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Essays About Energy Economics

A dissertation submitted in partial satisfaction of the
requirements for the degree
Doctor of Philosophy

in

Economics

by

Tamara Lynn Sheldon

Committee in charge:

Professor Richard Carson, Chair
Professor James Hamilton
Professor Mark Jacobsen
Professor David Victor
Professor Junjie Zhang

2015

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University of California, San Diego

2015

DEDICATION

To my family and friends for supporting me during this process. A special thanks to my husband, Tim, for his continual support as I took on this endeavor.

EPIGRAPH

Examine each question in terms of what is ethically and aesthetically right, as well as what is economically expedient. A thing is right when it tends to preserve the integrity, stability, and beauty of the biotic community. It is wrong when it tends otherwise.

—Aldo Leopold

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Chapter 3, in full, is currently being prepared for submission for publication of the material. Sheldon, Tamara L.; DeShazo, J.R. The dissertation author was the primary investigator and author of this paper.

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ABSTRACT OF THE DISSERTATION

Essays About Energy Economics

by

Tamara Lynn Sheldon

Doctor of Philosophy in Economics

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Professor Richard Carson, Chair

This dissertation looks at how the macro economy affects carbon dioxide emissions and evaluates policy designs intended to reduce emissions. The first chapter examines how the business cycle affects carbon dioxide emissions, finding that emissions respond more elastically to recessions than expansions, which results in future emissions forecasts that are lower on average but much less certain. The second chapter evaluates and proposes alternative, more effective designs of the State of California's Clean Vehicle Rebate Program, an incentive program to encourage the adoption of plug-in electric vehicles with the intent of reducing local air pollu-

tion and greenhouse gas emissions. The third chapter evaluates the effectiveness of another California policy to encourage the adoption of plug-in electric vehicles by granting drivers free single-occupant access to high-occupancy vehicle lanes.

Chapter 1

Asymmetric Effects of the Business Cycle on Carbon Dioxide Emissions: A New Layer of Climate Change Uncertainty

1.1 Introduction

Determining society's best response to global climate change is challenging due to the scientific and economic uncertainties about future forecasts. There are scientific uncertainties about how much the earth will warm as a function of greenhouse gas emissions. Economic uncertainties about growth and technological change translate into uncertainty about the amount of greenhouse gases emitted into the atmosphere. Recent literature has increasingly focused on how these uncertainties affect optimal policy and considers optimizing not only over the average climate impacts but also lowering the variance of climate impacts (Weitzman, 2011; Nordhaus, 2012; Pindyck, 2012; Hwang, Reynès, and Tol, 2013).

Emerging literature has started to look at how the business cycle affects optimal pollution and climate policy (Fischer and Heutel, 2013). For instance, Fischer and Springborn (2011) use a real business cycle model to show that intensity targets may be more attractive than emissions caps or taxes. Heutel (2012) finds that optimal emissions taxes and quotas are pro-cyclical.

This paper focuses on the implications of the business cycle towards uncertainty about emissions. Forecasting carbon dioxide emissions has significant implications for climate modeling, setting goals for international mitigation agreements, and setting caps for emissions trading schemes. The latest report from the Intergovernmental Panel on Climate Change (IPCC, 2013) states that while economic and population growth are the most important drivers of increasing carbon dioxide emissions, the contribution from economic growth has risen over the last ten years. However, it is well established that gross domestic product (GDP) does not smoothly increase over time, but instead fluctuates around a long-term growth trend, a pattern known as the business cycle. Despite the fundamental nature of the business cycle theory to modern economics, current emissions forecasts assume smooth growth trends and disregard the business cycle.

There is evidence that both energy intensity and emissions intensity change over the business cycle. Electricity consumption and primary energy use by the industrial sector fall more per decrease in GDP than they rise per unit increase in GDP. This may be due to lower use or retirement of older, less energy-efficient capital during recessions and greater use of and investment in newer, more energy-efficient capital during expansions. Emissions intensity may also change over the business cycle if fuel mix changes differentially. I find empirical evidence from the power sector to support both of these hypotheses.

This paper considers how the business cycle affects carbon dioxide emissions forecasts and questions the implicit assumption that the elasticity of emissions is constant with respect to GDP by allowing emissions to be asymmetrically affected by the business cycle. I first estimate a flexible reduced-form econometric forecasting model for the United States that predicts emissions as a function of GDP. The results indicate that emissions fall more sharply per unit change in GDP during a contraction than they rise during an expansion. Such an asymmetry is observed across time and in the majority of the top carbon-dioxide emitting countries.

Next, I use GDP simulations to compare emissions forecast for the United States using three different models: 1) a baseline model that assumes smooth growth, 2) a model that factors in the business cycle but assumes a symmetric response to expansions and contractions, and 3) a model that factors in the business cycle but allows an asymmetric response to expansions and contractions. With a 95% confidence interval, assuming average GDP growth of 3.42%, I forecast cumulative emissions between 2010 and 2100 to be 306-386 gigatons of carbon when the business cycle is factored in, relative to a baseline forecast with the same average level of economic growth of 363-365 gigatons of carbon.

In other words, when the business cycle is factored in, emissions are predicted to be lower on average, but much more uncertain. The lower average forecast

is driven by the greater responsiveness of emissions to contractions than to expansions, which causes a downwards ratchet effect. The intuition for the increase in uncertainty is as follows: there are an infinite number of GDP paths that can result in the same average long run growth rate, but there is only one smoothed path with a constant annual growth rate. Each GDP path results in a different emissions path. The integral under these emissions curves, or cumulative emissions, can be greater or less than the integral under the smoothed growth path. Therefore, holding average long run GDP growth constant, because we do not know what the path of the business cycle will be, there is uncertainty about how high future cumulative emissions will be. Holding total GDP growth constant, uncertainty from the business cycle results in an additional $.7^{\circ}\text{C}$ uncertainty in cumulative temperature change by 2100, relative to consensus warming estimates of 4°C . This is of a similar order of magnitude as the major physical science uncertainties in future temperature change.

The remainder of the chapter is organized as follows. Section 1.2 provides background information on emissions forecasting. Section 1.3 motivates the empirical model by discussing possible causes for an asymmetric response of emissions to the business cycle, finding evidence that suggests emissions may be more elastic during recessions than expansions. In Section 1.4, I set up an empirical forecasting model that accounts for the business cycle and allows for asymmetries. Section 1.5 discusses data and Section 3.5 discusses estimation results, including the primary result that emissions fall more sharply during recessions than expansions. In Section 1.7, I use simulations to show the impact of the results on emissions forecasting. Section 1.8 discusses the implications of the findings on welfare, Section 1.9 discusses the implications of the findings on international treaties and negotiations, and Section 1.10 concludes.

1.2 Background

Most emissions forecasts, including those of the IPCC and the U.S. Energy Information Administration (EIA), are based on the Kaya identity (IPCC, 2000; EIA, 2011a). The Kaya identity equates carbon dioxide emissions to the product of population, GDP per capita, energy intensity, and carbon intensity of energy (Kaya, 1990). There are two main categories of emissions forecasting models: calibrated structural models and reduced-form econometric models. Although modern economic theory tells us that the business cycle drives growth, emissions forecasting models disregard considerations of the business cycle and rely on average growth rate assumptions.

Calibrated structural models include bottoms-up engineering models and computable general equilibrium (or CGE) models. Bottoms-up models are used by the IPCC, the EIA, and the International Energy Association (IEA) and all use average economic growth. For example, in the IPCC emissions forecasts, population and technological growth are varied over a range of scenarios, and economic growth in each scenario is constant and either low, medium, or high. The lowest and highest growth rates assume gross world product rises 10 and 26 times current levels by 2100, respectively. The IPCC's Assessment Reports on Climate Change combine research from thousands of climate scientists and are widely influential in the global policy arena. However, the results of this report are based on the assumption that economic growth is constant over long time horizons. Growth may accelerate or decelerate from one decade to the next, but fluctuations around this average growth, or the business cycle, are ignored.

The International Energy Association's (IEA)'s influential annual World Energy Outlook reports' energy usage and emissions forecasts are generated from the IEA's World Energy Model (WEM). The WEM's primary assumptions include future oil prices and economic growth. The economic growth assumptions are based

on the OECD, IMF and World Bank’s estimates. WEM assumes a constant average growth rate over 10-15 year intervals (IEA, 2012).

In economics literature, computable general equilibrium (CGE) models and integrated assessment models (IAMs) also use average growth (Nordhaus, 2008; Golosov et al., 2014). For example, Nordhaus’s influential DICE model assumes an average total factor productivity for each decade, which drives economic growth via a production function (Nordhaus, 2008). Recent IAMs have built upon the DICE model, which is deterministic, to include economic uncertainty. One such example is Jensen and Traeger (2014), who build a stochastic IAM that allows for long-term growth uncertainty that results in a higher optimal carbon tax than the DICE model.

The advantage of reduced-form econometric forecasting models is that they require fewer structural assumptions and less data. Earlier econometric emissions forecasting models do not explicitly incorporate the business cycle and implicitly assume a constant elasticity of emissions with respect to economic growth (e.g., Schmalensee, Stocker, and Judson, 1998; Azomahou, Laisney, and Nguyen Van, 2006; Auffhammer and Carson, 2008; Aslanidis, 2009; Grunewald and Martínez-Zarzoso, 2009). Although these models are estimated using historical GDP data, they use average long run growth rates for their future emissions predictions.

Two recent papers start to consider how the business cycle affects carbon dioxide emissions. Heutel (2012) de-trends GDP data with an Hodrick-Prescott filter and uses an ARIMA model to estimate the response of carbon emissions to cyclical fluctuations in GDP, finding an estimated elasticity between 0.5 and 0.9. Doda (2014) uses a similar methodology to look at the global cyclicity of emissions, finding that emissions are pro-cyclical and more volatile than GDP. He also finds that this volatility is negatively correlated with GDP, under the assumption of a constant elasticity of emissions.

Carbon dioxide emissions are roughly proportional to fossil fuel energy usage (holding fuel mix constant), so the question is whether energy markets respond asymmetrically to macroeconomic shocks. Borenstein, Cameron, and Gilbert (1997) show that retail gasoline prices are more responsive to crude oil price increases than they are to crude oil price decreases. They suggest this may be due to inventory adjustment costs. Davis and Hamilton (2004) argue this oil price “stickiness” arises from “strategic considerations of how customers and competitors will react to price changes.” Gately and Huntington (2002) show that in both OECD and developing countries, energy demand is more elastic when price increases rather than decreases and that in non-OECD oil-exporting countries, energy demand is more elastic when income rises than when it falls. No studies have been published that relate asymmetries in the energy market to carbon emissions or consider if the business cycle affects emissions asymmetrically. This paper performs this analysis and calls into question the prevalent implicit assumption that the elasticity of emissions is constant with respect to economic growth.

1.3 Possible Drivers of Asymmetry

Emissions would respond asymmetrically to changes in GDP if either energy intensity (energy per \$ output) or emissions intensity (emissions per unit energy) change differentially over the business cycle. As of 2009, power generation accounted for about 40% of U.S. carbon dioxide emissions, transportation accounted for 34%, and other primary energy use, mostly by the industrial sector, accounted for 26% of emissions (EIA, 2011b). Tables 1.1 and 1.2 show the results of regressing electricity consumption and primary (non-electricity) energy consumption on positive and negative changes in GDP.¹ Column 1 in each table shows that total electric-

¹This is similar to the model discussed in detail in Section 1.4, except electricity and energy consumption are the dependent variables instead of emissions.

ity and primary energy are more responsive to decreases in GDP than increases in GDP. Column 2 in each table shows this asymmetry is likely driven by the industrial sector. This suggests that energy intensity changes over the business cycle.

The asymmetries observed in Tables 1.1 and 1.2 could be caused by the power and industrial sectors decreasing their use of or retiring older, less energy-efficient capital during recessions, while using more intensively or investing in newer, more energy-efficient capital during expansions. I look for evidence of this hypothesis using electricity generation data. I start with a model in which an operator's total power generation is the sum of generation by all fuel types by all of the operator's power plants:

$$G_i(t) = F_{1i}(t) + F_{2i}(t) + \cdots + F_{Ni}(t) \quad (1.1)$$

where

$G_i(t)$: total generation of operator i in month t

$F_{1i}(t)$: generation by fuel 1 of operator i in month t

$\vdots$

$F_{Ni}(t)$: generation by fuel N of operator i in month t

Taking the derivative of Equation 1.1 and rearranging results in:

$$\frac{\partial F_{1i}}{\partial t} = \left(1 - \frac{\frac{\partial F_{2i}}{\partial t}}{\frac{\partial G_i}{\partial t}} - \frac{\frac{\partial F_{3i}}{\partial t}}{\frac{\partial G_i}{\partial t}} - \cdots - \frac{\frac{\partial F_{Ni}}{\partial t}}{\frac{\partial G_i}{\partial t}} \right) \frac{\partial G_i}{\partial t} \quad (1.2)$$

$$\frac{\partial F_{1i}}{\partial t} = \delta_{it} \frac{\partial G_i}{\partial t} \quad (1.3)$$

Table 1.1: Electricity Use over the Business Cycle

Dependent Variable:	(1) Total	(2)	(3) Industrial	(4)	(5) Commercial	(6)	(7) Residential	(8)
Positive ΔY	0.906** (0.357)	1.151*** (0.354)	1.061** (0.510)	1.711*** (0.431)	1.097*** (0.314)	1.263*** (0.336)	0.795*** (0.258)	0.755** (0.291)
Negative ΔY	2.863*** (0.699)	2.184*** (0.685)	5.204*** (0.854)	3.404*** (0.841)	1.543* (0.803)	1.085 (0.765)	0.710 (0.516)	0.821 (0.602)
Lagged Y	0.705*** (0.031)	1.115*** (0.145)	0.232*** (0.052)	1.317*** (0.235)	0.926*** (0.022)	1.202*** (0.130)	0.748*** (0.017)	0.681*** (0.102)
Electricity Price	0.118*** (0.025)	0.131*** (0.024)	0.169*** (0.041)	0.203*** (0.034)	0.149*** (0.017)	0.158*** (0.017)	0.110*** (0.019)	0.108*** (0.020)
Constant	8.051*** (0.219)	30.280*** (7.810)	11.090*** (0.372)	70.040*** (12.140)	4.745*** (0.163)	19.760*** (7.074)	6.606*** (0.114)	2.980 (5.705)
Time Trend	N	Y	N	Y	N	Y	N	Y
Observations	41	41	41	41	41	41	41	41
R^2	0.988	0.989	0.901	0.925	0.996	0.996	0.996	0.996

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 1.2: Primary (Non-Electric) Energy Use over the Business Cycle

Dependent Variable:	(1) Total	(3) Industrial	(5) Commercial	(7) Residential	(8) Residential
Positive ΔY	0.399 (0.315)	0.202 (0.486)	0.432 (0.312)	0.276 (0.393)	0.271 (0.438)
Negative ΔY	1.497** (0.598)	3.617*** (1.054)	-1.167* (0.583)	-0.753 (0.686)	-0.741 (0.761)
Lagged Y	0.291*** (0.034)	0.656*** (0.192)	0.149*** (0.034)	-0.017 (0.039)	-0.024 (0.236)
Energy Price	-0.098*** (0.020)	-0.155*** (0.033)	-0.113*** (0.017)	-0.104*** (0.020)	-0.104*** (0.020)
Constant	28.640** (0.279)	41.170** (0.481)	7.174*** (0.283)	9.237*** (0.321)	8.822 (12.340)
Time Trend	N	N	N	N	Y
Observations	41	41	41	41	41
R^2	0.783	0.567	0.473	0.757	0.757

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

I can then write Equation 1.3 as the following estimable equation:

$$\Delta F_{1it} = \delta_{it} \Delta G_{it} + \varepsilon_{it} \quad (1.4)$$

Equation 1.4 can be further decomposed using business cycle indicators for whether or not the economy is in an expansion or contraction in each month:

$$\Delta F_{1it} = \delta_{it+} \Delta G_{it} 1_{\text{expansion}} + \delta_{it-} \Delta G_{it} 1_{\text{contraction}} + \varepsilon_{it} \quad (1.5)$$

In order to estimate Equation 1.5, I use data from the U.S. Department of Energy's EIA-923 and EIA-860 forms, which provide monthly electricity generation by fuel source for all power plants in the United States. The data are from from January 2001 to December 2012 for 7,854 plants operated by 3,627 operators. According to the official National Bureau for Economic Research (NBER) dating of recessions, the United States economy was in recession for 28 of the 144 months in the sample.

I estimate Equation 1.5 using ordinary least squares (OLS). The results are shown in Tables 1.3 and 1.4. In Table 1.3, differences utilize one month lags, i.e., $\Delta F_{1it} = F_{1i,t} - F_{1i,t-1}$, such that changes in generation are compared from one month to the next. In Table 1.4, differences utilize one year lags, i.e., $\Delta F_{1it} = F_{1i,t} - F_{1i,t-11}$, such that changes in generation are compared from one January to the next January and so on. This helps account for seasonal variation in fuel mix. In both tables, the indicator for contraction refers to whether or not the economy was in a recession in month t .

The coefficients on coal, natural gas, and nuclear generation are the largest because they account for the majority of generation. Notably, in both Tables 1.3 and 1.4, coal accounts for a much smaller share of the increase in generation during expansions, and a much larger share of the decrease in generation during contrac-

tions. The opposite holds true for natural gas. According to the EIA, the median coal plant in operation in the United States today was built in 1966, and most new generation capacity is natural gas. Therefore, these findings support that hypothesis that older capital (coal plants) is utilized less intensely and may be retired during contractions, while newer capital (natural gas plants) is utilized more intensely and may be added during expansions. This could be due to higher marginal costs of generation of older capital, which may require more maintenance and be less energy-efficient, requiring more energy input per kilowatt hour output. This could also be due to regulation if regulators only allow electricity generation from the dirtiest plants at times of high electricity demand. Additionally, since coal emits twice as much carbon dioxide per British thermal unit (Btu) as natural gas, the differential use of fuels over the business cycle could lead to differential emissions intensity over the business cycle, with the net effect that emissions from the electricity sector would fall relatively more per unit decrease in generation than they rise per unit increase in generation.

Table 1.3: Share of Change in Generation by Fuel Source Using One Month Lag

	(1) Coal	(2) Nat Gas	(3) Nuclear	(4) Other Fuels
Expansion	0.236*** (0.036)	0.466*** (0.070)	0.189*** (0.053)	0.101*** (0.028)
Contraction	0.459*** (0.045)	0.112*** (0.018)	0.293*** (0.042)	0.120*** (0.043)
Observations	359,910	359,910	359,910	359,910
R^2	0.331	0.479	0.234	0.121
Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1				

‘Expansion’ and ‘Contraction’ are indicator variables for if the economy was in an expansion or contraction that month multiplied by the change in generation since the previous month. ‘Other Fuels’ includes biomass, renewables, and petroleum. Standard errors are clustered at the operator level.

Table 1.4: Share of Change in Generation by Fuel Source Using One Year Lag

	(1) Coal	(2) Nat Gas	(3) Nuclear	(4) Other Fuels
Expansion	0.119*** (0.025)	0.553*** (0.070)	0.225*** (0.080)	0.102*** (0.035)
Contraction	0.607*** (0.031)	0.059*** (0.014)	0.275*** (0.025)	0.052 (0.033)
Observations	318,930	318,930	318,930	318,930
R^2	0.300	0.542	0.264	0.103
Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1				

‘Expansion’ and ‘Contraction’ are indicator variables for if the economy was in an expansion or contraction that month multiplied by the change in generation between that month and the corresponding month one year ago. ‘Other Fuels’ includes biomass, renewables, and petroleum. Standard errors are clustered at the operator level.

There is evidence that both energy intensity and emissions intensity change

over the business cycle. Electricity consumption and primary energy use by the industrial sector fall more per decrease in GDP than they rise per unit increase in GDP. This may be due to decreasing use of or retiring older, less energy-efficient capital during recessions, while using more intensively or investing in newer, more energy-efficient capital during expansions. Emissions intensity may also change over the business cycle if fuel mix changes differentially. Empirical evidence from the power sector supports both of these hypotheses.

1.4 Empirical Model

Kraft and Kraft's seminal 1978 article showed unidirectional causality from GNP to energy use in the United States. Since then, this relationship has become widely accepted. Although there has been debate over the direction of this causality, evidence from recent panel cointegration and error correction models supports Kraft and Kraft's findings (Stern, 2000; Mehrara, 2007; Coers and Sanders, 2013). In econometric models, the relationship between emissions and GDP has been specified as linear, polynomial, and non-parametric (e.g., Schmalensee, Stocker, and Judson, 1998; Azomahou, Laisney, and Nguyen Van, 2006; Auffhammer and Carson, 2008; Aslanidis, 2009; Grunewald and Martínez-Zarzoso, 2009). I begin with a linear time series model with finite lags of GDP:

$$E_t = k + \gamma_1 Y_{t-1} + \gamma_2 Y_{t-2} + \gamma_3 Y_{t-3} + \cdots + \gamma_N Y_{t-N} + \varepsilon_t \quad (1.6)$$

where

E_t : log of emissions

Y_t : log of GDP

ε_t : error term

Equation 1.6 can be rearranged as follows:

$$E_t = k + \gamma_1(Y_{t-1} - Y_{t-2}) + (\gamma_1 + \gamma_2)Y_{t-2} + \gamma_3Y_{t-3} + \cdots + \gamma_NY_{t-N} + \varepsilon_t \quad (1.7)$$

Equation 1.7 is the “symmetric” model. It accounts for the business cycle by letting γ_1 represent the responsiveness of emissions to recent changes in GDP, but it assumes a constant elasticity of emissions with respect to GDP. Because the model is log-log, one is tempted to interpret γ_t as the elasticity of emissions with respect to GDP. However, technically γ_t is only a responsiveness because it is a forecasting model and not a demand system. Nevertheless, I will follow common convention and use “elasticity” and “responsiveness” interchangeably. The “asymmetric” model is represented by Equation 1.8 and allows for γ_1 to vary during different growth regimes.

$$E_t = k + \gamma_{1+}(Y_{t-1} - Y_{t-2})1_{Y_{t-1} > Y_{t-2}} + \gamma_{1-}(Y_{t-1} - Y_{t-2})1_{Y_{t-1} < Y_{t-2}} + (\gamma_1 + \gamma_2)Y_{t-2} + \gamma_3Y_{t-3} + \cdots + \gamma_NY_{t-N} + \varepsilon_t \quad (1.8)$$

If the symmetric model is correct and the elasticity of emissions is constant, then $\gamma_{1+} = \gamma_{1-} = \gamma_1$. The asymmetric model therefore decomposes growth into regimes by allowing flexibility in the estimates of γ_1 .

1.5 Data

For the United States, both quarterly and annual data are used. Energy-related, carbon dioxide emissions data come from Andres, Boden, and Marland (2012) and are accessible via the U.S. Department of Energy’s Carbon Dioxide Information Analysis Center (CDIAC).² Annual emissions data are available for the

²I also use emissions data from the EIA (see Table 1.7) as a robustness check in Section 3.5. CDIAC emissions data are based on energy data from the United Nations. EIA emissions data

United States, other countries, and the world. The CDIAC converts estimates of fossil fuel consumption into estimated carbon emissions using thermal conversion factors. Available data include carbon emissions by fuel source, total carbon emissions, and carbon emissions per capita. Annual CDIAC emissions data for the United States from 1929-2011 are used in this paper. Similar data are used for the other countries. However, for some countries, not all years were available. The CDIAC's emissions data are measured in thousand metric tons of carbon. Also available from CDIAC are gridded monthly emissions estimates from around the world. I obtained quarterly United States emissions by integrating across all the latitude and longitude coordinates of the United States.

Real GDP data for the United States come from the Federal Reserve Bank of St. Louis's FRED (Federal Reserve Economic Data) database and are measured in 2009 dollars. The quarterly GDP data are seasonally adjusted. The quarterly emissions data are not seasonally adjusted; for this reason I include quarterly indicator variables in the quarterly model. For other countries and global GDP, I use GDP data adjusted by purchasing power parity (PPP)³, in constant 2005 international dollars, from the World Bank. From the World Bank's Pink Sheets I also obtain annual average price of crude petroleum (\$2005/bbl), price of Australian coal (\$2005/mt), and price of natural gas in the United States (\$2005/short ton), which I use for robustness checks.

Figure 1.1 shows that although the United States' carbon dioxide emissions continue to increase, per capita emissions appear to have peaked in the 1970s. Both total emissions and emissions per capita rose during the boom of the early 2000s and have fallen sharply since the downturn of 2008. Figure 1.2 compares the growth

focus on the United States and are based on EIA energy data. CDIAC country-level emissions data omit emissions from bunker fuel and non-fuel hydrocarbons, while the EIA data omit emissions from cement but include bunker fuel. The CDIAC and EIA country-level cumulative emissions data are within 1% of each other.

³Using GDP PPP controls for exchange rates and is often thought a better measure of economic well-being than non-adjusted GDP.

in emissions per capita to the growth in GDP per capita since 1930. Changes in emissions growth seem to exaggerate negative changes in GDP growth but not positive changes in GDP growth. Figure 1.3 shows the total emissions levels in 2011 for the top emitting countries. In 2011, China accounted for roughly 26% of global emissions, and the United States for roughly 16%.

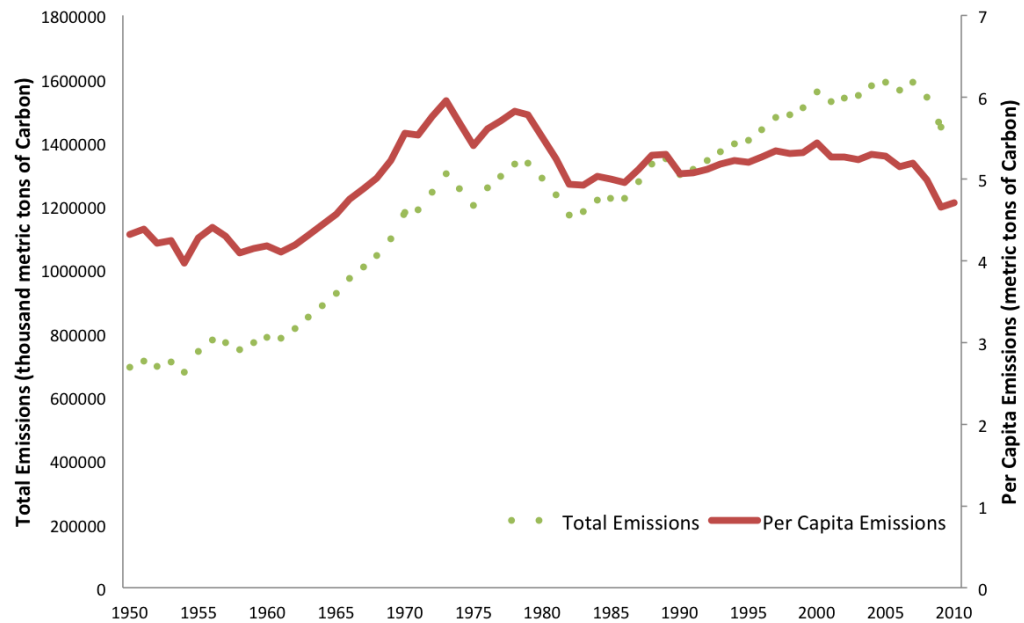


Figure 1.1: Historical carbon dioxide emissions in the United States

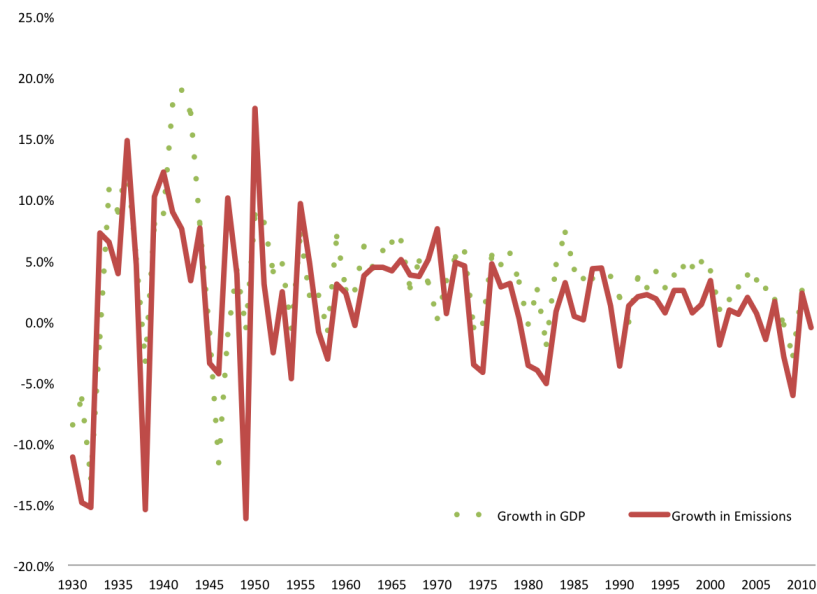


Figure 1.2: Historical growth of GDP and carbon emissions in the United States

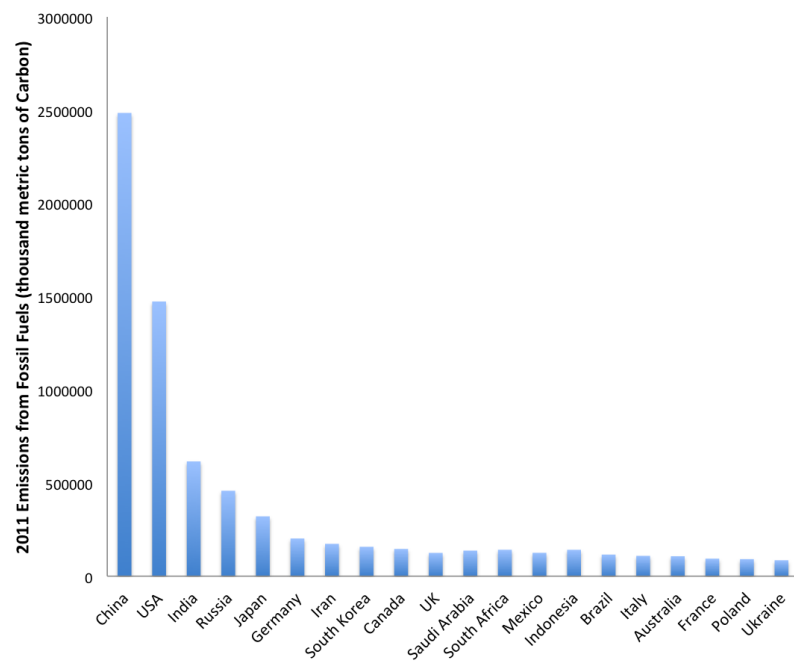


Figure 1.3: Total emissions of top 20 carbon-emitting countries in 2011

1.6 Results

1.6.1 United States

Table 1.5 shows the headline estimation results for the annual and quarterly symmetric and asymmetric models. The constant and coefficient on the last lag of GDP are consistent across all models. The quarterly symmetric model shows that responsiveness of emissions with respect to changes in GDP is 0.84, close to the annual coefficient of 0.75. The asymmetric model also shows that the effect of increases in GDP is statistically indistinguishable from zero, but that the effect of decreases in GDP is large and significant, with a coefficient of 1.5 in the annual model and 3.1 in the quarterly model. This difference is likely caused by the averaging out of the effects of quarters over the year. For example, a year in which GDP declines may see two quarters of GDP increases and two quarters of GDP decreases, such that sharp quarterly reductions in emissions might be offset by other quarters with increasing or flat emissions. Overall, estimation results of the quarterly model are consistent with estimation results of the annual model.

The results indicate that responsiveness of emissions is not constant over the business cycle. A Wald test⁴ rejects the null hypothesis that $\gamma_{1+} \neq \gamma_{1-}$ with a p-value of 0.06 and 0.02 in the annual and quarterly models, respectively. Emissions gradually grow as GDP grows, but then fall sharply when GDP declines.⁵ Thus, emissions fall more sharply per unit change in GDP during a contraction than they rise during an expansion. This finding is consistent with recent findings that carbon

⁴Standard hypothesis testing may not be valid if the data are non-stationary. Literature on the stationarity of GDP is mixed. Earlier panel unit root tests found evidence of non-stationarity of real GDP, while newer tests that allow for cross-sectional dependence find evidence against the existence of a unit root (Nelson and Plosser (1982); Rapach (2002); Hegwood and Papell (2007); Aslanidis (2014)). Using a Dickey-Fuller test, I cannot reject the existence of a unit root in the annual data, but I can reject the existence of a unit root in the quarterly GDP data.

⁵Heutel (2012) finds that emissions respond inelastically to the business cycle. However, in contrast, I find that emissions respond inelastically to GDP expansions, but *elastically* to GDP contractions.

dioxide emissions dropped more than they were expected to during recent Great Recession, to the surprise of the media and environmental community (EIA, 2010; Revkin, 2010).

That emissions fall more per unit GDP change during contractions than they rise during expansions is consistent with the finding in Section 1.3 that both electricity use and primary energy consumption in the industrial sector are more responsive to decreases than increases in GDP. This finding is also consistent with the finding in Section 1.3 that electricity generation from coal, which is more emissions-intense than natural gas, decreases relatively more during contractions, while generation from natural gas increases relatively more during expansions. The sharp decrease in emissions as GDP declines is consistent with the hypothesis that older, less efficient capital is used less and may be retired during contractions. The small to absent response in emissions to expansions has a few possible explanations. Newer capacity, both in the electricity generation and industrial sectors, tends to be more energy-efficient. Additionally, if energy costs increase as the economy expands, then businesses and consumers may temper energy use.

Table 1.5: Headline Results for United States

	(1) Annual Symmetric	(2) Annual Asymmetric	(3) Quarterly Symmetric	(4) Quarterly Asymmetric
ΔY	0.750*** (0.183)		0.835*** (0.305)	
Positive ΔY		0.331 (0.265)		0.252 (0.382)
Negative ΔY		1.504*** (0.438)		3.124*** (1.046)
Lagged Y	0.497*** (0.011)	0.484*** (0.013)	0.456*** (0.009)	0.451*** (0.009)
Constant	9.587*** (0.088)	9.714*** (0.117)	9.304*** (0.067)	9.359*** (0.072)
Observations	82	82	236	236
R^2	0.963	0.964	0.912	0.915
Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1				

The dependent variable is the natural log of annual (or quarterly, as indicated) carbon dioxide emissions. ' ΔY ' is the change in the natural log of GDP (between years t and $t-1$ in the annual model and between quarters $t-1$ and $t-4$ in the quarterly model). 'Positive ΔY ' and 'Negative ΔY ' are ΔY multiplied by indicators for whether or not GDP increased or decreased, respectively, between comparison periods. Lagged Y is the natural log of GDP in year $t-1$ for the annual models and in quarter $t-4$ for the quarterly models. The quarterly specifications include quarter dummies, which are not shown.

Table 1.6: Annual U.S. Results by Fuel Type (1980-2010)

	(1) Total	(2) Gas	(3) Liquid	(4) Solid
Positive ΔY	0.670* (0.345)	6.286 (7.583)	0.874 (0.537)	0.693* (0.371)
Negative ΔY	2.175** (0.798)	-16.94 (18.590)	1.372 (1.148)	3.931*** (0.704)
Lagged Y	0.341*** (0.023)	-0.212 (0.686)	0.230*** (0.032)	0.395*** (0.029)
Constant	10.990*** (0.209)	14.190** (5.996)	11.140*** (0.296)	9.473*** (0.263)
Observations	31	31	31	31
R^2	0.918	0.023	0.712	0.907
Robust standard errors in parentheses				
*** p<0.01, ** p<0.05, * p<0.1				

‘ ΔY ’ is the change in the natural log of GDP between years t and $t-1$. ‘Positive ΔY ’ and ‘Negative ΔY ’ are ΔY multiplied by indicators for whether or not GDP increased or decreased, respectively, from year $t-1$ to year t . Lagged Y is the natural log of GDP in year $t-1$. Column 1 uses natural log of total carbon dioxide emissions as the dependent variable. Columns 2, 3, and 4 use natural log of carbon dioxide emissions from gaseous fuels (i.e., natural gas), liquid fuels (i.e., oil), and solid fuels (i.e., coal) as the dependent variables, respectively.

Table 1.6 shows the estimation results of the asymmetric model not only for total emissions, but also by emissions source. Emissions from solid fuels, i.e., coal, exhibit the most significant asymmetry out of the three different fuel types. Emissions from coal decrease very sharply during contractions, with a coefficient of 3.9, and increase modestly during expansions, with a coefficient of 0.7. This is consistent with Section 1.3, which found that more coal capacity is taken offline during recessions. Emissions from liquid fuels, i.e., oil, also exhibit an asymmetry with respect to the business cycle, although the point estimates lack significance. This suggests that there may be an asymmetric behavioral response of drivers to

the business cycle.⁶ Column 2 shows that this is a poor model fit for emissions from natural gas.⁷

The main omitted variable of concern is energy prices, which affect short run demand for carbon-emitting fossil fuels. Table 1.7 shows the results if oil, coal, and natural gas prices are included in the model.⁸ The coefficients on all energy price variables are small and mostly not significantly different from zero. The other coefficients are little affected and still highly significant. As such, leaving energy prices out of the model should not cause an omitted variable problem.⁹ This suggests that the structural or behavioral causes of the asymmetry are not impacted by energy prices.

Columns 6 and 7 of Table 1.7 show that the results are qualitatively similar using an alternative source of emissions data. These alternative emissions data from the EIA omit emissions from cement but include bunker fuel emissions, whereas the CDIAC emissions data omit emissions from bunker fuel and non-fuel hydrocarbons. That the results from the two data sources are similar is unsurprising, as the CDIAC and EIA country-level cumulative emissions data are within 1% of each other. This suggests that emissions from cement, bunker fuels, and non-fuel hydrocarbons are not primary drivers of the observed asymmetry, because a similar asymmetry is estimated even when these emissions sources are omitted. Further robustness checks

⁶There is evidence that during oil price spikes, drivers immediately reduce vehicle miles traveled (VMT), but only substitute towards more fuel efficient vehicles in the long run (Cozad and LaRiviere, 2013). If an oil price spike precedes a recession, as is often the case, then drivers may immediately and sharply reduce VMT, delay purchase of new vehicles, and gradually substitute towards more fuel-efficient vehicles as the economy recovers.

⁷The poor model fit suggests that GDP is not a good predictor of natural gas emissions during this time period. This may be due to the natural gas price ceilings and resulting shortages of the 1980s. Davis and Kilian (2011) found that demand for natural gas exceeded sales by about 20% between 1950 and 2000, with the largest shortages during the 1970s and 1980s. During this time period, consumption could not increase as much as consumers would like during expansions, and there may have been excess demand even during contractions.

⁸I also include the interaction between the oil price and natural gas price, because the differential between the price of these fuels is often important (e.g., Atil, Lahiani, and Khuong, 2014; Brigida, 2014; Wolfe and Rosenman, 2014)

⁹Although this would not be the case if we wanted to look at long term adjustment to higher energy prices.

can be found in Appendix Tables 1.14 and 1.15.

Table 1.8 shows the estimation results broken down by time period. The annual specifications have fewer statistically significant coefficients due to limited observations. All point estimates for all columns suggest a similar if not sharper asymmetry as the headline specification. The smallest asymmetry is the period of 1929 to 1950. This demonstrates that the observed asymmetry in emissions with respect to the business cycle is fairly consistent across time, especially post-World War II, and is not driven by one time period or event.

Table 1.7: Annual U.S. Results including Robustness Checks (1)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Baseline		With Energy Prices		EIA	EIA with Energy Prices
Positive ΔY	0.331 (0.265)	0.355 (0.416)	0.191 (0.477)	0.359 (0.399)	0.500 (0.421)	0.179 (0.396)	-0.424 (0.395)
Negative ΔY	1.504*** (0.438)	2.568*** (0.790)	2.708*** (0.708)	2.055*** (0.648)	1.853** (0.701)	2.948*** (0.686)	2.526*** (0.727)
Lagged Y	0.484*** (0.013)	0.242*** (0.015)	0.319*** (0.026)	0.274*** (0.032)	0.276*** (0.033)	0.326*** (0.025)	0.308*** (0.029)
Oil Price				0.016 (0.022)	0.026 (0.022)		-0.019 (0.038)
Coal Price				-0.043 (0.031)	-0.076** (0.034)		-0.041 (0.039)
Nat Gas Price				-0.026 (0.023)	-0.118** (0.045)		0.045 (0.093)
Oil Price * Nat Gas Price					0.025** (0.010)		-0.003 (0.024)
Constant	9.714*** (0.117)	11.930*** (0.136)	11.210*** (0.247)	11.770*** (0.309)	11.840*** (0.322)	5.570*** (0.234)	5.928*** (0.335)
Observations	82	42	32	42	42	32	32
R^2	0.964	0.836	0.899	0.854	0.869	0.904	0.939

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The dependent variable is the natural log of annual carbon dioxide emissions in year t . In columns 1-5, annual emissions data are from the CDIAC and in columns 6-7, annual emissions data come from the EIA. ' ΔY ' is the change in the natural log of GDP between years t and $t-1$. 'Positive ΔY ' and 'Negative ΔY ' are ΔY multiplied by indicators for whether or not GDP increased or decreased, respectively, from year $t-1$ to year t . Lagged Y is the natural log of GDP in year $t-1$. 'Oil Price', 'Coal Price', and 'Nat Gas Price' are the natural logs of the average prices of these respective fuels in year t . A Wald test fails to reject the null hypothesis of joint insignificance of oil, coal and natural gas prices with a p-value of 0.23 in column 4. A Wald test for equality between coefficients on Positive ΔY and Negative ΔY in column 6 is rejected with p-value of 0.01.

Table 1.8: U.S. Results over Time

Time Period	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	1950-1960	1961-1975	Quarterly 1976-1990	1991-2009	1929-1950	1951-1975	Annual 1976-2000	2001-2012
Positive ΔY	0.546* (0.320)	0.451 (0.287)	-0.028 (0.544)	1.115*** (0.183)	0.595** (0.245)	0.479 (0.576)	0.506 (0.692)	0.650 (0.678)
Negative ΔY	2.356*** (0.646)	3.215*** (0.847)	3.042** (1.494)	2.859*** (0.247)	0.799* (0.415)	3.804 (4.475)	2.867* (1.476)	1.540 (0.912)
Lagged Y	0.484*** (0.059)	0.934*** (0.024)	0.068* (0.039)	0.310*** (0.016)	0.564*** (0.030)	0.753*** (0.035)	0.257*** (0.043)	-0.051 (0.146)
Constant	9.060*** (0.390)	6.057*** (0.165)	12.250*** (0.298)	10.420*** (0.125)	9.082*** (0.210)	7.562*** (0.289)	11.770*** (0.387)	14.720*** (1.384)
Observations	40	60	60	76	21	25	25	11
R^2	0.843	0.969	0.590	0.925	0.936	0.963	0.701	0.420

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

1.6.2 Top 20 Emitters

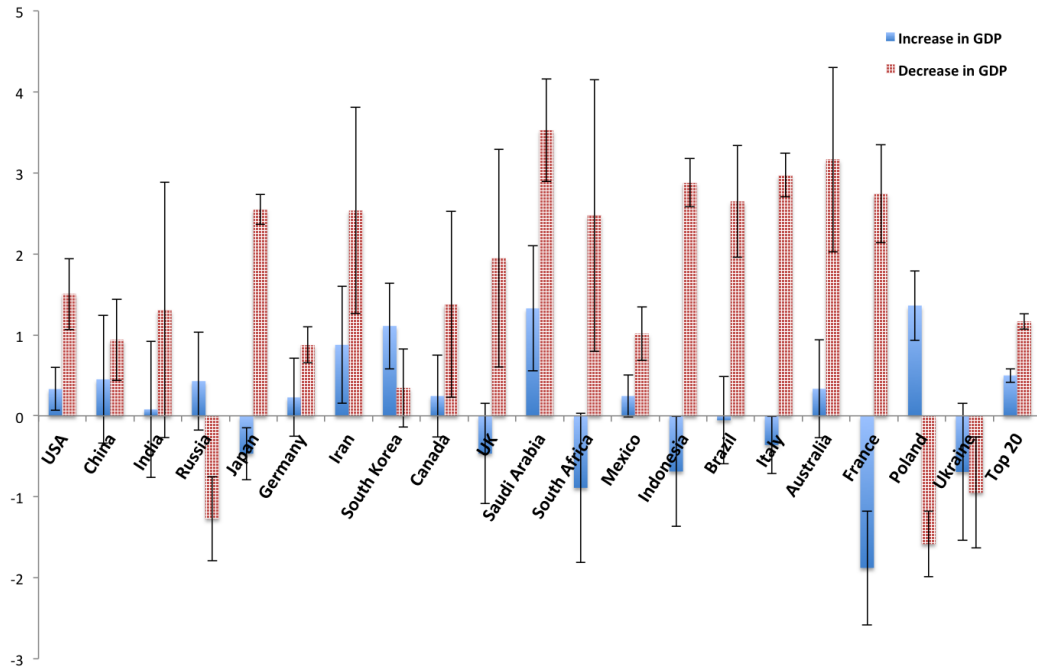


Figure 1.4: Estimated coefficients of asymmetric model for top 20 carbon dioxide-emitting countries and globally

Red (patterned) bars show estimates for elasticity of emissions with respect to negative changes in GDP (γ_{1-}). Blue (solid) bars show estimates with respect to positive changes in GDP (γ_{1+}). GDP data adjusted by purchasing power parity (PPP) is used for all countries except China and India. During the period during which this data is available, GDP adjusted by PPP did not decline for a single period in either country. I estimate the model for China and India using real GDP data, which are available for a longer time frame.

Figure 1.4 shows the estimation results for the top twenty carbon dioxide-emitting countries. Fourteen of these countries exhibit an asymmetry similar to the United States, with a responsiveness of emissions to increases in GDP that is small or near zero and a much larger responsiveness of emissions to declines in GDP. Five countries (Russia, South Korea, France, Poland, and Ukraine) exhibit different results.

Russia and Ukraine's emissions data only go back to 1992, after the collapse

of the Soviet Union. The 1990s was a transition period in these economies. Russia's energy sector was an important part of the country's economic recovery, and energy sector output may have been growing even during recessionary years. Ukraine's and to a certain extent Poland's economies are dependent on Russian supplied natural gas. If Russia supplies these countries with cheaper natural gas during difficult economic times, that could explain why Ukraine and Poland's emissions elasticity profiles are different than most other countries. Including a time trend in the estimation for Russia and Ukraine results in an asymmetry similar to that of the United States.

South Korea's economy was also transitioning during the 1980s, with an expanding industrial sector. Industrial output may have been trending strongly upwards, which could explain why emissions may have risen even during contractionary periods. Including a time trend in the estimation for South Korea also results in an asymmetry similar to that of the United States.

France is a special case, as the majority of its electricity is generated by nuclear power. The marginal cost of electricity production is therefore very small. Additionally, nuclear power does not emit carbon dioxide, so neither an increase nor decrease in nuclear generation will affect country-wide carbon dioxide emissions.

Figure 1.4 also shows the estimation results for a panel of the top twenty carbon dioxide-emitting countries.¹⁰ Total emissions from all top carbon emitters respond inelastically to increases in GDP and elastically to decreases in GDP. This demonstrates that the asymmetric result is not specific to the United States but instead is found in nearly all countries that are responsible for the majority of global emissions.

¹⁰The panel estimation uses a fixed effects model that accounts for serial correlation in panel data.

1.7 Forecasting Implications

1.7.1 Simulating the Business Cycle

In order to investigate the implications of my forecasting model, I need to simulate the business cycle. For this I employ a Markov regime-switching model adapted from the MS_Regress package for MATLAB (Perlin, 2010) that implements Hamilton's (1989) methodology to simulate a business cycle. Such a regime-switching model is a standard method of simulating business cycles and other macroeconomic cycles (e.g., Filardo, Andrew J.; Massmann, Mitchell, and Weale, 2003; Simo-Kengne et al., 2013). This is a regime switching model whereby the next-period state of the economy (i.e., expansion or recession) is determined by the economy's present state and a transition matrix, Γ , which dictates the probability of switching amongst various states.

Suppose the process of GDP growth is given by

$$y_{t+1} = y_t(\mu_{S_t} + \varepsilon_{S_t}) \quad (1.9)$$

Where y_t is GDP in period t , S_t is the state, and ε_{S_t} is a normally distributed error term with mean zero and variance $\sigma_{S_t}^2$. I allow for two states, expansion and contraction. Let State 1 be the expansionary state, with $\Delta y_t = \mu_1 + \varepsilon_1$ and $\varepsilon_1 \sim N(0, \sigma_1^2)$. Let State 2 be the contractionary state, with $\Delta y_t = \mu_2 + \varepsilon_2$ and $\varepsilon_2 \sim N(0, \sigma_2^2)$. These equations govern how GDP grows when it is in the respective state. Lastly, I need a transition matrix that defines the probabilities of being in a given state in time period t :

$$\Gamma = \begin{Bmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{Bmatrix} \quad (1.10)$$

The probability of staying in State 1 in the next period is p_{11} . The probability of switching from State 1 to State 2 is p_{21} . The probability of staying in State 2 is p_{22} , and the probability of transitioning from State 2 to State 1 in the next period is p_{12} .

I calibrate Γ and characterize the growth profile of each state for the United States according to Chauvet and Hamilton (2006). I then use this Markov regime-switching model to simulate a forecast of GDP growth through 2050.

Growth Rates (annual):

$$\mu^+ = 4.5\%$$

$$\mu^- = -1.2\%$$

$$\sigma_1^2 = \sigma_2^2 = 3.5\%$$

Transition Matrix (quarterly):

$$\Gamma = \begin{Bmatrix} .95 & .22 \\ .05 & .78 \end{Bmatrix} \quad (1.11)$$

To generate quarterly business cycle data, the Markov regime-switching model starts at period $t = 0$ in an expansionary period. Period $t = 1$ is also expansionary with a probability of 95% but switches to a contractionary regime with a probability of 5%. If period t is contractionary, it has a 78% probability of remaining contractionary in $t + 1$ and a 22% probability of switching to an expansionary regime. If period t is an expansionary period, the growth rate of y_t is a randomly generated, normally-distributed variable with a mean of $\frac{4.5\%}{4}$ and a standard deviation of $\frac{3.5\%}{4}$ (quarterly growth rates are a quarter of annual growth rates). If period t is a recessionary period, the growth rate of y_t is a randomly gener-

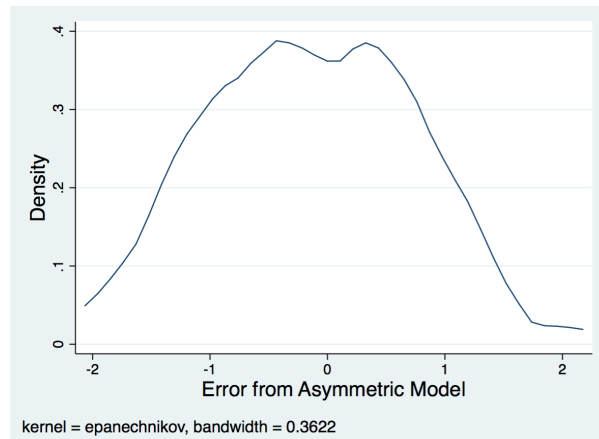
ated, normally-distributed variable with a mean of $\frac{-1.2\%}{4}$ and a standard deviation of $\frac{3.5\%}{4}$. I use this process to generate T periods of GDP data.

1.7.2 Asymmetric versus Baseline Model Fit

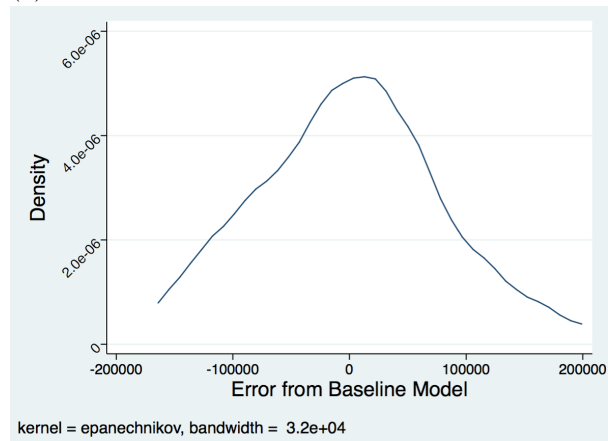
I use simulations to compare the fit of the asymmetric model to the “baseline” model of emissions forecasting. The baseline model is a proxy for how emissions are currently forecast, using average growth rates and a constant elasticity of emissions with respect to GDP. For the baseline model, I input average GDP growth into the symmetric model I estimated in Section 3.5. The goal of the model comparison is to see how accurately the models predict emissions.

In order to compare model fit, I first generate a GDP business cycle forecast as described in Section 1.7.1. Then I use the GDP simulations to predict emissions using the asymmetric forecasting model. Next, I fit the GDP simulations to the asymmetric model and calculate the residual error terms of the asymmetric model. I construct the smoothed growth path that has the same compound annual growth rate, or CAGR, as the respective business cycle forecast. I fit the smoothed GDP series to the symmetric model and calculate the residual error terms for the baseline model. I compare model fit by comparing the distribution of the residual error term of the asymmetric and baseline models. These distributions are shown in Figures 1.5a and 1.5b, respectively.

Both distributions appear to be normally distributed. The Jarque-Bera test, a goodness-of-fit test of whether the skewness and kurtosis of the sample data match a normal distribution, fails to reject a normal distribution for the asymmetric error distribution with a p-value of 0.60, and for the baseline error distribution with a p-value of 0.87. The variance of the asymmetric errors is 0.70, and the variance of the baseline errors is dramatically higher, 5.6×10^9 . This suggests that the baseline model has greater errors and does not predict emissions as well as the asymmetric



(a)



(b)

Figure 1.5: Kernel density estimate of predicted errors from asymmetric (1.5a) and baseline (1.5b) models

model.

Skewness is a measure of asymmetry of the distribution around the mean. Skewness of the asymmetric model errors is 0.06, and skewness of the baseline model errors is 0.16. The asymmetric model already accounts for an asymmetry, so it is not surprising that skewness of the model errors is close to zero. The positive skewness of the baseline model errors indicates that the right tail is longer or fatter than the left side, which is likely a result of the model's failure to take the business cycle asymmetry into account.

Damages from climate change are proportional to temperature change, which is a multiplicative function of climate sensitivity (how much temperature changes given radiative forcing) and radiative forcing (the increase in re-radiated solar energy absorbed by greenhouse gases in the atmosphere), which in turn is proportional to the concentration of greenhouse gases in the atmosphere. The distribution of forecasted carbon dioxide emissions is therefore proportional to the distribution of future climate change damages.

Regarding emissions distributions, Weitzman (2011) argues that a fatter upper tail assigns higher probabilities to catastrophic outcomes and therefore results in higher willingness to pay for abatement. Here, the kurtosis of the asymmetric errors is 2.3, and the kurtosis of the baseline errors is 2.6. The asymmetric model error distribution has higher negative excess kurtosis (is more platykurtic) than the baseline model error distribution, which implies that the distribution of errors for the asymmetric model has fatter tails. All else equal, the asymmetric forecasting model implies that willingness to pay for abatement is higher than the baseline model implies.¹¹

¹¹However, this must be balanced against the higher average emissions forecast of the baseline model.

1.7.3 Emissions Forecasting Simulations

One immediate implication of the asymmetry estimated in Section 3.5 is that if there is a contraction in the near term, emissions would decrease more than expected under the symmetric model. In order to investigate the longer run implications I generate GDP data, input the data into the forecasting models, and compare United States emissions forecasts that account for the business cycle to baseline forecasts.

Figure 1.6 shows three example simulations. The solid purple lines in the top row show three different GDP business cycle forecasts generated from the Markov regime-switching model. The dashed green lines are smoothed growth paths that have the same compound annual growth rate, or CAGR, as the respective business cycle forecast. Although the growth path of each column differs, the CAGR of each column is the same, 3.4%. The second and third rows in Figure 1.6 show total annual emissions and cumulative emissions, respectively. These graphs each display three different emissions forecasts. The dashed green line, or “baseline” forecast, is generated by inputting the smoothed GDP simulated data into the symmetric forecasting model.¹² The baseline forecast is a proxy for how emissions are currently forecast, using average growth rates and a constant elasticity of emissions with respect to GDP. The light blue solid line, or “symmetric” forecast, is generated by inputting the business cycle GDP simulated data into the symmetric forecasting model. The symmetric forecast accounts for the business cycle but still assumes a constant elasticity of emissions with respect to GDP. The dark red solid line, or “asymmetric” forecast, is generated by inputting the business cycle GDP simulated data into the asymmetric forecasting model. The asymmetric forecast fully accounts for the business cycle.

Within each column of Figure 1.6, although total GDP growth over the time

¹²This is the same baseline model used in Section 1.7.2.

period is equivalent amongst the baseline, symmetric, and asymmetric models, the different GDP paths produce different emissions paths. Ultimately, what matters in terms of climate change is cumulative emissions. Cumulative emissions are the integral under the annual emissions curves. When accounting for the business cycle, each column has a different emissions path and therefore results in different levels of cumulative emissions in 2100. Despite having the same total average GDP growth through 2100, cumulative emissions predicted by the asymmetric model in column *a* are approximately equal to the baseline model, cumulative emissions in column *b* are much lower than the baseline model, and cumulative emissions in column *c* are higher than the baseline model.

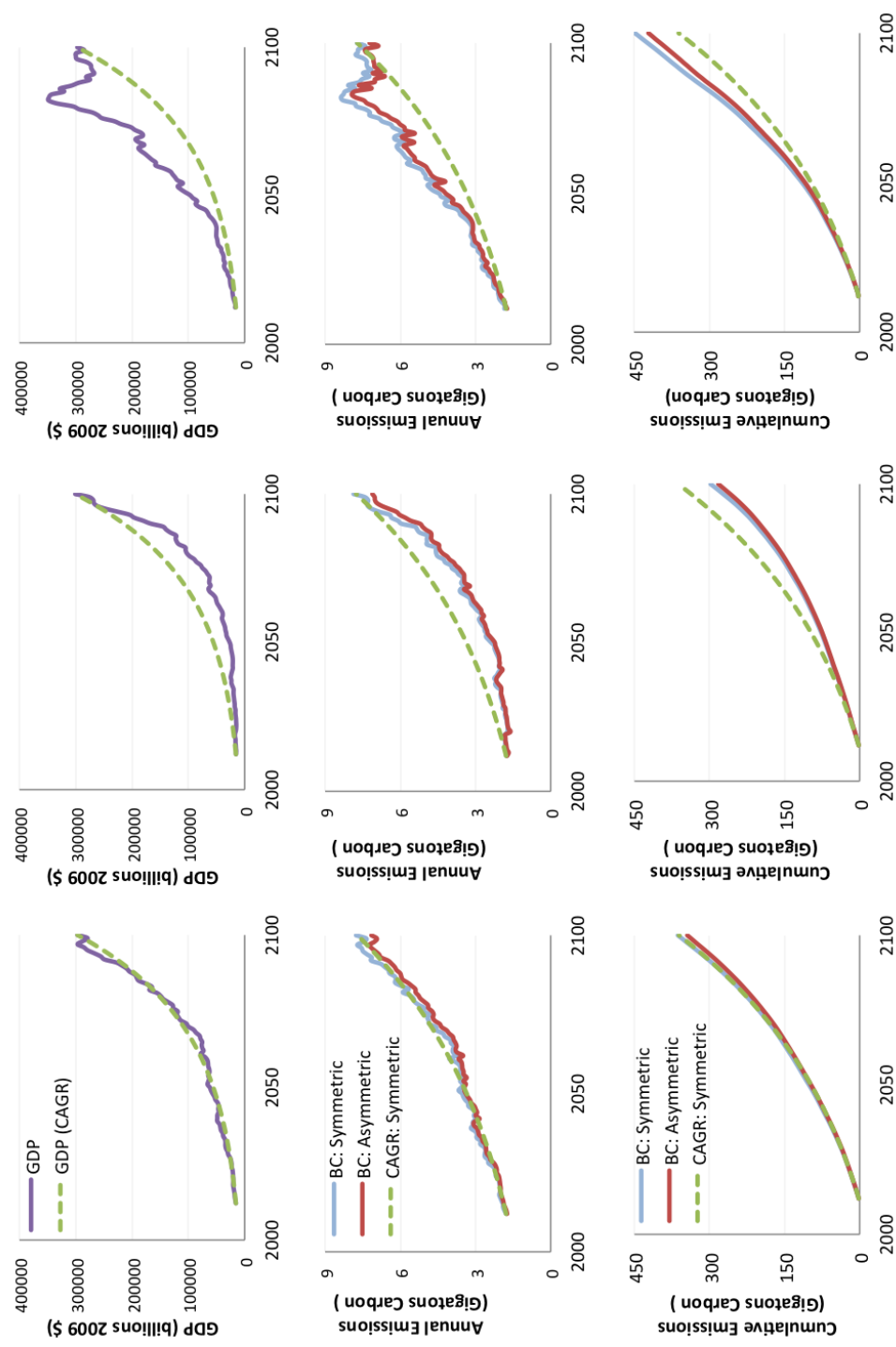


Figure 1.6: Path dependency of emissions on business cycle

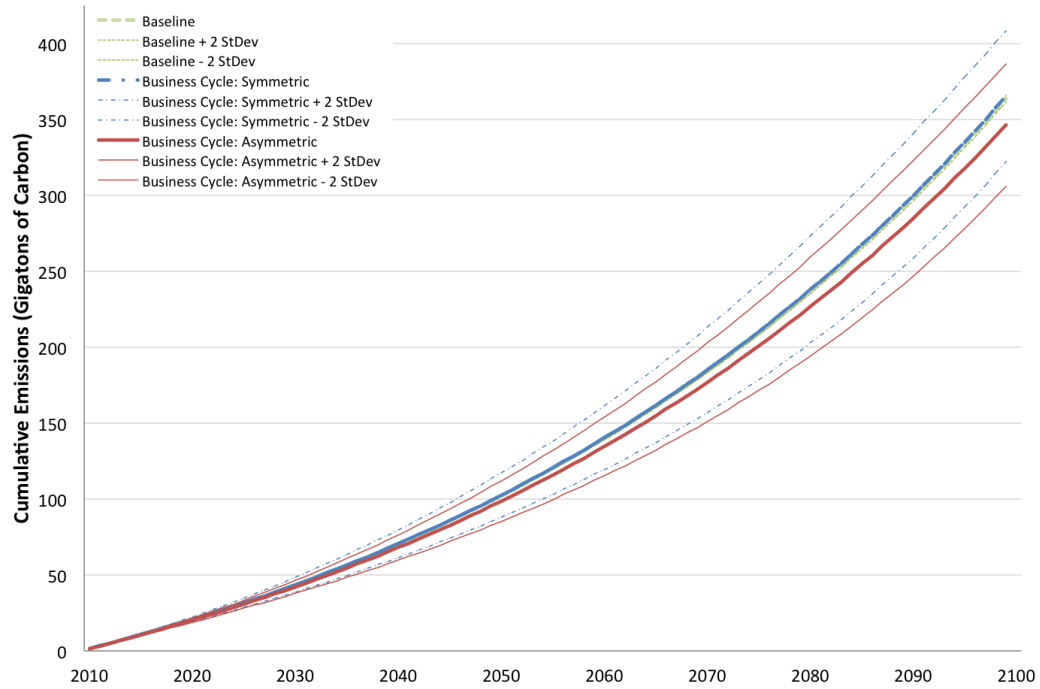


Figure 1.7: Forecasted cumulative emissions through 2100

Figure 1.7 shows the average cumulative annual emissions forecasts (thick lines) and 95% confidence intervals (thin lines) derived from 1,000 simulations. The business cycles model forecasts are generated by inputting 1,000 GDP simulations generated by the Markov regime-switching model that have a CAGR between 3.40%-3.44% into the symmetric and asymmetric forecasting models, respectively. The baseline forecasts are generated by inputting the smoothed growth path of the 1,000 GDP simulations into the symmetric forecasting model. Therefore, the business cycle and the baseline emissions forecasts are all generated by GDP paths with approximately the same CAGR, 3.42% ($\pm 0.02\%$). Average cumulative emissions in 2100 are 346 gigatons of carbon with a standard deviation of 20 in the asymmetric model, 365 gigatons of carbon with a standard deviation of 21 in the symmetric model, and 364 gigatons of carbon with a standard deviation of 1 in the baseline

model. Two features stand out in Figure 1.7. The average forecast for the asymmetric model, which fully accounts for the business cycle, is lower than that of the baseline and symmetric models. This is driven by the greater responsiveness of emissions to contractions than to expansions, which causes a downwards ratchet effect. Also, the confidence intervals of the symmetric and asymmetric forecasts are larger than that of the baseline forecast. The intuition for the increase in uncertainty is as follows: there are an infinite number of GDP paths that can result in the same average long run growth rate, but there is only one smoothed path with a constant annual growth rate. Each GDP path results in a different emissions path. The integral under these emissions curves, or cumulative emissions, can be greater or less than the integral under the CAGR path. Therefore, holding average long run GDP growth constant, because we do not know what the path of the business cycle will be, there is uncertainty about how high future cumulative emissions will be.

These simulations suggest that when the business cycle is factored in, predicted future emissions are lower on average than they would have otherwise been, but variance increases substantially. Average annual GDP growth in the baseline model would need to be 19% lower (2.77% versus 3.42%) or 7% higher (3.65% versus 3.42%) to result in the lower and upper confidence intervals predicted by the asymmetric model, respectively. In other words, assuming an average growth rate of 3.42% and accounting for business cycle uncertainty results in the same cumulative emissions forecast for 2100 as assuming a growth rate range of 2.77%-3.65% and not accounting for the business cycle.

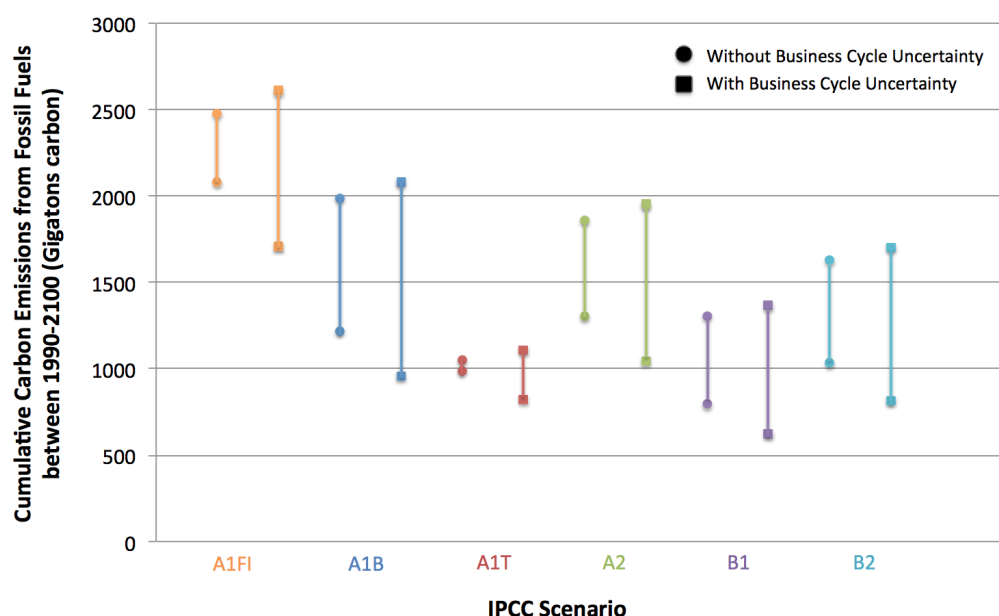


Figure 1.8: IPCC emissions forecasts without and with business cycle uncertainty. The forecasts without the business cycle are taken directly from the IPCC (2000). The forecasts with the business cycle overlay the additional uncertainty predicted by the asymmetric model on the IPCC forecasts.

Figure 1.8 shows the IPCC emissions forecasts based on the IPCC emissions scenario groups as described in IPCC (2000) both without and with the additional uncertainty from the business cycle.¹³ When business cycle uncertainty is included, not only does the total range of estimated emissions expand in both directions, but there is increased overlap between the scenarios. For example, A1FI and A1B do not overlap without the business cycle uncertainty, but they overlap considerably with business cycle uncertainty. The A1FI scenarios are fossil-fuel intense scenarios, while the A1B scenarios allow for an economy that is more “balanced” between fossil fuels and non-fossil fuels. That the business cycle uncertainty makes these scenarios

¹³The IPCC emissions scenarios forecast long run emissions under a variety of assumptions. The forecasts are based on the Kaya identity and the different scenarios are intended to show policy makers alternatives of how the future might unfold. Each scenario is based on a range of average economic growth, energy mix, technological change, population growth, and more.

less distinguishable from one another suggests that business cycle uncertainty is at least as important as, and may even dominate, other factors such as average GDP growth, energy mix, and technology.

Macroeconomic fluctuations are caused by a variety of factors that may result in shorter, longer, sharper, or more frequent business cycles. Reinhart and Rogoff (2009) analyze global financial crises since the mid fourteenth century. They find four primary causes for crises: inflation crises, currency crashes, banking crises, and debt crises/sovereign defaults. They also find that the average duration of default periods since World War II is three years, compared to the six years for default periods between 1800 and 1945. However, in more recent years there has been less time in-between default episodes.

As detailed in Ng and Wright (2013), the Great Recession was caused by deleveraging and financial market factors, whereas United States business cycles of the 1970s and 1980s were due to supply shocks and/or monetary policy. Expansions since the early 1980s were longer than previous post-World War II expansions (95 months versus 46 months on average) but had lower average growth rates (2.7% versus 5.4% per annum). Contractions before the early 1980s were followed by rapid recoveries, unlike contractions since. The Great Recession (18 months between 2007-2009) was shorter than pre-World War I recessions but longer than most post-World War II recessions. (Ng and Wright, 2013)

The business cycle also varies across countries with differing economic structures, which may affect the impact of the business cycle on long run emissions. A study of business cycles in 10 developed countries from 1970 through the mid 1990s demonstrates how business cycles vary across countries (Backus, Kehoe, and Kydland, 1993). Volatility of output over the business cycle is highest in the USA and Switzerland, followed by the United Kingdom, Italy, Germany and Canada. Volatility is lowest in France, followed by Austria, Japan, and Australia. Persistence of

the business cycle is highest in Switzerland, the United States, and Italy, and lowest in Austria, Australia, Germany, and the United Kingdom. Japan's correlation of output to USA output is the highest at .76 and the lowest for Austria at .38. Correlation of USA and European output is 0.66.

The most significant recent recession in Asia was the Asian Financial Crisis of 1997, which began in mid 1997 and had lingering effects through 1998. The Crisis started with collapse of Thai baht, which led to the devaluation of the Japanese and many Southeast Asian currencies, followed by a devaluation of stock markets and other assets. Many Asian countries and particularly Indonesia, South Korea and Thailand were impacted by the Crisis and experienced GDP drops upwards of 30%. This relatively short but sharp contraction in these countries was followed by a sharp recovery from the late 1980s to early 1990s, a period of time known as the "Asian economic miracle," with growth rates between 8-12%. (Moreno, 1998)

Table 1.9 illustrates the effect of business cycle parameters on cumulative emissions. A change in business cycle parameters does not affect baseline emissions forecasts. This is because the baseline forecasts utilize smoothed growth, which is nearly constant for all simulations, between 3.40%-3.44%. Average emissions predicted by the symmetric model are not affected by changes in the business cycle parameters. Longer contractions and more volatile business cycles result in more volatile emissions forecasts, however, since this volatility is symmetric, average emissions predictions are unchanged.

Similarly, emissions predicted by the asymmetric model, which fully incorporates the business cycle, are also more or less volatile as the business cycle parameters change. Average emissions predictions in this case are somewhat higher (lower) when business cycle growth is less (more) volatile. The higher (lower) the standard deviation of growth rates, the more (less) exaggerated the effect of the larger elasticity of emissions with respect to declines in GDP.

Table 1.9: Effect of Business Cycle Parameters on Cumulative Emissions in 2050

Business Cycles	Asymmetric			Symmetric			Baseline		
	Avg (GtC)	StDev (GtC)	StDev	Avg (GtC)	StDev (GtC)	StDev	Avg (GtC)	StDev (GtC)	StDev
Calibration ¹	95.3	3.7	3.8%	99.1	3.9	3.9%	98.6	0.1	0.1%
Less Frequent ²	95.4	3.7	4.0%	99.0	3.9	3.9%	98.6	0.1	0.1%
More Frequent ²	95.1	3.8	4.0%	98.8	4.0	4.1%	98.6	0.1	0.1%
Shorter Duration ³	95.5	3.4	3.5%	99.2	3.6	3.6%	98.6	0.1	0.1%
Longer Duration ³	95.1	3.9	4.1%	98.9	4.2	4.2%	98.6	0.1	0.1%
Less Volatile ⁴	95.6	2.6	2.7%	99.0	2.7	2.7%	98.6	0.1	0.1%
More Volatile ⁴	94.3	4.3	4.6%	98.5	4.6	4.7%	98.6	0.1	0.1%

¹The calibration case uses parameters from Chauvet and Hamilton (2006). The transition probabilities are $\gamma_{11} = .95$, $\gamma_{21} = .05$, $\gamma_{12} = .22$, and $\gamma_{22} = .78$, average growth during an expansion of $\mu_1 = 4.5\%$, average growth during a contraction of $\mu_2 = -1.2\%$, and standard deviation of growth of $\sigma_{1,2} = 3.5\%$.

²The less frequent contractions simulation uses a transition matrix with $\gamma_{11} = .98$ and $\gamma_{21} = .02$, while the more frequent uses $\gamma_{11} = .92$, and $\gamma_{21} = .08$.

³The shorter duration contractions simulation uses a transition matrix with $\gamma_{21} = .27$ and $\gamma_{22} = .73$, while the longer duration uses $\gamma_{21} = .17$ and $\gamma_{22} = .83$.

⁴The less volatile business cycle simulation uses $\sigma_{1,2} = 2.0\%$ and the more volatile uses $\sigma_{1,2} = 5.0\%$.

1.8 Welfare Implications

1.8.1 Implications for Optimal Investment in Abatement

Thus far I have shown that accounting for the business cycle results in future emissions forecasts being lower on average but much less certain. In this section I set up a simple model to explore how these results affect future consumption and optimal investment in abatement. In this model, a risk averse social planner maximizes the discounted sum of future utility, u , as follows:

Objective function:

$$\sum_{t=0}^{\infty} \beta^t E[u(c_t)] \quad (1.12)$$

Subject to a budget constraint and a law of motion of capital:

$$c_t + i_t \leq (1 - d_t)y_t \quad (1.13)$$

$$a_{t+1} = (1 - \delta)a_t + i_t, \quad (1.14)$$

where:

$$u(c_t) = \frac{c_t^{1-\rho}}{1-\rho} \quad (1.15)$$

$$d_t = \xi_t \left(e_t - \frac{a_t}{p_t} \right), \quad (1.16)$$

and where:

c_t : consumption

y_t : income

i_t : investment in abatement capital

a_t : abatement capital

d_t : damages from emissions

ξ_t : social cost of carbon

e_t : emissions	ρ : relative risk aversion (assume
p_t : price per unit of abatement	$\rho > 1$)
β : discount factor	δ : rate of depreciation

Maximizing the objective function subject to the budget constraint and law of motion of capital yields the following Euler equation:

$$u'(c_t) = \beta \left(\frac{\xi_t}{p_t} + 1 - \delta \right) \mathbb{E}[u'(c_{t+1})] \quad (1.17)$$

I assume that $\ln(c_{t+1}) \sim \mathcal{N}(\mu_{c,t+1}, \sigma_{c,t+1}^2)$. Lognormal distribution of consumption is a common assumption with some empirical support (Battistin, Blundell, and Lewbel, 2009). This distributional assumption implies that $\mathbb{E}[c_{t+1}] = e^{\mu_{c,t+1} + \frac{\sigma_{c,t+1}^2}{2}}$. This key assumption allows the uncertainty of emissions, $\sigma_{e,t}^2$, to enter the model in a simple form. Assuming y_t is deterministic facilitates comparison of consumption and investment in the baseline emissions case against the asymmetric emissions case for a given income. The log transformed mean and variance of consumption, $\mu_{c,t}$ and $\sigma_{c,t}^2$, are functions of mean and variance of emissions, $\mu_{e,t}$ and $\sigma_{e,t}^2$ and are derived from the arithmetic mean and standard deviation of consumption according to methodology proposed by Quan and Zhang (2003):

$$\sigma_{c,t+1}^2 = \ln \left(1 + \left(\frac{\xi_{t+1} \sigma_{e,t+1}}{\bar{c}_{t+1}} \right)^2 \right) \quad (1.18)$$

$$\mu_{c,t+1} = \ln(\bar{c}_{t+1}) - \frac{\sigma_{c,t+1}^2}{2} \quad (1.19)$$

The numerator of the fraction in Equation 1.18 is the arithmetic variance of consumption and $\bar{c}_t$ is the arithmetic average of consumption, which can be found using the budget constraint:

$$\bar{c}_t = y_t - \xi_t e_t + \frac{\xi_t}{p_t} \bar{a}_t - \bar{i}_t, \quad (1.20)$$

where $\bar{a}_t$ and $\bar{i}_t$ are what optimal abatement and investment would be if standard deviation of emissions were zero and emissions equaled average emissions in each period, i.e., $e_t = \mu_{e,t}$. Substituting Equations 3.3, 1.18, and 1.19 into the Euler equation (Equation 1.17) yields:

$$c_t = \left[\beta \left(\frac{\xi_t}{p_t} + 1 - \delta \right) \right]^{\frac{-1}{\rho}} \bar{c}_{t+1} \left(1 + \frac{\xi_{t+1}^2 \sigma_{e,t+1}^2}{\bar{c}_{t+1}^2} \right)^{\frac{-\rho}{2}} \quad (1.21)$$

Equation 1.21 shows that if there is no uncertainty in emissions, the third term drops out and consumption in period t equals the expected average consumption in period $t + 1$ times a discount factor determined by prices, depreciation, the discount rate, and risk aversion. Lower average emissions decreases damages and increases expected consumption. Greater variance of emissions and higher risk aversion decrease the third term, resulting in lower consumption.

To get an idea of the magnitude of these theoretical predictions, I plug in the GDP forecasts and average and standard deviations of the baseline and business cycle (asymmetric) emissions forecasts from the simulations in Section 1.7 and solve for the optimal path of consumption and investment in abatement. Emissions estimates are converted from metric tons of carbon to metric tons of carbon dioxide using the standard factor of 3.667. I specify a social cost of carbon starting at \$30 per ton of CO₂ and increasing over time at the same rate as GDP growth. Following Nordhaus (2008) I use a discount factor of 0.985.

I solve the model for a range of relative risk aversion levels and rates of depreciation. For each rate of depreciation, I recalibrate the price per unit of abatement. Interest here is focused on *relative* levels of abatement between the baseline and asymmetric models. The calibration parameters are set to yield a price that is

not too expensive to preclude investment, and yet not so low that maximum abatement is trivial. At high levels of depreciation, abatement capital must be refreshed each period, requiring a price per unit abatement only modestly higher than the social cost of carbon to induce investment. At low levels of depreciation, abatement capital accumulates over time, so the benefit of capital accumulated in the present accrues for many periods in the future. To yield comparable levels of abatement as scenarios with higher rates of depreciation requires a price per unit of abatement that is considerably higher than the social cost of carbon.

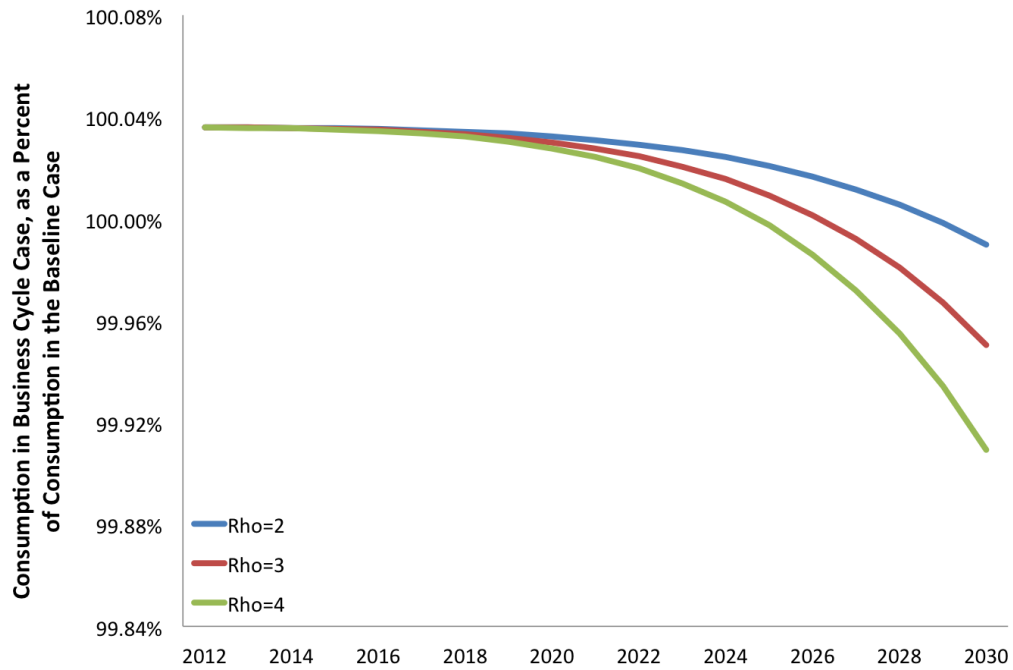


Figure 1.9: Optimal consumption in the business cycle case relative to the baseline case at different levels of risk aversion, ρ .

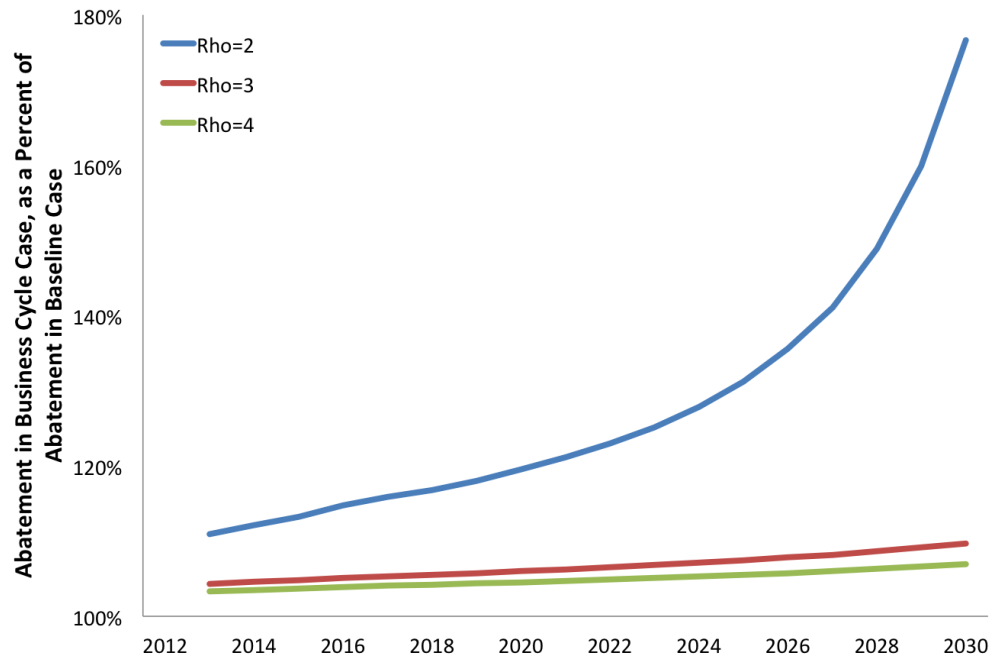


Figure 1.10: Optimal investment in abatement in the business cycle case relative to the baseline case at different levels of risk aversion, ρ .

Figures 1.9 and 1.10 illustrate the results of the exercise. In Figure 1.9, optimal consumption in the baseline case is normalized to 100%. This graph shows optimal consumption in the business cycle model as a percent of optimal consumption in the baseline model at different levels of risk aversion, ρ . The higher the risk aversion, the more the business cycle uncertainty matters, causing consumption in the business cycle to be relatively lower. Figure 1.9 also shows that due to lower average emissions in the business cycle model, average damages are lower, thus optimal consumption is higher in the asymmetric case than the baseline in earlier periods. Optimal consumption in the business cycle case is also greater than the baseline case in later periods when risk aversion is lower.

In Figure 1.10, optimal abatement in the baseline case is normalized to 100%. This graph shows optimal abatement in the business cycle model as a percent

of optimal abatement in the baseline model at different levels of risk aversion, ρ . Optimal investment in abatement is greater in the business cycle model than the baseline model. This is because the social planner is risk averse, and the standard deviation of emissions is higher in the baseline model. It is somewhat counter-intuitive that abatement in the business cycle case exceeds that of the baseline case relatively more at lower levels of risk aversion. This is probably due to consumption being relatively higher when risk aversion is lower. For example, unlike higher levels of risk aversion, with a ρ of 2, consumption in the business cycle case exceeds consumption in the baseline case even in later time periods. Since average damages are lower in the business cycle case, effective income is higher. This additional income is spent both on more consumption *and* more abatement as the social planner equalizes the marginal utility of consumption and abatement.

1.8.2 Implications for Climate Change Uncertainty

Climate models exhibit an approximately linear relationship between minimum peak temperature increase and cumulative emissions over the relevant range (Matthews and Caldeira, 2008; Allen et al., 2009; Matthews et al., 2009). This linear relationship can be written as follows (Stocker, 2013):

$$\Delta T_{min} = \beta * C_1 \tag{1.22}$$

where ΔT_{min} is the minimum peak warming assuming zero emissions from time t_1 onwards, β is the ‘peak response to cumulative emissions,’ and C_1 is the cumulative long-lived (carbon dioxide) greenhouse gas emissions until time t_1 . Depending on the physical climate model and its parameterization, β ranges from 1.3°C - 3.9°C per trillion metric tons of carbon (Allen et al., 2009).

The latest report from the IPCC states that without mitigation, likely warm-

Table 1.10: Predicted Warming by 2100

	Predicted Warming by 2100	
	Baseline Forecast	Business Cycle Forecast
Mean - 2σ	3.98°C	3.48°C
Mean Emissions	4.00°C	3.84°C
Mean + 2σ	4.02°C	4.21°C

Assuming $C_{2010} = 539.3\text{GtC}$ and $\beta = 1.31^\circ\text{C/TtC}$

ing¹⁴ by 2100 is 3.7°C-4.8°C (IPCC, 2014). Assuming initial cumulative emissions of 539 gigatons of carbon (GtC) in 2010 (Stocker, 2013), my baseline emissions forecast,¹⁵ which predicts additional cumulative emissions between 2010-2100 of 2525 GtC, results in $C_{2100} = 3064$ GtC. Assuming the baseline forecast results in 4°C of warming by 2100, this implies $\beta = \frac{4^\circ\text{C}}{3064\text{GtC}} = 1.31^\circ\text{C/TtC}$. Table 1.10 shows the predicted cumulative emissions and temperature increase in the baseline versus asymmetric business cycle emissions forecasting models, assuming $\beta = 1.31^\circ\text{C/TtC}$.

The baseline forecast predicts a 95% probability that the resulting temperature increase will range from 3.98°C-4.02°C. The business cycle forecast predicts a 95% probability that the resulting temperature increase will range from 3.48°C-4.21°C. The uncertainty of likely range of temperature increase predicted by the business cycle model is .73°C, which is .69°C more than the .04°C range predicted by the baseline model. Holding constant the average long run GDP growth forecast, uncertainty from the business cycle results in an additional .7°C of uncertainty in cumulative temperature change by 2100.¹⁶ While it is encouraging that the tem-

¹⁴The 95% confidence interval including uncertainties in climate sensitivity is 2.5°C to 7.8°C.

¹⁵I extrapolate to global emissions by assuming the United States share of global emissions remains a constant 14.4%, its share of global emissions in 2010. As growth in developing countries will likely exceed OECD growth over this century, the United States' share of global emissions will likely be smaller than its current share. The smaller the U.S. share of emissions, the larger total global emissions predictions for 2100, the larger the uncertainty in temperature change due to the business cycle. Therefore, predictions shown in table 1.10 may be conservative.

¹⁶Assuming an average temperature increase of 3.0°C or 5.0°C, uncertainty from the business cycle results in an additional 0.5°C and 0.9°C, respectively, uncertainty in cumulative warming by

perature change resulting from emissions forecast by the business cycle is likely to be lower on average than the baseline forecast, that warming could be 0.2°C greater than the baseline forecast is worrisome as climate damages are a convex function of temperature increase.

There are a variety of “feedback” parameters that influence climate sensitivity (which influences β in Equation 1.22). These feedback parameters are the major source of scientific uncertainty about how much the climate will warm given an increase in greenhouse gas concentrations. For example, as warming causes ice sheets to melt, there is less white ice to reflect the sun’s ultraviolet rays, and more blue water that absorbs ultraviolet light. This is a positive feedback loop wherein the more the climate warms, the more ice that melts, and the more ultraviolet light that is absorbed, which further increases warming. These feedback parameters are some of the most important known sources of uncertainty that influence future damages from climate change. Table 1.11 compares the additional uncertainty from the business cycle to scientific uncertainties arising from the major feedback parameters. Uncertainty in warming from the business cycle is greater than uncertainty due to feedback from changes in sea ice, land snow, and clouds and similar to uncertainty due to water vapor feedback. This implies that uncertainty in warming from the business cycle is of a similar order of magnitude as the major known scientific uncertainties.

2100.

Table 1.11: Business Cycle Uncertainty versus Scientific Uncertainty in Climate Sensitivity

	Magnitude of Uncertainty in Temperature Change
Business Cycle	0.69°C
Water Vapor	0.65-1.08°C
Sea Ice/Land Snow	0.03-0.09°C
Clouds	0.03-0.46°C

Uncertainty due to the business cycle is calculated as the difference in warming in 2100 from $\pm 2\sigma$ emissions scenarios between the business cycle forecasting model and the baseline model, as shown in Table 1.10. Scientific uncertainties are taken from Neelin (2010) and represent uncertainty in cumulative warming from a doubling of CO₂ concentrations (assuming radiative forcing of $4.3W/m^2$ for doubled CO₂) due to feedbacks from various physical factors.

1.9 Implications for Climate Treaties

Emissions forecasting is important for future planning, policymaking, mitigation, adaptation, and investment decisions. I have shown that omitting the business cycle overestimates average emissions and it also underestimates the uncertainty of future emissions. Accurately forecasting future emissions is critical to the success of global mitigation efforts, where countries sign treaties and commit to emissions targets.

The Kyoto Protocol has been less successful than intended partly due to poor emissions forecasting and resulting allocation of abatement targets. In 1992 when the Protocol was signed, its abatement targets were set relative to 1990 emissions levels. Countries with emissions targets accounted for 64% of 1996 global carbon dioxide emissions (Cooper, 2001). Industrialized Annex I countries were tasked with the majority of abatement relative to developing, non-Annex I countries.

The share of emissions covered under the Kyoto Protocol has fallen substantially in the last two decades, in large part due to faster than expected growth in non-Annex I countries. Developing and least developed countries accounted for 73% of emissions growth in 2004 (Raupach et al., 2007). Asian economies have been

the most significant driver of emissions growth. Auffhammer and Carson (2008) projected that Chinese emissions between 2000 and 2010 would be more than five times larger than estimated emissions reductions from Annex I countries by 2010 as a result of the Kyoto Protocol. In 2009, China accounted for approximately a quarter of global carbon dioxide emissions, while the USA and Europe accounted for approximately a third.

Additionally, when the Kyoto protocol was developed, Soviet economies were a relatively larger share of global economic growth and emissions. However, the dissolution of the Soviet Union in 1991 caused Soviet economies to collapse. Russia's and Ukraine's emissions fell well below their Kyoto target levels by 2008 and these countries were able to sell emissions credits for a windfall profit (Victor, Nakićenović, and Victor, 2001). Although Russia and Ukraine remain two of the world's largest emitters, they have made little effort to cut emissions (Lioubimtseva, 2010).

In short, although the Kyoto Protocol intended to cover a majority of global emissions, as a result of inaccurate emissions forecasting and unforeseen economic crises and expansions, binding targets now cover only a small fraction of global emissions.

Emissions forecasts and treaty targets could both be improved by factoring in business cycles. Policy makers should also consider how proposed policies could dampen or exacerbate the asymmetric, pro-cyclicity of emissions. For example, emissions targets could be indexed to economic growth, which would help ensure targets remain both realistic and binding.

Failure to account for the business cycle implies that emissions treaty participants will inevitably seek to renegotiate fixed targets. Dependency of emissions on business cycles suggests that emissions forecasts for a given target date will be better as the path of the business cycle reveals itself, creating a problem of time inconsistency. Policies made in the present based on current forecasts could become

sub-optimal in the future depending on the business cycle. This may delay climate actions as evidenced by United States inaction, or spur continual renegotiations, as we have seen with the United Nations Framework Convention on Climate Change. An alternative to indexing emissions targets to GDP would be to agree on price targets, which could lead to more stable policies than quantity targets.

1.10 Conclusion

There are many scientific and economic uncertainties about climate change that challenge our ability to predict and plan for the future. Current long-term carbon dioxide emissions forecasts rely on the assumption that the economic growth rate is constant over long time horizons and exclude the business cycle, thereby ignoring a fundamental component of the macro economy. There are a variety of reasons we may expect this assumption to be false. There is evidence that both energy intensity and emissions intensity change over the business cycle. Electricity consumption and primary energy use by the industrial sector fall more per decrease in GDP than they rise per unit increase in GDP. This may be due to lower use or retirement of older, less energy-efficient capital during recessions and greater use of and investment in newer, more energy-efficient capital during expansions.¹⁷ Emissions intensity may also change over the business cycle if fuel mix changes differentially. I find empirical evidence from the power sector to support both of these hypotheses.

Empirically, I test the implicit assumption that the elasticity of emissions is constant with respect to change in GDP. My results reject this hypothesis and indicate that emissions fall more sharply during a recession than they rise during an expansion. Such an asymmetry is observed across time and in the majority of

¹⁷This leads to questions regarding timing of capital investment and technological change over the business cycle that would be interesting areas of future research.

the top carbon-dioxide emitting countries.

The simulations in Section 1.7 show that even holding long run growth constant, different business cycle paths result in different levels of future cumulative emissions. While it is encouraging that emissions are likely to be lower on average when the business cycle is factored in, we also run a greater risk that emissions will be higher. The implications of this finding on optimal investment in mitigation depend on risk aversion, because we must weigh the prospect of lower average damages against an increase in uncertainty. I set up a simple social planner model in which even moderate risk aversion leads to optimal investment in abatement that is higher when the business cycle emissions forecast is used than when the baseline emission forecast is used.

Policy makers should be aware of this additional uncertainty and how the business cycle can affect future emissions and interact with climate change policies. Dependency of emissions on the business cycle suggests that emissions forecasts of a given target date will be better as the path of the business cycle reveals itself, creating a problem of time inconsistency. Policies made in the present based on current forecasts could become sub-optimal in the future depending on the business cycle. It may be prudent to consider indexing emissions targets to economic growth, which would help ensure targets remain both realistic and binding.

Holding GDP growth constant, I find that uncertainty from the business cycle results in an additional $.7^{\circ}\text{C}$ uncertainty in cumulative temperature change by 2100, relative to consensus warming estimates of around 4°C . This is of a similar order of magnitude as the major scientific uncertainties of future warming. A large literature exists on the physical science uncertainties of climate change, and much research is being done to reduce these scientific uncertainties. I have shown that the business cycle is a previously unconsidered source of climate change uncertainty that is perhaps as substantial as these scientific uncertainties. Economists should engage

in future research to improve our understanding of the causes and implications of this business cycle uncertainty.

1.11 Acknowledgement

Chapter 1, in part, is currently under submission for publication of the material. Sheldon, Tamara L.

1.12 Chapter 1 Appendix

1.12.1 Specification of Quarterly Emissions Model

Although climate scientists consider the emissions data from the CDIAC to be the best available, they caution that measurement error in the monthly estimates can be large.¹⁸ For this reason, I perform the analysis both at an annual and quarterly level. The annual emissions data have less measurement error, but there are fewer observations. The quarterly emissions data have more measurement error, but more observations allow for greater power.

The GDP data are seasonally adjusted, however, the emissions data are not. Therefore, I include quarter dummies in the quarterly model to adjust for seasonality. Table 1.12 shows a variety of lag specifications for ΔY , with column 1 using $Y_{t-1} - Y_{t-2}$, column 2 using $Y_{t-1} - Y_{t-3}$, and so on. Additional lags are not significant and do not change the estimates, so they are not reported. Column 3, with the lag structure $Y_{t-1} - Y_{t-4}$ is the model with the best fit in terms of R-squared¹⁹, Akaike information criterion (AIC), Bayesian information criterion (BIC), and root mean square error (RSME). For all specifications, the coefficient on increases in

¹⁸Personal communication with climate scientists from the Scripps Institute of Oceanography.

¹⁹All specifications have a higher R-squared values than their respective symmetric model specifications shown in Table 1.13, where the coefficients on change in GDP (ΔY) are much smaller than the coefficient on decreases in GDP (Negative ΔY) in the respective asymmetric specification.

GDP is not statistically different from zero.²⁰ The coefficient on decreases in GDP is close to 3 and significant for most specifications. For the preferred specification (column 3), a t-test rejects the hypothesis that the coefficient on increases in GDP is equal to the coefficient on decreases in GDP with a p-value of 0.02. In this model, it is the change in GDP from quarter $t - 1$ to quarter $t - 4$ that is important. This makes sense because if the economy contracts, it takes time for output and behavior to adjust. The preferred specification not only has the best fit of the quarterly specifications, but it is also the most similar in lag structure to the annual model, which uses 1-year lags.

Table 1.12: Quarterly Specification of Lag Structure

Lag Specification:	(1) (t-1)-(t-2)	(2) (t-1)-(t-3)	(3) (t-1)-(t-4)	(4) (t-2)-(t-3)	(5) (t-2)-(t-4)
Positive ΔY	0.682 (0.939)	0.374 (0.534)	0.252 (0.382)	0.853 (0.922)	0.577 (0.507)
Negative ΔY	2.100 (1.927)	2.847** (1.173)	3.124*** (1.046)	2.724 (2.012)	2.462** (1.192)
Lagged Y	0.453*** (0.009)	0.452*** (0.009)	0.451*** (0.009)	0.452*** (0.009)	0.452*** (0.009)
2nd Quarter Dummy	-0.128*** (0.015)	-0.124*** (0.015)	-0.124*** (0.015)	-0.124*** (0.015)	-0.125*** (0.015)
3rd Quarter Dummy	-0.087*** (0.015)	-0.085*** (0.015)	-0.082*** (0.015)	-0.082*** (0.015)	-0.079*** (0.015)
4th Quarter Dummy	-0.057*** (0.015)	-0.057*** (0.015)	-0.055*** (0.015)	-0.055*** (0.015)	-0.053*** (0.015)
Constant	9.336*** (0.073)	9.349*** (0.072)	9.359*** (0.072)	9.343*** (0.075)	9.340*** (0.074)
Observations	236	236	236	236	236
R^2	0.912	0.914	0.915	0.912	0.912
AIC	-508	-512	-515	-507	-508
BIC	-484	-488	-490	-483	-484
RMSE	0.081	0.081	0.080	0.081	0.081
Robust standard errors in parentheses					
*** p<0.01, ** p<0.05, * p<0.1					

The dependent variable is the natural log of quarterly carbon dioxide emissions. ‘ ΔY ’ is the change in the natural log of GDP between indicated quarters. ‘Positive ΔY ’ and ‘Negative ΔY ’ are ΔY multiplied by indicators for whether or not GDP increased or decreased, respectively, between quarters. Lagged Y is the natural log of GDP in the earlier quarter.

²⁰For the preferred specification (column 3), a t-test fails to reject the hypothesis that the coefficient on increases in GDP is equal to zero with a p-value of 0.51.

Table 1.13: Models: Quarterly Specifications (Symmetric)

Lag Specification:	(1) (t-1)-(t-2)	(2) (t-1)-(t-3)	(3) (t-1)-(t-4)	(4) (t-2)-(t-3)	(5) (t-2)-(t-4)
ΔY	1.083 (0.680)	0.961** (0.411)	0.835*** (0.305)	1.367* (0.684)	0.989** (0.401)
Lagged Y	0.454*** (0.009)	0.455*** (0.009)	0.456*** (0.009)	0.454*** (0.009)	0.454*** (0.009)
2nd Quarter Dummy	-0.129*** (0.015)	-0.128*** (0.015)	-0.127*** (0.015)	-0.126*** (0.015)	-0.126*** (0.015)
3rd Quarter Dummy	-0.086*** (0.015)	-0.086*** (0.015)	-0.085*** (0.015)	-0.084*** (0.015)	-0.083*** (0.015)
4th Quarter Dummy	-0.056*** (0.015)	-0.056*** (0.015)	-0.055*** (0.015)	-0.055*** (0.015)	-0.054*** (0.015)
Constant	9.320*** (0.066)	9.309*** (0.066)	9.304*** (0.067)	9.322*** (0.067)	9.317*** (0.067)
Observations	236	236	236	236	236
R^2	0.912	0.912	0.912	0.912	0.912
Robust standard errors in parentheses					
*** p<0.01, ** p<0.05, * p<0.1					

The dependent variable is the natural log of quarterly carbon dioxide emissions. ‘ ΔY ’ is the change in the natural log of GDP between indicated quarters. Lagged Y is the natural log of GDP in the earlier quarter.

1.12.2 Robustness Checks

I do not de-trend the data in my headline specification because there are two trends over time, the increase in GDP and the improvement in energy efficiency, and it is difficult to distinguish between these two trends. Table 1.14 includes a time trend in columns 3 and 4 and shows that the coefficients for deviations in GDP from the trend are very similar to the coefficients on changes in GDP in the headline specification. Columns 5 and 6 utilize Newey-West standard errors to account for auto-correlation in the error term. These standard errors are slightly larger than the robust standard errors of the headline specification, but they do not affect the significance of the coefficients.

Table 1.14: Annual U.S. Results including Robustness Checks (2)

	Headline (Annual) (1)	(2)	Time Trend (3)	(4)	Newey-West ¹ Std Errors (5)	(6)	Time Trend with Newey-West ¹ (7)	(8)
ΔY	0.750*** (0.183)		0.898*** (0.177)		0.750*** (0.202)		0.898*** (0.203)	
Positive ΔY		0.331 (0.265)		0.560* (0.300)		0.331 (0.267)		0.560* (0.321)
Negative ΔY		1.504*** (0.438)		1.496*** (0.290)		1.504*** (0.439)		1.496*** (0.299)
Lagged Y	0.497*** (0.011)	0.484*** (0.013)	0.900*** (0.078)	0.882*** (0.074)	0.497*** (0.014)	0.484*** (0.016)	0.900*** (0.102)	0.882*** (0.098)
Time Trend			-0.015*** (0.003)	-0.015*** (0.003)			-0.015*** (0.004)	-0.015*** (0.004)
Constant	9.587*** (0.088)	9.714*** (0.117)	35.410*** (5.107)	35.040*** (4.953)	9.587*** (0.113)	9.714*** (0.140)	35.410*** (6.761)	35.040*** (6.502)
Observations R^2	82 0.963	82 0.964	82 0.975	82 0.976	82	82	82	82
Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1								

¹The Newey-West standard error specification allows for a maximum lag order of autocorrelation of 1. Results are also robust to higher lag orders of autocorrelation.

Table 1.15 shows the results of the estimation of the asymmetric forecasting model when changes in GDP are broken down into smaller and larger increases and decreases in GDP. In no specification are the coefficients on positive changes in GDP significant. In column 3, smaller declines in GDP have a similar coefficient as the headline specification. The coefficient on larger declines in GDP is of greater magnitude but not statistically significant.

Table 1.15: Annual U.S. Results including Robustness Checks (3)

	(1)	(2)	(3)
Positive ΔY	0.331 (0.265)		
Positive ΔY ($\leq 4\%$)		-0.376 (0.824)	-0.716 (0.854)
Positive ΔY ($> 4\%$)		0.309 (0.267)	0.156 (0.292)
Negative ΔY	1.504*** (0.438)	1.544*** (0.440)	
Negative ΔY ($> -1\%$)			7.694 (5.923)
Negative ΔY ($\leq -1\%$)			1.679*** (0.453)
Lagged Y	0.484*** (0.013)	0.489*** (0.014)	0.486*** (0.015)
Constant	9.714*** (0.117)	9.686*** (0.124)	9.722*** (0.135)
Observations	82	82	82
R^2	0.964	0.964	0.965

Robust standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Chapter 2

Designing Policy Incentives for Cleaner Technologies: Lessons from California's Plug-in Electric Vehicle Rebate Program

2.1 Introduction

Policymakers design public incentives with the aim of inducing consumers to adopt innovative technologies that reduce environmental damages. Such incentives may include price subsidies, rebates, tax credits, sales tax exemptions, and subsidized financing. These policy incentives are currently deployed to induce consumers to adopt technologies such as alternative fuels and vehicles, energy and water efficient technologies, and renewable energy technologies, among others. While the critique of these incentives as “second best” from a social efficiency perspective is well known, researchers have paid much less attention to how to cost-effectively and equitably design these commonly encountered policy incentives.

We use California’s plug-in electric vehicle (PEV) rebate program as a reference case in order to explore the opportunity for both more cost-effective and equitable policy designs. In our policy setting, there are several possible sources of heterogeneity that the incentive policy’s design might leverage. First, the policy may set different rebate level for different products, in our case for Battery Electric Vehicles (BEVs) and Plug-in Hybrid Electric Vehicles (PHEVs). Second, a policy may employ price caps, which would make PEVs above the specified price ineligible for a rebate. Third, a policy could base rebate levels on heterogeneity among consumers. Recently California adopted legislation (SB 1271) requiring rebate levels to vary with consumers’ income levels but not specifying how rebates levels should vary.

We motivate our empirical analysis with a theoretical model of a social planner who must determine the rebate level to assign to consumers in order to maximize PEV purchases subject to a budget constraint. Our social planner faces heterogeneous consumers in their ex ante utilities for the new products, their marginal utilities of income, and the impact that a knowledge spillover has on the purchase of the new technology. Our model predicts that the social planner’s optimal rebate to

assign decreases as a consumer's ex ante value of the product increases. Consumer segments with high ex ante values for the product are more likely to purchase the product under any policy, thus qualifying in greater numbers for the rebate than are consumer segments with lower ex ante product values. As a result, targeting consumers with lower ex ante values is more cost-effective, requiring less public rebate revenue for the same change in consumer probabilities of product switching. Second, our model predicts that the social planner's optimal rebate increases as the consumer's own marginal utility of income increases. Any given rebate level is more effective in maximizing the sum of probabilities of purchasing the product for the segment of consumers who are relatively more price responsive.

Our fundamental contribution is an approach to simulating the cost-effectiveness of alternative policy designs. The relevant policy setting is one in which policymakers must set incentives levels across more than one product and for which consumers have product-differentiated demands. The basic elements of the analysis require that the researchers have estimates of 1) the price elasticities of demand for the relevant dimension of consumer heterogeneity (i.e., income classes in our case), 2) the distributions of consumers' willingness to pay for each product, and 3) prices for the products. The researcher can then explore through demand simulations how the assignments of financial incentives across products, consumer segments, and priced products will affect the number of total additional products purchased, the total cost of policy (e.g., required public revenues) and the cost effectiveness per additional product purchased. We also illustrate, for those interested, the use of a simple metric for comparing allocative equity across policy designs.

In order to evaluate the effects of a variety of rebate designs, we first develop and estimate an innovative empirical model of consumer vehicle choice. The centerpiece of our empirical analysis is a consumer vehicle choice model that enables us to model the consumer choices across all makes and models currently in the California

market. A statewide representative survey of 1,261 new car buyers in California enables us to identify individual preferences for conventional and alternative vehicle technology attributes, allowing us to estimate price elasticities of demand and willingness to pay for different vehicles. We integrate this data on vehicle sales and market structure to predict the effect of alternative rebate policy designs on our policy performance metrics.

We then use this model to simulate the performance of rebate designs. We find that the status quo policy is effective, increasing the market share of PEVs by at least 7%. The status quo policy offers \$1,500 and \$2,500 rebate for PHEVs and BEVs respectively. We find that incidence of free riding by consumers who would have purchased PEVs in the absence a rebates means that policy cost per *induced* PEV purchase is around \$30,000 for the status quo policy.

Our initial simulation of alternative policy designs explores the effects of changing rebate levels across the two vehicle technologies (BEVs and PHEVs). These simulations reveal the impacts of consumers' differing ex ante values (e.g., willingness to pay) for BEVs and PHEVs on the performance of rebate policies. For example allocating relative higher rebates to BEVs, for which consumers have a relatively lower value, reduces the number of total additional PEVs sold but also improves policy cost-effectiveness and lowers total policy costs. While some policymakers give BEVs relatively higher rebates because they believe BEVs produce relatively higher social benefits, our recommendations that BEVs receive relatively higher rebates compared to PHEVs is based solely upon a cost-effectiveness criteria.

Our second set of analyses explores the effects of vehicle price caps. A vehicle price cap policy excludes PEV adopters from a rebate who have relatively higher values for PEVs as expressed by their willingness to pay more for the PEV. Because relatively higher-income consumers tend to have relatively higher willingness to pay for PEVs, a vehicle price cap may render many higher-income PEV adopters inel-

igible for the rebate. Evaluating a vehicle price cap of \$60,000, we find that 10% fewer additional vehicles are sold, while cost-effectiveness improves and total program costs fall by 34%. However, we find that vehicle price caps do not appear to significantly improve the allocative equity as some policymakers have suggested they would. For the California market context, this appears to be true for two reasons. First, many higher-income consumers also purchase lower-priced PEVs. Second, a vehicle price cap does not influence how rebates to vehicles below the price cap are allocated across consumers of different incomes.

Our third set of analyses evaluates redesigning the existing rebate program to give consumers in lower-income classes relatively higher rebates. Rebate policy designs that are progressive with respect to income reduce the number of consumers who received rebates, but whom would have purchased the PEVs anyway. These policies also target lower-income consumers who have a higher marginal value for the rebate and who are less likely to purchase a PEV except in the presence of higher rebate levels. We find that these policies increase the number of additional PEVs sold per rebate dollar spent (i.e., the cost-effectiveness of the policy) relative to the status quo policy.

Overall, we find two types of policy designs are superior to California's status quo policy along performance dimensions. The first type of policy offers very progressive rebate levels based on consumer income levels. An example of this policy would offer consumers purchasing BEVs who make incomes of 1) less than \$25,000, a rebate of \$7,500, 2) \$25,000-\$50,000, a rebate of \$5,000, 3) \$50,000-\$75,000, a rebate of \$2,000, and 4) over \$75,000, no rebate. Consumers purchasing a PHEV in these same income categories would receive \$4,500, \$3,000, and \$1,000, respectively. For the second policy combines less progressive rebate schedule with a vehicle price cap. An example of this policy would implement \$60,000 vehicle price cap above which no rebate is offered while offering consumers making less than \$100,000 would

receive a rebate of \$5,000 for BEVs and \$3,000 for PHEVs. These policies sell at least as many PEVs over the next three years as the status quo policy, are more cost effective (e.g., PEV sold per dollar spent), have lower total policy costs, and result in a significantly greater allocative equity.

2.2 Literature on Design of Technology Adoption Policies

Our central thesis is that a fiscal policy could be improved by recognizing and leveraging heterogeneity among consumers. This idea first emerged in the modern economics literature with the discussion of design of tax policies (Diamond, 1970). However, this insight has not been widely developed and applied to the emerging literature on the design of incentives for innovative technology adoption policies. Instead, researchers concerned with technology adoption policies have to sought understand the types of externalities that may arise and how to best internalize these through our choice of policy instrument.

Researchers have argued that there may exist a distinct set of externalities around innovation, adoption, and diffusion of new technologies that goes beyond the standard health, safety, and environmental externalities that have motivated public regulations traditionally. The majority of these externalities take the form of sub-optimal knowledge spillovers among either consumers (i.e., learning by using) or producers (i.e., learning by doing) (e.g., Jaffe, Newell, and Stavins, 2002, 2005; Fischer and Newell, 2008; Bollinger and Gillingham, 2012). In the context of emerging innovative product markets, early adopters may face large private (learning) costs while producing large social (learning) benefits for later adopters leading to knowledge spillovers and adoption rates that are socially sub-optimal. Policies for innovative technologies with these externalities, these authors would argue, ought be

designed to achieve the socially optimal schedule of knowledge spillovers in addition to internalizing environmental or health externalities (Jaffe, Newell, and Stavins, 2005).

A large literature exists that evaluates optimal choice of policy instruments for these externalities (Gillingham, Newell, and Palmer, 2006). Tax and cap and trade policies establish *both* positive incentives for the adoption and use of relatively cleaner technologies *as well as* negative incentives for the adoption and use of relatively more polluting technologies. In contrast, policies such as rebates, tax credits, sales tax exemptions, and similar subsidies only establish positive incentives for the adoption and use of relatively cleaner technologies and thus are called “second best” policies. In the context of transportation policies, feebate policies have sought to replicate the effects of a tax policy by increasing the price of relatively more polluting vehicles while reducing the price of less polluting vehicles. Policy analyses of feebate policies often share our analytical approach of using estimates of consumers’ price elasticity of demand to evaluate changes in market share of the targeted vehicles.

Advocates of incentive policies often point to studies of demand for cleaner alternative vehicles which show that consumers have lower demand for, and less knowledge of, these vehicles than other internal combustion engine vehicles (Bunch et al., 1993; Brownstone, Bunch, and Train, 2000; Axsen and Kurani, 2009; Hidrue et al., 2011). Historically, three types of vehicle incentive policies have been evaluated by researchers: the aforementioned feebate policies, as well as hybrid-electric vehicle (e.g., Diamond, 2009; Chandra, Gulati, and Kandlikar, 2010; Beresteanu and Li, 2011; Jenn et al., 2013; Sierzechula et al., 2014), and “cash-for-clunkers” policies (e.g., Huang, 2010; Gayer and Parker, 2013; Li, Linn, and Spiller, 2013; Mian and Sufi, forthcoming). We compare our estimated effects of the California Vehicle Rebate Program on changes in market share with these studies in Section 4.

An issue related to policy instrument choice that has recently received attention is that consumers appear to respond differently to financial incentives of different types, but which convey the same net value to consumers (Chetty, Looney, and Kroft, 2009). Researchers have shown that consumers respond more to rebates and sales tax exemptions that occur nearer to the point of sale than to income tax incentives, which must be applied for and received at some later point in time. Gallagher, Sims, and Muehlegger (2011) provide an example for cleaner vehicle technologies when they report that Hybrid Electric Vehicle sales increase more in response to sale tax exemptions than to income tax credits/exceptions.

2.3 Theoretical Model

Suppose an individual purchases a PEV when her total utility from the decision is greater than her utility for purchasing any other vehicle. Let total utility, $u_{i,PEV}$, be her value for the PEV, w_i , minus the cost of the PEV, p , times her marginal utility of income, β_i .

$$u_{i,PEV} = w_i - \beta_i p \quad (2.1)$$

Assume that an individual's ex ante value for the PEV, v_i , may be increased due to spillovers as she learns more about the technology from other PEV drivers. Assume the spillover term is a linear function of how many other consumers purchase PEVs.

$$u_{i,PEV} = v_i + \lambda_i \sum_{j \neq i} PEV_j - \beta_i p \quad (2.2)$$

Consumers are heterogeneous in their ex ante utilities, their marginal utilities of income, and how much impact the spillovers have on them. The social planner can reduce PEV price for consumers by giving rebates:

$$u_{i,PEV} = v_i + \lambda_i \sum_{j \neq i} PEV_j - \beta_i(p - r_i) \quad (2.3)$$

The objective is to maximize the sum of consumer probabilities of purchasing PEVs by allocating the rebates cost effectively:

$$\max_{\{r_i\}} \sum_i \pi_i = \text{prob}(u_{i,PEV} > u_{i,k}) \quad \forall k \neq PEV \quad (2.4)$$

Assuming utilities are linear and the sources of actionable difference between consumers are observable, we can model probability as a conditional logit model:

$$\max_{\{r_i\}} \sum_i \pi_i = \frac{\exp(u_{i,PEV})}{\sum_k \exp(u_{i,k})} \quad (2.5)$$

The social planner can only affect $u_{i,PEV}$ by assigning rebates. The social planner cannot affect $u_{i,k}$ for $k \neq PEV$. Therefore, in this framework, maximizing the sum of the probabilities of choosing the PEV is equivalent to maximizing the sum of the utilities for the PEV:

$$\max_{\{r_i\}} \sum_i \pi_i \equiv \max_{\{r_i\}} \sum_i u_{i,PEV} = \max_{\{r_i\}} \sum_i \left[v_i + \lambda_i \sum_{j \neq i} \pi_j - \beta_i(p - r_i) \right] \quad (2.6)$$

$$S.T. \sum_i \pi_i r_i \leq \Re \quad (2.7)$$

where

π_i : Probability that consumer i selects a PEV

v_i : Ex-ante value to consumer i of selecting a PEV

λ_i : Marginal effect of spillover on individual i

β_i : Marginal utility of income of individual i

p : Price of PEV

r_i : Rebate assigned to individual i

$\mathfrak{R}$: Budget

We can solve the constrained maximization problem as follows, where equation 2.8 is the Lagrangian and equation 2.9 is the first order condition that results from taking the derivative of the Lagrangian with respect to r_i :

$$\mathfrak{L} = v_i + \lambda_i \sum_{j \neq i} \pi_j - \beta_i(p - r_i) + \gamma \left(\mathfrak{R} - \pi_i r_i - \sum_{j \neq i} \pi_j r_j \right) \quad (2.8)$$

$$\beta_i + \lambda_i \sum_{j \neq i} \lambda_j \beta_i = \gamma \left[\pi_i + r_i \left(\beta_i + \lambda_i \sum_{j \neq i} \lambda_j \beta_i \right) - \sum_{j \neq i} \lambda_j \left(\beta_i + \lambda_i \sum_{j \neq i} \lambda_j \beta_i \right) r_j \right] \quad (2.9)$$

If there are N new car buyers, then there are N first order conditions similar to equation 2.9, one for each car buyer. We can solve these first order conditions for γ and set them equal to each other:

$$\begin{aligned} \gamma &= \frac{\beta_1 + \lambda_1 \sum_{j \neq 1} \lambda_j \beta_1}{\pi_1 + r_1 \left(\beta_1 + \lambda_1 \sum_{j \neq 1} \lambda_j \beta_1 \right) - \sum_{j \neq 1} \lambda_j \left(\beta_1 + \lambda_1 \sum_{j \neq 1} \lambda_j \beta_1 \right) r_j} \\ &= \frac{\beta_2 + \lambda_2 \sum_{j \neq 2} \lambda_j \beta_2}{\pi_2 + r_2 \left(\beta_2 + \lambda_2 \sum_{j \neq 2} \lambda_j \beta_2 \right) - \sum_{j \neq 2} \lambda_j \left(\beta_2 + \lambda_2 \sum_{j \neq 2} \lambda_j \beta_2 \right) r_j} = \dots \end{aligned}$$

$$= \frac{\beta_n + \lambda_n \sum_{j \neq n} \lambda_j \beta_n}{\pi_n + r_n \left(\beta_n + \lambda_n \sum_{j \neq n} \lambda_j \beta_n \right) - \sum_{j \neq n} \lambda_j \left(\beta_n + \lambda_n \sum_{j \neq n} \lambda_j \beta_n \right) r_j} \quad (2.10)$$

The stylized case where $N=2$ is instructive because it can help illustrate the influences of varying the characteristics of two different consumers. In this case, equation 2.10 becomes

$$\frac{\beta_1 + \lambda_1 \lambda_2 \beta_1}{\beta_2 + \lambda_1 \lambda_2 \beta_2} = \frac{\pi_1 + r_1 (\beta_1 + \lambda_1 \lambda_2 \beta_1) - \lambda_2 (\beta_1 + \lambda_1 \lambda_2 \beta_1) r_2}{\pi_2 + r_2 (\beta_2 + \lambda_1 \lambda_2 \beta_2) - \lambda_1 (\beta_2 + \lambda_1 \lambda_2 \beta_2) r_1}, \quad (2.11)$$

where subscript 1 represents the consumer of interest and subscript 2 represents an arbitrary second consumer. Rearranging equation 2.11 we can solve for the optimal rebate r_1 :

$$r_1 = \frac{(1 + \lambda_2) r_2}{(1 + \lambda_1)} + \frac{\pi_2}{\beta_2 (1 + \lambda_1 \lambda_2) (1 + \lambda_1)} - \frac{\pi_1}{\beta_1 (1 + \lambda_1 \lambda_2) (1 + \lambda_1)} \quad (2.12)$$

Comparative Statics:

Optimal rebate decreases as own probability (ex ante value) increases:

$$\frac{\partial r_1}{\partial \pi_1} < 0 \quad (2.13)$$

Optimal rebate increases as other's probability (ex ante value) increases:

$$\frac{\partial r_1}{\partial \pi_2} > 0 \quad (2.14)$$

Optimal rebate increases as own marginal utility of income increases:

$$\frac{\partial r_1}{\partial \beta_1} > 0 \quad (2.15)$$

Optimal rebate decreases as other's marginal utility of income increases

$$\frac{\partial r_1}{\partial \beta_2} < 0 \quad (2.16)$$

The purchase of a PEV can result in a positive externality, which we term a spillover. The optimal rebate can increase or decrease as a function of own marginal effect of spillover. However, all else equal (if $\pi_1 = \pi_2$ and $\beta_1 = \beta_2$), then optimal rebate decreases as own marginal effect of spillover increases:

$$\frac{\partial r_1}{\partial \lambda_1} < 0 \quad (2.17)$$

Optimal rebate may increase or decrease as a function of others' marginal effect of spillover. However, all else equal (if $\pi_1 = \pi_2$ and $\beta_1 = \beta_2$), then optimal rebate increases as other's marginal effect of spillover increases:

$$\frac{\partial r_1}{\partial \lambda_2} > 0 \quad (2.18)$$

These comparative statics show that rebates should target consumers with high marginal utility of income and low ex ante value for PEVs. The comparative statics also show us that spillovers affect optimal rebate targeting. All else equal, rebates should target consumers that will have the largest spillover impact, i.e., the most influential consumers.

2.3.1 Cost-effectiveness analysis of rebate designs across two technologies

In our empirical analysis, we will limit ourselves to a cost-effectiveness analysis of alternative rebate designs rather than evaluating the socially optimal rebate design. We do not know the marginal social benefits (e.g., avoided externalities) associated with PEV purchases which would be needed to define a social optimum. However, the social planner's problem above makes several predictions (e.g., Equations 2.13-2.16) about how to improve the cost-effectiveness of rebate policy designs with information readily available to the economists' standard demand analyses.

We will adapt and apply this model prediction to our empirical and simulation setting in order to increase the number of PEVs sold per public dollar spent (e.g., cost-effectiveness). We will consider the policy problem of setting rebate levels for two types of PEVs, BEVs and PHEVs, for which consumers have very different ex ante values. We will find that the consumers' ex ante values are lower for BEVs than PHEVs. From Equation 2.13, we predict that if rebate levels are relatively higher for BEVs as compared to PHEVs then the policy will be relatively more cost-effective. We also consider the policy problem of setting rebate levels when the marginal utility of income varies across consumer (e.g., income) classes. We find that lower-income classes have a higher marginal utility of income than do higher-income classes. Equation 2.15 suggests that relatively higher rebate levels for relatively lower income classes will produce relatively more cost-effective policy outcomes.

2.4 Empirical Model and Simulations

2.4.1 Empirical Model

The probability of a new car buyer selecting vehicle k can be described as the new car buyer population-weighted average of the probabilities of new car buyers selecting vehicle k :

$$Prob(V_k) = \frac{\sum_{i=0}^N w_i Prob_i(V_k)}{\sum_{i=0}^N w_i} \quad (2.19)$$

where

$Prob(V_k)$: Average probability of purchasing vehicle k

$Prob_i(V_k)$: Probability of individual i purchasing vehicle k

w_i : Weight on individual i needed to make the sample representative of the new car buying population

The probability of individual i selecting vehicle k is the product of the probability of individual i selecting the make of vehicle k out of all available makes, the probability of individual i selecting the body type of vehicle k out of all available body types, and the probability of individual i choosing vehicle k over all other vehicles of the same make and body type:

$$Prob_i(V_k) = Prob_i(M_k) Prob_i(B_k) Prob_i(V_k | M_k, B_k) \quad (2.20)$$

where

M_k : Make of vehicle k

B_k : Body type of vehicle k

Assuming linear utility with standard Type 1 extreme value errors, we can model each probability component as a conditional logit.

$$Prob_i(B_k) = \frac{\exp(v_{1i}(B_k))}{\sum_{j=0}^N \exp(v_{1i}(B_j))} \quad (2.21)$$

$$Prob_i(M_k) = \frac{\exp(v_{2i}(M_k))}{\sum_{j=0}^N \exp(v_{2i}(M_j))} \quad (2.22)$$

$$Prob_i(V_k|M_k, B_k) = \frac{\exp(v_{3i}(V_k|M_k, B_k))}{\sum_{j=0}^N \exp(v_{3i}(V_j|M_j, B_j))} \quad (2.23)$$

$$(2.24)$$

where

v_{1i} , v_{2i} , and v_{3i} : Linear utility functions of individual i

2.4.2 Data

We administered an online survey to a representative sample of Californian new car buyers and obtained a sample of 1,261 completed surveys¹. The survey first gathers household, vehicle, and demographic data. Next, the survey elicits body and brand preferences. Respondents are asked to choose the top two vehicle body types (out of twelve options) they are most likely to select for their next new vehicle purchase, as shown in Figure 2.1. Then respondents are asked to select the top three brands (out of the twenty most popular brands by sales volume in California in 2012) they are most likely to select for their next new vehicle purchase, as shown in Figure 2.2.

¹More details on the survey methodology can be found in DeShazo, Sheldon, and Carson (2015).

Which of the following body types are you most likely to choose for your next new vehicle purchase? Please scroll down.

Compact Sedan
(for example, Toyota Corolla or Honda Civic)



Midsized Sedan
(for example, Nissan Altima or Kia Optima)



Full-Size Sedan
(for example, Ford Taurus or Chevrolet Impala)



Compact SUV
(for example, Honda CR-V or Jeep Cherokee)



Midsized SUV
(for example, Toyota Highlander or Ford Explorer)



Full-Size SUV
(for example, Chevrolet Tahoe or Cadillac Escalade)



Wagon
(for example, Subaru Outback or Kia Soul)



Hatchback
(for example, Ford Focus or Toyota Prius)



Coupe
(for example, Ford Mustang)



Convertible
(for example, Mazda Miata)



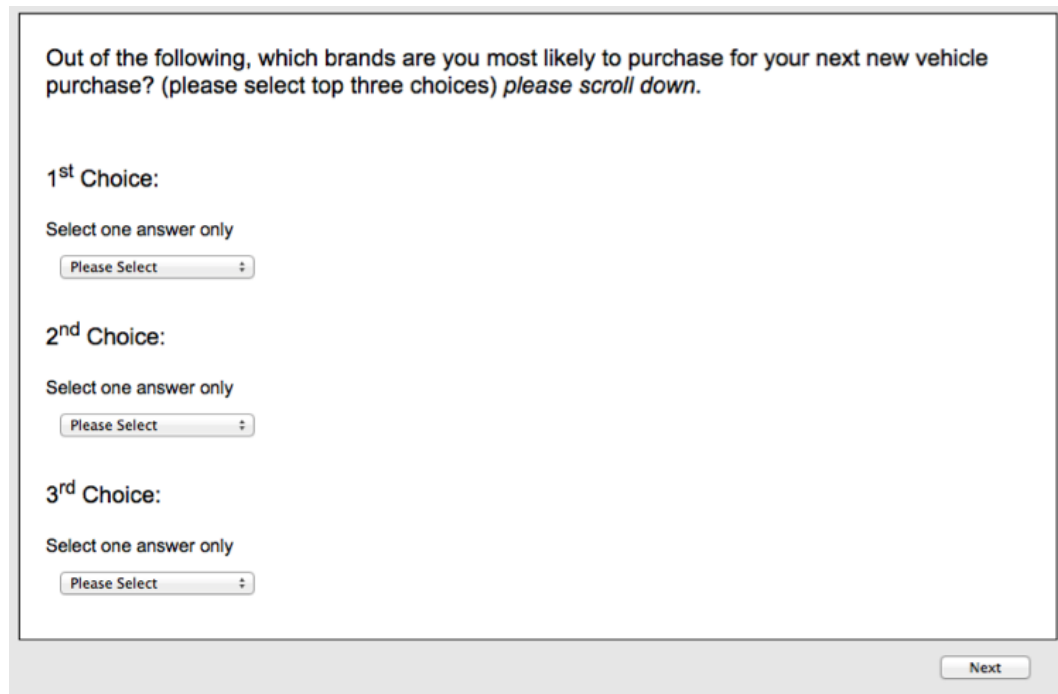
Minivan or Van
(for example, Honda Odyssey)



Truck
(for example, Chevrolet Silverado)



Figure 2.1: New Car Buyer Survey: Body Choice



Out of the following, which brands are you most likely to purchase for your next new vehicle purchase? (please select top three choices) *please scroll down.*

1st Choice:

Select one answer only

Please Select ▾

2nd Choice:

Select one answer only

Please Select ▾

3rd Choice:

Select one answer only

Please Select ▾

Next

Figure 2.2: New Car Buyer Survey: Brand Choice

Respondents are then shown four sets of five vehicles, as shown in Figure 2.3, and in each set are asked to choose which of the five vehicles they are most likely to select for their next new vehicle purchase. The total set of twenty vehicles respondents choose from includes all conventional vehicles (including internal combustion engine vehicles, hybrid electric vehicles, and diesel-fueled vehicles) on the new vehicle market as of fall of 2013 that are of both the top brand and top body selected by respondents. The remainder of the twenty includes a random draw of vehicles that are of the top body choice and second or third brand choice, or of the second body choice and top brand choice. In cases where the set of vehicles that meets these criteria is less than twenty, the remainder of the vehicles are a random selection of vehicles that are of either one of the top body selections or of the top brand selections. Finally, respondents are asked to choose which one of the four vehicles chosen as top picks out of the twenty vehicles in the previous five questions they are most

likely to select for their next new vehicle purchase, as shown in Figure 2.4. This ‘top’ vehicle and its characteristics are carried through to subsequent questions in the survey.

If the set of vehicles to choose from were those in the table below, what would your choice be?

For QC: 'MercedesBenzcompactsedan2','Nissancompactsedan1','AudicompactSUV5','MitsubishicompactSUV1','VolkswagencompactSUV1'

	Vehicle 1	Vehicle 2	Vehicle 3	Vehicle 4	Vehicle 5
Brand and Model	Mercedes Benz C-Class Sedan	Nissan Sentra Sedan	Audi SQ5 SUV	Mitsubishi Outlander Sport SUV	Volkswagen Tiguan SUV
Refueling cost (per mile)	\$0.18	\$0.15	\$0.20	\$0.17	\$0.22
Purchase price	\$35,350	\$15,990	\$51,900	\$19,470	\$22,995
Select your first choice	☐	☐	☐	☐	☐

Next

Figure 2.3: New Car Buyer Survey: Top Vehicle Choice

Here are the vehicles you selected earlier as your top choices. From these, please pick your overall first choice and second choice of vehicle that you would be most likely to purchase if you were purchasing a new vehicle now.

For QC: 'Fordcompactsedan2','Hondacompactsedan1','Nissancompactsedan1','ToyotacompactSUV1'

	Vehicle 1	Vehicle 2	Vehicle 3	Vehicle 4
Brand and Model	Ford Focus Sedan	Honda Civic Sedan	Nissan Sentra Sedan	Toyota RAV4 SUV
Refueling cost (per mile)	\$0.15	\$0.14	\$0.15	\$0.17
Purchase price	\$16,310	\$18,165	\$15,990	\$23,300
Select your first choice	☐	☐	☐	☒
Select your second choice	☐	☒	☐	☐

Next

Figure 2.4: New Car Buyer Survey: Top Vehicle Choice

The purpose of selecting a top conventional vehicle is twofold. First, it allows the respondent to self-identify with the subspace of the large new vehicle market that

she is most likely to purchase from in the future. This is important because PEV availability is currently constrained to a subset of brands and body types (mostly small sedans and hatchbacks). Second, we pivot off the top vehicle in the subsequent choice experiment, meaning that respondents choose between conventional, BEV, and PHEV versions of their top vehicles, and price of the alternatives is a function of the price of the respondent's top vehicle. This results in respondents facing more realistic choices.

Respondents are provided with information on BEV and PHEV technologies and introduced to PEV attributes, including refuel price, electric range, and single-occupant high occupancy vehicle (HOV) lane access. Finally, respondents are asked to choose between the conventional version, two BEV versions, and two PHEV versions of the vehicle they previously indicated as their top choice. Attribute levels vary for each vehicle version, with price pivoting off the price of the existing conventional vehicle. An example choice set is shown in Figure 2.5. By choosing between five versions of the top vehicle, respondents are encouraged to assume that everything else (e.g., trim and performance) except the listed attributes are identical. This allows us to see how respondents make tradeoffs between vehicle technology, price, refuel cost, electric range, and HOV lane access.

Please choose the vehicle you would be most likely to purchase if you were purchasing a new vehicle.

	Vehicle 1	Vehicle 2	Vehicle 3	Vehicle 4	Vehicle 5
Fuel Type	gasoline	all-electric	all-electric	dual-fuel	dual-fuel
Brand and Model	Toyota RAV4 SUV	Toyota RAV4 SUV	Toyota RAV4 SUV	Toyota RAV4 SUV	Toyota RAV4 SUV
Electric range	0 miles	75 miles	200 miles	60 miles	10 miles
Gasoline range	300 miles	0 miles	0 miles	300 miles	300 miles
Fuel cost per gasoline mile	\$0.18 Like \$4.40 gal gas	n/a	n/a	\$0.12 Like \$2.80 gal gas	\$0.08 Like \$2.00 gal gas
Fuel cost per electric mile	n/a	\$0.06 Like \$1.50 gal gas	\$0.06 Like \$1.50 gal gas	\$0.04 Like \$0.90 gal gas	\$0.06 Like \$1.50 gal gas
HOV Access	No	No	No	Yes	Yes
Purchase Price	\$23,300	\$29,125	\$34,950	\$26,795	\$24,465
Select your top choice	☐	☐	☐	☐	☐

Next

Figure 2.5: New Car Buyer Survey: PEV vs. Conventional Vehicle Choice Module

In order to validate the new car buyer survey data, we cross-check the sample of new car buyers and vehicle class share with the Caltrans 2010-2012 California Household Travel Survey (Caltrans, 2013). We also compare our estimated vehicle brand shares with the actual market shares from the California New Car Dealer Association's California Auto Outlook from the fourth quarter of 2013 (CNCDA, 2013). These comparisons are shown in Tables 2.1 and 2.2.

Table 2.1: UCLA New Car Buyer Survey Population[†]

	Caltrans Survey, Full Population, Weighted Population	Caltrans Survey, New Car Buyers, Weighted Population	UCA New Car Buyer Survey, Weighted Population
Household Size			
1 person	24.5%	16.3%	13.2%
2 people	30.0%	30.2%	33.5%
3 people	16.4%	18.7%	19.8%
More than or equal to 4 people	29.1%	34.9%	33.4%
Number of Household Vehicles			
None	8.0%	3.7%	2.8%
1	32.7%	26.3%	29.6%
2	37.2%	42.9%	42.3%
More than or equal to 3 vehicles	22.0%	27.2%	25.3%
Ethnicity			
White	68.7%	75%	75.3%
African American	4.4%	4%	6.5%
Multi-Racial	7.1%	3%	1.5%
Other	19.8%	18.6%	16.8%
Household Ownership			
Own	72.2%	76.8%	62.0%
Rent	27.6%	23.0%	35.0%
Other	0.1%	0.0%	2.9%
Income			
<10k	5.6%	2.9%	5.1%
10-25k	16.2%	9.8%	7.6%
25k-35k	10.4%	7.4%	7.7%
35k-50k	13.6%	11.7%	9.4%
50k-75k	15.9%	16.1%	16.9%
75k-100k	12.8%	15.2%	22.5%
100k-150k	11.9%	16.1%	18.8%
>150k	13.6%	21.0%	12.1%
Drivers in Household			
None	4.9%	1.6%	0.3%

[†]: Compared to Caltrans (2013) California 2010-2012 Household Travel Survey

Continued on next page

Table 2.1: UCLA New Car Buyer Survey Population,[†] continued from previous page

	Caltrans Survey, Full Population, Weighted Population	Caltrans Survey, New Car Buyers, Weighted Population	UCA New Car Buyer Survey, Weighted Population
1	30.9%	23.2%	19.4%
2	45.2%	50.9%	51.1%
3	13.9%	17.4%	16.3%
More than or equal to 4 drivers	5.2%	6.8%	6.8%
Sex			
Male	48.2%	49.1%	51.3%
Female	51.8%	50.7%	48.5%
Age			
Under 18	24.2%	0.1%	0.0%
18-24	10.2%	2.0%	16.2%
25-54	38.5%	50.8%	58.0%
55-64	10.7%	27.7%	14.0%
65 or over	16.5%	19.4%	10.2%
Employment			
Employed	54.0%	66.7%	63.3%
Unemployed	46.0%	32.9%	36.7%
Household Type			
Single family, detached	69.2%	74.9%	64.9%
Single family, attached	7.8%	7.3%	9.9%
Mobile Home	3.3%	1.9%	2.6%
Building with 2 or more apartments	19.5%	15.7%	22.2%
Boat, RV, Van, etc.	0.0%	0.0%	0.2%
Education			
Not a high school graduate, 12 grade or less	7.4%	3.4%	7.1%
High school graduate	14.8%	11.0%	24.7%
Some college credit but no degree	18.7%	18.1%	23.2%
Associate or technical school degree	11.4%	11.0%	10.6%
Bachelor's or undergraduate degree	26.2%	30.4%	21.0%
Graduate or professional degree	21.4%	26.0%	13.2%
Vehicle Body Type			
Sedan	47.7%	46.3%	42.2%

[†]: Compared to Caltrans (2013) California 2010-2012 Household Travel Survey

Continued on next page

Table 2.1: UCLA New Car Buyer Survey Population,[†] continued from previous page

	Caltrans Survey, Full Population, Weighted Population	Caltrans Survey, New Car Buyers, Weighted Population	UCA New Car Buyer Survey, Weighted Population
SUV	18.0%	19.9%	28.3%
Truck	11.5%	10.5%	3.1%
Coupe	6.5%	6.2%	6.4%
Convertible	1.2%	1.4%	9.8%
Hatchback	3.6%	3.7%	5.6%
Wagon	3.1%	3.3%	2.3%
Minivan or Van	8.3%	8.7%	2.2%

[†]: Compared to Caltrans (2013) California 2010-2012 Household Travel Survey

2.4.3 Simulations

We predict PEV sales as follows:

1. Estimate $Prob_i(M_k)$ for each income class using a rank-ordered logit. Predicted probabilities from this estimation are shown in Table 2.2.
2. Estimate $Prob_i(B_k)$ using a conditional logit. Covariates include body-specific constants and interactions with number of children and number of cars in household. The estimation results are shown in Table 2.4. Predicted probabilities of purchasing different body types are different for individuals with different numbers of children and household vehicles. Table 2.4 shows the average probabilities across the sample.
3. Estimate $Prob_i(V_k|M_k, B_k)$ using a conditional logit. Covariates include purchase price (MSRP), refueling cost, electric range, BEV and PHEV constants,

and an indicator for single-occupant HOV lane access. The estimation results are shown in Table 2.5.

4. Using the representative sample of new car buyers from the survey and the characteristics of existing conventional and PEVs on the market², predict PEV purchase probabilities for each individual in the sample according to Equation 2.20. Integrate PEV purchase probabilities over the weighted sample of new car buyers.
5. Reduce PEV purchase prices by specified rebate amount and redo step 4 to predict probabilities of purchasing existing PEVs given the different levels of rebates

Table 2.2: Estimation Results: Brand Choice

	Actual CA		Probability of Purchase as Estimated by a Rank-Ordered Logit							
	Market	Weighted	All	Income	Income	Income	Income	Income	Income	
	Share	Survey Share	Incomes	Under \$25k	\$25-\$50k	\$50-\$75k	\$75-\$100k	\$100-\$175k	Over \$175k	
Acura	1.4%	3.0%	2.7%	2.7%	2.2%	3.3%	2.3%	2.6%	4.2%	
Audi	1.7%	3.8%	3.2%	4.7%	1.1%	2.8%	3.0%	2.8%	9.4%	
BMW	4.0%	5.0%	4.5%	3.1%	3.1%	3.6%	4.1%	6.3%	8.4%	
Buick	0.5%	1.7%	1.3%	1.9%	0.5%	1.3%	0.3%	2.6%	1.8%	
Cadillac	0.8%	1.4%	1.1%	1.5%	0.6%	2.4%	0.7%	0.8%	1.3%	
Chevrolet	7.4%	9.0%	8.8%	7.4%	9.7%	8.8%	11.1%	7.6%	4.9%	
Chrysler	0.6%	1.6%	1.2%	2.1%	1.7%	0.6%	0.9%	1.4%	0.5%	
Dodge	2.2%	2.7%	2.7%	5.7%	3.3%	2.7%	2.3%	1.2%	2.4%	
Fiat	0.5%	0.7%	1.0%	3.3%	0.4%	0.2%	0.5%	1.3%	0.0%	
Ford	10.8%	10.8%	10.9%	10.8%	9.5%	10.0%	12.5%	12.3%	6.5%	
GMC	1.4%	1.7%	1.6%	3.0%	3.1%	0.9%	0.7%	1.2%	0.8%	
Honda	12.1%	15.2%	15.4%	16.9%	15.5%	17.4%	17.1%	12.2%	12.5%	
Hyundai	3.9%	2.9%	3.3%	1.9%	5.0%	3.7%	2.2%	4.1%	1.7%	
Infiniti	0.9%	1.2%	1.1%	1.1%	1.0%	0.6%	2.1%	0.9%	0.1%	
Jaguar	0.2%	0.1%	0.4%	0.4%	0.1%	0.0%	0.3%	0.9%	0.2%	
Jeep	1.9%	1.6%	1.7%	2.2%	2.1%	2.3%	1.1%	1.5%	1.3%	
Kia	3.4%	1.7%	2.0%	2.8%	2.5%	1.9%	1.5%	1.9%	0.5%	
LandRover	0.5%	0.6%	0.8%	0.1%	1.2%	1.4%	0.8%	0.5%	1.0%	
Lexus	3.2%	3.1%	3.4%	1.2%	4.7%	2.9%	2.9%	3.9%	6.2%	
Lincoln	0.3%	0.5%	0.8%	1.8%	0.0%	0.2%	0.7%	1.3%	0.8%	
Mazda	2.2%	1.5%	1.3%	0.7%	2.3%	0.6%	0.6%	2.0%	1.1%	
Mercedes	3.2%	2.2%	2.0%	0.3%	2.0%	1.6%	1.7%	2.7%	4.0%	
MINI	0.8%	0.6%	0.5%	0.3%	0.2%	0.7%	0.2%	1.2%	0.3%	
Mitsubishl	0.4%	0.2%	0.6%	0.6%	0.8%	1.4%	0.5%	0.0%	0.0%	
Nissan	7.5%	4.2%	4.6%	3.9%	5.1%	5.7%	4.8%	4.0%	2.8%	
Porsche	0.6%	0.2%	0.4%	0.2%	0.1%	0.6%	0.3%	0.3%	1.5%	
Scion	1.0%	0.8%	1.2%	2.8%	0.5%	1.5%	1.8%	0.3%	0.7%	
Smart	1.0%									
Subaru	2.5%	2.6%	2.2%	1.4%	3.1%	1.3%	1.3%	2.4%	5.7%	
Tesla	0.5%	0.6%								
Toyota	17.5%	15.8%	16.4%	12.5%	16.2%	17.3%	17.9%	16.2%	16.7%	
Volkswagen	3.4%	2.0%	2.1%	1.7%	2.1%	1.0%	2.9%	2.7%	1.2%	
Volvo	0.4%	0.9%	0.9%	0.9%	0.5%	1.4%	0.7%	0.8%	1.5%	

²The PEVs on the market as of fall 2013 and their characteristics are shown in Table 2.10 in the Appendix.

Table 2.3: Estimation Results: Body Choice

Body Type	Average Probability
Compact Sedan	15.2%
Midsize Sedan	16.0%
Full-size Sedan	9.5%
Compact SUV	12.8%
Midsize SUV	11.1%
Full-size SUV	6.8%
Wagon	2.4%
Hatchback	5.7%
Coupe	7.5%
Van or Minivan	2.2%
Truck	3.5%
Convertible	7.3%

Table 2.4: Estimation Results: Body Choice

Variable	Estimated Coefficient
Compact Sedan	1.662*** (0.108)
Midsized Sedan	1.690*** (0.108)
Full-size Sedan	1.028*** (0.111)
Compact SUV	1.455*** (0.110)
Midsized SUV	1.295*** (0.112)
Full-size SUV	0.667*** (0.118)
Van or Minivan	-0.497*** (0.163)
Hatchback	0.616*** (0.126)
Wagon	-0.394** (0.157)
Compact *Number Children	-0.201*** (0.049)
Midsized*Number Children	-0.171*** (0.051)
Sportscar*Number Vehicles	0.248*** (0.030)
Observations	28,959

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 2.5: Estimation Results: Vehicle Choice

Variable	Estimated Coefficient
Vehicle Price*Income Under \$25k	-0.075*** (0.028)
Vehicle Price*Income \$25-50k	-0.062*** (0.023)
Vehicle Price*Income \$50-75k	-0.048*** (0.016)
Vehicle Price*Income \$75-100k	-0.054*** (0.018)
Vehicle Price*Income \$100-175k	-0.038*** (0.014)
Vehicle Price*Income Over \$175k	-0.089*** (0.025)
BEV*SedanHatchback	-1.989*** (0.205)
BEV*SUV	-2.090*** (0.250)
BEV*Sportcar	-2.208*** (0.278)
BEV*VanTruck	-1.687*** (0.336)
PHEV	-0.333** (0.167)
Range	0.009*** (0.001)
Refuel	-0.038 (0.041)
HOV	0.261*** (0.058)
Observations	24,940

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note on Substitution Possibilities in the Model

Each individual has a probability of purchasing each vehicle. The probability of an individual purchasing a Volt is the probability of her choosing a Chevrolet times the probability of her choosing a compact sedan times the probability of her

choosing the Volt over alternative Chevrolet compact sedans.

The probability of choosing each brand is estimated using a rank ordered logit and is only a function of household income since almost all of the brands offer a range of body types. The implicit substitution pattern across brands is the proportionate one associated with the standard independence of irrelevant alternatives assumption. However, because all brands are assumed to be available, there is effectively no induced substitution across brands.

The probability of choosing each body type is estimated using a conditional logit as a function of respondents' top body picks and household demographics and using the model to predict the probabilities for each individual. Individuals' probabilities can change, but only as a function of household demographics (i.e., number of children and number of household vehicles). Therefore, in this model there is effectively no induced substitution across bodies as a function of vehicle price.

However, even if an individual's most preferred body type is a compact sedan, her probability of purchasing a RAV4 BEV (an SUV) will still change as the rebate for the RAV4 increases, since the individual has a full set of probabilities and the rebate increases the individual's probability of purchasing a RAV4 over other Toyota SUVs. Effectively, the model assumes that a rebate on a PEV in a given class impacts an individual's probability of purchasing that PEV versus other vehicles in that class, but does not impact the individual's probability of purchasing a vehicle in the given class.

2.4.4 State Level Plug-In Electric Vehicle Policies

Currently, several states offer financial incentives that reduce the purchase price for PEVs through direct rebate, tax credit, and sales tax exemptions. Table 2.6 shows the incentives offered by these states. The amount of incentive PEV buyers

receive can be determined through a few different methods. California provides fixed rebates, and the amount is lower for PHEVs than BEVs. Some other states, such as Massachusetts and Pennsylvania, provide fixed amount of rebates for vehicles with battery capacity above a certain threshold. Colorado, Maryland, and South Carolina determine the amount of incentive by battery capacity, and while they set a maximum amount for rebate, they do not fix the amount for which each vehicle model is eligible. In states like Illinois, Georgia, Louisiana, and West Virginia, PEV buyers multiply the MSRP by a percentage to determine the incentive amount they are eligible for; if the amount is above the maximum set by the state, they receive the maximum incentive available. New Jersey and Washington State provide sales tax exemptions for BEVs, but not PHEVs.

The California Clean Vehicle Rebate Projects currently provide rebates of \$2,500 for BEVs and \$1,500 for PHEVs. As of August 2014 this program had offered more than 50,000 rebates totaling over \$100 million since its inception in 2010. Plug-in electric vehicles are also eligible to use high occupancy vehicle lanes in California until January 1, 2019.

Table 2.6: State Level Incentives

State	CA	CO	GA	IL	LA
Incentive type	Rebate	Tax Credit	Tax Credit	Rebate	Tax Credit
Maximum amount for PHEV	\$1,500	\$6,000.00	\$0.00	\$4,000.00	\$3,000.00
Maximum amount for BEV	\$2,500	\$6,000.00	\$5,000.00	\$4,000.00	\$3,000.00
Maximum amount for a Chevrolet Volt (\$35,170 for a 2015 model, 17.1 kwh)	\$1,500	\$4,731.57	\$0.00	\$3,517.00	\$3,000.00
Maximum amount for a Nissan LEAF (\$29,010 for 2015 model, 24 kwh)	\$2,500	\$5,162.40	\$5,802.00	\$2,901.00	\$2,901.00
How is it determined?	Fixed, by fuel type	A formula of purchase price (deducting federal tax credit) times battery capacity in kWh then divided by 100	20% of purchase price or \$5,000, whichever is less	10% of MSRP, up to \$4,000 for eligible models	10% of the vehicle purchase price, or \$3,000, whichever is less

State	MD	MA	NJ	PA	SC
Incentive type	Tax Credit	Rebate	Sales Tax Exemption	Rebate	Tax Credit
Maximum amount for PHEV	\$3,000	\$2,500.00	N/A	\$2,000.00	\$2,000.00
Maximum amount for BEV	\$3,000	\$2,500.00	N/A	\$2,000.00	\$0.00
Maximum amount for a Chevrolet Volt (\$35,170 for a 2015 model, 17.1 kwh)	\$2,138	\$2,500.00	\$0.00	\$2,000.00	\$2,000.00
Maximum amount for a Nissan LEAF (\$29,010 for 2015 model, 24 kwh)	\$3,000	\$2,500.00	\$2,030.70	\$2,000.00	\$0.00
How is it determined?	\$125 per kWh battery capacity	Fixed, by battery capacity	Zero-emission vehicles	By battery capacity (PHEVs with battery capacity less than 10 kwh receives \$1,000	Base tax credit is \$667 for a car that has 4kwh batteries. Each add'l kwh receives another \$111.

State	TX	UT	WA	WV
Incentive type	Rebate	Tax Credit	Sales Tax Exemption	Tax Credit
Maximum amount for PHEV	\$2,500	\$605.00	N/A	\$7,500.00
Maximum amount for BEV	\$2,500	\$605.00	N/A	\$7,500.00
Maximum amount for a Chevrolet Volt (\$35,170 for a 2015 model, 17.1 kwh)	\$2,500	\$605.00	\$0.00	\$7,500.00
Maximum amount for a Nissan LEAF (\$29,010 for 2015 model, 24 kwh)	\$2,500	\$605.00	\$87.03	\$7,500.00
How is it determined?	Fixed for eligible models	Fixed	Vehicles that run exclusively on electricity, natural gas, propane and other alternative fuels	35% against purchase price up to \$7,500

2.5 Results and Discussion

Table 2.7: PEVs Sold by Type of Policy

Policy	Income	BEV Rebate	PHEV Rebate	Baseline BEVs Sold	Baseline PHEVs Sold	Add'l BEVs Sold	Add'l PHEVs Sold	Additional PEVs Sold	Total PEVs Sold
Status Quo Policy	Under \$25k	\$2,500	\$1,500	2,899	6,203	473	719	9,699	158,335
	\$25-\$50k	\$2,500	\$1,500	6,065	18,191	775	1,278		
	\$50-\$75k	\$2,500	\$1,500	10,313	18,667	664	963		
	\$75-\$100k	\$2,500	\$1,500	6,349	16,981	645	1,001		
	\$100-\$175k	\$2,500	\$1,500	19,822	35,735	985	1,250		
	Over \$175k	\$2,500	\$1,500	4,060	3,371	557	389		
Policy 1: Equaling Rebates	Under \$25k	\$2,000	\$2,000	2,899	6,203	373	805	10,602	159,258
	\$25-\$50k	\$2,000	\$2,000	6,065	18,191	614	1,716		
	\$50-\$75k	\$2,000	\$2,000	10,313	18,667	528	1,290		
	\$75-\$100k	\$2,000	\$2,000	6,349	16,981	512	1,342		
	\$100-\$175k	\$2,000	\$2,000	19,822	35,735	784	1,670		
	Over \$175k	\$2,000	\$2,000	4,060	3,371	440	526		
Policy 2: Uniformly Decreasing Rebates	Under \$25k	\$2,000	\$1,000	2,899	6,203	373	512	6,999	155,655
	\$25-\$50k	\$2,000	\$1,000	6,065	18,191	614	846		
	\$50-\$75k	\$2,000	\$1,000	10,313	18,667	528	639		
	\$75-\$100k	\$2,000	\$1,000	6,349	16,981	512	664		
	\$100-\$175k	\$2,000	\$1,000	19,822	35,735	784	832		
	Over \$175k	\$2,000	\$1,000	4,060	3,371	440	255		
Policy 3: Vehicle Price Cap at \$60,000	Under \$25k	\$2,500	\$1,500	2,899	6,203	410	719	8,651	157,308
	\$25-\$50k	\$2,500	\$1,500	6,065	18,191	649	1,269		
	\$50-\$75k	\$2,500	\$1,500	10,313	18,667	515	944		
	\$75-\$100k	\$2,500	\$1,500	6,349	16,981	507	995		
	\$100-\$175k	\$2,500	\$1,500	19,822	35,735	847	1,227		
	Over \$175k	\$2,500	\$1,500	4,060	3,371	194	377		
Policy 4: Aggressive Rebate Increase with Income Cap	Under \$25k	\$5,000	\$3,000	2,899	6,203	1,016	1,515	13,471	162,128
	\$25-\$50k	\$5,000	\$3,000	6,065	18,191	1,629	2,610		
	\$50-\$75k	\$5,000	\$3,000	10,313	18,667	1,370	1,954		
	\$75-\$100k	\$5,000	\$3,000	6,349	16,981	1,342	2,036		
	\$100-\$175k	\$0	\$0	19,822	35,735	-	-		
	Over \$175k	\$0	\$0	4,060	3,371	-	-		
Policy 5: Progressive Rebate Increase by Income	Under \$25k	\$7,500	\$4,500	2,899	6,203	1,635	2,392	9,434	158,090
	\$25-\$50k	\$5,000	\$3,000	6,065	18,191	1,629	2,610		
	\$50-\$75k	\$2,000	\$1,000	10,313	18,667	528	639		
	\$75-\$100k	\$0	\$0	6,349	16,981	-	-		
	\$100-\$175k	\$0	\$0	19,822	35,735	-	-		
	Over \$175k	\$0	\$0	4,060	3,371	-	-		
Policy 6: Aggressive Increase with Price Cap	Under \$25k	\$5,000	\$3,000	2,899	6,203	888	1,515	12,452	161,108
	\$25-\$50k	\$5,000	\$3,000	6,065	18,191	1,377	2,591		
	\$50-\$75k	\$5,000	\$3,000	10,313	18,667	1,075	1,915		
	\$75-\$100k	\$5,000	\$3,000	6,349	16,981	1,069	2,023		
	\$100-\$175k	\$0	\$0	19,822	35,735	-	-		
	Over \$175k	\$0	\$0	4,060	3,371	-	-		
Policy 7: Progressive Rebate with Price Cap	Under \$25k	\$7,500	\$4,500	2,899	6,203	1,442	2,392	8,837	157,493
	\$25-\$50k	\$5,000	\$3,000	6,065	18,191	1,377	2,591		
	\$50-\$75k	\$2,000	\$1,000	10,313	18,667	408	626		
	\$75-\$100k	\$0	\$0	6,349	16,981	-	-		
	\$100-\$175k	\$0	\$0	19,822	35,735	-	-		
	Over \$175k	\$0	\$0	4,060	3,371	-	-		

Table 2.8: PEV Rebate Costs by Type of Policy

Policy	Income	BEV Rebate	PHEV Rebate	BEV Budget	PHEV Budget	Total PEVs Sold	Total Cost (\$ Millions)
Status Quo Policy	Under \$25k	\$2,500	\$1,500	\$8,431,349	\$10,383,030	158,335	\$291
	\$25-\$50k	\$2,500	\$1,500	\$17,101,072	\$29,202,579		
	\$50-\$75k	\$2,500	\$1,500	\$27,442,629	\$29,444,460		
	\$75-\$100k	\$2,500	\$1,500	\$17,484,884	\$26,973,264		
	\$100-\$175k	\$2,500	\$1,500	\$52,018,618	\$55,478,170		
	Over \$175k	\$2,500	\$1,500	\$11,541,233	\$5,639,740		
Policy 1: Equaling Rebates	Under \$25k	\$2,000	\$2,000	\$6,545,083	\$14,016,504	159,258	\$319
	\$25-\$50k	\$2,000	\$2,000	\$13,358,461	\$39,813,000		
	\$50-\$75k	\$2,000	\$2,000	\$21,681,786	\$39,913,772		
	\$75-\$100k	\$2,000	\$2,000	\$13,721,774	\$36,646,760		
	\$100-\$175k	\$2,000	\$2,000	\$41,213,544	\$74,811,156		
	Over \$175k	\$2,000	\$2,000	\$9,000,554	\$7,793,533		
Policy 2: Uniformly Decreasing Rebates	Under \$25k	\$2,000	\$1,000	\$6,545,083	\$6,714,527	155,655	\$208
	\$25-\$50k	\$2,000	\$1,000	\$13,358,461	\$19,036,334		
	\$50-\$75k	\$2,000	\$1,000	\$21,681,786	\$19,305,549		
	\$75-\$100k	\$2,000	\$1,000	\$13,721,774	\$17,644,670		
	\$100-\$175k	\$2,000	\$1,000	\$41,213,544	\$36,566,955		
	Over \$175k	\$2,000	\$1,000	\$9,000,554	\$3,626,610		
Policy 3: Vehicle Price Cap at \$60,000	Under \$25k	\$2,500	\$1,500	\$5,525,708	\$8,734,800	157,308	\$191
	\$25-\$50k	\$2,500	\$1,500	\$12,516,008	\$26,627,751		
	\$50-\$75k	\$2,500	\$1,500	\$12,416,557	\$20,625,015		
	\$75-\$100k	\$2,500	\$1,500	\$11,125,314	\$23,355,006		
	\$100-\$175k	\$2,500	\$1,500	\$26,472,618	\$40,322,793		
	Over \$175k	\$2,500	\$1,500	\$2,510,984	\$748,341		
Policy 4: Aggressive Rebate Increase with Income Cap	Under \$25k	\$5,000	\$3,000	\$19,576,601	\$23,152,788	162,128	\$359
	\$25-\$50k	\$5,000	\$3,000	\$38,472,680	\$62,401,798		
	\$50-\$75k	\$5,000	\$3,000	\$58,415,640	\$61,862,019		
	\$75-\$100k	\$5,000	\$3,000	\$38,452,482	\$57,049,903		
	\$100-\$175k	\$0	\$0	\$0	\$0		
	Over \$175k	\$0	\$0	\$0	\$0		
Policy 5: Progressive Rebate Increase by Income	Under \$25k	\$7,500	\$4,500	\$34,009,626	\$38,679,027	158,090	\$215
	\$25-\$50k	\$5,000	\$3,000	\$38,472,680	\$62,401,798		
	\$50-\$75k	\$2,000	\$1,000	\$21,681,786	\$19,305,549		
	\$75-\$100k	\$0	\$0	\$0	\$0		
	\$100-\$175k	\$0	\$0	\$0	\$0		
	Over \$175k	\$0	\$0	\$0	\$0		
Policy 6: Aggressive Rebate Increase with Price Cap	Under \$25k	\$5,000	\$3,000	\$13,441,267	\$19,856,328	161,108	\$266
	\$25-\$50k	\$5,000	\$3,000	\$28,674,486	\$57,222,993		
	\$50-\$75k	\$5,000	\$3,000	\$27,636,150	\$44,163,728		
	\$75-\$100k	\$5,000	\$3,000	\$25,057,919	\$49,793,339		
	\$100-\$175k	\$0	\$0	\$0	\$0		
	Over \$175k	\$0	\$0	\$0	\$0		
Policy 7: Progressive Rebate with Price Cap	Under \$25k	\$7,500	\$4,500	\$24,318,527	\$33,734,336	157,493	\$167
	\$25-\$50k	\$5,000	\$3,000	\$28,674,486	\$57,222,993		
	\$50-\$75k	\$2,000	\$1,000	\$9,720,202	\$13,432,334		
	\$75-\$100k	\$0	\$0	\$0	\$0		
	\$100-\$175k	\$0	\$0	\$0	\$0		
	Over \$175k	\$0	\$0	\$0	\$0		

Table 2.9: Comparison of Policy Performance Metrics

Policy	Additional PEVs Sold	Additional PEVs Sold*	Total Cost- Effectiveness	Addt'l Dollar Needed to Induce One Addt'l PEV*	Total Cost (\$ Millions)	Total Cost* (\$ Millions)	Allocative Equity
Status Quo Policy	9,699	N/A	\$30,017	N/A	\$291	N/A	42%
Policy 1: Equaling Rebates	10,602	903 (+9%)	\$30,044	+\$27 (+0.09%)	\$319	+\$27 (+9.4%)	42%
Policy 2: Uniformly Decreasing Rebates	6,999	-2,700 (-28%)	\$29,778	-\$239 (-0.7%)	\$208	-\$83 (-28%)	42%
Policy 3: Vehicle Price Cap at \$60,000	8,651	-1,048 (-10%)	\$22,075	-\$7,942 (-26%)	\$191	-\$100 (-34%)	45%
Policy 4: Aggressive Rebate Increase with Income Cap	13,471	3,772 (+39%)	\$26,677	-\$3,340 (-11%)	\$359	+\$68 (+23%)	73%
Policy 5: Progressive Rebate Increase by Income	9,434	-265 (-3%)	\$22,743	-\$7,274 (-24%)	\$215	-\$77 (-26%)	100%
Policy 6: Aggressive Increase with Price Cap	12,452	2,753 (+28%)	\$21,349	-\$8,668 (-29%)	\$266	-\$25 (-8.7%)	72%
Policy 7: Progressive Rebate with Price Cap	8,837	-862 (-9%)	\$18,910	-\$11,107 (-37%)	\$167	-\$124 (-43%)	100%

* Compared to Status Quo Policy

We use these simulations to evaluate a variety of alternative rebate policy designs, the results of which are presented in Tables 2.7, 2.8 and 2.9. These results

characterize the performance of alternative policy designs over approximately the next 3 years (i.e., 2014-2016) in California. They assume that consumers face the same choice set of PEVs and prices that are currently available in the California market and that annual vehicle sales will be flat over the next three years.

2.5.1 Simulating the California Status Quo Rebate Policy

We first simulate the status quo rebate policy in California, which offers all income classes the same rebates of \$2,500 for the purchase of a BEV and \$1,500 for the purchase of a PHEV. Table 2.7 describes the baseline number of BEVs and PHEVs purchased by each income class (i.e., the number of BEVs and PHEVs that would have been purchased even if there was no rebate) as well as the additional vehicles induced by the policy design.

Micro-dynamics across income groups and vehicle technologies.

Next we reflect on two observed patterns predicted earlier by our model that can be observed in the simulation results for the status quo rebate policy as shown in Table 2.7. First, these simulated estimates reflect the consumers' relative ex ante preferences for PHEVs over BEVs in nearly every income class, with consumers in several income classes purchasing 2 to 3 times as many PHEVs as BEVs. Second, in general, the lower income classes have lower ex ante values for both BEVs and PHEVs, purchasing fewer vehicles than do the middle and upper-middle income classes.

Interestingly, consumers in the highest income class (above \$175,000) appear to behave somewhat differently (see Table 2.7). Their ex ante value for PEVs is lower than that of the middle income classes, perhaps reflecting their preference for high performance luxury vehicles, which are less likely to be found among existing PEVs. In addition, unlike any other income class, they prefer BEVs (4,060) to PHEVs (3,371), revealing the importance of the Tesla Model S for this income class.

A cost-effectiveness measure. For the status quo policy, the total of additional vehicles purchased across all income classes is estimated to be 9,699 over the next three years. In Table 2.8, we calculate the revenue costs by income group and by vehicle technology. Summing the rebates over vehicle type and income class gives us the estimated total status quo program costs of \$291 million over the next 3 years. Dividing the additional vehicles purchased by the total cost gives us a policy cost-effectiveness measure which we calculate to be \$30,017 per additional vehicle as shown in Table 2.9. For the status quo policy, every additional PEV purchased (over the baseline of what would have been purchased in the absence of rebates) requires California to spend \$30,017 per vehicle. Our simulation suggests that 42% of the value of the rebates allocated goes to consumers making less than \$75,000 under the status quo policy.

Comparisons with other rebate policies. Our model predicts that 148,636 PEVs would have been sold in the absence of the status quo policy. Note, though, that these consumers would still be eligible for the larger federal tax incentive (up to \$7,500) as well as local government rebates and reduced-cost parking and charging policies. We find that the current rebate, which has a weighted value across BEVs and PHEVs of about \$1,838, induces the purchase of 9,699 PEVs, a 7% increase in PEV sales, or a 0.2% increase in total market share. As a point of comparison, Sierzechula et al. (2014) use ordinary least squares regression analysis of financial incentives in 30 countries to suggest that an increase in rebate level of \$1,000 is correlated with an increase in the observed market share of .06% for PEVs.

We are able to compare this estimate to two other types of vehicle rebate studies, those for hybrid electric vehicles (HEVs) and those for scrappage, or “Cash for Clunkers,” programs. Analyzing the Energy Policy Act of 2005, Jenn et al. (2013) find that for most vehicles, rebates levels in the \$1,000-\$3,000 range are correlated with a 7%-12% increase in sales. Gallagher, Sims, and Muehlegger (2011)

find that a tax incentive of \$1,000 is associated with a 3%-5% increase in sales for HEVs, while a comparable sales tax waiver is associated with a 45% increase in HEV sales. Analyzing the Canadian Hybrid Electric Vehicle rebate programs in different provinces, a Chandra, Gulati, and Kandlikar (2010) ordinary least square regression analysis finds that a rebate increase of \$1,000 is correlated with an increase in hybrid sales of 26%.

The federal and several state Cash for Clunkers rebate programs have been evaluated. Analyzing the Consumer Assistance to Recycle and Save Act (2009), Huang (2010) uses a regression discontinuity approach to infer that an \$1,000 rebate causes a 7% increase in sales of more fuel efficient vehicles. Gayer and Parker (2013) find the same program causes a 6%-15% monthly increase in market share at various months during the program. Other evaluations include Li, Linn, and Spiller (2013) and Mian and Sufi (forthcoming).

We find that our estimate falls within the range produced by existing studies but is on the lower end of the distribution. That a rebate of a similar magnitude would be slightly less effective for PEVs than for HEVs or other fuel efficient vehicles should not be surprising for several reasons. First, PEVs require consumers behaviorally change their refueling practices, including purchasing an at-home charging station in most cases. Second, this study was conducted during a period of high unemployment and relatively lower vehicle purchases than the timeframes utilized by some of the HEV studies that produced higher market share estimates but did not control for these market conditions (Gallagher, Sims, and Muehlegger, 2011).

2.5.2 Changing Rebate Levels Across Vehicle Technologies

Alternative rebate policies 1 and 2 explore the effects of equalizing the rebates and uniformly lowering the rebates across the vehicle technologies, respectively.

Equalizing rebates across vehicle technologies. Some observers have

argued that PHEVs appear to generate similar magnitudes of electric miles traveled; therefore they should be given rebate levels comparable to BEVs. Policy 1 illustrates what would happen in this market if policymakers reduce the BEV rebate by \$500 (from \$2,500) and increase the PHEV rebate by \$500 (from \$1,500), making the effective rebate for both vehicle technologies \$2,000.

To examine the effects of Policy 1, consider the response of consumers in the \$25,000-\$50,000 income class in Table 2.7. Compared to the status quo policy, these consumers will purchase slightly fewer additional BEVs (614 versus 775, a decrease of 161 vehicles or 21%) and modestly more PHEVs (1,716 versus 1,278, an increase of 438 or 34%). The large increase in PHEV purchases reflects larger consumer *ex ante* values for the PHEVs. Therefore, more consumers were relatively more likely to buy PHEVs even before their rebate was increased.

As a result of reducing the rebate on the BEVs by \$500, its cost-effective measure (BEV budget divided by additional BEVs sold) improves (falling from \$32,691 to \$32,445 per vehicle). However, the reverse is true for the \$500 increase in rebate levels for PHEVs, causing PHEV cost-effectiveness (PHEV budget divided by additional PHEVs sold) to fall (rising from \$28,059 to \$28,981 per vehicle) compared to the status quo policy. The net effect is to slightly worsen total cost effectiveness of the policy to \$30,044 per induced PEV purchase versus \$30,017 under the status quo policy. Thus, even if the magnitude of the positive externality associated with driving a PHEV were equal to that of driving a BEV, our analysis suggests that equalizing the rebate would not be a cost-effective use of public funds. Consideration needs to be given not just to the change in the total number of PHEV vehicles sold under Policy 1 but also to the revenue opportunity costs.

This effect also is seen at the programmatic level. In comparing the status quo policy with Policy 1 of equal rebate levels, many more additional vehicles are sold under Policy 1, increasing from 9,699 to 10,602, an increase of 10% in the

number of additional PEVs purchased, which is driven by a 30% increase in the number of additional PHEVs purchased. The total cost of the program rises from \$291 million to nearly \$319 million. This is largely because Policy 1 increases the rebate by \$500 to the 99,148 consumers who would have purchased a PHEV in the absence of any rebate, and even though it induces an additional 7,349 PHEVs to be purchased. This is offset slightly by a \$500 rebate reduction to the 49,508 BEVs that would have been purchased without the policy and a reduction in the number of additional BEVs sold by only 848.

In summary, increasing relative rebates on vehicle technologies with relatively higher consumer ex ante values increases the total additional number of vehicles purchased *ceteris paribus*. However, increasing relative rebates on vehicle technologies with relatively higher consumer ex ante values *worsens the cost-effectiveness* of the overall program since it increases the magnitude of the rebate payouts to those who would have purchased the higher valued vehicle technology anyway.

Uniformly reducing the rebate levels across technologies. Policy-makers might consider uniformly reducing rebate levels because budgetary pressure or a belief that government interventions are no longer justified. In Tables 2.7 and 2.8, Policy 2 reduces both the BEV and PHEV rebate levels by \$500, from \$2,500 and \$1,500, respectively. In comparison with the status quo policy, we observe consumers in all income classes purchasing fewer additional PHEV and BEV vehicles. The total reduction in additional vehicles can be observed by comparing the 6,999 additional vehicles purchased under Policy 2 with the 9,699 additional vehicles purchased under the status quo policy, a difference of roughly 2,700 additional vehicles or a 28% reduction. Total policy costs fall by over \$80 million since both the eligible consumers in the baseline and additional consumers all receive lower rebates by \$500. However, because of the commensurate fall in the number of additional vehicles under Policy 2, the cost-effectiveness performance of Policy 2, relative to the

status quo, improves only a small amount, falling from \$30,017 to \$29,778. While uniformly lowering the eligible rebates does lower total program costs, it improves cost-effectiveness only minimally.

Allocative equity with reduced rebates. Some policymakers have suggested reducing rebate levels because they view the status quo policy as favoring wealthy consumers. We are able to evaluate the allocative impacts of moving from the status quo policy to a reduced rebate level policy, such as alternative Policy 2, which achieves a uniform reduction of \$500 in all rebates. What we observed is that allocative equity does not change greatly because levels are reduced. We use the percent of rebates allocated to consumers with incomes of less than \$75,000 as a measure of allocative equity. The status quo policy allocates 42% of rebates to consumers with incomes less than \$75,000 while Policies 1 and 2 also allocate approximately 42% to similar consumers.

2.5.3 The Effect of a Vehicle Price Cap on Rebate Eligibility

Recently policymakers at the California Air Resources Board have proposed a price cap as means to increase the effectiveness and equity of California's rebate policy. Such a policy design would allow only vehicles below a certain price level to qualify for a rebate. For Policy 3, we consider a vehicle price cap of \$60,000, the results of which we present Tables 2.7, 2.8 and 2.9. For the California market, Policy 3 would historically exclude only the Tesla Model S (a BEV) from a rebate but would prospectively also exclude the Porsche Panamera and the Cadillac ELR (both PHEVs) from a rebate. Our vehicle choice model captures the consumer response for all of these vehicles.

The results of making only vehicles under a price cap of \$60,000 eligible for the current rebates are shown in Tables 2.7, 2.8 and 2.9 by comparing Policy 3 with the status quo. Focusing on where the relative impacts are likely to be greatest,

consider consumers with incomes over \$175,000 for Policy 3. While these wealthy consumers purchase slightly fewer additional PHEVs (377 vs. 389), they purchase many fewer BEVs (194 vs. 557) when shifting from the status quo to a price cap of \$60,000. If the policy goal was to give Tesla owners fewer rebates, then this approach appears to succeed. Smaller reductions in relative purchases of PHEVs and BEVs occur for consumers in the other income classes, reflecting the fact that fewer of them are affected by a price cap of \$60,000.

In aggregate, the shift from the status quo to a price cap results in a reduction in the total number of additional vehicles being sold (8,651 vs. 9,699, a 10% reduction). This policy design also significantly improves the cost-effectiveness of each additional vehicle sold, causing the cost to fall substantially from \$30,017 to \$22,075, a 26% reduction. What was perhaps most surprising is how much the total program costs fall, from \$291 million to \$191 million, a reduction of around \$100 million, or 34%. The policy decision here may hinge on beliefs about how much technology from these high end vehicles gets filtered down later to other market segments, for example, with Toyota's adoption of a substantial amount of Tesla technology into a BEV version of its popular RAV 4.

2.5.4 Income-Tested Rebate Policies

Another proposed approach to redesigning the existing rebate program is to give consumers in lower income classes relatively higher rebates. Policymakers may choose to do this because either they know that targeting rebates towards consumers with lower ex ante values will improve cost-effectiveness or because they are concerned about improving this program's allocative equity. There are several designs this policy could take.

Policy 4 assesses an increase in rebate levels but also a cap on income eligibility, meaning consumers above a specified income (\$100,000 for this policy) do

not qualify for the rebate. All consumers making less than \$100,000 would receive a rebate of \$5,000 for BEVs and \$3,000 for PHEVs. Compared to the status quo policy, this policy design results in significantly more additional PEVs being sold; increasing from 9,699 to 13,471 for a 3,772, or 39% increase. This policy design also represents an increase in cost-effectiveness, dropping from \$30,017 to \$26,677 for a \$3,340 reduction, or an 11% improvement. However, despite reduction in dollars spent per additional vehicle, the 39% increase in the additional number of vehicles sold caused the total cost of this policy design to increase from \$291 million for the status quo to \$359 million, for an increase of over \$68 million, or 23%. Allocative equity increases from 42% for the status quo policy to 73% for this policy. Thus, this policy design improves the number of additional PEVs sold, policy cost-effectiveness, and allocative equity but it does substantially increase the total cost of the program.

We next consider a progressive rebate schedule, which is designed to bring down total program cost. Policy 5 offers progressive rebate levels with an income cap. For BEVs, this policy would offer consumers making 1) less than \$25,000, a rebate of \$7,500, 2) \$25,000-\$50,000, a rebate of \$5,000, 3) \$50,000-\$75,000, a rebate of \$2,000, and 4) over \$75,000, no rebate. Consumers purchasing a PHEV in these same income categories would receive \$4,500, \$3,000, and \$1,000, respectively. This policy results in approximately the same number of additional PEVs being sold as does the status quo policy: 9,434 vehicles compared to 9,699 vehicles for the status quo. This policy is also among the most cost-effective, comparable to the price cap policy (3) at \$22,743 per additional PEV compared to \$22,075 for the price cap policy. Its total policy costs are also among the lowest of any policy considered so far. This policy has total cost of \$215 million compared to \$291 million for the status quo policy, a reduction of \$76 million or 26%. This policy scores 100% on our allocative equity measure since all of the rebates go to consumers making less than \$75,000. *Policy 5 is therefore superior to the status quo policy along all policy*

performance dimensions.

2.5.5 Income-Tested Policies with Price Caps

Lastly, we may try to improve these income-tested policies by adding price caps. Intuitively, we expect the addition of a vehicle price cap to reduce the number of additional vehicles sold but also to improve the cost-effectiveness measure, reduce total costs, and possibly to improve allocative equity.

Policy 6 evaluates the addition of a vehicle price cap of \$60,000 to Policy 4 (Policy 4 generated the largest number of additional PEVs purchased, improved cost-effectiveness, and allocative equity but did so at the largest program costs.). Adding a vehicle price cap as in Policy 6 causes approximately 1,000 fewer vehicles to be purchased compared to Policy 4 but this still represents a 2,753 or a 28% increase in additional vehicles purchased over the status quo policy. Cost-effectiveness improves significantly falling from \$26,667 to \$21,349 per additional vehicle purchased when comparing policies 4 and 6. Allocative equity is about the same across the policies 4 and 6. However, total program cost falls dramatically from \$360 million to \$266 million, a \$54 million or 15% reduction comparing policies 4 and 6. It should be noted that Policy 6 costs of \$266 million are less than the \$291 million of the status quo program. Policy 6 represents an improvement over the status quo policy along all performance dimensions.

Policy 7 adds a vehicle price cap to Policy 5, which has a progressive rebate schedule capping income eligibility at \$75,000. Recall that Policy 5 was already superior to the status quo policy along all dimensions. However, adding the vehicle price cap reduces the additional number of vehicles sold to 8,837 from 9,699 under the status quo policy, a reduction of 862 vehicles or 9%. While a net reduction in the number additional vehicles sold may be viewed as an unacceptable consequence of this policy by some, it does produce the greatest improvement in policy cost-

effectiveness, reducing public dollars spent per additional vehicle from \$30,017 to \$18,910, a reduction of \$11,007 or 37% per vehicle. It also reduces the total program costs from \$291 million to \$167 million, a savings of \$124 million, or 43%.

2.6 Conclusion

Our objective has been to illustrate how commonly used set of “second-best” policies can leverage several types heterogeneity among consumers or products in order improve policy performance. These include differences in consumers’ ex ante value (e.g., willingness to pay) for specific technologies, their marginal utility of income, and the price levels of the technologies. These difference can be used to improve a broader set of policies that rely on price subsidies, rebates, tax credits, sales tax exemptions, and subsidized financing to target consumers’ adoption technologies such as alternative fuels and vehicles, energy and water efficient technologies, and renewable energy technologies, among others.

As we show, the economic information needed to identify how to incorporate consumer heterogeneity can be obtained from relatively simple empirical consumer choice studies. Even in the case of mis-measurement, e.g., if the estimated price elasticity of demand is inaccurately estimated, the basic tenants of our theoretical model and proposed policy modifications still hold. The results of our policy simulations would be the same in direction though likely of increased or decreased magnitude.

Our basic approach enables economists to identify feasible superior policy designs. Our specific analysis suggests that policymakers can re-design PEV rebate programs such as California’s to induce the sale of more PEVs, achieving greater allocative equity at a lower total cost to the state taxpayers. First, we focus on two policy designs that have the ability to 1) increase total or hold constant the additional PEVs purchased, 2) decrease total government costs, and 3) increase

allocative equity. Our analysis of Policy 4 shows that without a significant reduction in the number of additional PEVs purchased, we can dramatically increase allocative efficiency while saving \$77 million compared to the current policy. Similarly, Policy 6 offers the greatest number of additional PEVs sold (28% greater than the status quo) for a policy that costs less (by 9%) than the status quo policy.

2.7 Acknowledgement

Chapter 2, in full, is currently under submission for publication of the material. DeShazo, J.R.; Sheldon, Tamara L.; Carson, Richard T. The dissertation author was the primary investigator and author of this paper.

2.8 Chapter 2 Appendix

Table 2.10: PEVs on the Market as of Fall 2013

Make	Body	Model	Type	MSRP	Range	Refuel (mpge)	Refuel \$/gal
Smart	convertible		BEV	\$ 28,000	68	107	0.77
Smart	hatchback		BEV	\$ 25,000	68	107	0.77
Chevrolet	compact sedan	Volt	PHEV	\$ 34,185	38	98	0.84
Ford	compact sedan	Focus Electric	BEV	\$ 35,170	76	99	0.83
Toyota	compact SUV	RAV4 EV	BEV	\$ 49,800	103	74	1.11
Chevrolet	hatchback	Spark	BEV	\$ 26,685	82	109	0.76
Chevrolet	hatchback	Spark	BEV	\$ 27,010	82	109	0.76
Fiat	hatchback	500 Elettrica	BEV	\$ 31,800	90	108	0.76
Honda	hatchback	Fit EV	BEV	\$ 36,625	82	105	0.78
Nissan	hatchback	Leaf	BEV	\$ 29,650	73	102	0.81
Nissan	hatchback	Leaf	BEV	\$ 32,670	73	102	0.81
Nissan	hatchback	Leaf	BEV	\$ 35,690	73	102	0.81
Toyota	hatchback	Prius Plug In	PHEV	\$ 30,800	11	95	0.87
Toyota	hatchback	Prius Plug In	PHEV	\$ 35,715	11	95	0.87
Chevrolet	coupe	Cadillac ELR	PHEV	\$ 75,000	37	98	0.84
Porsche	full-size sedan	Panamera S E-Hybrid	PHEV	\$ 99,000	20	98	0.84
Tesla	midsize sedan	Model S	BEV	\$ 71,070	265	94	0.88
Tesla	midsize sedan	Model S	BEV	\$ 81,070	265	94	0.88
Tesla	midsize sedan	Model S	BEV	\$ 94,570	265	94	0.88
Ford	midsize sedan	Fusion Energi	PHEV	\$ 35,525	21	92	0.90
Ford	midsize sedan	Fusion Energi	PHEV	\$ 37,325	21	92	0.90
Honda	midsize sedan	Accord Plug In	PHEV	\$ 39,780	10	105	0.78
Ford	wagon	C-Max Energi	PHEV	\$ 32,920	21	100	0.82

Chapter 3

How does the presence of HOV lanes affect plug-in electric vehicle adoption in California?
A generalized propensity score approach

3.1 Introduction

Policymakers commonly design policies with the goal of increasing consumers' adoption of newer, less-polluting technologies, including advanced clean vehicles.¹ A common policy approach has been to grant these advanced clean vehicles access to high occupancy vehicle (HOV) lanes in an effort to increase the utility that drivers derive from the use of these vehicles.² Historically, nine states adopted such policies for hybrid vehicles. Currently fourteen states have similar policies for plug-in electric and natural gas vehicles with more states likely to offer future policies for hydrogen fuel cell vehicles (DeShazo et al., 2015).

In this paper we identify the causal impacts of these policies on the adoption of plug-in electric vehicles (PEVs) in the state of California between 2010 and 2013. Complicating the evaluation of this policy is the fact that HOV lanes are geographically distributed highly unevenly throughout the state of California as are prospective new car buyers who might adopt these vehicles. Researcher have shown that the average advanced vehicle owner is willing to pay a premium for access to HOV lanes in the case of both hybrid vehicles (Shewmake and Jarvis, 2014) and PEVs (DeShazo, Sheldon, and Carson, 2015). In light of this it is somewhat puzzling that several correlational studies have shown a weak relationship between hybrid sales with HOV lane access (Diamond, 2008; Gallagher, Sims, and Muehlegger, 2011). What has been missing in this literature, and what we estimate for PEVs, is the causal relationship between variation in geographic access to the HOV lane miles and geographic sales of advanced clean vehicles.

Specifically, we use a generalized propensity score matching approach to estimate the impact of HOV lanes on PEV sales, controlling for the probability of

¹Other types of incentives in place to encourage PEV adoption include a federal rebate program, the California Clean Vehicle Rebate program, reduced electricity rates for PEVs and publicly subsidized refueling infrastructure.

²For a discussion of the social costs of these policies see Bento et al. (2014) and Shewmake and Jarvis (2014).

treatment (HOV lanes density). Standard propensity score matching conditions on a binary variable, e.g., whether or not a census tract is near HOV lanes. However, we are interested in a continuous conditioning variable, namely how many miles of HOV lanes a census tract is near. First, we estimate a generalized propensity score (GPS) for each census tract, which tells us how many miles of HOV lanes are likely to be within a given radius of a census tract, based on a large set of covariates such as income, race, age, education, political views, and commuting patterns. Then, controlling for propensity score, we estimate a dose-response function, which tells us how PEV sales change as the number of nearby HOV lanes increases. Plug-in electric vehicles (PEVs), which include battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs), have been gaining traction in the California market in recent years. We evaluate effects for both BEVs and PHEVs.

We motivate our empirical analysis with a theoretical model, wherein a consumer can opt to pay a premium for a private good (upgrade to a PEV) in order to gain access to a certain quality and quantity of a public good (HOV lanes). At the optimal level of public good provision, the ratio of the marginal benefit to marginal cost of the quantity of HOV lanes is equal to the ratio of the marginal benefit to the marginal cost of the quality of HOV lanes. In order to craft the optimal policy for quasi-public goods such as HOV lanes, policy makers need to set the price of access, the quantity of public good, and the quality of the public good. Our approach could be applied to other quasi-public goods in order to identify the shape of the marginal utility curve over a spectrum of varying quantity or quality of the public good.

3.2 Theoretical Model

Consumers can purchase a private good, a PEV, for a premium over a conventional vehicle to gain access to a certain quantity and quality of public good, HOV lanes. Let the price of a conventional, internal combustion engine (ICE) ve-

hicle be p_{ice} . Suppose there exists a PEV that is otherwise identical to the ICE. The PEV can be purchased for a premium of α over the ICE vehicle price, i.e., $p_{pev} = p_{ice} + \alpha$. Consumer i will purchase the PEV if the utility from the PEV is greater than the utility from the ICE that she is otherwise planning to purchase, i.e., if $u_{pev} > u_{ice}$.

Suppose a social planner has the ability to create q miles of HOV lanes of quality l at cost $c(q, l)$ to which PEVs have free single-occupancy access. We can think of quality as a measure of desirability of HOV lane placement, congestion, and other factors that may influence consumer utility from driving in a given HOV lane. The social planner seeks to maximize the utility to consumers of purchasing PEVs, subject to a budget $\mathfrak{B}$:

$$\max_{\{q, l\}} \sum_i u_{i, pev} \quad (3.1)$$

$$S.T. \ c(q, l) \leq \mathfrak{B} \quad (3.2)$$

The utility to consumer i of purchasing the ICE is her *ex ante* utility for the vehicle minus the price of the vehicle, $u_{i, ice} = v_i - p_{ice}$. The utility to consumer i of purchasing the PEV is her *ex ante* utility for the vehicle, minus the price of the vehicle, plus her utility from HOV lane access, $f_i(q, l)$, plus some value w_i , which represents the consumer's preference for the PEV relative to the ICE. For example, w_i may be positive if the consumer derives utility from knowing that she is contributing less to air pollution, or w_i may be negative if the consumer is averse to behavioral changes such as plugging the vehicle in to charge. Therefore, $u_{i, pev} = v_i - p_{ice} - \alpha + f_i(q, l) + w_i$. Equation 3.1 then becomes

$$\max_{\{q, l\}} \sum_i v_i - p_{ice} - \alpha + f_i(q, l) + w_i = \max_{\{q, l\}} \sum_i f_i(q, l) \quad (3.3)$$

The Lagrangean of the constrained maximization problem is therefore

$$\mathfrak{L} = f_i(q, l) + \lambda[\mathfrak{B} - c(q, l)] \quad (3.4)$$

Simplifying the first order conditions, we find

$$\frac{\left(\frac{\partial f_i}{\partial q}\right)}{\left(\frac{\partial c}{\partial q}\right)} = \frac{\left(\frac{\partial f_i}{\partial l}\right)}{\left(\frac{\partial c}{\partial l}\right)} \quad (3.5)$$

Equation 3.5 implies that at the optimal level of public good provision, the ratio of the marginal benefit to marginal cost of the quantity of HOV lanes is equal to the ratio of the marginal benefit to the marginal cost of the quality of HOV lanes. In our empirical section, we estimate a dose-response curve that tells us about the shape of $\frac{\partial f_i}{\partial q}$ over different ranges of q . Combined with knowledge on the marginal cost of HOV lane provision, policy makers could use this information to identify the optimal level of q .

3.3 Methodology

Propensity score matching is a technique to remove biases in the comparison of treatment groups such that the effectiveness of treatment can be estimated. Standard propensity score matching conditions on a binary treatment variable; however, we are interested in evaluating the effect of a continuous treatment, i.e., HOV lane density. Therefore we follow the generalized propensity score (GPS) matching technique laid out by Hirano and Imbens (2005) to evaluate the effect of HOV lanes on our outcome variable, PEV sales.

First we assume a distribution of treatments, N_i , given covariates, X_i . Each treatment is defined as the number of miles of HOV lanes within a 30-mile radius of the population centroid of a census tract. Covariates include a rich set of de-

mographic, geographic, and socioeconomic variables at the census tract level. Since treatments are count data, we assume that given the covariates, the treatments follow a Poisson distribution:³

$$N_i|X_i \sim \text{Poisson}(\lambda) \quad (3.6)$$

One of our two key assumptions is weak unconfoundedness, or independence of treatment given covariates, $Y_i(n) \perp N|X$, where $Y_i(n)$ is our outcome variable, PEV sales. In other words, we assume that after controlling for a rich set of census tract characteristics, assignment of HOV lanes is independent of PEV sales.⁴

We estimate the parameters of the distribution ($\hat{\lambda}$) using maximum likelihood estimation. We refer to this as the “first estimation stage.” We then calculate the estimated GPS, $\hat{R}_i$ for each census tract i :

$$\hat{R}_i = \exp\left((N_i * \ln(\hat{\lambda}) - \hat{\lambda}) - \ln(N_i!)\right) \quad (3.7)$$

In standard propensity score matching, the propensity score is the predicted probability of treatment. In the continuous case, the generalized propensity score is the probability that treatment level equals N , which in our case is the number of nearby HOV lanes.

Next we estimate the conditional expectation of the outcome as a function of treatment and GPS:⁵

³A Poisson regression results in a lower pseudo R^2 than a lognormal or negative binomial regression.

⁴The weak unconfoundedness assumption is not statistically testable. Reverse causality is one potential violation of this assumption. We cannot rule out the possibility that it is PEV sales driving HOV lane construction decisions, however, we find this unlikely to be the case. Another potential violation of this assumption is correlation between the error terms of the HOV lane variable and PEV sales, which would occur if an omitted variable affected both HOV lanes and PEV sales. We also find this to be unlikely as the decision to construct HOV lanes is made at the state level and affects many local jurisdictions. It is unlikely, though not impossible, that a census tract with a local government keen on promoting local PEV sales influences HOV lane decisions.

⁵We use a fractional polynomial function as described in Section 3.5.3.

$$E[Y_i|N_i, \hat{R}_i] = f(N_i, \hat{R}_i) \quad (3.8)$$

where $\hat{R}_i$ is the estimated GPS from Equation 3.7. We refer to this as the “second estimation stage.” If we assumed a quadratic functional form, for example, Equation 3.8 would be:

$$E[Y_i|N_i, \hat{R}_i] = \alpha_0 + \alpha_1 N_i + \alpha_2 N_i^2 + \alpha_3 \hat{R}_i + \alpha_4 \hat{R}_i^2 + \alpha_5 N_i \hat{R}_i \quad (3.9)$$

The second key assumption is that the set of covariates is orthogonal to treatment status given GPS, i.e., $X \perp 1\{N = n\} | r(n, X)$. That is, we assume that controlling for GPS removes biases in comparisons across treatment statuses.⁶ This assumption, together with the weak unconfoundedness assumption, implies that treatment is uncounfounded given GPS. In other words, if our two key assumptions hold, then we remove biases associated with differences in covariates and can compare treatment groups to estimate the causal effect of treatment.

Finally we calculate the estimated average potential outcome at treatment level n as (using the quadratic example):

$$E[\hat{Y}(n)] = \frac{1}{M} \sum_{i=1}^M (\hat{\alpha}_0 + \hat{\alpha}_1 n + \hat{\alpha}_2 n^2 + \hat{\alpha}_3 \hat{r}(n, X_i) + \hat{\alpha}_4 \hat{r}(n, X_i)^2 + \hat{\alpha}_5 n \hat{r}(n, X_i)) \quad (3.10)$$

where $\hat{r}$ is recalculated for each n using the first estimation stage, $\hat{\alpha}_1$ through $\hat{\alpha}_5$ are the coefficients estimated from the second estimation stage, and M is the total number of census tracts in California.

We calculate the estimated average potential outcome for each level of treatment n in order to estimate the entire dose-response function. The dose-response

⁶In Section 3.5.2 we find support for this assumption.

curve shows how a marginal increase in treatment, i.e., an increase in nearby HOV lanes, impacts PEV sales. We bootstrap the standard errors and cluster the standard errors at the county level.

This methodology has several advantages. First, we can estimate marginal effectiveness of treatment at different treatment levels rather than estimating the average effect of treatment. This allows us to better understand heterogeneity across treatment groups. Second, this approach is flexible. We assume that controlling for covariates, treatment follows a Poisson distribution. The GPS is a measure of how many HOV lanes a census tract is likely to have, compared to what we would expect using a Poisson distribution. Such assumptions would not be possible using standard regression techniques.

The GPS technique is fairly new and has been used relatively infrequently in the economic literature. Hirano and Imbens (2005) apply the methodology to estimate the effect of the lottery prize size on winners' subsequent labor earnings. Other studies estimate the effect of duration and quality of training programs (Flores et al., 2012; Kluve et al., 2012; Dammert and Galdo, 2013). There have also been studies in the medical and healthcare literature using GPS (Moodie, Pai, and Klein, 2009; Slavov, 2010; Jiang and Foster, 2013). This paper is a novel application of GPS with an unusual geographic treatment, miles of HOV lanes. Our unit of analysis, the census tract, allows us to explore geographic heterogeneity by aggregating estimated effects at the metropolitan area level.

3.4 Data

PEV registration data were purchased from R.L. Polk & Company and include PEV registrations by month and by census tract for the state of California during the period of February 2010 through December 2013. The resolution of this data is by model type. Each model is classified as a battery electric vehicle (BEV),

which has only an electric engine, or a plug-in hybrid electric vehicle (PHEV), which has both an electric engine and an internal combustion engine. In this analysis we use cumulative PEV sales as of December 2013 as the outcome variable.

The treatment variable is the number of miles of HOV lanes within a 30-mile radius of the population centroid of a census tract as of December 2013.⁷ The data on geographical locations of HOV lanes in California are collected by Caltrans and made public on the Caltrans website. Figure 3.1 shows HOV lane density and PEV registration density in the county of Los Angeles. Figure 3.1a shows that HOV lane density is highly correlated with urban areas. PEV density, as shown in Figure 3.1b, appears to be relatively uncorrelated with HOV lanes.⁸ Instead, greater PEV density is found in more affluent and coastal areas. PEV-dense census tracts are found both in census tracts with high and low HOV lane densities.

Most of the covariates are socio-demographic variables from the U.S. Census Bureau’s 5-year 2008-2012 American Community Survey (ACS). We also use the share of a voting district voting “no” on California Proposition 23 as a measure of its green propensity. California Proposition 23 was a 2010 ballot measure to suspend AB 32, the “Global Warming Solutions Act of 2006.” A higher proportion of “no” votes should correlate to a higher green propensity, and vice versa. Average gasoline prices in December 2013 by census tract were obtained from Gas Buddy Organization Inc. Average overnight electricity rates in December 2013 by census tract were obtained directly from utilities’ rate schedules. Lastly, publicly-available PEV charger density (Level 1 Chargers, Level 2 Chargers, and DC Fast Chargers within a 5-mile radius of the population centroid of each census tract) as of December 2013 were obtained from the U.S. Department of Energy’s Alternative Fuels Data

⁷The average length of weekday home to work trips in California is 26 miles (Caltrans, 2013). A 30-mile radius is large enough to encapsulate most commuters’ daily commutes but small enough to retain variation across census tracts.

⁸This supports the first key assumption from Section 3.3 that assignment of HOV lanes is independent of PEV sales.

Center. PEV charger density is a measure of amenability of the built environment to PEV ownership.

Table 3.4 in the Appendix shows average covariate levels for census tracts in the bottom, middle, and top third of the HOV lane distribution. The group with the fewest HOV lanes has an average of 10 miles of HOV lanes within a 30-mile radius. The middle group has an average of 116 miles, and the top group has an average of 287 miles.⁹ Census tracts with more HOV lanes tend to be more urban, with greater population density, have lower “yes” vote on Proposition 23, higher gas prices, higher median home values, and more workers with medium to long commutes by automobile. Census tracts with more HOV lanes also have less agricultural industry, which is likely because urban areas tend to have more HOV lanes than rural areas. Census tracts that have more HOV lanes have more households without heat, which may be correlated with coastal locations. Areas with more HOV lanes have more racial diversity, also a likely proxy for urban areas. Employment, income, sex, and age do not appear to be substantially different across the groups.

3.4.1 Choice of Covariates

Since we have hundreds of potential explanatory variables and want to avoid over-fitting, we need a methodology to systematically decide which covariates to include. We use classification and regression tree analysis (CART), a data mining technique, in order to determine which coefficients to include in the model. A classification tree chooses a covariate for the first node that maximizes the information gain of the dependent variable. It branches according to the chosen covariate and then at each of the daughter nodes, another covariate is chosen that maximizes information gain. The covariates chosen by the daughter nodes need not be the

⁹Note that one mile of six-lane highway with two HOV lanes in either direction would count as 4 miles of HOV lanes.

same. This procedure continues until the number of data points at a node hits a pre-specified minimum or when no further gain can be made. Lastly, the tree is “pruned” using iterative methods. The main advantage of this methodology as compared to piecewise regression is that it allows for much more flexible functional form (Varian, 2014).

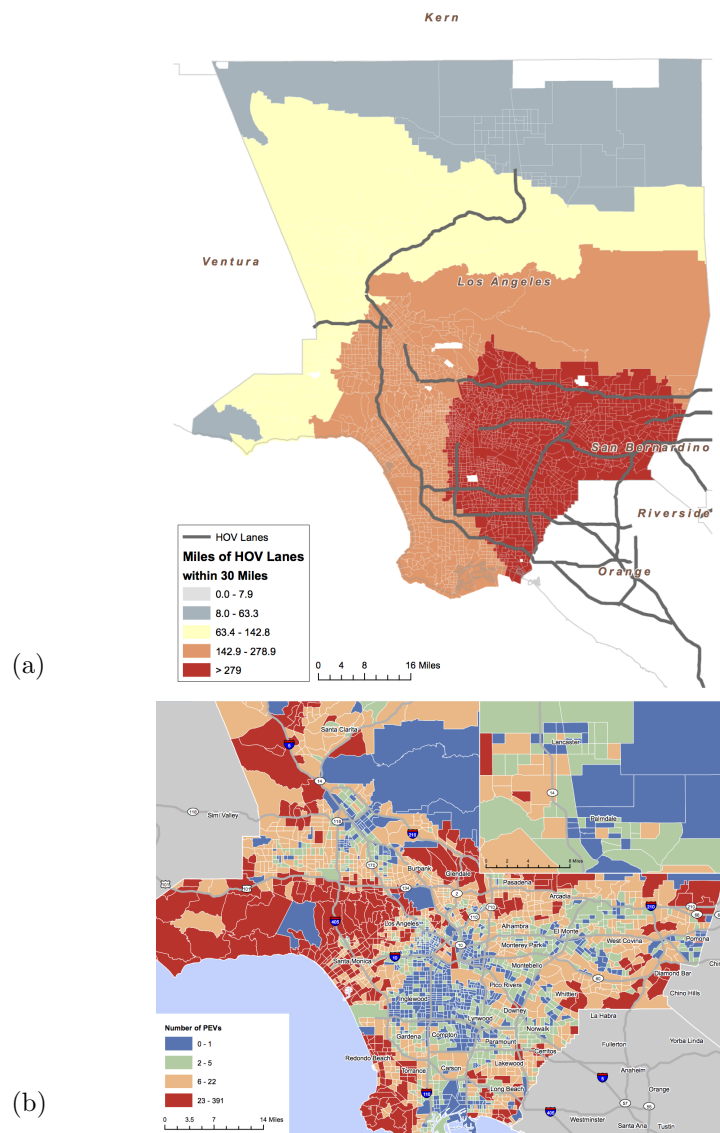


Figure 3.1: HOV Lane and PEV Registration Density in Los Angeles County

3.5 Results

3.5.1 Common Support

Common support is necessary for propensity score matching to ensure sufficiency of comparison groups. Common support requires that there is overlap in the covariate distributions between the treated and untreated populations. For the binary case, one typically compares the propensity score distribution of the treated group with that of the non-treated group and removes observations from either distribution without overlap. For continuous treatment, we can test for common support following the approach of Flores et al. (2012).

We divide observations into three groups of approximately equal size according to treatment level. We evaluate the GPS for all observations at the median treatment of the first group and compare the distribution of this GPS for the first group to the distributions of the other groups. We then evaluate the GPS at the median treatment levels of the second and third groups and repeat the analogous comparison of distributions. Figure 3.2a shows the distribution of the GPS scores for Group 1 versus Groups 2 and 3. Figures 3.2b and 3.2c show the distributions of GPS scores evaluated at the medians of Group 2 and Group 3, respectively. There is considerable overlap in the distributions. We exclude from further analysis all observations without overlap. This ensures that each census tract can be compared to another census tract with a similar GPS but different level of treatment.

3.5.2 Balancing of Covariates

We also test for balancing of the covariates, i.e., that controlling for GPS sufficiently removes biases in covariates. In the binary case we would simply compare the covariate means between the treated and untreated groups before and after matching. In our continuous treatment case, we follow Hirano and Imbens (2005)

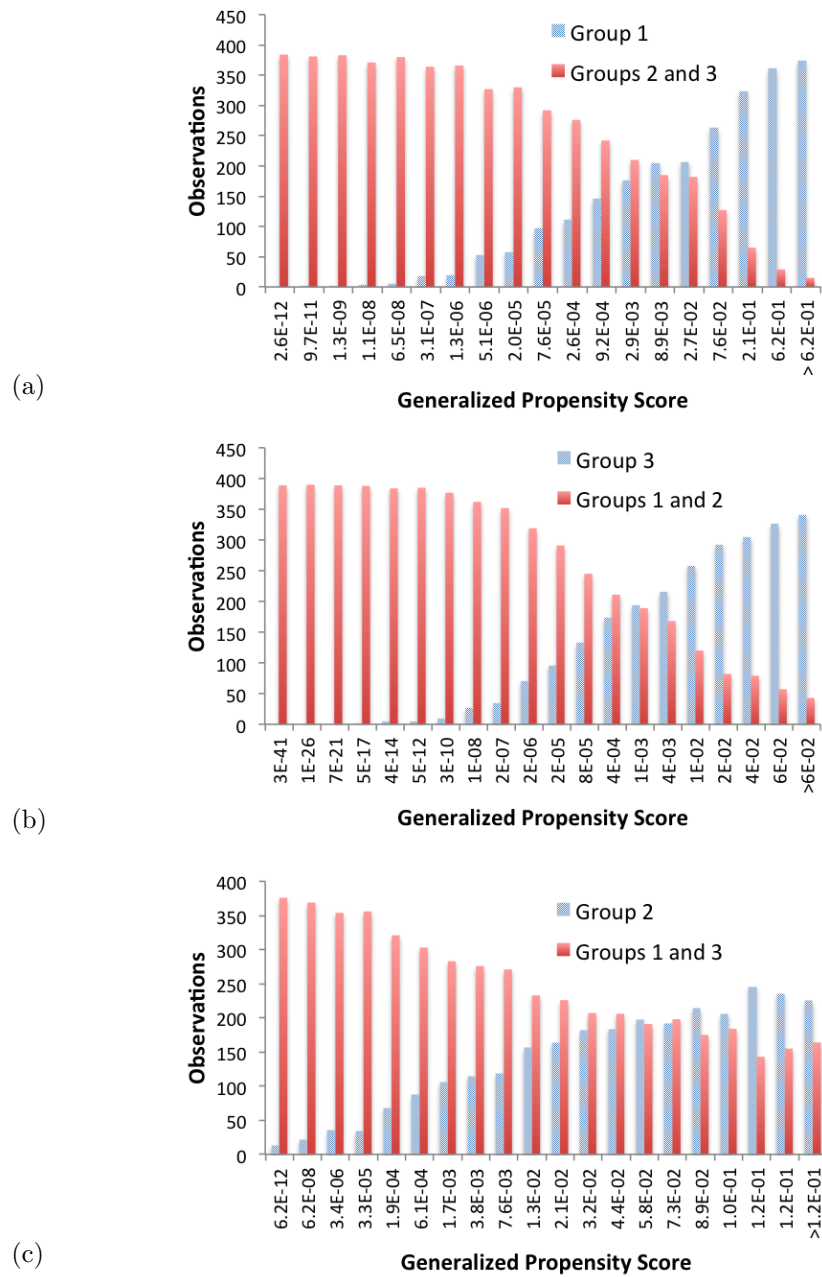


Figure 3.2: Common Support

and use a “blocking on the score” approach. We divide the sample into three intervals according to treatment. Within each interval, we compute the GPS for all observations at the median of the treatment interval. We divide each treatment interval into five blocks by quintiles of the GPS evaluated at the median of the treatment interval. Then we compare the means of a covariate between a given block and observations from different treatment intervals with similar GPS. Lastly we calculate a weighted average over the five blocks of each treatment interval and use a t-test to determine if the difference in covariate means is significant. We repeat this for every treatment interval and for every covariate. If GPS perfectly balances the covariates, the differences in covariate means should not be statistically greater than zero.

The results of the blocking on the score methodology for testing the balancing property of the GPS are shown in Table 3.5 in the Appendix. For each covariate, we test whether the mean of the covariate is significantly different across groups. Without adjusting for the GPS, the t-statistics for the majority of covariates (85%) reject the null hypothesis of equality of means at the 5% level of significance. In other words, before adjusting for the GPS, the treatment and control groups exhibit very different characteristics. After adjustment, however, more than two-thirds (69%) fail to reject the null hypothesis at the 5% level. In other words, after controlling for the GPS, the covariates of the treatment and control groups are very similar. This suggests that adjusting for the GPS greatly improves the balance of the covariates.

3.5.3 First and Second Stage Estimation

Table 3.6 in the Appendix shows the results of the first estimation stage, a Poisson regression of the treatment variable on covariates. The coefficients show how different characteristics impact GPS, which is probability of treatment level.

The estimation results suggest that census tracts with more commuters and higher population density, among other characteristics, are predicted to have more HOV lanes. This is consistent with Figure 3.1a, which shows that more urban areas have more HOV lanes.

Before estimating the second stage, we need to assume a functional form for f in Equation 3.8. Most previous studies have assumed a low order polynomial. Lower order polynomials are limited in their curvature, while higher order polynomials may fit poorly at extreme covariate values. Fractional polynomials, which allow for both integer and non-integer value polynomials as well as natural logs, are more flexible than standard polynomials (Royston and Altman, 1994). We utilize an algorithm by Royston and Ambler (1998) for model selection, which selects the multivariable fractional polynomial that best predicts the outcome from the right hand side variables based on goodness of fit statistical tests. Table 3.1 shows the results of the second estimation stage, regression of PEV registrations on the fractional polynomial function of treatment and GPS.

Table 3.1: Stage 2 Estimation Results

Outcome:	(1) PEV	(2) PHEV	(3) BEV	(4) Prius Plug-In
$\widetilde{T}_1$	13.790*** (0.709)	6.841*** (0.330)	6.740*** (0.442)	2.261*** (0.126)
$\widetilde{T}_2$	-3.997*** (0.208)	-1.871*** (0.097)	-2.064*** (0.130)	-0.568*** (0.037)
$\widetilde{GPS}$	-0.066*** (0.011)	-0.033*** (0.005)	-0.023*** (0.006)	-0.006*** (0.002)
Constant	13.700 (0.330)	7.140 (0.154)	6.980 (0.205)	2.353 (0.058)
Observations	5,843	5,843	5,843	5,842
R^2	0.062	0.070	0.042	0.064
Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1				
where $\widetilde{T}_1 = \left(\frac{Treatment+1}{100}\right) - 1.38$ $\widetilde{T}_2 = \left(\frac{Treatment+1}{100}\right)^2 - 1.91$ $\widetilde{GPS} = \ln(GPS + 5.98 * 10^{-39}) + 5.22$				

3.5.4 Dose-Response Curves

The generalized propensity score framework essentially removes biases in comparisons across groups by flexibly controlling for GPS, a measure of probability of treatment that takes into account a census tract's characteristics. Once we control for GPS, provided the assumptions in Section 3.3 are satisfied, we can compare PEV registrations across census tracts with different amounts of HOV lanes.

We construct a dose-response curve by recalculating the GPS at each level of potential treatment and using the second stage results to predict the average potential outcome, as explained in Section 3.3. Figure 3.3 shows the resulting dose-response curves. The dose-response curves isolate the effects of changes in treatment on PEV sales and are effectively a series of marginal effects. This allows us to predict

marginal changes in PEV sales as a function of marginal changes in HOV lanes. While the shape of the dose-response curves contains useful information, such as exhibition of decreasing marginal returns, we must use caution in our extrapolations from the dose-response curves.¹⁰

Figure 3.3a suggests that nearby HOV lanes have a statistically significant impact on PEV sales, with the first 20 miles of HOV lanes within a 30-mile radius resulting in an additional 2 cumulative PEV purchases. An additional 20 miles of HOV lanes (for a total of 40 miles) results in an additional 2 PEV purchases. The curve flattens out after about 140 miles of HOV lanes, which results in an additional 10 PEV purchases in total (6 additional after the first 40 miles). These are substantial effects, especially when considering that census tracts are generally only a few square miles in area, meaning that an HOV lane could be in the 30-mile radius of many census tracts.

Figures 3.3b and 3.3c show the dose-response curves for PHEVs and BEVs, respectively. These two dose-response curves have very similar shapes and flatten out at approximately the same point, after 140 miles of HOV lanes. The main difference is that the error bounds on the PHEV curve are narrower. This suggests that the impact of the HOV lane policy is similar across vehicle technologies, and one technology type or model does not appear to drive the main result in Figure 3.3.

¹⁰For example, if we were to assume there were no HOV lane policy for PEVs, such that we assumed each census tract had zero HOV lanes, the errors from summing all the marginal changes would be very large and PEV sales predictions would have confidence intervals too large for the exercise to be meaningful.

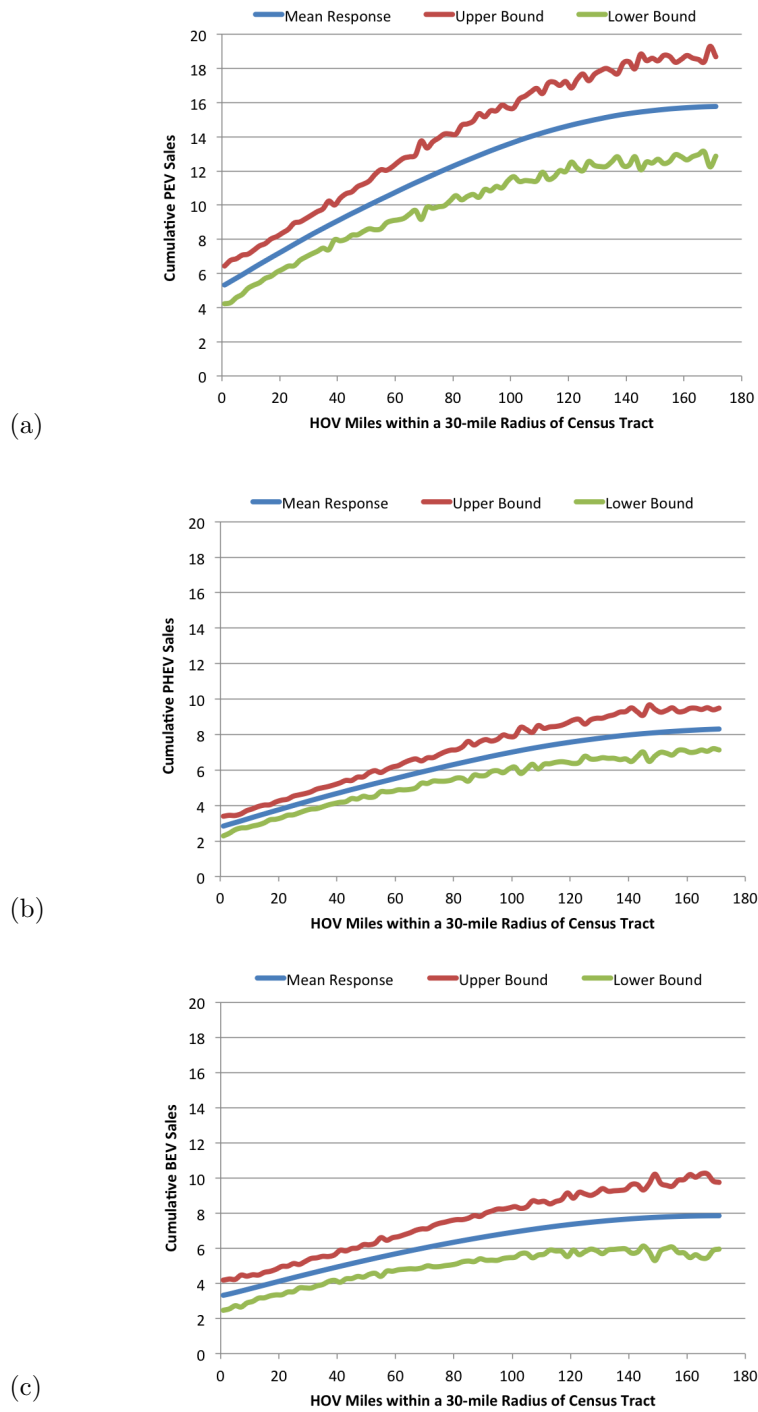


Figure 3.3: Dose-response curves

3.5.5 Simulations

The first stage estimation coefficients in Table 3.6 show which covariates are associated with higher numbers of HOV lanes, and therefore higher generalized propensity scores. The second stage estimation results in Table 3.1 show that more HOV lanes (that is, a higher level of treatment) are associated with higher PEV registrations, with the negative quadratic term suggesting decreasing marginal returns to treatment. Table 3.2 summarizes relevant characteristics for California’s largest metropolitan areas.¹¹

Table 3.2: California Metropolitan Area Characteristics[†]

	San Diego	Los Angeles	San Francisco	Sacramento
PEV Registrations (cumulative)	8.8	6.7	8.3	4.0
PHEV Registrations (cumulative)	3.8	4.4	3.7	2.1
BEV Registrations (cumulative)	5.3	2.8	4.9	2.2
HOV Miles (30-mile Radius)	10	229	98	38
GPS	.004	.005	.007	.023
Population	4,949	3,819	4,171	4,485
Commuters	2,285	1,791	2,270	1,886
Population Density (per sq. mile)	7,129	17,334	28,818	5,207
Area (Land, sq. mile)	6.7	0.4	0.2	3.1
Prop 23 “Yes” Vote	43%	29%	18%	37%
Avg Gas Price (\$)	3.63	3.66	3.70	3.44
Avg Electric Price (cents)	6.8	12.6	11.9	11.9
Commute by Auto: Under 15min	21%	15%	8%	21%
Commute by Auto: 30-60min	25%	30%	17%	26%
Commute by Auto: Over 60min	4%	8%	4%	5%
Level 1 Chargers (5-mile Radius)	2	6	71	4
Level 2 Chargers (5-mile Radius)	58	73	166	47
DC Chargers (5-mile Radius)	0.4	0.5	0.7	0.4

[†]All characteristics shown are the mean across census tracts in each metropolitan area.

Los Angeles has the highest average number of HOV lanes within a 30-mile radius of a census tract at 229 miles, followed by San Francisco (98), Sacramento (38), and San Diego (10). Census tracts in Sacramento and San Francisco have the

¹¹A more thorough characterization can be found in Appendix Table 3.7.

highest GPS on average, and those in San Diego and Los Angeles have the lowest. The first stage estimation results in Table 3.6 suggest that census tracts with more commuters, greater population density, higher average gas prices, and more drivers with daily commutes greater than a half hour, among other characteristics, will have higher GPS.

The level of actual treatment, or miles of HOV lanes, will determine where a census tract is located on the dose-response curve and what marginal effects are relevant. Census tracts with fewer than 60-80 HOV lane miles will be located on the linear part of the dose-response curve, while those with more HOV lane miles will be located on the flat part of the dose-response curve. Therefore, we would expect areas with fewer HOV lanes, such as San Diego and Sacramento, to be responsive to marginal changes in HOV lane miles, and we would expect areas with very many HOV lanes, such as Los Angeles, to be relatively unresponsive to marginal changes in HOV lane miles.

We use our results to simulate how an increase or decrease in HOV lanes would affect PEV sales in California's largest cities. For each census tract, we increase or decrease the number of HOV lanes by a given percent and predict the number of PEV sales using the second stage estimates shown in Table 3.1. We are then able to integrate PEV sales over all census tracts in a given city. Table 3.3 shows how cumulative PEV sales are predicted to change, both in percentage terms and in terms of number of vehicles, if the number of miles of HOV lanes in a city increased or decreased.¹²

Los Angeles seems to already be at the flat part of the dose-response curve, where HOV lane density is already high enough in most census tracts that additional HOV lanes do not further impact PEV sales. Los Angeles has the most HOV lanes

¹²The cumulative PEV sales at 100% of current HOV lanes (i.e., no change in HOV lanes) have been normalized to actual sales for each city. Our empirical model identifies the incremental effect of HOV lanes on PEV sales but does not estimate the intercept for each census tract.

Table 3.3: Simulation Results

HOV Lanes, % of Actual	PEV Sales (Feb 2010-Dec 2013), % of Actual				
	California	San Diego	Los Angeles	San Francisco	Sacramento
70%	93.8%	94.0%	96.4%	84.0%	83.1%
80%	96.2%	96.0%	98.3%	89.9%	87.9%
90%	98.3%	98.0%	99.4%	95.2%	94.0%
100%	100.0%	100.0%	100.0%	100.0%	100.0%
110%	101.4%	101.9%	100.4%	104.2%	105.8%
120%	102.6%	103.9%	100.5%	107.7%	111.4%
130%	103.6%	105.8%	100.6%	110.6%	116.9%

HOV Lanes, % of Actual	PEV Sales (Feb 2010-Dec 2013)				
	California	San Diego	Los Angeles	San Francisco	Sacramento
70%	61,011	5,137	4,058	1,345	1,020
80%	62,586	5,246	4,136	1,440	1,078
90%	63,923	5,354	4,181	1,526	1,154
100%	65,037	5,465	4,208	1,602	1,227
110%	65,966	5,570	4,223	1,669	1,298
120%	66,736	5,675	4,231	1,725	1,367
130%	67,378	5,783	4,234	1,773	1,434

out of the four cities. This suggests the Los Angeles area is relatively saturated in HOV lanes, such that all consumers will be less responsive to further increases in HOV lane access. Notice that if there were 30% fewer HOV lanes in Los Angeles, it would still have more HOV lanes than any other city in California. Importantly, this finding does not mean that California's HOV lane policy has not induced PEV sales in Los Angeles. Indeed, HOV lane access may have motivated a substantial number of PEV sales in the area, but our analysis identifies only the marginal effects of marginal changes in HOV lane access.

San Francisco and Sacramento PEV sales are predicted to be the most sensitive to changes in HOV lane density. A 10% decrease (increase) in HOV lanes is associated with a 4.8% decrease (4.2% increase) in San Francisco and a 6% decrease (5.8% increase) in Sacramento. That PEV sales are lower in these cities than San Diego and Los Angeles and also more sensitive to HOV lane density suggests that

a larger proportion of marginal PEV sales in San Francisco and Sacramento are motivated by drivers who are responsive to marginal increases in access to HOV lanes.

San Diego has both the highest number of PEV registrations and the lowest number of HOV lanes out of all four metropolitan areas. That San Diego PEV registrations are so high suggests that factors other than HOV lane access are motivating San Diego drivers to adopt PEVs. The lower marginal responsiveness of San Diego drivers to changes in HOV lanes is likely due to the fact that San Diego has so few HOV lanes to begin with. We might expect drivers' value of this policy to jump up once a certain minimum scale of HOV travel lanes is achieved. In San Diego a 30% increase HOV lanes only translates into about 3 additional miles of HOV lanes near each census tract.

3.6 Caveats and Conclusion

We have developed an approach that identifies both a state-wide average marginal effect of HOV lane access on PEV sales and geographic-specific estimates that accommodate local variation on policy treatment. Our estimated treatment effects are conditioned on several factors. First, our estimated marginal effects are for a new product market and a policy that has been in place for four years. Therefore, we are measuring a treatment effect over a considerable period of time for early and middle-market adopters, who may be less responsive to the time and cost savings associated with increased HOV lane access than will be future PEV adopters. Our approach, when combined with a future discrete policy change, may allow future researchers to identify per year effects rather than cumulative effects. Second, the impacts of this policy may depend upon both other policies and market conditions that affect the total costs of owning PEVs. Changes in PEV market prices relative to conventional vehicle, gasoline and electricity prices, as well as

vehicle purchase incentives and refueling infrastructure subsidies could affect our findings. Lastly, as discussed in our theoretical model, as congestion changes in existing HOV lanes, so too will drivers' willingness to pay to access these lanes.

3.7 Acknowledgement

Chapter 3, in full, is currently being prepared for submission for publication of the material. Sheldon, Tamara L.; DeShazo, J.R. The dissertation author was the primary investigator and author of this paper.

3.8 Chapter 3 Appendix

Table 3.4: Descriptive Statistics

Covariate	HOV Lanes (30-mile radius)		
	Bottom Third	Middle Third	Top Third
HOV Lanes within 30-mile Radius	10	116	287
Cumulative PEV Registrations	4	13	8
Cumulative PHEV Registrations	2	7	5
Cumulative BEV Registrations	2	7	3
Population	4,824	4,642	4,466
Commuters	1,974	2,117	2,015
Area (Land, mi^2)	48	4	1
Population Density (per mi^2)	4,306	8,660	12,660
Prop 23 "Yes" Vote	44%	33%	35%
Avg Gas Price (\$)	3.54	3.60	3.63
Avg Electric Price (cents/kWh)	10.5	11.3	10.3
Industry: Construction	4%	4%	3%
Industry: Transport	2%	3%	3%

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Table 3.4: Descriptive Statistics, continued from previous page

Covariate	HOV Lanes (30-mile radius)		
	Bottom Third	Middle Third	Top Third
Industry: Manufacturing	4%	6%	7%
Industry: Agriculture	3%	0%	0%
Industry: Education	11%	13%	12%
Industry: Wholesale	2%	2%	2%
Industry: Management	6%	9%	7%
Employed	53%	59%	58%
Unemployed	8%	7%	7%
Has Mortgage	71%	77%	76%
Has 2nd Mortgage	17%	21%	18%
Income: \$10-\$15k	6%	4%	6%
Income: \$20-\$25k	6%	4%	5%
Income: \$25-\$30k	5%	4%	5%
Income: \$30-\$35k	5%	4%	5%
Income: \$35-\$40k	5%	4%	5%
Income: \$45-\$50k	4%	3%	4%
Income: \$50-\$60k	8%	7%	8%
Income: \$125-\$150k	5%	7%	5%
Median Rent (\$1,000s)	1.2	1.5	1.3
Median House Value (\$10,000s)	29.9	50.0	44.8
Poverty Rate	16%	11%	15%
Heat: Solar	0.1%	0.1%	0.1%
Heat: Oil	1%	0%	0%
Heat: Electric	26%	23%	23%
Heat: None	2%	2%	6%
Race: Black	5%	7%	7%
Race: White	73%	60%	54%

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Table 3.4: Descriptive Statistics, continued from previous page

Covariate	HOV Lanes (30-mile radius)		
	Bottom Third	Middle Third	Top Third
Race: Asian	7%	18%	15%
Single, Attached House	6%	9%	8%
Single House	84%	74%	63%
Mobile House	8%	3%	2%
Houseunits: 3-4	6%	6%	7%
Houseunits: 10-19	4%	5%	8%
House Value: Under \$20k	3%	1%	1%
House Value: \$100-\$150k	10%	5%	3%
House Value: \$150-\$300k	33%	19%	21%
House Value: Over \$1,000k	4%	11%	7%
Male: 25-34	7%	7%	8%
Male: 45-54	7%	7%	7%
Male: 55-64	6%	6%	5%
Male: 75-84	2%	2%	2%
Female: 35-44	6%	7%	7%
Female: Over 85	1%	1%	1%
Age: 15-24	15%	14%	15%
Age: 35-44	13%	14%	15%
Age: 45-54	14%	15%	14%
Age: 65-74	7%	7%	6%
Foreign: Naturalized	8%	14%	16%
Foreign, Entry: 1990-1999	24%	25%	25%
Moved, High School or Less	40%	33%	44%
Moved, College	47%	48%	43%
Moved from Other State	11%	5%	5%
Commute: Walk	3%	3%	3%

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Table 3.4: Descriptive Statistics, continued from previous page

Covariate	HOV Lanes (30-mile radius)		
	Bottom Third	Middle Third	Top Third
Commute: Public Transport	2%	8%	7%
Commute: Motorcycle	0%	0%	0%
Commute by Auto: Under 15min	28%	19%	17%
Commute by Auto: 30-60min	21%	26%	30%
Commute by Auto: Over 60min	7%	9%	8%
Leave Home 7-8am	26%	25%	24%
Leave Home 9-10am	6%	9%	9%
Leave Home 10am-noon	5%	5%	5%
Education: High School	23%	19%	21%
Education: Some College	34%	28%	27%
Education: College	49%	51%	45%
Education: MA	6%	10%	6%
Education: Professional Degree	2%	3%	2%
Level 1 Chargers (5-mile Radius)	2	17	8
Level 2 Chargers (5-mile Radius)	21	54	57
DC Chargers (5-mile Radius)	0.2	1.0	0.7

Table 3.5: Number of HOV Miles[†]

Covariate	G1		G2		G3	
	Adjusted	Unadjusted	Adjusted	Unadjusted	Adjusted	Unadjusted
Population	0.06	0.00	0.17	0.36	0.16	0.00
Population Density	0.00	0.00	0.03	0.01	0.00	0.00
Area (Land)	0.09	0.00	0.11	0.24	0.00	0.00
Commuters	0.08	0.24	0.29	0.00	0.49	0.10
Prop 23 "Yes" Vote	0.00	0.00	0.00	0.00	0.57	0.34
Avg Gas Price	0.01	0.00	0.04	0.53	0.00	0.00
Avg Electric Price	0.00	0.00	0.00	0.00	0.04	0.00
Industry: Construction	0.20	0.12	0.19	0.44	0.32	0.02
Industry: Transport	0.15	0.00	0.57	0.82	0.11	0.00
Industry: Manufacturing	0.03	0.00	0.00	0.00	0.04	0.00
Industry: Agriculture	0.00	0.00	0.02	0.00	0.24	0.00
Industry: Education	0.39	0.90	0.26	0.00	0.11	0.00
Industry: Wholesale	0.03	0.00	0.81	0.00	0.06	0.00
Industry: Management	0.00	0.00	0.01	0.00	0.25	0.00

[†]: p-value of t-test of H_0 that populations are the same (reject H_0 if $p < 5\%$)

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Table 3.5: Number of HOV Miles,[†] continued from previous page

Covariate	G1		G2		G3	
	Adjusted	Unadjusted	Adjusted	Unadjusted	Adjusted	Unadjusted
Employed	0.13	0.00	0.51	0.00	0.17	0.00
Unemployed	0.21	0.00	0.31	0.00	0.31	0.14
Has Mortgage	0.06	0.00	0.03	0.00	0.27	0.76
Has 2nd Mortgage	0.29	0.00	0.44	0.00	0.19	0.00
Income: \$10-\$15k	0.13	0.04	0.09	0.00	0.20	0.00
Income: \$20-\$25k	0.16	0.00	0.10	0.00	0.27	0.00
Income: \$25-\$30k	0.18	0.00	0.07	0.00	0.09	0.00
Income: \$30-\$35k	0.06	0.00	0.10	0.00	0.27	0.00
Income: \$35-\$40k	0.16	0.00	0.10	0.00	0.37	0.00
Income: \$45-\$50k	0.24	0.00	0.22	0.00	0.20	0.02
Income: \$50-\$60k	0.13	0.00	0.38	0.00	0.19	0.09
Income: \$125-\$150k	0.06	0.00	0.31	0.00	0.11	0.00
Median Rent (\$1,000s)	0.12	0.00	0.23	0.00	0.24	0.01
Median House Value (\$10,000s)	0.00	0.00	0.00	0.00	0.25	0.00
Poverty Rate	0.11	0.00	0.24	0.00	0.09	0.00

[†]: p-value of t-test of H_0 that populations are the same (reject H_0 if $p < 5\%$)

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Table 3.5: Number of HOV Miles,[†] continued from previous page

Covariate	G1		G2		G3	
	Adjusted	Unadjusted	Adjusted	Unadjusted	Adjusted	Unadjusted
Heat: Solar	0.49	0.03	0.40	0.03	0.17	0.00
Heat: Oil	0.24	0.00	0.21	0.22	0.24	0.02
Heat: Electric	0.05	0.00	0.16	0.00	0.05	0.00
Heat: None	0.02	0.00	0.00	0.00	0.18	0.00
Race: Black	0.15	0.00	0.06	0.01	0.24	0.07
Race: White	0.00	0.00	0.00	0.00	0.01	0.00
Race: Asian	0.00	0.00	0.00	0.00	0.30	0.07
Single, Attached House	0.09	0.00	0.17	0.00	0.47	0.40
Single House	0.03	0.00	0.22	0.07	0.00	0.00
Mobile House	0.02	0.00	0.07	0.04	0.19	0.00
Houseunits: 3-4	0.29	0.00	0.59	0.70	0.35	0.00
Houseunits: 10-19	0.26	0.00	0.07	0.00	0.00	0.00
House Value: Under \$20k	0.06	0.00	0.40	0.00	0.23	0.00
House Value: \$100-\$150k	0.00	0.00	0.16	0.00	0.09	0.00
House Value: \$150-\$300k	0.03	0.00	0.00	0.00	0.25	0.00

[†]: p-value of t-test of H_0 that populations are the same (reject H_0 if $p < 5\%$)

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Table 3.5: Number of HOV Miles,[†] continued from previous page

Covariate	G1		G2		G3	
	Adjusted	Unadjusted	Adjusted	Unadjusted	Adjusted	Unadjusted
House Value: Over \$1,000k	0.00	0.00	0.00	0.00	0.09	0.30
Male: 25-34	0.23	0.01	0.58	0.10	0.07	0.00
Male: 45-54	0.11	0.00	0.04	0.00	0.53	0.02
Male: 55-64	0.37	0.17	0.10	0.00	0.16	0.00
Male: 75-84	0.04	0.00	0.18	0.09	0.07	0.00
Female: 35-44	0.21	0.00	0.24	0.00	0.20	0.00
Female: Over 85	0.02	0.00	0.82	0.85	0.07	0.00
Age: 15-24	0.15	0.00	0.00	0.00	0.41	0.01
Age: 35-44	0.04	0.00	0.07	0.00	0.08	0.00
Age: 45-54	0.15	0.00	0.03	0.00	0.34	0.00
Age: 65-74	0.10	0.00	0.61	0.66	0.13	0.00
Foreign: Naturalized	0.00	0.00	0.00	0.00	0.09	0.00
Foreign, Entry: 1990-1999	0.32	0.01	0.26	0.00	0.54	0.44
Moved, High School or Less	0.29	0.97	0.08	0.00	0.02	0.00
Moved, College	0.32	0.00	0.18	0.00	0.03	0.00

[†]: p-value of t-test of H_0 that populations are the same (reject H_0 if $p < 5\%$)

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Table 3.5: Number of HOV Miles,[†] continued from previous page

Covariate	G1		G2		G3	
	Adjusted	Unadjusted	Adjusted	Unadjusted	Adjusted	Unadjusted
Moved from Other State	0.21	0.41	0.17	0.33	0.12	0.87
Commute: Walk	0.05	0.00	0.08	0.01	0.48	0.13
Commute: Public Transport	0.00	0.00	0.00	0.00	0.50	0.01
Commute: Motorcycle	0.37	0.01	0.57	0.47	0.88	0.00
Commute by Auto: Under 15min	0.07	0.00	0.00	0.00	0.04	0.00
Commute by Auto: 30-60min	0.02	0.00	0.12	0.14	0.00	0.00
Commute by Auto: Over 60min	0.20	0.00	0.06	0.00	0.45	0.64
Leave Home 7-8am	0.22	0.00	0.33	0.00	0.18	0.00
Leave Home 9-10am	0.00	0.00	0.00	0.00	0.26	0.00
Leave Home 10am-noon	0.02	0.00	0.10	0.00	0.38	0.31
Education: High School	0.20	0.00	0.07	0.00	0.19	0.19
Education: Some College	0.00	0.00	0.00	0.00	0.11	0.00
Education: College	0.40	0.00	0.31	0.00	0.02	0.00
Education: MA	0.05	0.00	0.02	0.00	0.15	0.00
Education: Professional Degree	0.11	0.00	0.30	0.00	0.28	0.05

[†]: p-value of t-test of H_0 that populations are the same (reject H_0 if $p < 5\%$)

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Table 3.5: Number of HOV Miles,[†] continued from previous page

Covariate	G1		G2		G3	
	Adjusted	Unadjusted	Adjusted	Unadjusted	Adjusted	Unadjusted
Level 1 Chargers (5-mile Radius)	0.00	0.00	0.00	0.00	0.08	0.00
Level 2 Chargers (5-mile Radius)	0.00	0.00	0.04	0.00	0.05	0.00
DC Chargers (5-mile Radius)	0.00	0.00	0.00	0.00	0.12	0.00

[†]: p-value of t-test of H_0 that populations are the same (reject H_0 if $p < 5\%$)

Table 3.6: Stage 1 Estimation Results

	HOV Miles
Population	-6.18e-05*** (3.49e-06)
Commuters	7.08e-05*** (7.66e-06)
Population Density	7.12e-06*** (1.96e-07)
Area (Land)	-0.014*** (0.0003)
Prop 23 "Yes" Vote	1.136*** (0.018)
Avg Gas Price	0.625*** (0.013)
Avg Electric Price	0.015*** (0.0006)
Industry: Construction	-1.337*** (0.065)
Industry: Transport	6.189*** (0.073)
Industry: Manufacturing	4.406*** (0.042)
Industry: Agriculture	-20.260*** (0.185)
Industry: Education	1.883*** (0.041)

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Table 3.6: Stage 1 Estimation Results, continued from previous page

	HOV Miles
Industry: Wholesale	10.320*** (0.093)
Industry: Management	-0.631*** (0.049)
Employed	-0.335*** (0.040)
Unemployed	0.358*** (0.048)
Has Mortgage	-0.247*** (0.013)
Has 2nd Mortgage	-0.597*** (0.015)
Income: \$10-\$15k	-0.872*** (0.042)
Income: \$20-\$25k	-0.683*** (0.046)
Income: \$25-\$30k	-0.460*** (0.045)
Income: \$30-\$35k	-0.200*** (0.045)
Income: \$35-\$40k	0.277*** (0.047)
Income: \$45-\$50k	0.381*** (0.049)

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Table 3.6: Stage 1 Estimation Results, continued from previous page

	HOV Miles
Income: \$50-\$60k	0.399*** (0.037)
Income: \$125-\$150k	-0.279*** (0.039)
Median Rent (\$1,000s)	-0.004 (0.005)
Median House Value (\$10,000s)	0.008*** (0.0002)
Poverty Rate	-0.477*** (0.024)
Heat: Solar	-8.800*** (0.379)
Heat: Oil	-8.615*** (0.328)
Heat: Electric	-0.998*** (0.013)
Heat: None	2.179*** (0.030)
Race: Black	0.094*** (0.019)
Race: White	-1.534*** (0.014)
Race: Asian	-1.931*** (0.018)

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Table 3.6: Stage 1 Estimation Results, continued from previous page

	HOV Miles
Single, Attached House	-0.018 (0.013)
Single House	-0.983*** (0.010)
Mobile House	-0.959*** (0.021)
Houseunits: 3-4	-0.198*** (0.020)
Houseunits: 10-19	-0.419*** (0.022)
House Value: Under \$20k	-1.408*** (0.045)
House Value: \$100-\$150k	-2.184*** (0.022)
House Value: \$150-\$300k	-0.871*** (0.0001)
House Value: Over \$1,000k	-0.424*** (0.014)
Male: 25-34	0.596*** (0.055)
Male: 45-54	-1.093*** (0.106)
Male: 55-64	-0.406*** (0.071)

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Table 3.6: Stage 1 Estimation Results, continued from previous page

	HOV Miles
Male: 75-84	-0.082 (0.133)
Female: 35-44	-0.142 (0.100)
Female: Over 85	5.864*** (0.125)
Age: 15-24	1.042*** (0.033)
Age: 35-44	1.625*** (0.064)
Age: 45-54	1.408*** (0.074)
Age: 65-74	1.831*** (0.061)
Foreign: Naturalized	1.549*** (0.026)
Foreign, Entry: 1990-1999	-0.326*** (0.0134)
Moved, High School or Less	1.058*** (0.060)
Moved, College	0.814*** (0.069)
Moved from Other State	-0.388*** (0.029)

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Table 3.6: Stage 1 Estimation Results, continued from previous page

	HOV Miles
Commute: Walk	0.453*** (0.037)
Commute: Public Transport	-1.136*** (0.025)
Commute: Motorcycle	-0.833*** (0.182)
Commute by Auto: Under 15min	-0.276*** (0.020)
Commute by Auto: 30-60min	2.517*** (0.018)
Commute by Auto: Over 60min	2.174*** (0.024)
Leave Home 7-8am	-0.643*** (0.021)
Leave Home 9-10am	1.282*** (0.031)
Leave Home 10am-noon	1.203*** (0.039)
Education: High School	-1.130*** (0.029)
Education: Some College	-0.676*** (0.030)
Education: College	-1.217*** (0.096)

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Table 3.6: Stage 1 Estimation Results, continued from previous page

	HOV Miles
Education: MA	-0.763*** (0.074)
Education: Professional Degree	0.471*** (0.095)
Level 1 Chargers (5-mile Radius)	0.004*** (0.0001)
Level 2 Chargers (5-mile Radius)	-0.001*** (3.47e-05)
DC Chargers (5-mile Radius)	0.012*** (0.0008)
Constant	2.940*** (0.088)
Observations	5,843

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 3.7: City Characteristics

Variable	San Diego		Los Angeles		San Francisco		Sacramento	
	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev
HOV Miles (30-mile Radius)	10	2	229	64	98	6	38	1
GPS	.004	.047	.005	.010	.007	.012	.023	.024
Population	4,949	2,634	3,819	1,128	4,171	1,615	4,485	1,737
Commuters	2,285	1,352	1,791	568	2,270	970	1,886	749
Population Density (per mi^2)	7,129	5,732	17,334	15,540	28,818	20,750	5,207	2,884
Area (Land, mi^2)	6.7	52.1	0.4	0.5	0.2	0.3	3.1	11.4
Prop 23 "Yes" Vote	43%	6%	29%	6%	18%	4%	37%	6%

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Table 3.7: City Characteristics, continued from previous page

Variable	San Diego		Los Angeles		San Francisco		Sacramento	
	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev
Avg Gas Price (\$)	3.63	0.10	3.66	0.14	3.70	0.11	3.44	0.06
Avg Electric Price (cents)	6.8	-	12.6	0.3	11.9	-	11.9	-
Industry: Construction	4%	2%	4%	3%	2%	2%	4%	2%
Industry: Transport	2%	1%	2%	1%	2%	2%	3%	2%
Industry: Manufacturing	5%	3%	6%	4%	4%	2%	3%	2%
Industry: Agriculture	1%	1%	0%	1%	0%	0%	0%	1%
Industry: Education	12%	4%	11%	4%	13%	5%	12%	4%
Industry: Wholesale	1%	1%	2%	1%	1%	1%	1%	1%
Industry: Management	8%	4%	8%	3%	13%	7%	6%	3%
Employed	56%	10%	60%	8%	63%	11%	56%	9%
Unemployed	6%	3%	8%	3%	6%	3%	9%	4%
Has Mortgage	75%	13%	77%	15%	72%	15%	76%	13%
Has 2nd Mortgage	20%	8%	19%	12%	19%	11%	20%	7%
Income: \$10-\$15k	5%	4%	7%	6%	6%	7%	6%	5%
Income: \$20-\$25k	5%	3%	6%	4%	4%	3%	5%	3%
Income: \$25-\$30k	5%	3%	6%	4%	3%	3%	5%	3%
Income: \$30-\$35k	5%	3%	5%	3%	4%	2%	5%	3%
Income: \$35-\$40k	4%	3%	5%	3%	3%	2%	5%	3%
Income: \$45-\$50k	4%	2%	4%	3%	3%	2%	4%	3%
Income: \$50-\$60k	8%	4%	8%	4%	6%	3%	8%	4%
Income: \$125-\$150k	6%	4%	4%	4%	7%	5%	5%	4%
Median Rent (\$1,000s)	1.4	0.4	1.3	0.4	1.5	0.4	1.1	0.3
Median House Value (\$10,000s)	42.0	20.8	44.3	21.5	72.2	24.8	24.8	11.3
Poverty Rate	13%	9%	17%	10%	13%	9%	15%	11%
Heat: Solar	0%	0%	0%	0%	0%	0%	0%	0%
Heat: Oil	0%	1%	0%	0%	0%	1%	0%	0%
Heat: Electric	31%	15%	28%	13%	29%	16%	35%	14%
Heat: None	4%	4%	6%	7%	3%	3%	1%	1%
Race: Black	5%	6%	4%	4%	7%	10%	9%	8%
Race: White	73%	16%	56%	19%	52%	21%	63%	19%
Race: Asian	10%	11%	14%	13%	31%	19%	13%	11%
Single, Attached House	9%	10%	6%	6%	18%	17%	7%	7%
Single House	68%	28%	50%	34%	40%	34%	78%	24%
Mobile House	4%	9%	1%	4%	0%	0%	3%	7%
Houseunits: 3-4	5%	6%	5%	7%	12%	11%	7%	9%
Houseunits: 10-19	7%	7%	10%	9%	11%	12%	5%	6%
House Value: Under \$20k	2%	6%	0%	2%	0%	2%	2%	5%
House Value: \$100-\$150k	4%	6%	2%	7%	1%	3%	12%	12%
House Value: \$150-\$300k	22%	18%	19%	19%	4%	8%	44%	19%
House Value: Over \$1,000k	6%	15%	7%	15%	24%	22%	1%	2%
Male: 25-34	8%	4%	9%	4%	11%	6%	7%	3%
Male: 45-54	7%	2%	7%	2%	8%	3%	7%	2%
Male: 55-64	5%	2%	5%	2%	6%	2%	5%	2%
Male: 75-84	2%	1%	2%	1%	2%	1%	2%	1%
Female: 35-44	7%	2%	7%	2%	7%	3%	7%	2%
Female: Over 85	1%	1%	1%	1%	1%	2%	1%	1%
Age: 15-24	16%	9%	14%	6%	11%	7%	15%	5%
Age: 35-44	13%	3%	16%	4%	17%	5%	13%	3%

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Table 3.7: City Characteristics, continued from previous page

Variable	San Diego		Los Angeles		San Francisco		Sacramento	
	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev
Age: 45-54	14%	4%	14%	3%	14%	4%	14%	3%
Age: 65-74	6%	3%	6%	3%	7%	3%	6%	3%
Foreign: Naturalized	11%	6%	19%	7%	21%	11%	9%	5%
Foreign, Entry: 1990-1999	24%	10%	25%	8%	24%	9%	29%	12%
Moved, High School or Less	34%	19%	46%	21%	27%	17%	35%	15%
Moved, College	50%	11%	43%	15%	49%	9%	52%	11%
Moved from Other State	31%	538%	3%	9%	5%	6%	3%	4%
Commute: Walk	3%	4%	3%	4%	10%	11%	2%	4%
Commute: Public Transport	3%	4%	12%	12%	32%	9%	3%	3%
Commute: Motorcycle	0%	1%	0%	1%	1%	1%	0%	1%
Commute by Auto: < 15min	21%	8%	15%	7%	8%	4%	21%	8%
Commute by Auto: 30-60min	25%	10%	30%	8%	17%	8%	26%	10%
Commute by Auto: > 60min	4%	4%	8%	5%	4%	3%	5%	4%
Leave Home 7-8am	25%	6%	25%	7%	26%	7%	27%	7%
Leave Home 9-10am	7%	4%	10%	6%	11%	5%	6%	3%
Leave Home 10am-noon	5%	3%	6%	3%	6%	4%	5%	3%
Education: High School	19%	8%	20%	6%	14%	8%	22%	8%
Education: Some College	32%	9%	24%	7%	20%	6%	36%	7%
Education: College	52%	12%	45%	15%	52%	10%	55%	11%
Education: MA	8%	6%	6%	5%	13%	7%	6%	4%
Education: Professional Degree	3%	3%	2%	3%	5%	4%	2%	3%
Level 1 Chargers (5-mi Radius)	2	3	6	7	71	21	4	7
Level 2 Chargers (5-mi Radius)	58	65	73	53	166	48	47	67
DC Chargers (5-mi Radius)	0.4	0.8	0.5	0.9	0.7	1.0	0.4	1.2

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