATCHING RESULTS FOR SALES

TAX INCENTIVES

<table>
<thead>
<tr>
<th></th>
<th>Energy-Efficiency Spending (millions)</th>
<th>Sierra Club Memberships</th>
<th>Income</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>Before Matching</td>
<td>After Matching</td>
<td>Before Matching</td>
</tr>
<tr>
<td>Treatment mean</td>
<td>24,586</td>
<td>24,586</td>
<td>24,842</td>
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<td>Control mean</td>
<td>33,638</td>
<td>15,556</td>
<td>14,675</td>
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<td>88.28</td>
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<td>0.57</td>
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<td>K-S Bootstrap p-value</td>
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<td>0.00</td>
</tr>
<tr>
<td>K-S Statistic</td>
<td>0.29</td>
<td>0.45</td>
<td>0.37</td>
</tr>
</tbody>
</table>

Population

<p>| | | | |</p>
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<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Treatment mean</td>
<td>6,970,709</td>
<td>6,970,709</td>
<td></td>
</tr>
<tr>
<td>Control mean</td>
<td>5,866,086</td>
<td>5,086,633</td>
<td></td>
</tr>
<tr>
<td>Std mean diff</td>
<td>15.53</td>
<td>26.50</td>
<td></td>
</tr>
<tr>
<td>T-test p-value</td>
<td>0.59</td>
<td>0.47</td>
<td></td>
</tr>
<tr>
<td>Variance ratio (Tr/Co)</td>
<td>1.22</td>
<td>1.34</td>
<td></td>
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<tr>
<td>K-S Bootstrap p-value</td>
<td>0.3</td>
<td>0.10</td>
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<tr>
<td>K-S Statistic</td>
<td>0.26</td>
<td>0.38</td>
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</tr>
</tbody>
</table>
REFERENCES


VITA

ALISON RIGGIERI

Alison Riggieri was born in Springfield Massachusetts, but was raised in Millbury MA., a suburb of Worcester, MA. She attended Millbury Public Schools until high school, at which time she entered The Bancroft School in Worcester, MA. Riggieri then went to Rensselaer Polytechnic Institute, where she received a dual B.S. in Electrical Engineering and Science and Technology Studies. In 2005, she went to Georgia Institute of Technology to pursue a doctoral degree in public policy. When she is not working on his research, Ms. Riggieri enjoys staying active through soccer, running, and rock climbing.