POWERING DEMAND: SOLAR PHOTOVOLTAIC SUBSIDIES IN CALIFORNIA

Kenneth D. Reddix II

A dissertation submitted to the faculty of the University of North Carolina at Chapel Hill in partial fulfillment of the requirements for the degree of Doctor of Philosophy in the Department of Economics.

Chapel Hill
2015

Approved by:

Brian McManus

Donna B. Gilleskie

Clement Joubert

Helen V. Tauchen

Andrew Yates

ABSTRACT

KENNETH D. REDDIX II: Powering Demand: Solar Photovoltaic Subsidies in California.
(Under the direction of Brian McManus)

Households' decisions to purchase solar photovoltaic systems are characterized by large up-front costs, differentiated products, and uncertainties about future government subsidies. This study analyzes the interplay of these factors using a dynamic discrete choice model. I use a newly assembled dataset, that covers all installations from 2002 through 2006 in California at the household level, to estimate demand for solar panel installations. I find that across the distribution of housing values, households are price elastic with respect to both temporary and permanent changes in price. Also, I find that elasticities vary across the distribution of housing values. The marginal effect of technological innovation is significant and positive with respect to the probability of purchase. I find that a 1% increase in the efficiency rate increases the probability of purchase by 6.4%. This is result is compounded by the fact that efficiency rates increase 30% over the sample period. Through counterfactual simulations, I show that in the absence of government subsidies 49.5% of all purchases would not have occurred. Additionally, over 70% of the total reduction in market capacity when subsidies are removed is directly attributable to larger capacity installations. Lastly, I find no evidence that household behavior is affected by the uncertainty associated with future subsidy regimes.

I dedicate this dissertation to my best friend, soulmate, and wife Cynthia. I would not be here today without your guidance, patience, unending support, and unconditional love.

You are truly amazing.

Te amo Bella.

To my father Ken and my mother Susan, I want to express my deep appreciation for your dedication to my education, and the unconditional love and support you have given me throughout my life.

I am so proud to be your son.

I love you both with all of my heart.

ACKNOWLEDGMENTS

First and foremost, I want to thank my advisor Brian McManus for his guidance and patience throughout the duration of this project. Both his willingness to let me learn through experience, and his timing to provide support when I needed it most played an important role in my growth as an economist, researcher, and writer. I want to thank my incredible committee members Donna Gilleskie, Clement Joubert, Helen Tauchen, and Andy Yates for their comments, conversations, tough questions, guidance and unending support. I want to thank a dear friend of mine Yoshiharu Kobayashi for lengthy conversations, unconditional friendship, and for introducing me to the field of economics. I want to thank Chrystie Burr, Justin Contat, J.R. DeShazo, Jonathon Hughes, Tiago Pires, Forrest Spence, all of the participants at the Camp Resources Workshop, all of the participants at the CU Environmental and Resource Economics Workshop, and all the participants of the UNC Applied Micro Seminar for their comments and suggestions. I want to thank UNC Libraries for providing funds to acquire housing data and for their kindness. I want to thank the wonderful staff at the California Energy Commission for answering all of my questions and granting me access to their dataset.

TABLE OF CONTENTS

LIST OF TABLES . . . . **viii**

LIST OF FIGURES . . . . **x**

1 Introduction **1**

2 Institutional Background **6**

2.1 Solar Panels 6

2.2 Subsidies and Tax Credits 8

3 Model **16**

3.1 Households' Problem 16

3.2 Utility From Purchase 18

3.3 Utility From Waiting 22

3.4 Tax Policies 23

3.5 Identification 28

4 Data **29**

5 Estimation **44**

6 Results **53**

6.1 Static Models 53

6.2 Dynamic Models 56

6.3 Model Fit 61

6.4 Elasticities 63

7 Counterfactuals **68**

8 Conclusion **78**

A Assumptions and Copulas **79**

A.1 Assumptions 79

A.2 Brief Summary of Copula Functions 80

B Additional Data Considerations **83**

C Additional Results and Counterfactual Simulations **97**

C.1 Additional Count Regression Results 97

C.2 Estimation Results 97

C.3 Counterfactual Simulations 100

BIBLIOGRAPHY **107**

LIST OF TABLES

4.1 Household Characteristics (Purchasers) 32

4.2 Household Characteristics (Full Population) 34

4.3 Household Characteristics (Reduced Population from Survey) 36

4.4 Full Set of Solar Panels 43

4.5 Set of Purchased Solar Panels 43

6.1 Number of Installations Per Day (Unconditional) 54

6.2 Number of Installations Per Day Conditional on 6-Month Bins 54

6.3 Models for Daily Installations 55

6.4 Static Model Estimation Results 57

6.5 First Stage Estimation Results from 2001-2010 58

6.6 Second Stage Estimation Results 60

6.7 Empirical vs Simulated Choice Probabilities 64

6.8 Empirical vs Simulated Choice Probabilities by Capacity Bin 65

6.9 Price Elasticity Given a 1% Increase in Price 66

6.10 Marginal Effect of a 1% Increase in Efficiency Rates 67

7.1 Change in Purchase without Government Intervention (Pes) 69

7.2 Change in Purchase (%) without Government Intervention by Capacity (Pes) 70

7.3 Additional Capacity (kW) Installed with Government Intervention (Pes) 72

7.4 Marginal Increase in Installations given a 10% Increase in the Subsidy (Pes) 76

7.5 Marginal Increase in Installations given a 10% Increase in the Subsidy (AR) 76

7.6 Number of Installations under Pessimism without Uncertainty 77

7.7 Number of Installations under Auto-renewal without Uncertainty 77

B.1 Summary Statistics 83

C.1 Models for Semi-Annual Installations 97
C.2 Second Stage Estimation Results (Reduced Sample) 98
C.3 Second Stage Estimation Results with an Additional Regime Change 99
C.4 Change in Purchase without Government Intervention (PF) 101
C.5 Change in Purchase (%) without Government Intervention by Cap (PF) 102
C.6 Additional Capacity (kW) Installed with Government Intervention (PF) 103
C.7 Change in Purchase without Government Intervention (AR) 104
C.8 Change in Purchase (%) without Government Intervention by Cap (AR) 105
C.9 Additional Capacity (kW) Installed with Government Intervention (AR) 106

LIST OF FIGURES

2.1 Subsidy Rates over Time 9

2.2 Subsidy Rate and Number of Installations Per Period 11

2.3 Average Tax Credit Per Watt 12

2.4 Medium Capacity Solar Panel System Prices in San Francisco 15

3.1 Case 1: Perfect Foresight 24

3.2 Case 2: Pessimistic Beliefs 26

3.3 Case 3: Auto-Renewal Beliefs 27

4.1 Electricity Prices by Utility Company 37

4.2 Price Per Watt by MSA 39

4.3 Price Per Watt by Capacity Bin in Los Angeles 40

4.4 Efficiency Rates over Time 42

7.1 Additional Capacity Installed with Subsidy by Capacity Bin 73

7.2 Number of Installations as a Function of % of Subsidy 75

B.1 Number of Installations Per Month and Subsidy Rate 84

CHAPTER 1

INTRODUCTION

In 2013, the market for solar panel systems reached a value of $12 billion dollars with an average annual growth rate of 50%. High growth rates in the solar market are attributed to the widespread use of subsidies and tax credits by federal and state governments, and sharp reductions in the cost of solar panels. The U.S. Energy Information Administration reports that federal funding for solar power increased 530%, from $179 million to $1.13 billion dollars, between the years of 2007 to 2010.[1] Since 2001, California has provided over $2 billion dollars in demand-side subsidies for solar panel systems, and consequently leads the United States in residential solar electricity generation.

For a household participating in a durable good market, the decisions of when to purchase and what to purchase are both important. Particularly in markets that are characterized by rapid technological innovation and declining market prices, a household might delay the decision to purchase for the option value of waiting. The California residential market for solar panel systems is similarly characterized by steady technological innovation and falling market prices, but is also subjected to multiple short-lived subsidy regimes. Short-lived subsidy regimes, lasting 2 to 3 years, are used to temporarily reduce prices and stimulate households' demand for solar panel systems. For these reasons, it is important to model the demand for solar panel systems in a dynamic framework. I introduce a structural model of dynamic demand for solar panel systems that includes uncertainty about future prices and future subsidies, and I estimate the model using a newly assembled data set at the household level. The model is used to investigate the implications of multiple short-lived subsidy regimes, evaluate price elasticities, and measure the effectiveness

---

[1] http://www.eia.gov/analysis/requests/subsidy/pdf/subsidy.pdf

of demand-side subsidies.

In a dynamic setting, households make decisions considering both the expectation regarding the change in prices over time and the level of prices within a period. In the solar panel market, forming expectations about the change in prices requires households to consider the change in market prices for solar panel systems and the existence of future subsidy regimes. Market prices for solar panel systems decline throughout the sample period with the price of an average solar panel system falling more than 20%. To account for market price uncertainty, households are not fully informed about the pricing process for solar panel systems, but instead expect future market prices to follow a Markovian process. This assumption, while simple, allows for households to be correct on average about the evolution of prices while still accounting for price uncertainty. Households are fully informed about the schedule of subsidy rates within a particular regime, but lack information about future regimes. To account for this uncertainty, households are assumed to have beliefs regarding the existence of future regimes. Three separate deterministic belief structures are tested in the paper. The estimation results show that demand is fairly robust to assumptions regarding households beliefs about future subsidy regimes. The findings indicate that during the sample period there does not seem to be an advantage of multiple regimes versus one long regime with respect to the total number of purchases in the market.

I evaluate both the short-run and long-run price elasticities for households in the market for solar panel systems. I consider the short-run case where all prices temporarily increase in one period and return to previous levels. Households are fully informed about the change in prices and results indicate that households are price elastic in the short run, due to the ability to substitute purchases intertemporally. I also consider the long-run case where all prices receive a permanent increase and do not return to previous levels. Results indicate that households are price elastic in the long run but are less elastic relative to short run price elasticities. Estimates suggest that price elasticities vary with respect to housing value.

To consider these factors, I use a California Energy Commission's dataset that tracks all residential solar panel system purchases from 2002 through 2006. The data include an approval date, total purchase price, total subsidy, capacity of the system installed, brand and model number of the system, and physical address of the household. I collect household-specific data on housing characteristics, solar irradiation, and electricity prices for all households in California. Additional data on household characteristics allow for the estimation of price responsiveness by housing value, and the role of housing characteristics on the decision to purchase. To complement household data, I collect detailed product characteristics for over 1,000 solar panel systems. Product-specific characteristics allow for the inclusion of technological innovations and extension to a multi-product choice set.

I estimate a household-level dynamic demand model for solar panel systems. In the model, a household decides between purchasing one of the available systems in the market and postponing purchase. If the household decides to purchase a system, it receives the expected discounted lifetime utility from the system and leaves the market indefinitely. If the household decides to postpone purchase, it continues to participate in the market the following period and the choice problem repeats. Before deciding, the household is fully informed of the prices, subsidies, product characteristics, and tax credits for the current period. The household has limited information about future prices of solar panel systems and holds beliefs about subsidy rates offered in the future. Using this information, the household forms an expected value of continuing in the market considering uncertainty, beliefs, and making a purchasing decision. The model is estimated using a two stage procedure similar to Rust (1994).

I contribute to the literature on solar panel adoption and policy in several ways. I improve upon current research by introducing a model that accounts for household and product-level observed heterogeneity and the uncertainty that consumers face regarding future prices and subsidies. The results show that the impact of uncertainty regarding future subsidies is minimal in the case of the solar market. Households are found to be price elastic with average short-run price elasticities of -1.6, and average long-run price elasticities are found to be lower relative to short-run price elasticities by 8%, suggesting that households are substituting demand intertemporally. The California Emerging Renewable Energy program was effective at incentivizing over 54% of all purchases during the two regimes.

This paper contributes to the growing literature exploring the impact of subsidies for solar panel systems. Bollinger and Gillingham (2010) explore a clustering pattern in the data on solar panel purchases and exploit exogenous variation in subsidies across utility regions to estimate peer effects. They find evidence of peer effects and estimate the impact of a purchases on the duration of time until the next purchase within a zip code. Hughes and Podlesky (2013) regress the number of installations on fixed effects and rebate levels to analyze the effectiveness of subsidies on solar installations and find that subsidies account for over 58% of purchases during their sample period. Burr (2014) compares the effectiveness and efficiency of different types of subsidies in a structural dynamic framework. She experiments with discount rates and finds interesting results with respect to public versus private discount rates. Her results suggest that subsidies account for over 85% of purchases in her dataset and finds the welfare neutral social cost of carbon to be $100 per metric ton. I contribute to the literature by investigating the effects of multiple subsidy regimes on the purchase of solar panel systems and discussing the impact of subsidies on both the total number of market purchases and the total market capacity. I find 49.5% of purchases would not have occurred in the absence of subsidies, and of the total loss in market capacity from the absence of subsidies, 70% is directly attributable to the reduction in the purchase of larger capacity systems.

In addition, this paper also contributes to the recent literature that uses structural models of dynamic consumer behavior. There are two prominent lines of research in this literature. The first line explores the purchasing decision for high tech products in markets where both prices and technology are changing rapidly (Melnikov 2001, Carranza 2007, Nair 2007, Prince 2008, Gowrisankaran and Rysman 2012). The research in this area focuses on either the introduction of a new product into the market or the decision to replace an existing product. Gowrisankaran and Rysman (2012) investigate the purchase and replacement decision for consumers in the digital camcorder market, and include unobserved heterogeneity in both the marginal utility of quality and the marginal utility for money. Accounting for this heterogeneity allows for the model to capture the trade-off between quality and timing of replacement for consumers. I use a model similar to Gowrisankaran and Rysman's (2012) but without the decision to replace. I segment the marginal utility of quality and money by household-level observable characteristics to allow for heterogeneity in preferences for different segments of the solar market. Additionally, I explicitly model the impact of price uncertainty on the decision to purchase.

The rest of the paper is organized as follows: Chapter 2 discusses the solar market, Chapter 3 discusses the model, and utility specifications, Chapter 4 discusses data, Chapter 5 details the estimation procedure, Chapter 6 reports demand estimates and discusses fit, price elasticities and marginal effects, Chapter 7 reports results from counterfactual simulations, and Chapter 8 concludes.

CHAPTER 2

INSTITUTIONAL BACKGROUND

2.1 Solar Panels

Solar panel systems generate electricity from sunlight. The electricity production capability of a solar panel system is a function of the system's capacity rating and the hours of usable sunlight at the installation site. Capacity ratings are a measure, in kilowatts (kW), of the maximum power a system can produce under controlled test conditions[1]. Over the course of a day, a solar panel system receives sunlight and generates electricity in units of kilowatt hours (kWh). Total generation of electricity for the day is the product of the total hours of sunlight and the capacity rating of the system.

How well a solar panel system converts sunlight into electricity is measured by the efficiency rate of the system. Efficiency rates are a function of capacity rating, Photovoltaics for Utility Systems Applications test conditions (PTC), and the physical size of a system expressed as:

$$\mathit{Eff} = \frac{Capacity}{Size * PTC} \tag{2.1}$$

Equation 2.1 shows the inverse relationship between the efficiency rate and the physical size of a solar panel system, when capacity is held constant. For two solar panel systems with identical capacity ratings, if one system has a higher efficiency rate relative to the other, the system with the higher efficiency rate will have a smaller physical footprint. Given equivalent hours of sunlight, the

[1]There are two test conditions used for solar panel systems in the state of California. The first, standard test conditions (STC), reflect the solar panel's production under ideal conditions. All panel characteristics are tested including capacity rating, voltage, amps, and temperature. The state of California uses an additional measure known as Photovoltaics for Utility Systems Applications test conditions (PTC) that test the panel in a controlled environment that mimics real world conditions. These measures are performed by an independent third-party testing facility. The subsidy program uses PTC capacity ratings to determine the amount of subsidy an installation site receives

two systems will produce the same amount of electricity, but the system with the higher efficiency rate uses less physical area.

At the time of generation, electricity produced by the solar panel system is available for either immediate consumption by the household or the electricity is sold on to the grid. To manage the direction of the generated electricity, net meters are required to be installed for all solar panel systems approved by the subsidy program. A net meter directs the flow of generated electricity and tracks the quantity demanded and quantity supplied of electricity for the household.[2] This enables households that install a solar panel system to be both a consumer and producer of electricity.

A solar panel system is a durable good and by definition produces a multi-period stream of benefits for the household. The duration of the benefits, generation of electricity for solar panel systems, is conditional on the characteristics of the system purchased, weather at the installation site, maintenance, and other factors at both the manufacturing and installation levels. Since the solar panel systems in the sample period are in their infancy, the lifespan of the solar panel system is approximated using warranty information provided by the manufacturer. The average solar panel system comes with a warranty that covers the first 25 years of use, split between the first 10 years and the subsequent 15. For the first 10 years, the warranty guarantees that the power output will not go below 90% of the installed capacity rating. For the next 15 years, the warranty guarantees at least 80% of the installed capacity rating. Assuming constant degradation, the average solar panel system degrades at a rate of 0.9% per year, and continues to generate electricity well beyond the warranty period. [3]

---

[2]Generally speaking, a net meter prioritizes the flow of electricity from the solar panels for consumption first and supplying to the grid as a secondary objective. During solar electricity production periods, the net meter will direct solar generated electricity to the household until quantity demanded is satisfied or all solar generated electricity is being consumed by the household. In the first case of quantity demanded being satisfied, the remaining solar generated electricity will be sold onto the grid. In the second case of all solar generated electricity being consumed, the net meter will buy from the grid to satisfy the household's demand for electricity.

[3]The assumption of a constant degradation rate is for simplicity. There does not exist data on the rate in which solar panel production will degrade over time.

2.2 Subsidies and Tax Credits

The California Emerging Renewables Energy program was established by the California Energy Commission (CEC) in 1998 following Assembly Bill 1890 and Senate Bill 90 for distributing funds collected to support renewable electricity generation technologies (Guidebook 2001). The intent of the fund is to subsidize the purchase of renewable energy technologies through intervention on the demand side of the market. To subsidize the residential market, the CEC introduced capacity-based subsidies, an instrument that provides one-time monetary transfers based on the capacity rating of the system installed.[4] The subsidy a household receives is a function of the capacity rating of the system and the subsidy rate available on the date of approval. The regimes during the sample period differ concerning the subsidy rates offered, but all regimes use capacity-based subsidies.

The CEC rebate program consists of three consecutive subsidy regimes lasting 2 to 3 years each from 1998 until 2007. At the beginning of a subsidy regime, the CEC published a public guidebook that provides households with information about the rebate program. The guidebook includes information about the degree and timing of subsidy rates, eligibility requirements, and eligible costs by a particular regime. The guidebook does not provide information about a future subsidy regime, and this lack of information introduces uncertainty into the household's choice problem.

Figure 2.1 illustrates the three subsidy regimes that occur during the sample period. The vertical axis represents the subsidy rate in dollars per watt installed. The horizontal axis is the years covered during the sample period and are represented in 6-month intervals. The vertical dashed lines represent a change in the subsidy regime. The first vertical dashed line on January of 2003 represents the beginning of the first 6-month period of the second subsidy regime. The second dashed line at July of 2005 represents an unscheduled change in the subsidy rate during the second subsidy regime. The third dashed line at January of 2007 represents the beginning of the first 6-month period of the third subsidy regime. The step function represents the subsidy rate for a

[4] The CEC uses a production based subsidy for commercial grade installations.

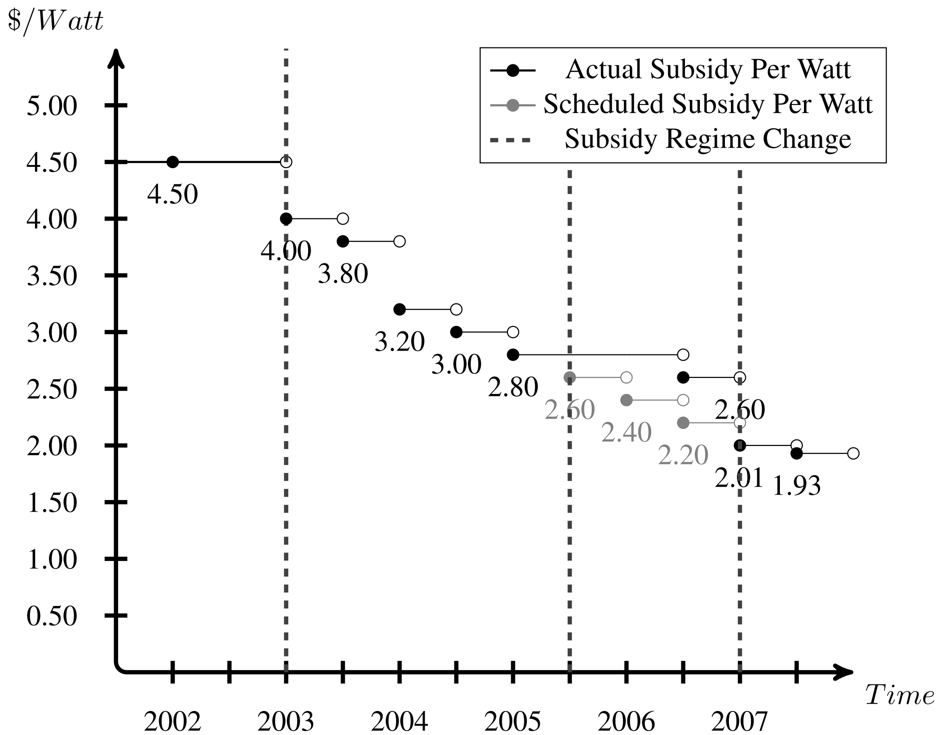


Figure 2.1: Subsidy Rates over Time

6-month period. The solid circles identify the beginning period of the rate and hollow circles identify the expiration of the rate. For example in Figure 2.1 the second step begins on January 1, 2003, with a solid circle, at a rate of $4.00 per watt and the rate ends on June 30, 2003 shown by the hollow circle. The next subsidy rate of $3.80 per watt begins on July 1, 2003 and expires on December 31, 2003. The black circles identify subsidy rates that actually occurred during the time period specified and the gray dots identify subsidy rates that were scheduled but never realized.

The first subsidy regime begins in 2001 with a fixed subsidy rate of $4.50 per watt. This rate remains unchanged until the end of 2002 when the regime expires. During the regime, subsidies reduce the price of an average solar panel system by 46%, decreasing the price by $19,000. The second subsidy regime begins in 2003 and continues through the end of 2006. The regime begins with an initial rate of $4.00 per watt, and decreases $0.20 semi-annually with an additional $0.40 decrease in January of 2004.[5] In spring 2005, the CEC released a revision to the 2003 public

[5]In Figure 2.1 and 2.2, subsidy rates after 2005 in gray illustrate the proposed schedule from the 2003 public guidebook.

guidebook that suspended the scheduled subsidy decrease and held the January 2005 subsidy rate of \$2.80 fixed for an additional year. In July of 2006, the subsidy rate incurred the scheduled \$0.20 decrease before the regime ended in December. The suspension of the scheduled decrease generated a \$0.40 per watt difference in the subsidy rate relative to the original schedule. This difference reduced the price of an average solar panel system by an additional 5% or \$1,500. After the second subsidy regime, the distribution of funds specific to solar panel installations was handed over to the new California Solar Initiative (CSI).

The California Solar Initiative is the third subsidy regime in the sample. The CSI begins in 2007 with a \$2.01 subsidy rate[6] and is scheduled to actively provide subsidies until 2016. The CSI program introduced a new system for the timing of subsidy rate changes and the conditions under which they transition. Subsidy rates are set at the state level following a rate schedule, but the transition between rates occurs at the utility region level. In 2007, all utility regions start at the same rate in the subsidy schedule.[7] The transition between subsidy rates is a function of the total amount of solar electricity generated in the utility region and a region-specific level of total generation to trigger the transition.

In Figure 2.2 the subsidy rate step function is overlaid by the number of installations in the sample period. The right-most vertical axis represents the number of installations and the height of the vertical gray bars correspond to the number of installations in each 6-month period.

I hesitate to make causal claims about purchasing patterns by focusing solely on the subsidy rates, and instead I discuss interesting patterns that emerge from the data. In general, the subsidies seem to be generating a response from households in the population. For the first half of the second regime, quantity demand is decreasing as subsidy rates fall. As a naive observation, quantity demanded is expected to fall as subsidies decrease and prices remain the same. During this period, the market price of a solar panel system is decreasing but at a rate slower relative to the decrease in subsidies. This results in the net price per watt for a solar panel system increasing from 2002

[6] Inflation-adjusted subsidy rate.

[7] The CSI rate scheduled is provided in the Appendix.

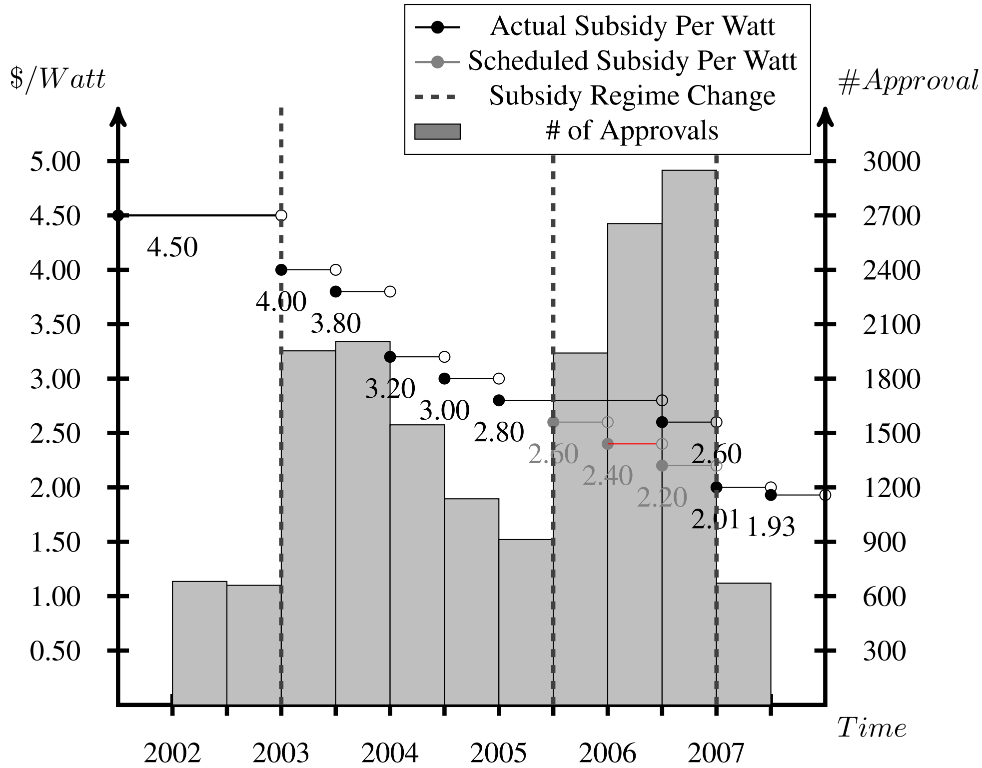


Figure 2.2: Subsidy Rate and Number of Installations Per Period

through 2005. Additionally, households know the schedule of subsidy rates within the regime and given their expectation about future prices the expected change in the net price per watt of a solar panel system is positive and increasing. Both the increase in the level of the net price per watt and the expected positive change in net prices between periods lowers the probability of purchase for households in the market. It is not surprising to see quantity demanded decreasing during this period.

A second feature of Figure 2.2 is the increase, for the remainder of the regime, in quantity demanded following an unscheduled change in the subsidy rate in 2005. At the onset of the delay, quantity demanded almost doubles.[8] The delay in the scheduled decrease of the subsidy impacts per period net prices as well as households expectations about the change in net prices. Also, the increase in quantity demanded occurs three periods from the end of the second subsidy regime. In the data, there is evidence of a positive correlation between the number of periods left in a regime

[8]In Figure 2.2, quantity demanded doubles after the second vertical dashed line. During the first 6-month period of 2005, 900 installations occur and in second half of 2005 installations go beyond 1800.

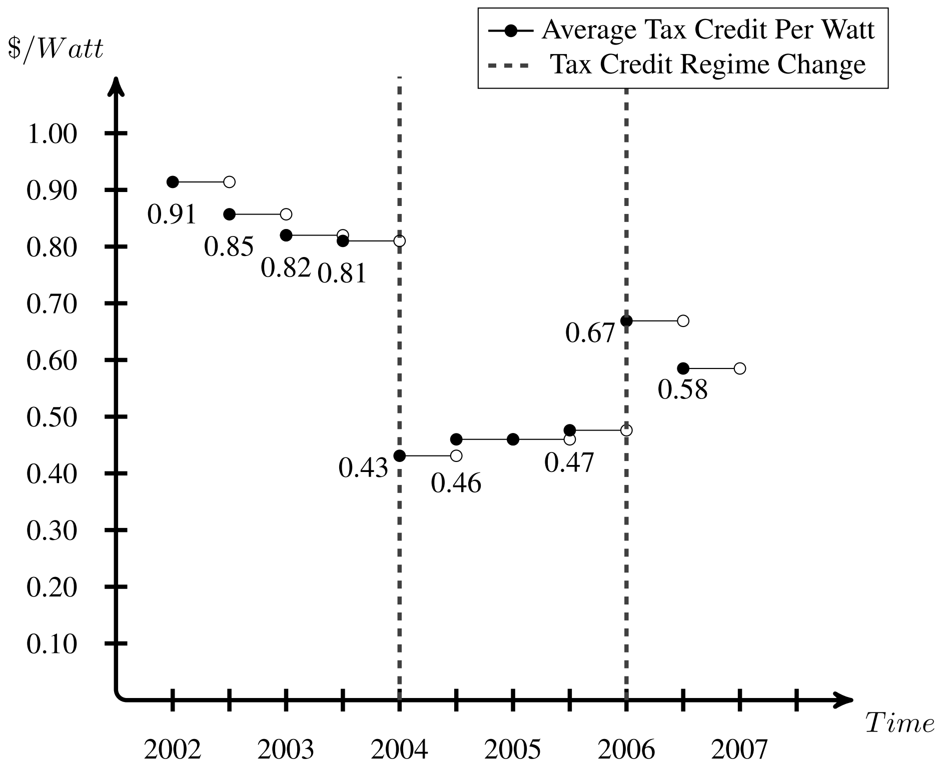


Figure 2.3: Average Tax Credit Per Watt

and quantity demanded, likely due to the uncertainty regarding future subsidies. Both features of the market would contribute to the increase in quantity demanded during this time period.

Tax credits are offered during the sample period in addition to the CEC subsidy program. Tax credits are intended as a secondary source of subsidy. The amount of credit a household receives is calculated from the net price of a system after accounting for the CEC subsidy. There are three tax credit regimes that overlap with the sample period. The regimes differ by rate schedule and the maximum allowable credit.

From 2001 through 2003, California offered a tax credit equal to the minimum of 15% of the net price up to a maximum amount of $4.50 per watt. In all instances, households received a tax credit equal to 15% of the net price paid. In 2004 and 2005, the state offered a similar tax credit, but reduced the percentage to 7.5% of the net price and kept the maximum at $4.50 per watt. A similar result occurred; all purchases qualified for the tax credit of 7.5% of net price paid with no households receiving the maximum per watt amount offered. At the beginning of 2006, the state did not renew the solar tax credit, but the federal government offered a nationwide tax credit. The federal tax credit increased the rate to 20% of the net price but capped the maximum total tax credit at \$2000. In all instances, households were provided with \$2000 in federal tax credits.

Due to the structure of the tax credits, the credit per watt varies across capacities and Metropolitan Statistical Areas (MSA). The variation across capacity occurs as a result of net price varying across capacity. Similarly, variation in net prices across MSAs generate variation in the credit per watt received by a household. In Figure 2.3, I show the average tax credit received for each 6-month period during the sample. The vertical axis represents the tax credit per watt and the horizontal axis is the sample period discretized into 6-month bins. The step function represents the average tax credit for each period.

During the first regime, average credits range from \$0.91 per watt to \$0.81 per watt. The decrease in the credit per watt over the period reflects the decrease in the net price of a system occurring at the same time. In the second regime, the tax credit is reduced by 50% with the credit per watt starting at \$0.43 per watt and increasing to \$0.47 per watt. In the third regime, the credit per watt increases to \$0.67 per watt. The standard deviation of the average tax credit per watt varies over the sample period. The largest variation occurs during the third regime because all households receive a fixed tax credit regardless of the capacity of the solar panel system installed. This results in larger capacity systems receiving a lower per watt tax credit.

In Figure 2.4, I show the evolution of prices for a medium size (2.72kW) solar panel installation in the San Francisco area during the sample period. The vertical axis represents the price per watt for a solar panel system, and the horizontal axis represents time in 6-month periods starting in 2002 and ending in 2007. Each time period has three prices represented on the graph. The black dot represents the market price for the solar panel system during the 6-month time period. The dark gray dot represents the net price of the system after accounting for the subsidy. The red dot represents the net price of the system after accounting for the subsidy and tax credit.

There are two important trends to focus on in Figure 2.4. First, the CEC subsidies are the main component in the reduction of solar panel system prices compared to tax credits. During the first 6-month period of 2002 the government reduced the price of a solar panel system by over 55%. Of the total reduction, CEC subsidies account for 78.2% of the total price reduction for medium sized installations while the tax credit accounts for 21.8% of the price reduction. Throughout the sample period the overall percentage reduction in the price decreases, but the subsidy continues to be the largest contributor to the overall reduction in price. This does not discount the importance of the tax credit but it provides support for the investigation into the effects of the subsidy program on the household's decision to purchase a solar panel system. Second, it is important to note that the net price of purchasing a solar panel system is increasing after 2004. This is a direct result of the subsidies and tax credits decreasing at a higher rate relative to the reduction in the market price for a solar panel system. A similar trend occurs for solar panel installations across capacity level and MSA.

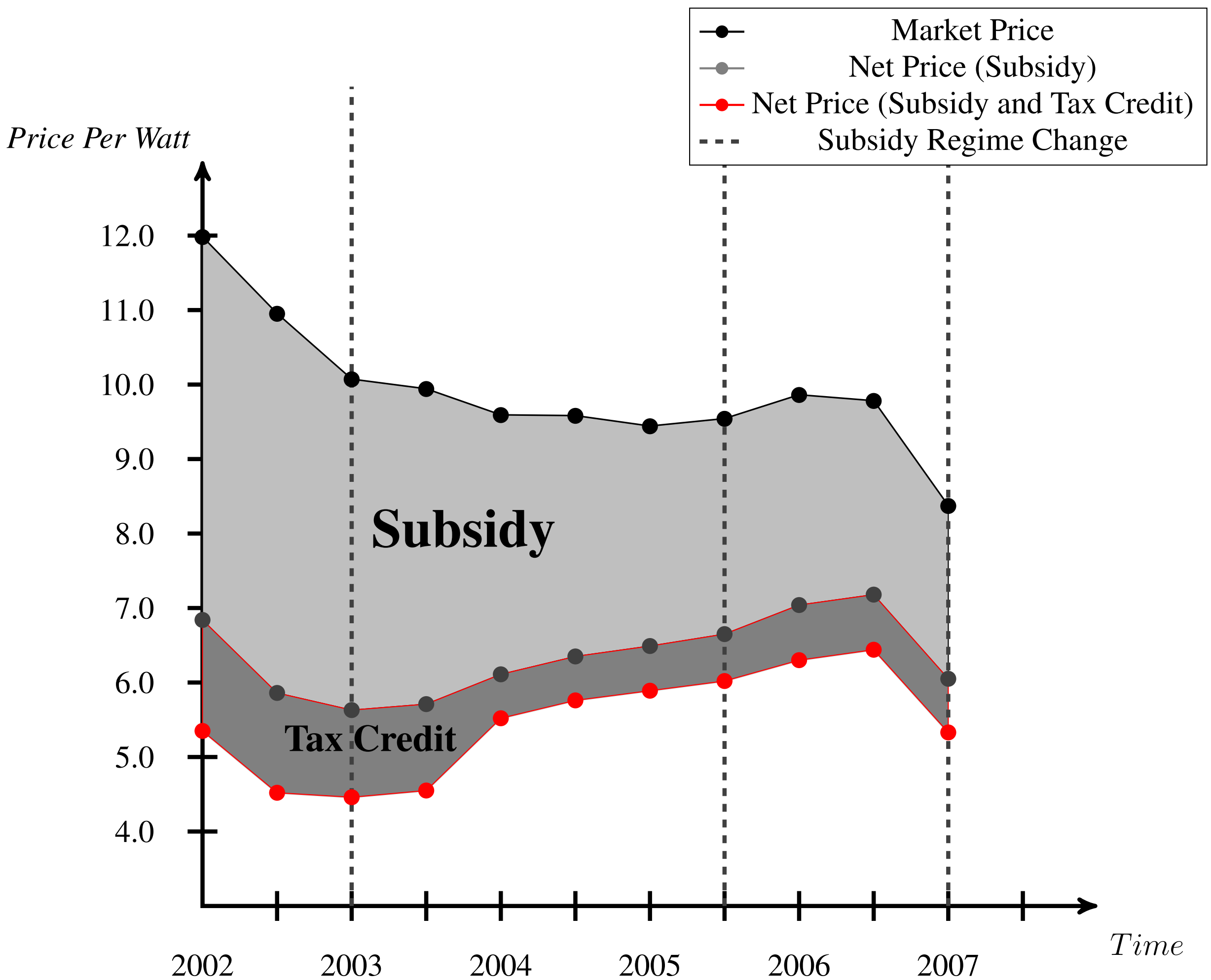


Figure 2.4: Medium Capacity Solar Panel System Prices in San Francisco

CHAPTER 3

MODEL

3.1 Households' Problem

At the beginning of the sample, no households in the market own a solar panel system. During each period, households face the decision to purchase a solar panel system or postpone purchase. Households that postpone purchase continue to be active in the market during the following period. Households that purchase are removed from the market permanently and receive a stream of benefits for the lifetime of the system. Households are constrained to purchase at most one system per period and at most one system during their lifetime. Households do not have access to a resale market, and are unable to upgrade the system after installation.[1]

The market is populated by a set of households $i \in \{1, 2, \ldots, N\}$ making purchasing decisions in an infinite-horizon discrete-time framework. A household evaluates the alternatives, s_{it}, from the set of capacities available in the market. The full choice set of products and capacities is large and as a simplification the choice set is aggregated to five options. The choice set includes the outside option of not purchasing and four solar panel systems differentiated by capacity rating and

[1] The decision to constrain households to one purchase per lifetime is backed by the combination of empirical evidence, high prices, and the durability of solar panels.

represented by the set S, where

$$S = \begin{cases} 0 & \text{Outside Option} \\ 1 & \text{Small} \\ 2 & \text{Medium} \\ 3 & \text{Large} \\ 4 & \text{Extra Large} \end{cases}$$

In the choice set, zero represents the outside option of not purchasing and options one through four represent small (1.80kW), medium (2.72kW), large (4.14kW), and extra large (6.51kW) capacities. Capacities are time invariant, I discretize the distribution of capacities over the sample period into quartiles with support of zero to 10kW, the maximum allowable system capacity. I set the mean of each quartile to represent the capacity rating for each option in the choice set.

At the beginning of each period, households have full information about the current period's state space $\Omega_t = \{P_t^e, P_t^{sp}, Z_t, S, \epsilon_t, \tau_t\}$. The state space includes the vector of electricity prices, P_t^e; the vector of solar panel system prices, P_t^{sp}; the vector of product characteristics, Z_t; the set of capacities, S; the vector of taste shocks, ϵ_t; and the vector of tax subsidies and credits, τ_t. Households are assumed to know the distribution of the state variables $G\left(\Omega_{t+1}|\Omega_t\right)$. Households select an alternative each period from the choice set to maximize their expected lifetime utility.

Initially, the market contains all households and is defined as $M_1 = N$. At the end of each period, the market is adjusted to account for households that purchase. The next period's market size is equal to, $M_{t+1} = M_t - \sum_{i \in M_t} 1\left(s_{it} \neq 0\right)$, the market size at the beginning of the period minus the number of households that purchase in the same period. Including the endogenous change in the size of the market eliminates the potential bias discussed below.

As households purchase and leave the market, the demand for solar panel systems shifts to reflect the change in the distribution of households participating in the market. It is important to adjust the market for changes in the distribution of household types and the number of market participants to reduce potential bias on the price coefficients. The bias enters by leaving a growing set of households in the market that are perfectly price inelastic and due to their non-responsiveness to price changes put downward pressure on the parameter estimates for price. To remove the bias, I track the number of households that purchase and leave the market and adjust the market size after each period.

3.2 Utility From Purchase

Let $\omega_t = \{P_t^e, P_t^{sp}, Z_t, S, \tau_t\}$ represent the state variables without the household-level taste shocks, ϵ_t. The indirect lifetime utility from purchasing a solar panel system of size s at time t is:

$$U_{ist}\left(\omega_t, \epsilon_t; \theta, \alpha\right) = \theta_1 + \theta_2 ln\left[PV_{ist}\left(p_{it}^e; \delta\right)\right] + \theta_{3i} z_t - \alpha_i ln\left(\left(p_{ist}^{sp} - \tau_{st}\right) q_s\right) + \theta_{4MSA_i} + \epsilon_{ist} \quad (3.1)$$

The indirect utility function is comprised of the present value from purchase, non-price product characteristics, the net price after receiving subsidies and tax credits, a MSA level fixed effect at the time of purchase, and a purchase shock that is assumed to be distributed iid Type I extreme value. The details of each part of the utility function are discussed below.

The second term in the utility specification, PV_{ist}, represents the present value of electricity generated over the lifetime of the solar panel system for household i purchasing product s during period t. I define the present value as:

$$PV_{ist}\left(p_{it}^e; \delta\right) = \sum_{k=t}^{\infty} \left[\beta^{k-t} \left(1 - \delta^{sp}\right)^{k-t} \left(1 + \delta^e\right)^{k-t} p_{it}^e q_s h_i^{sun}\right] \quad (3.2)$$

where the bracketed term is summed over the lifetime of the system, and includes the following components:

- p_{it}^e the price of electricity for household i
- q_s the capacity of solar panel system s
- h_i^{sun} the hours of sunlight for household i
- δ^e escalation rate for electricity prices
- δ^{sp} capacity rating degradation rate
- β discount rate

On the right hand side of Equation 3.2, the term $p^e_{it}q_sh^{sun}_i$ is the flow of revenue received each period for the generation of solar electricity. The revenue term consists of the product of the price of electricity for household i at time t, p^e_{it}, and the total amount of solar generated electricity during period t. The amount of solar generated electricity is calculated as the product of the capacity of system s, q_s, and the average hours of sunlight household i receives, h^{sun}_i, over a 6-month period. The present value is calculated by adjusting the revenue stream each period to account for the decrease in electricity generation due to the degradation of the system, changes in future electricity prices, and discounting future income.

I calculate a constant degradation rate for solar panel systems during the sample based on data from manufacturer-provided warranties. I assume the calculated rate to be a constant percentage decrease in the production capabilities of the system and is consistent with the guaranteed production listed in the warranty. In the present value equation, the degradation rate is represented as $\delta^{sp} \in (0, 1)$ and reduces solar electricity generation by $\delta^{sp}\%$ each period. Including the degradation rate helps improve the approximation of the present value of owning a solar panel system by accounting for the eventual reduction in the generation of electricity. The reduction in capacity decreases the quantity of electricity produced and leads to a reduction in revenue. Similarly, the evolution of electricity prices must be accounted for in the revenue equation.

The price of electricity is a key variable for calculating the present value of purchasing a solar panel system. In the dynamic framework it is reasonable to believe that households form expectations about future electricity prices when making their purchasing decision. A simple way to account for future changes in the price of electricity is to assume a constant escalation rate for electricity prices. A more complex way is to model the process as Markovian and have consumers form expectations over future prices. The latter option of implementing the price of electricity as a stochastic state variable can be added to the present value computation albeit with a high computational cost. To reduce the computational complexity, I assume a constant escalation rate to calculate the present value of purchasing a solar panel system, and use an inflation-adjusted average escalation rate calculated by the U.S. Energy Information Administration (EIA).[2] Lastly, all households in the sample are assumed to discount future income by a rate of β.

In Equation 3.1, the third term, $\theta_{3i} z_t$, captures the effect of non-price product characteristics on the households decision problem, specifically the efficiency rate of a solar panel system. The parameter enters the utility specification linearly and expands to include rooftop space as a dimension of observable consumer-level heterogeneity. I discretize the distribution of rooftop space in the sample into three bins that represent small, medium, and large rooftop space households.[3] I normalize the parameters relative to large rooftop space households. I interact the non-price product characteristic covariate with the additional parameters designating both small and medium rooftop space households.

$$\theta_{3i} = \theta_{31} + \theta_{32} 1 \left(x_i^{roof} = \text{small} \right) + \theta_{33} 1 \left(x_i^{roof} = \text{medium} \right) \tag{3.3}$$

The first term in the Equation 3.3 captures the mean preference for efficiency rates in the sample population of large rooftop space households. The second and third term capture the additional utility received by households with either small or medium roof space. The decision to interact efficiency rates and roof space is best understood when considering the importance of physical area at an installation site.

Consider a household with roof space of 50 square meters. Given rooftop space and efficiency rates at the beginning of the sample, the household is constrained physically to installing a solar panel system no larger than 5kW. By the end of the sample period, the average efficiency rate increases by 30%, and the largest capacity rating for the same installation site increases to 6.5kW. The innovation in the efficiency rate over the sample period increases the semi-annual flow benefit from purchase by \$200 leading to a total increase of \$4000 in the present value of purchase. The

[2] In Figure 4.1 the electricity rates are shown for each major utility company over the sample period. Additionally, a trend line is added that represents the escalation rate for electricity prices.

[3] The measure for rooftop space is an approximation using the square footage of the home and the number of stories

improvement in the present value of purchase from the larger capacity system may incentivize the household to delay purchase until efficiency rates are sufficiently high.

In Equation 3.1, the fourth term is the natural log of the net price of a solar panel system. The total net price per watt is comprised of the market price per watt, p_{ist}^{SP}, subtracted by the approved subsidy per watt and tax credit per watt, τ_{st} for household i and capacity size s at time t. The total net price of a solar panel system is calculated as the product of the total net price per watt and the capacity, q_s, for choice s.[4] The coefficient α_i on the net price captures the disutility from the net price of a solar panel system.

As a starting point, I discretize the distribution of housing values, at the state level, into terciles and assign each household in the sample population to a housing value bin. The bins represent low, medium, and high value homes, and serve as a proxy for wealth in the utility specification. The price coefficient α_i in Equation 3.4 includes additional parameters interacted with an indicator function identifying a household's housing value. By including α_i, I introduce an observable measure of household-level heterogeneity in the estimation of price responsiveness.

$$\alpha_i = \alpha_1 + \alpha_2 1(x_i^{value} = \text{medium}) + \alpha_3 1\left(x_i^{value} = \text{high}\right) \tag{3.4}$$

I estimate the disutility from log prices in the sample population for households in the low housing value category with the α_1 coefficient. I estimate the differences in disutility that households of medium and high value receive from the net price with the parameters α_2 and α_3.

The next term, $\theta_{4\text{MSA}_i}$, is a Metropolitan Statistical Area (MSA) level fixed effect received at the time of purchase. I include an MSA-level fixed effect in the model to reduce the presence of endogeneity from omitted variables that are correlated with covariates in the model. Some examples of this might be the average environmental preferences within a MSA, advertising or marketing for solar panel subsidies, or pollution levels within a MSA.

In areas that are more ”green” or environmentally friendly households might receive additional

[4] It is important to note that while capacity is time invariant, the total net price per watt varies over time by the market price, subsidy, and tax credit

social utility from installing a solar panel system that is not accounted for in the current specification. The unobserved social benefit from installing solar panels could be correlated with prices making price endogenous in the model. The MSA fixed effect is included to capture variation from a time invariant MSA level preference for green products and the social utility associated with it. Another potential source of variation is advertising or marketing for either the solar panel subsidies or solar panel installations in general. Lastly, MSA level characteristics that are correlated with clean energy, level of pollution in the MSA, could generate endogeneity issues in the model. For example, a household in L.A., where pollution is persistently high, might purchase a solar panel system and receive unobserved utility from the belief that the system will help reduce pollution in the local area and provide positive externalities to the community.

3.3 Utility From Waiting

In markets with durable goods, capturing the option value of waiting is important in explaining the choice behaviors observed by households (Melnikov 2001, Gowrisankaran and Rysman (2012)). The option value of waiting is the expected utility from participating in a future market. The household choice-specific value function for choosing not to purchase is represented by V_i.

$$V_i\left(\omega_t, \epsilon_t; \theta, \alpha\right) = \delta^f_{i0t} + \epsilon_{i0t} + \beta \int_{\omega_{t+1}} \int_{\epsilon_{t+1}} V_i\left(\omega_{t+1}, \epsilon_{t+1}; \theta, \alpha\right) G\left(\omega_{t+1}, \epsilon_{t+1} | \omega_t, \epsilon_t\right) d\omega_{t+1} d\epsilon_{t+1} \tag{3.5}$$

The contemporaneous indirect utility from not purchasing is characterized by a flow utility, δ^f_{i0t}, that is normalized to zero and an additive preference shock, ϵ_{i0t}. The last term on the right hand side of Equation 3.5 represents the option value of waiting, and is integrated over the conditional joint distribution of the state variables, $G\left(\omega_{t+1}, \epsilon_{t+1} | \omega_t, \epsilon_t\right)$. Intuitively, the term captures the mean utility a household expects to receive by waiting to purchase considering future prices, technology, subsidies, tax credits, and preference shocks.

Information about the evolution of the state variables is necessary for households to form an expectation about their future value of staying in the market. Two state variables are assumed to be stochastic: the price of solar panel systems and preference shocks. Households are assumed to know the distribution of their future preference shocks and are able to integrate over them. Households are assumed to believe that the price per watt for solar panel systems follow a Markovian process. Specifically, households expect that the price per watt for a solar panel system follows a first order autoregressive specification,

$$P_{it+1}^{SP} = \delta_{i1} + \delta_{i2} P_{it}^{SP} + \mu_{it+1} \tag{3.6}$$

where μ_{it+1} is normally distributed iid shock with mean zero and variance σ_{sp}^2. The autoregressive parameter δ_{i2} satisfies the condition for stationarity $0 < \delta_{i2} < 1, \forall i$.

In Equation 3.6, I allow for the pricing process to differ across MSAs and allow local market conditions to influence households expectations about future prices. A vast majority of installations occur by local installers within the MSA and as such markets can be treated separately. Changes in local market demand and supply conditions should generate differences across MSAs in the pricing process to the extent that markets are independent. I compare the results of the per MSA estimation of Equation 3.6 to a state-level pricing process, in which I assume that households believe that solar panel system prices evolve similarly across capacity and MSA.

3.4 Tax Policies

Over the three subsidy regimes, information regarding policy changes becomes publicly available only at the time of the change. The uncertainty households have regarding future subsidy regimes and changes to rate schedules creates uncertainty that enters into the dynamic choice problem. Household beliefs regarding future regime changes can generate anticipatory behavior. Anticipatory behavior has been shown to impact the effectiveness of a regime change (Mertens and Ravn, 2010; Crepon et al, 2010, Blundell et al. 2014). To examine this, I specify deterministic cases that vary by household beliefs regarding the existence and rate schedule of a future regime. The deterministic cases are a simplistic way to capture anticipation effects that might arise from beliefs about future regimes and control for them in estimation.

I investigate three cases of deterministic beliefs: perfect foresight, pessimism, and auto-renewal. I use these cases as an initial investigation into anticipatory behavior in the solar market. To help

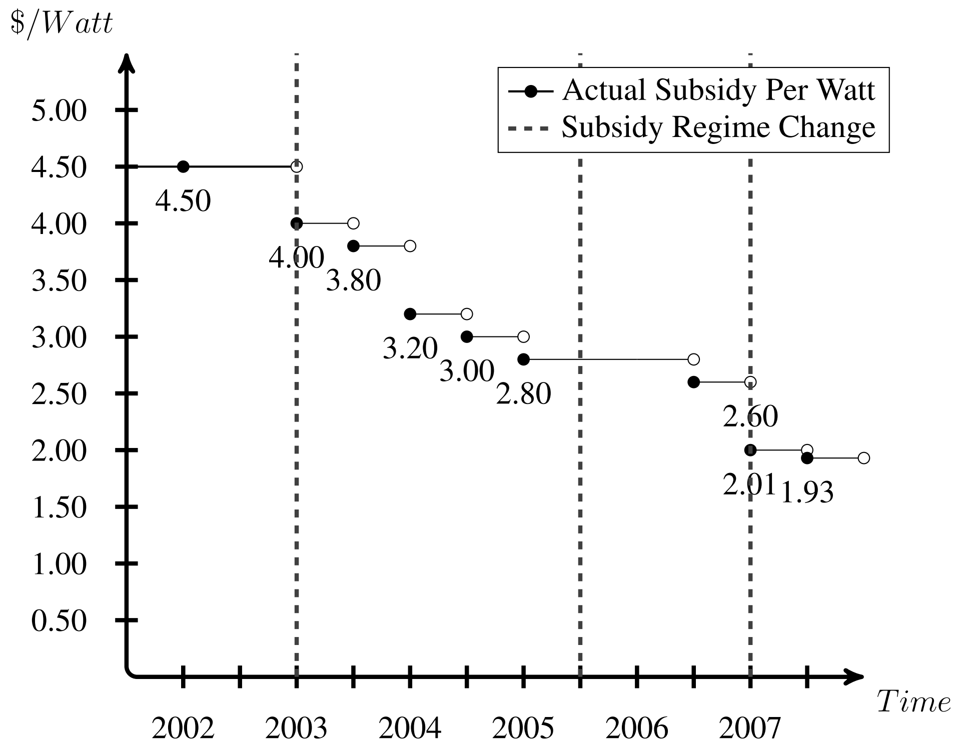


Figure 3.1: Case 1: Perfect Foresight

describe the cases, let $Pr(\tau'|\tau)$ be defined as the probability that future regime τ' occurs conditional on the household being in subsidy regime τ. Note that all households in the population are assumed to share the same beliefs regarding future regimes.

In the first case, I assume that households have full information about all regimes, and can predict the future perfectly. Perfect foresight implies that households have the following beliefs

$$Pr(\tau'|\tau) = \begin{cases} 1 & \text{if } \tau' = \tau_{true} \\ 0 & \text{Otherwise} \end{cases} \tag{3.7}$$

where τ_{true} represents the true future subsidy regime. Figure 3.1 illustrates the information households have under perfect foresight during the sample period. The vertical axis represents the subsidy rate per watt and the horizontal axis is the sample period discretized into 6-month bins. Note, under perfect foresight households are not subject to the scheduled subsidy rates that were not actualized represented in gray in Figure 2.1.

In the second case, I assume that all households are pessimistic and believe that no additional subsidies are offered after the expiration of the current regime. Pessimism implies that the discrete probability density function takes the following form

$$Pr(\tau'|\tau) = \begin{cases} 1 & \text{if } \tau' = 0 \\ 0 & \text{Otherwise} \end{cases} \tag{3.8}$$

where households believe with probability one that no future subsidy regimes will exist. In Figure 3.2a, I show a household's belief regarding the existence of a future regime conditional on being in the first regime of the sample period. When a new subsidy regime is reached the household updates their information about the new policy but retains the same beliefs about the existence of a future subsidy. In Figure 3.2b, I illustrate the transition to the second subsidy regime and how the belief regarding a future regime does not change. The beliefs enter the households' problem through the expectation of future prices, and is expected to decrease the option value of waiting relative to the perfect-foresight case.

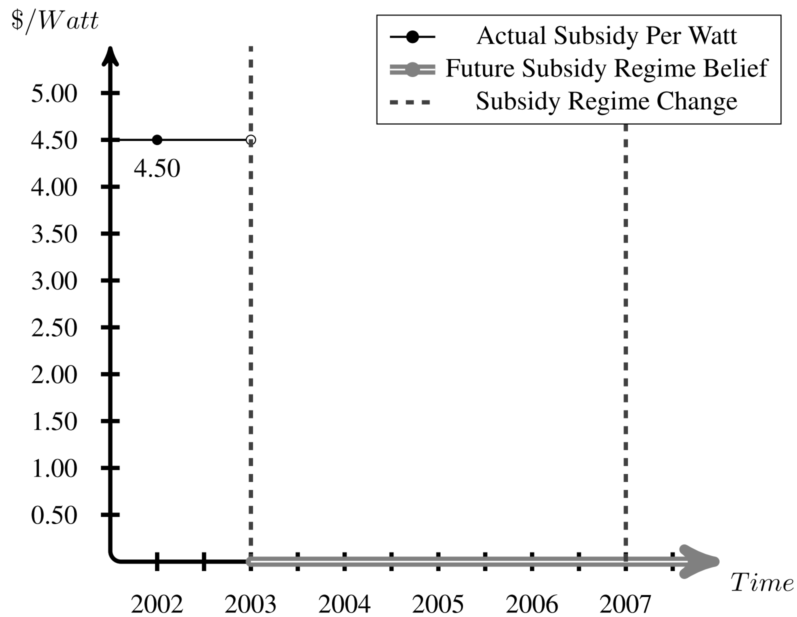
In the third case, auto-renewal, households believe that the final subsidy rate in the present regime will continue after the regime expires. Auto-renewal implies that the discrete probability density function takes the following form

$$Pr(\tau'|\tau) = \begin{cases} 1 & \text{if } \tau' = \tau^f \\ 0 & \text{Otherwise} \end{cases} \tag{3.9}$$

where τ^f represents the final rate in the current subsidy regime τ. In Figure 3.3a, I illustrate a household's belief about future subsidies conditional on being in the first subsidy regime. I show in Figure 3.3b how the belief about a future regime does not change when a new regime is enacted but the future subsidy rate is updated.[5]

[5] In Figure 3.3b I use two gray arrows to illustrate beliefs about a future subsidy regime. The top gray arrow represents household beliefs after the subsidy rate change is announced in July of 2005. The lower gray arrow represents household beliefs before the rate change is announced.

(a) Subsidy Regime One



(b) Subsidy Regime Two

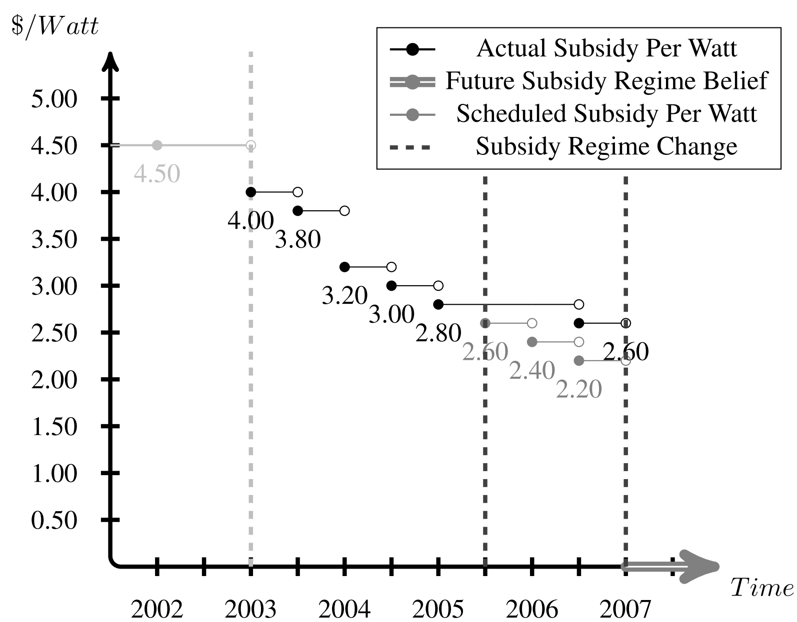


Figure 3.2: Case 2: Pessimistic Beliefs

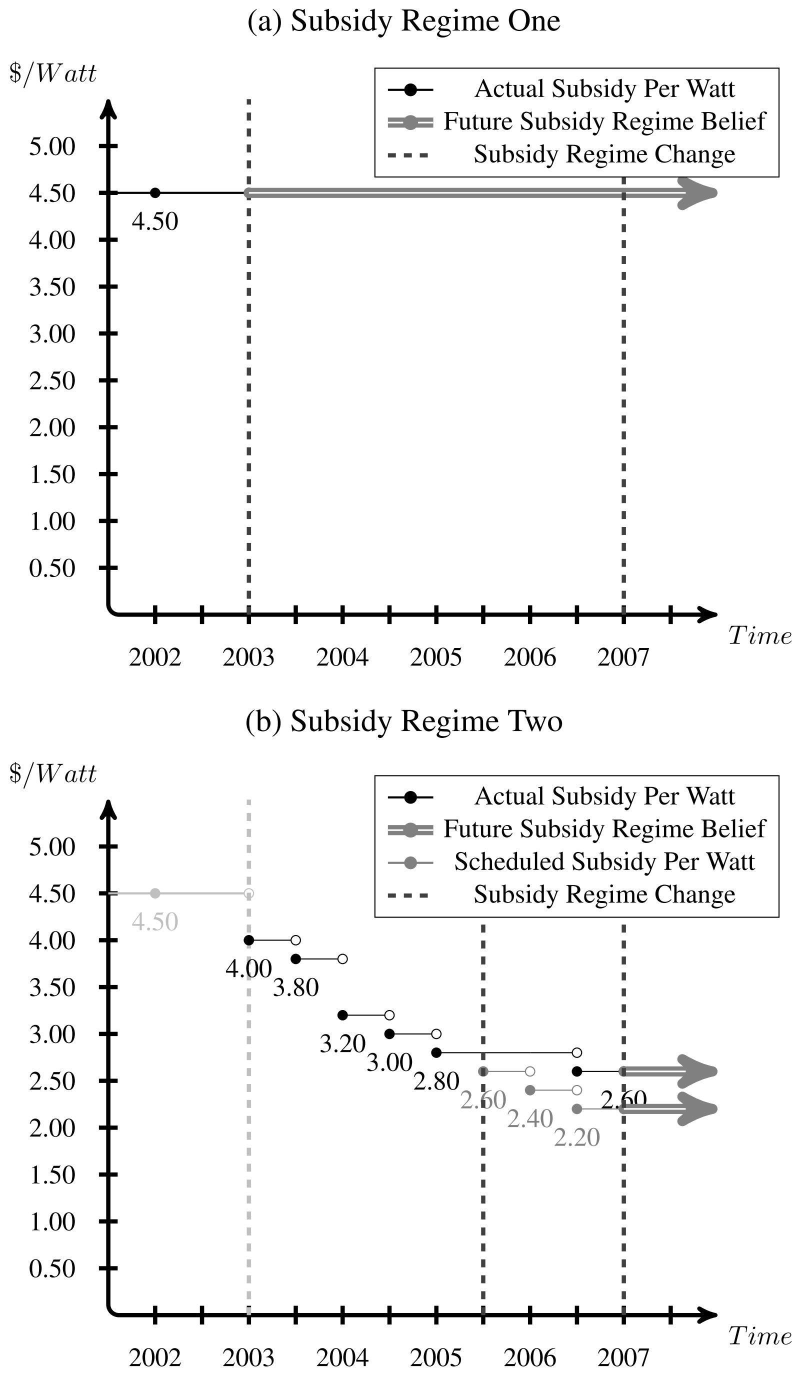


Figure 3.3: Case 3: Auto-Renewal Beliefs

3.5 Identification

The identification strategy presented is fairly standard and follows the dynamic consumer demand literature closely. Generally, changes in the market share of a product s associated with a change in a product characteristic of good s helps identify the mean utility from a characteristic. The identification of the parameter on price, present value of purchase, and technological innovation are discussed below in detail.

The coefficients on the net price of a solar panel system are identified by variation in uptake that are associated with variation in the net price. Specifically, identification of the vector of parameters α_i comes from variation in purchasing behavior within each tercile of the housing value distribution that is associated with variation in the net price. Variation in the net price over time of solar panel systems occur through three channels that are exogenous to the households choice problem. First, the price of solar panels depends on a global market and price variation comes from exogenous market forces: inputs for production (e.g. variation in the price of silicon), technological shocks to the production process, and global demand for solar panels. Second, the price of installing a solar panel system varies due to changes in installation costs for the installer such as: learning by doing (e.g. returns to experience), technological innovation with respect to mounting equipment, and economies of scale. Third, subsidy rates and tax credits vary over the sample period supplying an additional layer of exogenous price variation.

Variation in purchase related to variation in the present value of purchase over time identifies the parameter θ_2. The present value of purchase varies over time through changes in the average price of electricity. The price of electricity varies over time based on regulatory agencies' decisions at the utility level, regional demand for electricity, and input costs.

The vector of parameters θ_{3i} on the non-price product characteristic, efficiency rate, is identified by changes in purchasing patterns within each tercile of the distribution over roof space associated with variation in efficiency rates. Efficiency rates exogenously vary over time through technological innovations that occur on the supply side of the market (e.g. research and development of new products).

CHAPTER 4

DATA

I assemble a new dataset from a variety of sources to estimate the model in Chapter 3. I use choice data from the California Energy Commission's (CEC) Emerging Renewable Program that covers eight years of residential solar panel installations in the state of California. I expand the choice data by collecting detailed housing and solar panel characteristic data for each observation in the CEC dataset. I pair these with relevant datasets that include measures of usable sunlight hours and electricity prices during the sample period. To complete the panel, I simulate households that are active in the solar panel market but do not purchase during the sample. The following section discusses each of the above points in detail.

The CEC data track all households who purchase a solar panel system and receive a tax subsidy from 1998 through 2006. These data include the address of the residence, capacity of the system installed, total price paid, subsidy received, make and model of the installed solar panel system, subsidy approval date, installation completion date, and the utility region in which the household is located. I drop the first three years of data due to missing information and low numbers of purchase during that time period. Additionally, I drop both commercial and utility-scaled installations and keep purchases made by residential households. Lastly, I drop observations where the price per watt is below \$4.00 or greater than \$30.00.[1] This results in a dataset that consists of 12,736 observations of purchase for the sample period of 2002 through 2006.

I expand the data from the CEC by adding housing characteristics for each purchaser. I collect the housing characteristics by matching the physical address of the purchaser with the real estate website Zillow.com and scrape the relevant information. For each purchaser, I retrieve information

[1]A report by the CEC, Wiser, Bolinger, Cappers, and Margolis (2006), discusses how these are most likely input errors and should not be used as valid prices.

on the value of the home, number of stories, square footage, number of bedrooms, and year built.[2] As a redundancy check, I perform a similar task but with an alternative data source, Trulia.com, and match housing characteristics with address information.

In Table 4.1, I present descriptive statistics specific to households that purchase during the sample. The columns of the table are separated by geographic region. The first column shows descriptive statistics for all purchasers at the statewide level. The second through the fifth column are separated by MSA: 1) Los Angeles-Long Beach-Riverside, 2) San Francisco-San Jose-Oakland, 3) San Diego-Carlsbad-San Marcos, and 4) Fresno-Madera-Sacramento.[3] The San Francisco-San Jose area has the highest average home values at $841,070 with the coastal MSAs, Los Angeles and San Diego, following with an average home value of $560,000. The more in-land region, Fresno and Sacramento, have the lowest average housing value at $373,066.

The San Francisco metropolitan statistical area makes up 47% of the total number of purchases in the data with 5986 solar panel system installations. Purchasers in San Francisco have the smallest average roof space at 183.49 m^2 and install smaller than average capacity systems, 3.54kW, relative to the rest of the state. Also, purchasers in San Francisco buy slightly earlier in the sample, on average, and pay higher prices per watt for the systems. The descriptive statistics suggest that a higher share of early adopters of solar panel systems live in the San Francisco area.

I simulate the population of households for each zip code in the CEC dataset. The simulated households are generated using a dataset from Dataquick. The data include marginal distribution information at the zip-code level that describes housing characteristics of potential market participants.[4] The data characterizes households within each zip code by five housing characteristics: housing value, the number of stories, square footage, the number of bedrooms, and the year the house was built. For each characteristic, the dataset includes the first two moments of the marginal

[2]Zillow.com uses an algorithm for housing value named Zestimate that considers recent sales of similar homes and neighborhood characteristics when estimating the housing value.

[3]It is important to note that not all zip codes within the MSAs are represented in Table 4.1. I drop all zip codes with less than 5 purchases during the sample period. The result is a total of 345 zip codes used in estimation.

[4]This includes single family homes, both detached and attached. Multi-family homes such as condominiums and apartment buildings are excluded from the data.

distribution, number of observations, correlations between the housing characteristics, and the quartiles of the marginal distribution. The matrix of correlations between housing characteristics provides useful information by improving the accuracy of the simulated populations.

I use a copula function to create a joint distribution of housing characteristics and simulate the entire population of households in each zip code. The copula function is assumed to be multivariate normally distributed (Gaussian Copula) with mean zero and a covariance-variance matrix Σ. The matrix Σ is calculated using the correlation measures between characteristics and the variance of each characteristic. Zip codes are independently simulated using a multivariate normal copula with each zip code having a unique Σ matrix.

The copula function creates a joint distribution of household characteristics from a set of marginal distributions. The Gaussian copula provides structure by enforcing the correlations that exist between the housing characteristics when simulating households.[5] The result is a simulated population of households characterized by a vector of discrete housing characteristics from a normal distribution.

I merge the simulated dataset and the set of purchasers by matching housing characteristics. For each zip code, I search the simulated dataset for a vector of housing characteristics that match identically with the vector of housing characteristics for each purchaser. Once a match is found, I replace the simulated household with the matched purchaser. The process is performed for all purchasers and across all zip codes represented in the sample. This results in a dataset of 2,272,841 households in the market for residential solar panel installations that includes both households that purchase and do not purchase during the sample period. With over 2 million households participating in the market for solar panel systems and only 12,736 purchases during the sample, the size of the choice probabilities are a potential concern in estimation. To improve the choice probabilities, I reduce the market size for each MSA informed by a survey conducted in California about attitudes toward renewable energy.

[5]The details of the simulation process are provided in the appendix.

	Statewide		L.A. (MSA 1)		S.F. (MSA 2)		S.D. (MSA 3)		Fresno, Sac (MSA 4)	
Variable	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
House Value ($)	648,238.2	578,874.3	560,617.4	556,968.2	841,070.5	653,065.4	567,821.4	415,624.5	373,066.3	305,644.4
# of Beds	3.57	0.99	3.69	.98	3.57	1.01	3.61	0.97	3.45	0.94
Bath	2.7	0.99	2.87	1.07	2.61	.99	2.77	0.97	2.63	0.89
# of Stories	1.28	0.48	1.25	0.47	1.34	0.52	1.07	0.28	1.24	0.44
Square Feet	2342.26	1068.37	2493.83	1201.64	2222.82	1041.20	2433.29	982.97	2421.30	1028.38
Square Meter	217.6	99.25	231.68	111.63	206.50	96.73	226.06	91.32	224.94	95.54
Roof Space (m^2)	197.64	98.59	211.90	110.77	183.49	95.79	219.30	91.47	204.62	93.42
Annual Sunlight (h)	1820.29	93.83	1920.55	98.88	1757.18	47.45	1894.93	41.44	1834.68	78.55
Year Built	1974.51	26.12	1980.27	21.49	1965.51	28.01	1976.93	21.98	1986.69	20.11
System Price ($)	36,887.75	18,524.89	39,778.23	20,081.09	35,303.22	17,704.24	35,880.97	17,501.99	38,321.07	18,992.52
Kw	3.80	1.95	4.10	2.15	3.54	1.77	3.86	2.01	4.03	2.02
Period Purchased	5.48	2.81	6.333	2.939	5.491	2.769	5.99	2.93	5.81	2.68
Price Per Watt	9.94	1.70	9.97	1.65	10.12	1.69	9.60	1.68	9.69	1.69
Subsidy Per Watt	3.39	0.79	3.47	0.81	3.38	0.78	3.51	0.86	3.27	0.74
Tax Credit	2313.14	1295.46	2484.68	1439.67	2252.87	1281.14	2325.61	1215.26	2298.03	1234.61
Observations	12736	-	2265	-	5986	-	1430	-	3056	-

Table 4.1: Household Characteristics (Purchasers)

In 2001, an independent study was contracted by the California Energy Commission, conducted by Marylander Marketing Research, with the stated purpose of determining awareness and attitude toward renewable energy sources among households and businesses in California. In the survey households were asked several questions regarding their history with renewable energy sources, knowledge of renewable energy, and their desire to have a renewable energy source at their residence.

The question of interest for reducing the market size asked households the following question: *What is the likelihood of installing a solar, wind, or fuel cell renewable energy system at your home?*

1. *Definitely Would Install*
2. *Probably Would Install*
3. *Might or Might Not Install*
4. *Probably Would Not Install*
5. *Definitely Would Not Install*

The survey finds that, conditional on not ever owning a renewable energy system, 15% of the population answered either definitely or probably would install, 23% said they might or might not install, and 62% answered that they either probably or definitely would not install. The large share of households answering negatively suggest a reduction in the population of market participants is appropriate during the sample period.

The survey includes an additional table that breaks down the household response to the question above by MSA. The survey finds that 31% of households in San Jose, 10% of households in Los Angeles, 26% of households in San Diego, and 10% of households in Fresno definitely or probably would install a renewable energy home at their residence. I reduce the market size by resizing the population in each zip code with respect to the MSA percentages above. First, I include all purchasers in the reduced market data. Next, I randomly select a sample population of households from each zip code to be market participants. The process results in a dataset that consists of 505,557 total households participating in the solar market for the sample period. Table 4.3 details the distribution of household characteristics at the state level and by MSA of the reduced sample

	Market		MSA 1		MSA 2		MSA 3		MSA 4	
Variable	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
House Value ($)	665,786.9	544,291.9	648,580.3	563,777.8	726,080.1	511,284.8	611,607.1	436,920.6	560,643.5	687,867.6
# of Beds	3.31	.95	3.47	.96	3.26	.96	3.23	.96	3.34	.86
# of Stories	1.42	.5	1.47	.5	1.56	.52	1.01	.12	1.33	.47
Square Footage	1982.1	869.68	2147.64	937.35	1878.16	823.75	1966.88	901.14	2069.86	810.42
Square Meter	184.14	80.8	199.52	87.08	174.49	76.53	182.73	83.72	192.3	75.29
Roof Space (m^2)	142.86	74.68	148.51	78.33	121.34	60.49	181.29	84.01	158.52	75
Year Built	1970.89	21.42	1975.48	18.11	1964.58	23.25	1974.56	17.24	1979.7	18.37
Population	2,272,841	-	523,867	-	1,049,047	-	379,807	-	320,120	-

Table 4.2: Household Characteristics (Full Population)

used in estimation.

Outside of housing characteristics, households face location-specific exogenous characteristics in the form of electricity prices by utility region and the number of hours of sunlight at their residence. The data on electricity prices originates from the websites of the three largest utility companies in California: Pacific Gas and Electric (PGE), Southern California Edison (SCE), and San Diego Gas and Electric (SDGE). These three utility companies supply electricity to over 85% of all households in California and more importantly provide electricity to the zip codes in the sample. Within all three utility companies, there is a menu of electricity rate plans that households can choose from. The plans are based on either baseline quantity-tiered pricing or time-of-use pricing. I am not able to take advantage of the detailed pricing data without information on the type of plan a household chooses and their consumption of electricity. Instead, I use a dataset from the California Public Utility Commission (CPUC) that calculates average prices for residential electricity consumption for each utility region over time.[6]

In Figure 4.1 the electricity price per kilowatt hour is represented on the vertical axis and the horizontal axis represents time, beginning in 2002 and ending in 2010. The electricity prices are deflated to 2006 price levels with rate changes only occurring annually.[7] Average electricity prices are generally increasing over the time period. The relatively high prices in 2002 are a residual effect from the deregulation of electricity markets that occurred in the late 1990s and early 2000. San Diego Gas and Electric have the highest electricity prices throughout the time period shown. Average electricity prices are similar between Pacific Gas and Electric and Southern California Edison, but PGE prices tend to be slightly higher.

I gather data for the number of hours of sunlight a household receives from the National Renewable Energy Laboratory's (NREL) Typical Meteorological Year (TMY3) dataset. The data are collected by 74 weather stations located across California that record a variety of meteorological measures. Using the data, I aggregate from a hourly measure of sunlight to a 6-month measure.

[6]The restrictions that arise from using average electricity rate data are discussed in the appendix.

[7]For clarity, the electricity prices are fixed for the year and do not transition as the figure suggests.

	Market		MSA 1		MSA 2		MSA 3		MSA 4	
Variable	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
House Value ($)	685,944.3	522,521.1	650,646.5	578,742.3	727,492.3	512,557.7	611,583	440,091.8	551,016.9	683,787.8
# of Beds	3.28	.96	3.47	.96	3.26	.96	3.23	.95	3.35	.87
# of Stories	1.43	.51	1.47	.5	1.56	.52	1.02	.13	1.33	.47
Square Footage	1943.25	863.74	2169.35	961.9	1882.33	827.64	1969.45	901.29	2111.2	846.13
Square Meter	180.53	80.24	201.54	89.36	174.87	76.89	182.97	83.73	196.14	78.61
Roof Space (m^2)	139.06	73.51	151.14	80.79	121.97	61.26	181.4	83.96	162.08	77.37
Year Built	1968.7	22.22	1975.74	18.4	1964.61	23.33	1974.71	17.21	1980.19	18.7
Population	505,557	-	52,156	-	323,327	-	98,371	-	31,703	-

Table 4.3: Household Characteristics (Reduced Population from Survey)

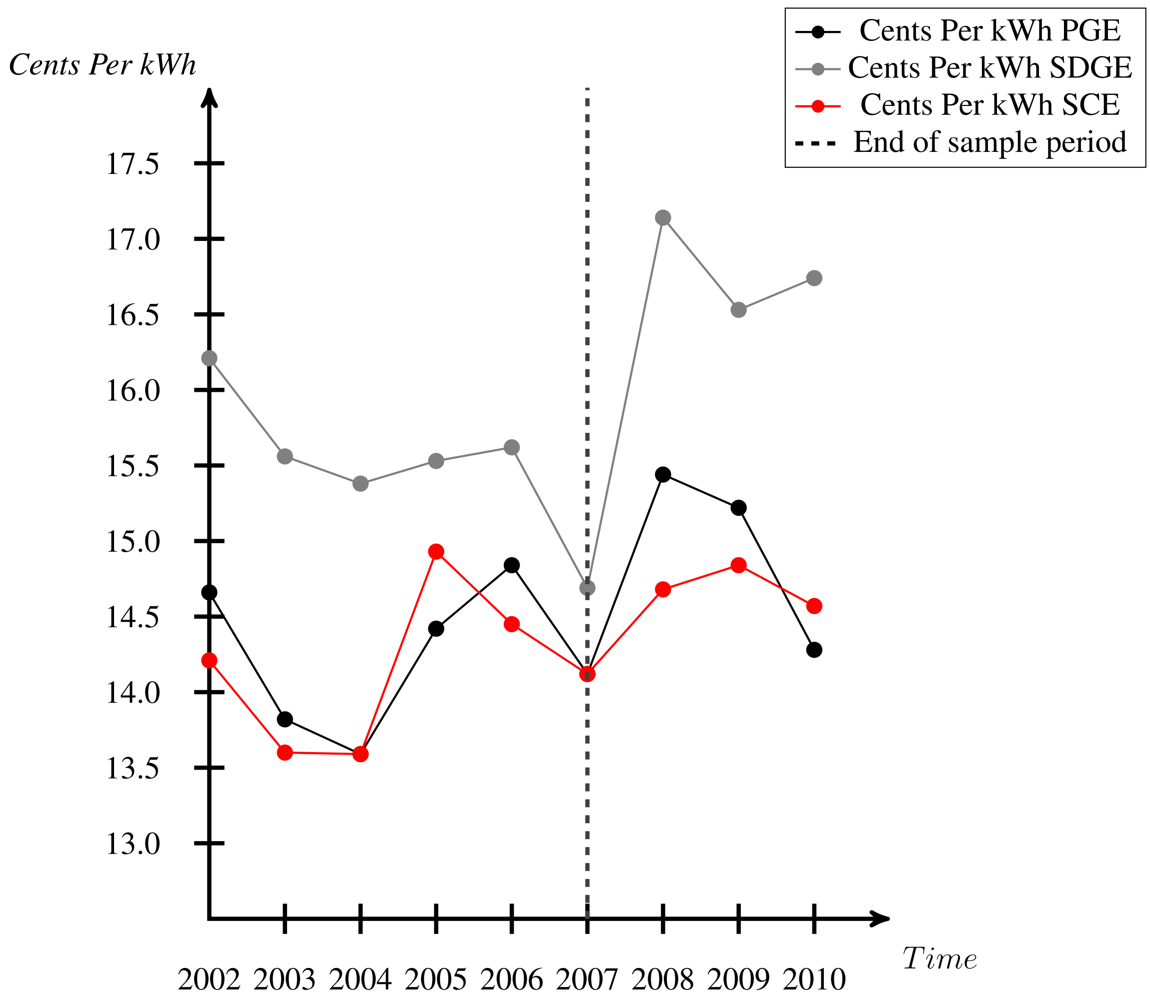


Figure 4.1: Electricity Prices by Utility Company

I average the semi-annual hours of sunlight over the years during the sample to create a time invariant measure of the average number of hours of sunlight a location receives. The geographical longitude and latitude of each station is differenced with the latitude and longitude of the center of each zip code, and the station closest to the zip code is used to measure sunlight hours.[8] Annual average sunlight hours are presented in Table 4.1 across the state and for each MSA. There is substantial variation in annual sunlight across the MSA regions with an average of 1820.29 hours of sunlight and a standard deviation of 93.83 hours. The least amount of sunlight occurs in the San Francisco region where the average is 1757.18 hours of sunlight. The largest amount of sunlight occurs in the Los Angeles region where the households receive an average of 1920.55 hours of sunlight annually. On average households in California receive 5 hours of usable sunlight per day. The difference between the hours of sunlight received in San Francisco and Los Angeles is approximately 32 days of average sunlight.

Households choose over a set of solar panel systems that vary by capacity, price, and technology. The data on solar panel system capacity and price are included in the CEC dataset and are shown in Table 4.1 above. While the average total price of a solar panel system is similar across MSAs there is variation in both the capacity of the system installed and the price per watt. In Figure 4.2 the average price per watt of a solar panel system is shown by MSA over the sample period. At the beginning of the sample prices are closely matching but after 2003 the gap between the average prices increases. The largest gap shows up between San Francisco and San Diego where at one point they differ by $1 per watt installed.

The aggregation of price per watt into an average for all installations is a bit misleading. Figure 4.3 displays the price per watt within the Los Angeles MSA by capacity bin and over the sample period. The figure shows evidence of size discounting occurring in the solar market. I find that extra-large capacity systems have significantly lower prices per watt relative to small capacity solar panel systems. There is almost a $2.00 price per watt difference between the small capacity installations and extra large capacity installations during 2005. Note that prices seem to trend

[8] The distance is taken using using the haversine formula. The haversine formula is an equation that finds the distance between any two points on the surface of a sphere. Simply put, it measures the distance as the crow flies.

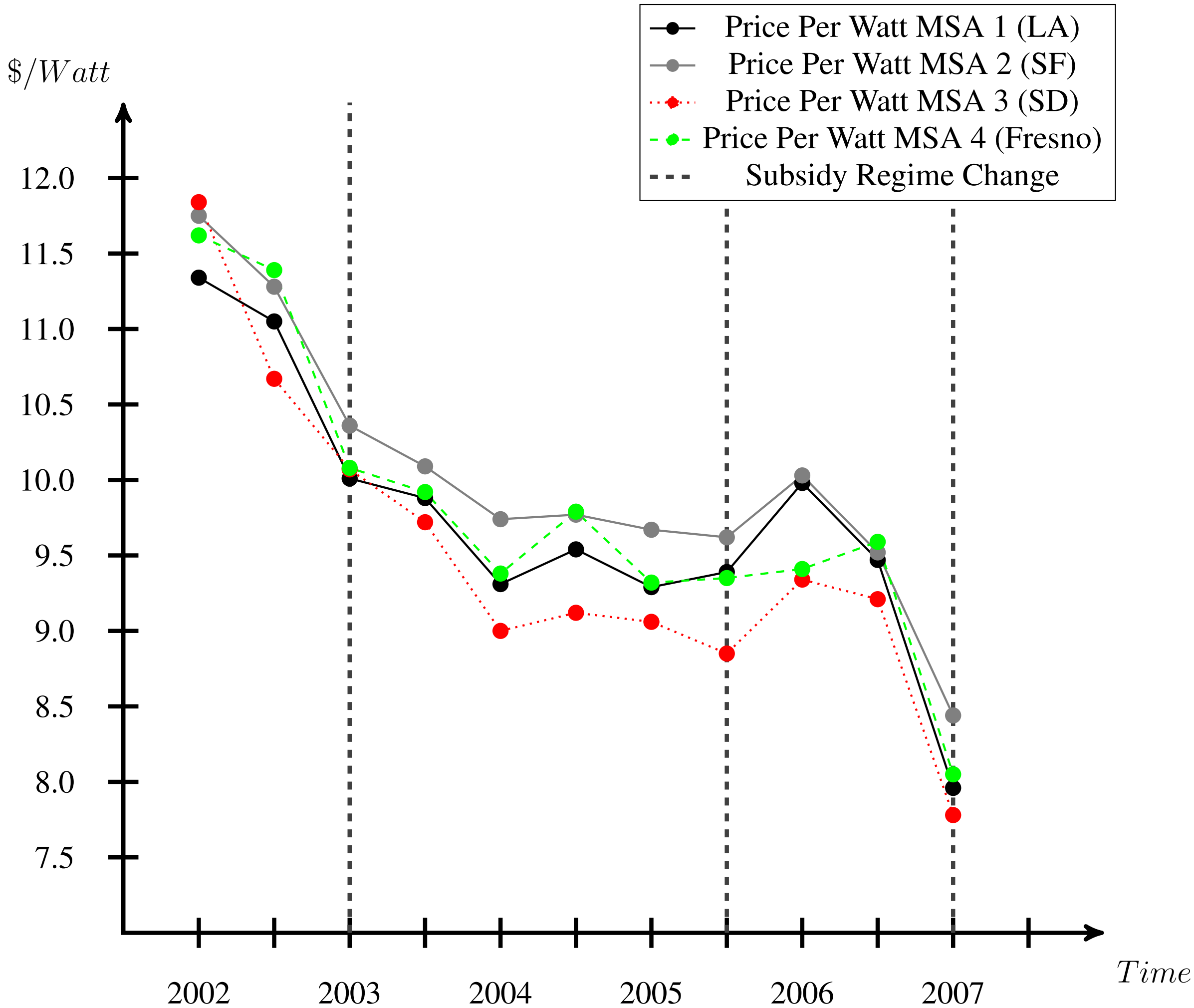


Figure 4.2: Price Per Watt by MSA

similarly over time both across capacity bins and across MSAs. Also, there is a growing difference in the price level of solar panels systems over time.

A solar panel system is a collection of solar panels joined together to generate an output of electricity. The characteristics of a solar panel system depends directly on the characteristics of the solar panels in the group. In the CEC dataset all households purchase a solar panel system that is a collection of one unique solar panel. Solar panel system characteristics are created by collecting non-price product characteristics for each brand and model combination of solar panels observed in the CEC dataset.

I gather solar panel product characteristics from manufacturers' specification sheets for each of the unique solar panels. The specification sheets provide information about the STC/PTC capacity

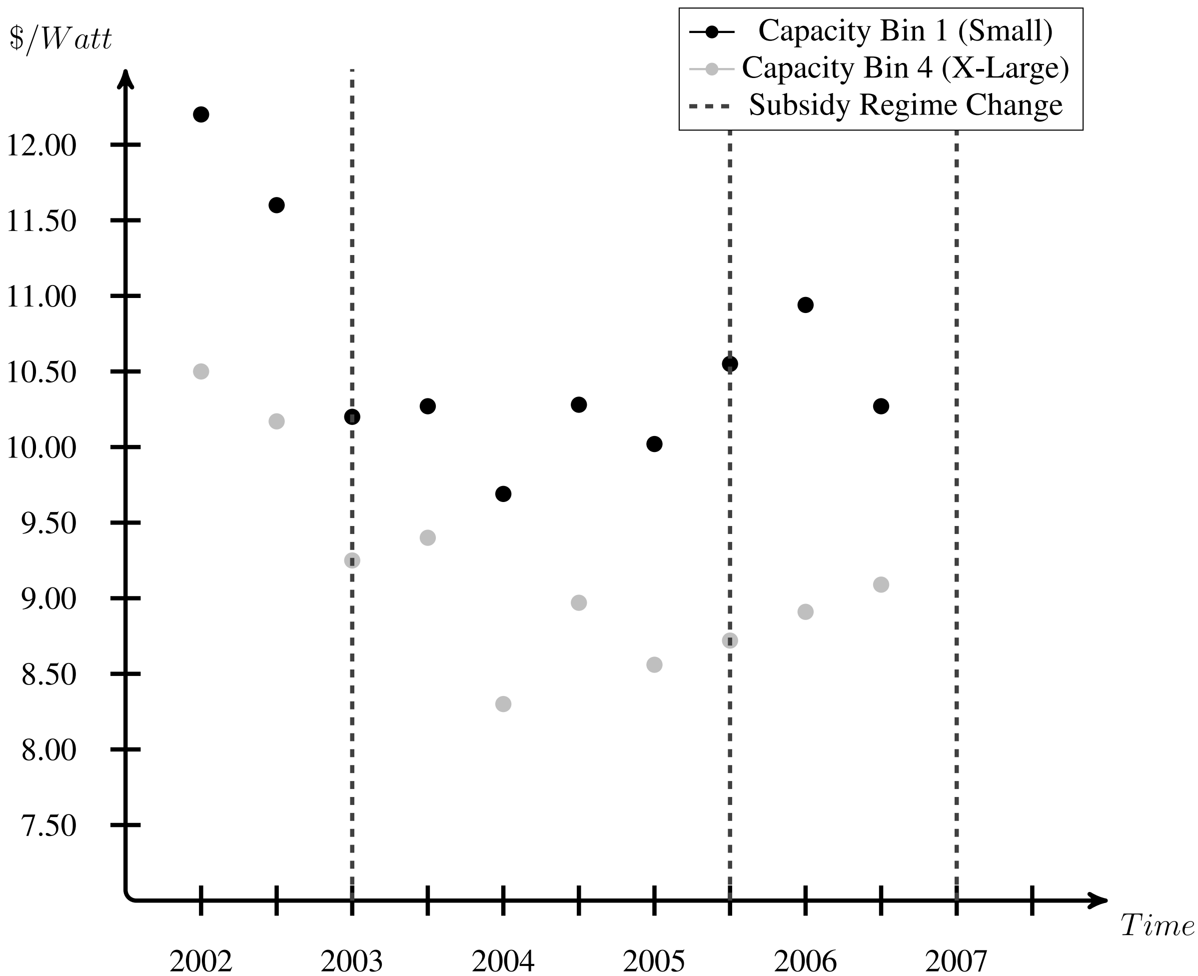


Figure 4.3: Price Per Watt by Capacity Bin in Los Angeles

rating, efficiency rate, physical size, type of panel, warranty information, and additional technical details for a specific solar panel.[9] Two tables are included to show the distribution of characteristics in the full sample of solar panels and the more restricted sample used in estimation. The full set of unique solar panels is shown in Table 4.4 and the set of panels that result from constraints imposed on the purchase data are represented in Table 4.5.

The two tables show the narrowing of the solar panel market after imposing restrictions on geographic location, total capacity of the system, and measurement error in reporting of prices. The market for residential solar panels is different relative to the entire market. First, average PTC capacity rating per panel is 40kW less in the residential market relative to the entire market.[10] Also, the maximum capacity rating of a solar panel in the residential market is 297kW where in the broader market the maximum capacity rating of a solar panel is 779.8kW. The physical size of an average solar panel in the residential market is smaller both in physical area, 1.22 m^2 versus 1.49 m^2 in the larger market, and weight, 15.44 kg versus 18.12 kg in the broader market. Lastly, average efficiency rates in the residential market are less relative to the broader market with close to a 9% difference in the efficiency rate. The findings suggests that the broader market for solar panels is not the appropriate choice set for residential households. Instead, the characteristics of solar panel systems used in estimation are constrained to the restricted sample.

I capture innovation in solar panel technology through the improvement in efficiency ratings of solar panels over the sample period. In Figure 4.4 average efficiency rates are shown over time. The vertical axis represents efficiency rates in percentage terms with an average efficiency rate of 10.46% at the beginning of the sample period. Over the sample, efficiency rates are trending upwards and increase a total of 29% from 2002 to 2007.

---

[9] A sample of a specification sheet is included in appendix.

[10] The first measure of capacity is the standard test condition (STC) ratings. STC ratings are provided by the manufacturer and are the result of an in-lab test of the panel. The second measure of capacity is PVUSA test condition (PTC) ratings. PTC ratings are more realistic and result from controlled testing in an outdoor setting. With respect to the subsidies, PTC ratings are used to measure the overall capacity of a system when calculating the amount of subsidy an installation receives.

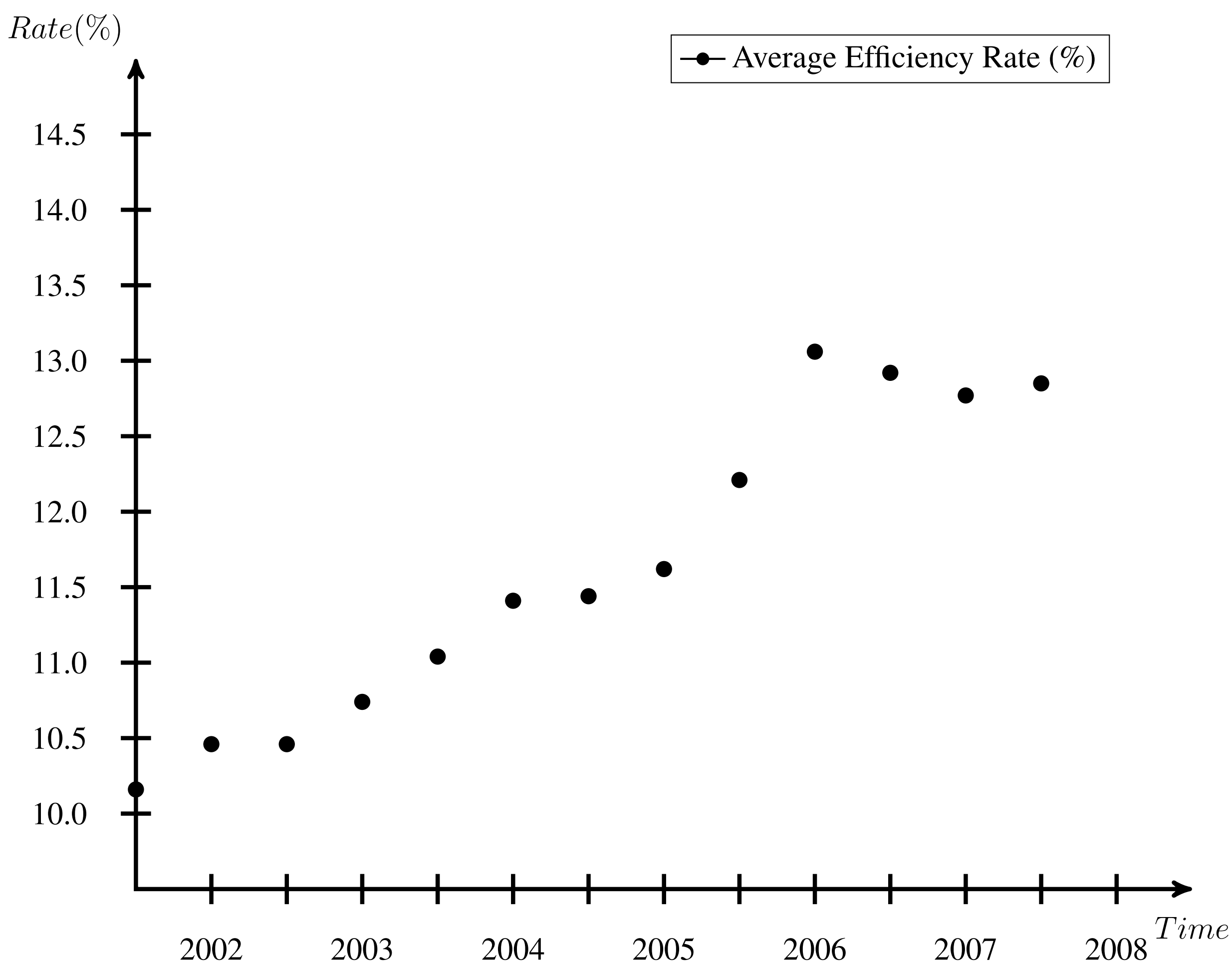


Figure 4.4: Efficiency Rates over Time

Variable	Obs	Mean	Std. Dev.	Min	Max
STC Capacity Rating	1016	189.56	69.36	14	864
PTC Capacity Rating	1016	169.69	63.24	11.8	779.8
Efficiency Rates	1016	11.67	2.19	2.35	18.48
Panel Area (m^2)	1016	1.49	1.09	.12	18.59
Panel Depth (mm)	972	43.89	13.18	2.5	213
Weight (Kg)	967	18.12	6.99	1.9	67

Table 4.4: Full Set of Solar Panels

Variable	Obs	Mean	Std. Dev.	Min	Max
STC Capacity Rating	271	147.61	53.21	17	330
PTC Capacity Rating	271	131.88	47.84	15.7	297
Efficiency Rates	271	10.82	2.4	2.35	16.48
Panel Area (m^2)	271	1.22	.37	.35	2.43
Panel Depth (mm)	266	45.12	10.32	2.5	60
Weight (Kg)	265	15.44	6.98	2.2	48.5

Table 4.5: Set of Purchased Solar Panels

CHAPTER 5

ESTIMATION

To estimate the model discussed in Chapter 3, I impose several assumptions to reduce computation time and provide tractability in estimation. Given the assumptions, estimation of the dynamic discrete choice problem is accomplished using three-stage maximum likelihood estimation with a combination of Rust's (1987,1994) nested fixed point algorithm (NFXP) and backwards induction to estimate the continuation value of staying in the market. The first stage of the estimation routine recovers parameters that govern the transition of solar panel system prices. Using the estimated parameters for solar panel system prices, the second stage of the estimation iterates over a nested loop. The inner loop estimates the continuation value of staying in the market and the outer loop estimates parameters through maximum likelihood estimation. The third stage corrects consistency issues with the covariance matrix of second-stage parameter estimates by using the consistent estimate of the parameter vector from the first two stages to maximize the full log-likelihood equation. Altogether the three stage algorithm is able to estimate the dynamic discrete choice problem and generate consistent parameter estimates. The details of the assumptions, algorithm, and calculation of standard errors are discussed in what follows.

The Bellman equation representing the household's per period maximization problem is framed as a decision between purchasing one of four available products in the market or choosing to forgo purchase and take the continuation value of staying in the market for an additional period. From chapter 3, the household's maximization problem is modeled as:

$$V_{it}\left(\omega_t, \epsilon_t; \theta\right) = max\{\epsilon_{i0t} + \beta \int_{\omega_{t+1}} \int_{\epsilon_{t+1}} V_{it+1}\left(\omega_{t+1}, \epsilon_{t+1}; \theta\right) G\left(\omega_{t+1}, \epsilon_{t+1} | \omega_t, \epsilon_t\right) d\omega_{t+1} d\epsilon_{t+1}, \\ max_{s\in\{1,2,3,4\}} U_{ist}\left(\omega_t, \epsilon_t; \theta\right)\} \quad (5.1)$$

The first term on the right hand side of equation 5.1 represents the utility a household receives when deciding to forgo purchase and stay in the market the next period. The second term on the right hand side of the equation, $U_{ist}(\omega, \epsilon; \theta)$, represents the utility a household receives by choosing optimally from the set of available products in the market.

In equation 5.1 the state variable ω and ϵ are jointly determined from a conditional joint density function $G(\omega_{t+1}, \epsilon_{t+1}|\omega_t, \epsilon_t)$. By assuming conditional independence, the Bellman equation can be rewritten to simplify the problem:[1]

$$V_{it}(\omega_t, \epsilon_t) = max\{\epsilon_{i0t} + \beta \int_{\omega_{t+1}} \int_{\epsilon_{t+1}} V_{it+1}(\omega_{t+1}, \epsilon_{t+1}) f(\epsilon_{t+1}|\omega_{t+1}) d\epsilon_{t+1} h(\omega_{t+1}|\omega_t) d\omega_{t+1},$$
$$max_{s \in \{1,2,3,4\}} U_{ist}(\omega_t, \epsilon_t; \theta)\} \quad (5.2)$$

The joint density $G(\omega_{t+1}, \epsilon_{t+1}|\omega_t, \epsilon_t)$ from equation 5.1 is separated into two conditional densities. The simplification implies that: (i) given today's state, ω_t, the ϵ's are independent over time, (ii) conditional on today's state, ω_t, the next periods state ω_{t+1} is independent of ϵ_t.

Since the utility from purchase does not include a continuation value it is helpful at this point to focus on the utility from foregoing purchase. First, the inner-most integral is defined as:

$$E_\epsilon V_{it+1}(\omega_{t+1}) = \int_{\epsilon_{t+1}} V_{it+1}(\omega_{t+1}, \epsilon_{t+1}; \theta) f(\epsilon_{t+1}|\omega_t) d\epsilon_{t+1} \quad (5.3)$$

The type I extreme value distributional assumption for the ϵ taste shocks simplifies the integral in equation 5.3 to the familiar closed form solution:

$$E_\epsilon V_{it+1}(\omega_{t+1}) = log\left[\sum_{s=1}^{S} e^{(V_{it+1}(\omega_{t+1}, s; \theta))} + e^{(V_{it+1}(\omega_{t+1}, 0; \theta))}\right] \quad (5.4)$$

The expected future utility from choosing to postpone purchase is simplified as the integration

[1] Rust (1994) discusses complications when estimating the model specified above, and introduces several standard assumptions to reduce computational complexity and ensure consistency. The only one discussed here is the conditional independence assumption. Conditional independence is satisfied if and only if the joint density $p(\omega_{t+1}, \epsilon_{t+1}|\omega_t, \epsilon_t)$ can be factored as $f(\epsilon_{t+1}|\omega_{t+1}) g(\omega_{t+1}|\omega_t)$.

of equation 5.4 over the stochastic state variables. The expected future utility from choosing to postpone purchase is defined as the function:

$$EV_{it}\left(\omega_t, \epsilon_t; \theta\right) \;\; = \;\; \int_{\omega_{t+1}} E_\epsilon V_{it+1}\left(\omega_{t+1}\right) h\left(\omega_{t+1}|\omega_t\right) \tag{5.5}$$

The revised maximization problem is rewritten using the notation above as:

$$V_{it}\left(\omega_t, \epsilon_t; \theta\right) = max\left\{\epsilon_{i0t} + \beta EV_{it}\left(\omega_t, \epsilon_t; \theta\right), \, max_{s\in\{1,2,3,4\}} U_{ist}\left(\omega_t, \epsilon_t, s; \theta\right)\right\} \tag{5.6}$$

The estimation strategy relies on maximum likelihood estimation to recover the parameters of the model. The likelihood function for the market is the product of the conditional choice probability and the conditional density for the state variables over the households in the market, sample period, and the choice set.

$$L\left(\theta\right) \;\; = \;\; \prod_{i\in M_t}\prod_{t=1}^{T}\prod_{k\in S}\left[Pr\left(s_{it}|\omega_t;\theta\right) Pr\left(\omega_t|\omega_{t-1}\right)\right]^{1(s_{it}=k)} \tag{5.7}$$

The full log-likelihood for the dynamic discrete choice model is:

$$LL\left(\theta\right) \;\; = \;\; \sum_{i\in M_t}\sum_{t=1}^{T}\sum_{k\in S} 1\left(s_{it}=k\right)\left[log\left(Pr\left(s_{it}|\omega_t;\theta\right)\right) + log\left(Pr\left(\omega_t|\omega_{t-1};\theta\right)\right)\right] \tag{5.8}$$

Maximizing the log-likelihood function in equation 5.8 is complicated and computationally burdensome to solve. Rust (1994) proposes a three-stage estimation routine to reduce the computation time, but allow for the estimation of consistent parameters. To reduce computation, the full vector of parameters is split into two vectors, $\theta = \{\theta_f, \theta_\omega\}$ where the parameters in θ_ω can be estimated independently of the conditional choice probabilities and the parameters in θ_f are independent of the state transitions. The full maximum likelihood estimation is split into two partial likelihood equations. The log-likelihood is rewritten below to reflect the two-stage nature of the estimation strategy.

$$LL(\theta) = \sum_{i \in M_t} \sum_{t=1}^{T} \sum_{k \in S} 1(s_{it} = k) \, log\left(Pr\left(s_{it} | \omega_t; \theta_f, \theta_\omega\right)\right) + \sum_{i \in M_t} \sum_{t=1}^{T} log\left(Pr\left(\omega_t | \omega_{t-1}; \theta_\omega\right)\right) \quad (5.9)$$

The first stage estimates the first order autoregressive process that governs household beliefs regarding the transition of solar panel system prices. The parameters of the pricing process are estimated using partial maximum likelihood estimation of the second term in equation 5.9, which does not require the nested fixed point algorithm.[2] Formally, solar panels system prices are assumed to follow an AR(1) process with normally distributed iid errors of mean zero and variance σ_P^2.

$$P_t^{SP} = \theta_{\omega 1} + \theta_{\omega 2} P_{t-1}^{SP} + \nu_t \quad (5.10)$$

Estimation of the pricing process assumes the first period price to be deterministic, $f_{P_1^{SP}}(p_1^{SP}) = 1$ and maximizes the partial likelihood conditional on the solar panel system price in the first period. The partial conditional likelihood function is defined as:

$$L_1^\omega = \prod_{k=2}^{T} f_{P_k^{SP} | P_{k-1}^{SP}} \left(p_k^{SP} | p_{k-1}^{SP}, \theta_\omega\right) \quad (5.11)$$

The partial conditional log likelihood is:

$$LL_1^\omega = \sum_{k=2}^{T} log\left[\frac{1}{\sqrt{2\Pi\sigma_P^2}} \exp\left(-\frac{1}{2} \frac{(p_k^{SP} - \theta_{\omega 1} - \theta_{\omega 2} p_{k-1}^{SP})^2}{\sigma_P^2}\right)\right] \quad (5.12)$$

Maximizing the equation 5.12 results in consistent estimates of the parameters $\theta_{\omega 1}$, $\theta_{\omega 2}$, and σ_P.

The vector of parameter estimates, $\hat{\theta}^\omega$, enter the second stage as consistent estimates. The goal during the second stage of estimation is to recover the utility parameters and the continuation value of staying in the market. As previously stated, within the sample period of the model the value function is non-stationary and the inner-loop of the fixed point algorithm is not guaranteed to

[2] In the case of separate markets the parameter vector γ will be estimated for each MSA in the market.

converge.[3] To work around this problem, I assume the periods outside of the sample are stationary and use the nested fixed point algorithm to solve for the vector of continuation values in the last period.[4] The final period in the sample is denoted by T and the vector of parameters $\theta = \{\widehat{\theta}^{\omega}, \theta^{f}\}$ is compressed for space.

$$V_{iT}\left(\omega_T, \epsilon_T; \theta\right) = max\left\{\epsilon_{i0T} + \beta EV_{iT}\left(\omega_T, \epsilon_T; \theta\right), \, max_{s\in\{1,2,3,4\}} U_{isT}\left(\omega_T, \epsilon_T, s; \theta\right)\right\} \tag{5.13}$$

In equation 5.13, the utility from choosing to purchase a solar panel system is modeled as a discounted lifetime utility value, $U_{isT}\left(\omega_T, \epsilon_T, s; \theta\right)$. The assumptions that households only purchase one system in their lifetime and are assumed to not repeat purchase allows for modeling utility as a one time transfer to the household. Also, the econometrician is able to ignore the current holding of a solar panel system for each household and the state space is reduced which simplifies estimation. Calculating the continuation value of waiting to purchase requires a more computationally intensive approach and is the focus of the following discussion.

First, the continuation value for household i in the final period T is calculated and is represented as:

$$EV_{iT}\left(\omega_T, \epsilon_T; \theta\right) = \int_{\omega_{T+1}} log\left[\sum_{s=1}^{S} e^{\left(V_{iT+1}(\omega_{T+1}, s; \theta)\right)} + e^{\left(V_{iT+1}(\omega_{T+1}, 0; \theta)\right)}\right] h\left(\omega_{T+1}|\omega_T\right) \tag{5.14}$$

Equation 5.14 is estimated using an iterative approach that is a variant of the nested fixed point algorithm described in Rust (1987, 1994). The time subscripts are dropped because of the stationarity assumption. From Rust (1994), the equation defining the fixed point EV_θ is written as $T_\theta(EV_\theta)$, where the nonlinear operator T_θ is a mapping from the Banach Space B back onto itself,

---

[3]One only needs to look as far as the effect of time until the end of a subsidy regime to find non-stationarity of the value function. The non-stationarity breaks one of the main requirements for convergence of the nested fixed point algorithm and we are no longer assured that the fixed point exists or is unique.

[4]Stationarity implies that the continuation value is Markovian, depends on the current state, and the continuation value is time invariant. Given two periods, period t and $t + k$, where the state space is equivalent in both periods $\omega_t = \omega_{t+k}$ then the continuation value will be equivalent in each period. The time subscript can be dropped for periods outside of the sample period and a fixed point can be reached.

$T_\theta : B \rightarrow B$, and is defined by:

$$T_\theta(W)(\omega) = \int_{\omega'} log\left[\sum_{s=1}^{S} e^{W(\omega',s;\theta)} + e^{W(\omega',0;\theta)}\right] h(\omega'|\omega) \tag{5.15}$$

$$= \int_{\omega'} log\left[\sum_{s=1}^{S} e^{U_{is}(\omega';\theta)} + e^{W(\omega',0;\theta)}\right] h(\omega'|\omega) \tag{5.16}$$

The algorithm begins with an initial guess for the vector of continuation values, EV_i^0, and an initial guess for the vector of utility parameters θ_f^0 along with the estimated parameters $\hat{\theta}_\omega$ from the first stage. Given these initial values, the vector of continuation values is calculated as $EV_i^1 = T_\theta(EV_i^0)$.

$$EV_i^1 \equiv T_\theta(EV_i^0)(\omega) = \int_{\omega'} log\left[\sum_{s=1}^{S} e^{U_{is}(\omega';\theta)} + e^{EV_i^0}\right] h\left(\omega'|\omega\right) \tag{5.17}$$

A second vector of continuation values is calculated using the same vector of parameters θ_f^0 and $\widehat{\theta}_\omega$, but the newly calculated vector of continuation values EV_i^1 is used in place of the initial guess EV_i^0. The second vector of continuation values is calculated as $EV_i^2 = T_\theta(EV_i^1)$ using equation 5.15.

$$EV_i^2 \equiv T_\theta(EV_i^1)(\omega) = \int_{\omega'} log\left[\sum_{s=1}^{S} e^{U_{is}(\omega';\theta)} + e^{EV_i^1}\right] h\left(\omega'|\omega\right) \tag{5.18}$$

The calculated vectors of continuation values $\{EV_i^2, EV_i^1\}$ are differenced for all individuals and checked for convergence against a tolerance level of 1.0×10^{-13}. If the differenced values are within the tolerance level for all individuals then the iteration ends and convergence is accomplished. Otherwise, the algorithm repeats using the second calculated vector of continuation values as the initial guess for the next iteration. This process continues until convergence is accomplished.

At convergence the final vector of continuation values is set as the calculated vector of continuation values $\widehat{EV_i} = EV_i^f, \forall i$. From the calculated vector of continuation values, backwards induction is used to calculate continuation values for all periods within the sample. Backwards induction begins at period T-1 with the vector of continuation values as a function of the state space, the vector of parameters, and the period T's calculated continuation value.

$$\widehat{EV}_{iT-1}\left(\omega_{T-1},\epsilon_{T-1};\theta,\widehat{EV}_i\right)=\int_{\omega_T} log\left[\sum_{s=1}^{S} e^{U_{isT}(\omega_T;\theta)}+e^{\widehat{EV}_i}\right]h\left(\omega_T|\omega_{T-1}\right) \tag{5.19}$$

The backwards induction algorithm continues by iterating the process backwards through the sample period. The algorithm ends once the continuation value for the first period in the sample is calculated.

$$\widehat{EV}_{i1}\left(\omega_1,\epsilon_1;\theta\right) = \int_{\omega_2} log\left[\sum_{s=1}^{S} e^{U_{is2}(\omega_2;\theta)}+e^{\widehat{EV}_{i2}(\omega_2;\theta)}\right]h\left(\omega_2|\omega_1\right) \tag{5.20}$$

Given the calculated matrix of continuation values, the inner loop terminates and passes the calculated values to the outer loop. The outer loop uses the estimated vector of parameters for the solar panel price evolution and the calculated matrix of continuation values to estimate the remaining utility parameters, θ^f, via maximum likelihood estimation by solving the following maximization problem.

$$\hat{\theta}_f = argmax \sum_{i\in M_t}\sum_{t=1}^{T}\sum_{k\in S} 1\left(s_{it}=k\right) log\left[Pr\left(s_{it}\mid\omega_t;\theta_f,\hat{\theta}_\omega\right)\right] \tag{5.21}$$

The conditional choice probabilities $Pr\left(s_{it}\mid\omega_t;\theta_f,\hat{\theta}_\omega\right)$ take on the familiar closed form solution from the Type I Extreme Value distributional assumption for the ϵ's.

$$Pr\left(s_{it}|\omega_t;\theta\right)=\frac{exp\left(V_{it}\left(\omega_t,s_{it};\theta\right)\right)}{\sum_{k\in S} exp\left(V_{it}\left(\omega_t,k;\theta\right)\right)} \tag{5.22}$$

After recovering estimates for $\hat{\theta}_f$, the outer loop terminates and the algorithm repeats. The newly estimated parameters $\hat{\theta}_f$ are passed to the inner loop and the process of calculating the matrix of continuation values repeats. The algorithm continues to iterate the nested loops until the difference in the likelihood values of two iterations is below the tolerance level.

The parameter estimates from the first stage are consistent, but the process of maximizing the likelihood in two stages introduces estimation error into the second stage. The covariance

variance matrix formed by inverting the fisher information matrix from the partial likelihood in equation 5.21 will be inconsistent. The inconsistency is due to the presence of estimation error from the first stage estimate of $\widehat{\theta}_\omega$ that is brought into the second stage estimation routine. A third stage is introduced to correct the inconsistency in the covariance matrix by maximizing the full log-likelihood function using the consistent estimated parameters from the first and second stage $\widehat{\theta} = \{\widehat{\theta}_f, \widehat{\theta}_\omega\}$ as initial values for maximizing the full log likelihood equation.

The third stage uses the Newton-step estimator to maximize the full log-likelihood. The Newton-steps are calculated as the difference between the current vector of parameters, $\widehat{\theta}_c$, and a step size parameter γ multiplied by the search direction term.

$$\widehat{\theta}_n = \widehat{\theta}_c - \gamma \widehat{S}(\widehat{\theta}_c) \tag{5.23}$$

The search direction, $\widehat{S}$, is calculated using the negative of the information matrix for the full log-likelihood.[5] The Newton step estimator is shown to produce parameter estimates that are asymptotically equivalent to full information maximum likelihood and will produce consistent estimates of the covariance matrix.

From the estimated parameters in the third stage, standard errors are calculated using the inverse of the Fisher Information matrix. The Fisher Information matrix is estimated by taking the expectation of outer product of the score of the log-likelihood equation.

$$\widehat{I}(\hat{\theta})_{i,j} = E\left[\frac{\partial}{\partial\hat{\theta}_i} LL(\hat{\theta}) \times \frac{\partial}{\partial\hat{\theta}_j} LL(\hat{\theta}) \middle| \hat{\theta}\right] \tag{5.24}$$

Equation 5.24 is equivalent to the covariance variance matrix of the score of the log-likelihood function with respect to the estimated parameters $\widehat{\theta}$. The standard error for the estimated vector of parameters is calculated as the square root of the quotient of the inverse of the Fisher Information

[5]The search direction is typically calculated using the Hessian matrix for the Newton steps. From the information matrix equality for maximum likelihood estimation, we know that the expected value of the Hessian of the log-likelihood function equals the negative of the expected value of the outer product of its gradient.

Matrix and the number of observations for each parameter k.[6]

$$\hat{s}(\hat{\theta}_k) = \left(\frac{\widehat{I}^{-1}(\hat{\theta})_{k,k}}{\sum_{t=1}^{T} N_t} \right)^{\frac{1}{2}} \tag{5.25}$$

[6]The Cramer-Rao bound states that the inverse of the Fisher Information matrix is a lower bound on the variance of any unbiased estimator.

CHAPTER 6

RESULTS

In this chapter, I present demand estimates for both static and dynamic models and compare the results. First, I discuss two static models: 1) reduced form and 2) structural static model of consumer demand. Next, I discuss the first stage of the dynamic model and assumptions regarding the evolution of solar panel prices. Then, I present second stage estimates for the three specifications of the dynamic demand model. Next, I present evidence with respect to the models ability to fit the data. Lastly, I end the chapter with an analysis of demand estimates using price elasticities and marginal effects.

6.1 Static Models

I specify two static models of solar panel system purchase as a baseline comparison for the dynamic specifications. The first model follows Hughes and Podolefksy (2013) and investigates the relationship between the number of installations and subsidy rates. Second, I present a static structural model of solar panel purchase under the assumption that households are myopic. In the following section, I briefly discuss the specifications and present the parameter estimates.

First, I model the relationship between the number of solar panel installations per day and the available subsidy rate. In Equation 6.1 the number of installations in period t, Q_t, is regressed on the per watt subsidy rate τ_t, semi-annual fixed effects $\theta_{3,y}$, and an iid error term ϵ_t.

$$Q_t = \theta_1 + \theta_2\tau_t + \theta_{3,y} + \epsilon_t \tag{6.1}$$

I present the descriptive statistics for the number of installations per day and the subsidy rate in Table 6.1. The unconditional mean of the number of installations per day is 6.97 with a variance of 359.43 that is over 51 times the mean. In Table 6.2 the conditional mean and variance is presented

Variable	Obs	Mean	Var	Min	Max
# Installations	1826	6.97	359.43	0	438
Subsidy Rate	1826	3.68	0.83	2.60	5.14

Table 6.1: Number of Installations Per Day (Unconditional)

Semi-Annual	Obs	Mean	Var	Min	Max
Jan-Jun 2002	181	2.70	16.23	0	20
Jul-Dec 2002	184	2.48	26.02	0	29
Jan-Jun 2003	181	8.38	1133.25	0	438
Jul-Dec 2003	184	8.50	447.08	0	160
Jan-Jun 2004	182	6.44	115.79	0	78
Jul-Dec 2004	184	4.90	87.72	0	67
Jan-Jun 2005	181	3.77	53.58	0	61
Jul-Dec 2005	184	8.23	56.47	0	37
Jan-Jun 2006	181	11.64	1017.46	0	336
Jul-Dec 2006	184	12.65	555.60	0	209

Table 6.2: Number of Installations Per Day Conditional on 6-Month Bins

for the number of installations per 6-month period. In all 6-month periods, the conditional variance is greater than the conditional mean. These findings suggest that the count data is overdispersed and that a Poisson model may not be appropriate. I estimate Equation 6.1 using both Poisson and Negative Binomial regressions and test for overdispersion.

I show the results of estimation of Equation 6.1 in Table 6.3. The Poisson and Negative Binomial regressions are estimated with annual fixed effects and semi-annual fixed effects. In Table 6.3 the first two columns of results are estimated with annual fixed effects. The parameter estimates for the subsidy rate are not significant in either the Poisson and Negative Binomial regression results. The third and fourth column of results are estimated with semi-annual fixed effects and are the preferred estimates.[1] The parameter on the subsidy rate is negative with a coefficient of -0.607 that is significant at the 1% level for both specifications. This implies that a 1 unit change in the subsidy rate will decrease the log count of the number of installations by 0.607. I find that a $0.10

[1] I perform a Likelihood Ratio test comparing the Poisson model to the Negative Binomial model. The Likelihood Ratio test rejects the null hypothesis that the overdispersion parameter is zero with a chi-squared value of 2134.2 with one degree of freedom in favor of the Negative Binomial model.

	Poisson	Neg. Binomial	Poisson	Neg. Binomial
Subsidy Rate	-0.085	0.322	-0.607***	-0.607***
	(0.089)	(0.437)	(0.019)	(0.070)
% Change in Installations	-0.83%	0.3%	-4.6%	-4.6%
Constant	1.392	0.787	4.118***	4.118***
	(0.456)	(2.239)	(0.062)	(0.281)
6-month Effects	N	N	Y	Y
Year Effects	Y	Y	N	N
LL	-15738.417	-4946.49	-15560.34	-4935.736
Wald Chi2	2725.80	143.28	3081.95	164.79
Prob > chi2	0.00	0.00	0.00	0.00
Observations	1826	1826	1826	1826

Table 6.3: Models for Daily Installations

increase in the subsidy rate will decrease the number of installations by 4.6%. This result is counter to theory and suggests that a different model is needed to capture the complexity of the decision to purchase.[2]

The second model is a myopic specification of the structural model discussed in Chapter 3. I specify two versions of the model. First, I estimate the model without a present value term. Second, I include capacity and capacity squared to capture utility from having a larger capacity system installed.

The utility specification for the first case of the static model for household i choosing system s is:

$$U_{ist}\left(\omega_t, \epsilon_t; \theta, \alpha\right) = \begin{cases} \theta_1 + \theta_{2i} z_t - \alpha_i ln\left(\left(p_{ist}^{SP} - \tau_{st}\right) q_s^{sp}\right) + \theta_{3MSA_i} + \epsilon_{ist} & s \in \{1,2,3,4\} \\ \epsilon_{i0t} & s = 0 \end{cases}$$

I present the estimates for the static model in Table 6.4. The first column describes the estimates from the first specification of the static model. The parameter estimates are of the expected sign. Households receive disutility, albeit close to zero, from higher net prices with both medium and high value homes receiving less disutility relative to the low value homes. In the second column,

[2] Additional models are estimated using the number of semi-annual purchases. I present the results of estimation in Table C.1 located in the Appendix.

I show estimates from the second specification of the static model that includes a capacity and capacity squared term. Similarly, I find that the parameter estimates are of the expected sign. The capacity terms help soak up variation in purchase related to changes in the present value due to the correlation between capacity and the present value of purchase. Parameter estimates show that households get positive utility from larger capacity systems with diminishing returns starting at 7.3 kW. The estimated coefficient on the net price is much larger in magnitude relative to the first specification with a value of -1.791 indicating that households are more responsive to prices than in the first model. The larger magnitude price coefficient is consistent with findings in the literature regarding price sensitivity in durable good markets with highly priced goods.

The second specification estimates are the preferred results from the structural static model. I perform a likelihood ratio test and reject the null model, specification 1, in favor of specification 2 with a LR test statistic of 399.24 from a chi-square distribution with 2 degrees of freedom.

In the reduced form model, I find a negative relationship between the number of installations and the subsidy rate. The result implies that demand slopes upward, and the current policy over-subsidizes the solar panel market. The static structural model corrects the under-predicting of price elasticities by explicitly modeling the households decision problem. From the static structural model, I find that households are price elastic and that the number of purchases would be increased by more aggressive subsidies. The concern with the static structural model is how the estimated parameters are impacted by non-purchase. The model will have a tendency to over-predict the parameter on price to rationalize households delaying purchase.

6.2 Dynamic Models

I describe the results of the dynamic consumer demand model presented in Chapter 3. The estimates are presented for each of the deterministic belief structures regarding future subsidy regimes. I begin with a discussion about the first stage estimates for the pricing process and present the results of estimation. Next, I discuss the second stage of estimation and present results for each of the three belief cases. Lastly, I simulate and discuss price elasticities and the marginal effects of technological innovation.

In the first stage of the dynamic model, I estimate the first-order autoregressive process for the

	(1)	(2)
Efficiency (%)	0.446***	0.645*
	(0.010)	(0.016)
Eff*Small Roof	0.150***	0.150*
	(0.002)	(0.002)
Eff*Medium Roof	0.064***	0.064*
	(0.001)	(0.001)
ln Net Price ($)	-0.118**	-1.791*
	(0.02)	(0.095)
ln Net Price*Med Value	0.037***	0.037*
	(0.002)	(0.002)
ln Net Price*High Value	0.016***	0.016*
	(0.002)	(0.002)
Capacity (kW)		0.993*
		(0.053)
Capacity^2		-0.068*
		(0.004)
Constant	-9.523***	1.95
	(0.199)	()
MSA FE	Y	Y
LL	-100487.68	-100288.06
Number Of Observations	505558	505558

Table 6.4: Static Model Estimation Results

	Statewide	L.A.	S.F.	S.D.	Fresno
Lagged Price	0.932***	0.940***	0.927***	0.893***	0.970***
	(0.048)	(0.091)	(0.039)	(0.070)	(0.055)
Constant	0.297	0.244	0.364	0.579	-0.097
	(0.426)	(0.815)	(0.331)	(0.599)	(0.404)
σ_μ	0.338	0.509	0.359	0.476	0.469
Observations	21	21	21	21	21

Table 6.5: First Stage Estimation Results from 2001-2010

evolution of solar panel system prices. I estimate two specifications of the pricing process. First, I estimate Equation 6.2 for each MSA i. Second, I estimate an alternative specification using the same equation but that is aggregated to the state level. To aggregate the values, I use a weighted average of solar panel prices across capacities and MSA to create a statewide average price per watt.

$$P_{it+1}^{SP} = \delta_{i1} + \delta_{i2} P_{it}^{SP} + \mu_{it+1} \tag{6.2}$$

The estimated parameters for both specifications of the AR(1) process are presented in Table 6.5. In the first column I present the estimated coefficients for the second specification. I find the estimated parameter on lagged price positive and significant with a magnitude of 0.932. In the second through fifth column, I present the estimated coefficients from the first specification. I find that all parameter estimates on lagged price are significant and of magnitudes that vary from 0.970 in Fresno to 0.893 in San Diego. I use the statewide estimated coefficients for the second stage of the dynamic model given the similarities between the estimates.

The second stage of estimation maximizes the log likelihood of the conditional choice probabilities given the estimates from the first stage. I estimate three specifications of the model that correspond to the deterministic belief structures discussed in Chapter 3: Perfect Foresight (PF), Pessimism (Pes), and Auto-renewal (AR). In Table 6.6, I present the estimates for each specification. The columns vary by the belief structure imposed on households. In the three specifications I assume a 2.2% escalation for the price of electricity, a 0.9% per-period solar panel degradation rate, and a discount rate of $\beta = 0.95$ for both future utility and income. I use 50 Halton draws to approximate the integral for the price distribution for the pessimism and auto-renewal specifications.

The parameter estimates for both the natural log of the present value of purchase and the natural log of the net price are significant and of the correct sign across all specifications. I find that households, on average, prefer larger present value benefits from purchase. Also, households gain disutility from higher net prices, and consumers in medium and high value homes receive less disutility from net prices relative to the low housing value population. The results suggest that price responsiveness and subsidy responsiveness in the California solar panel system market varies by housing value.

The difference across dynamic specifications in the present value and net price parameters are a result of the differences in the household beliefs regarding future subsidy regimes. The dynamic model allows households to make purchasing decisions on both the level of prices within the period and the expected change in the price between periods.

If prices are falling rapidly households may wait to purchase until the expected change in prices is closer to zero. In this sense, a household's belief about a future subsidy directly affects the household's expectation about future prices and impacts, in the dynamic sense, their expectation about the change in price over time.

In the case of pessimism, the estimated parameter on the net price is less in magnitude than the estimated parameter in the auto-renewal case. This accords with expectations regarding the effect of pessimistic beliefs on the estimated parameters. The total number of purchase increases from 630, in 2002, to over 1800, in 2003 after the second subsidy regime. Under the assumption that households believe that no future subsidies exist, a household in the first subsidy regime expects the change in future prices to be large and positive. Given the belief, the model rationalizes household behavior by reducing the magnitude of the parameter on net price. The reduction is due to the combination of the expected change in price being large and positive, and the increase in quantity demanded occurring after the subsidy change.

A similar logic holds for the auto-renewal case, households believe that the next subsidy regime will offer a subsidy rate equal to the current regime's final rate. Additional to the subsidy belief,

Sub Belief Solar Price	PF -	Pes State	AR State
ln PV ($)	1.180***	1.139***	1.198***
	(0.048)	(0.073)	(0.074)
Efficiency (%)	0.659***	0.646***	0.659***
	(0.011)	(0.014)	(0.015)
Eff*Small Roof	0.163***	0.162***	0.164***
	(0.002)	(0.002)	(0.002)
Eff*Med Roof	0.074***	0.073***	0.075***
	(0.001)	(0.001)	(0.002)
ln Net Price ($)	-1.359***	-1.314***	-1.380***
	(0.052)	(0.079)	(0.08)
Price*Med Value	0.041***	0.0414***	0.0419***
	(0.002)	(0.002)	(0.002)
Price*High Value	0.019**	0.0190***	0.0195***
	(0.002)	(0.002)	(0.002)
Constant	-11.346	-11.262	-11.312
MSA FE	Y	Y	Y
LL	-100041.87	-100042.53	-100036.21
# Of Obs	505558	505558	505558
Escalation Rate	2.2%	2.2%	2.2%
Halton Draws	-	50	50

Table 6.6: Second Stage Estimation Results

households expect prices to decline. The combination of expectations about prices and beliefs about subsidies generates the expectation that net prices are falling. The expectation of lower prices in the future increases the household's value of waiting to purchase. Using the same example as above, the model rationalizes household behavior as price responsiveness and increases the magnitude of the coefficient on the net price.

I find consistency in the estimated parameter on efficiency rate and the interaction between efficiency rate and roof size across the three specifications. The estimated parameter on efficiency rate is positive and significant indicating that, on average, households prefer a higher efficiency rate. Also, I find that households with the smallest rooftop space prefer higher efficiency rates relative to both medium and large rooftop homes. This accords with the argument suggested in Chapter 2 regrading smaller rooftop space households preferring a higher efficiency rate due to the constraints or extra costs of installing a physically larger size system. Interestingly, the estimated parameters on efficiency rates do not vary over the static and dynamic specifications. This pattern can be explained by the small changes in efficiency rates between periods or that the expected change in technology might not have been a significant factor in the households dynamic decision to purchase.

6.3 Model Fit

I check the appropriateness of additional variables for observable heterogeneity by running the following likelihood ratio tests for each specification.

1. Heterogeneity by Housing Value: $H_0 : \alpha_2 = \alpha_3 = 0$, $H_a : \alpha_2 \neq \alpha_3 \neq 0$

2. Heterogeneity by Rooftop Space: $H_0 : \theta_{32} = \theta_{33} = 0$, $H_a : \theta_{32} \neq \theta_{33} \neq 0$

3. Medium and High Housing Values: $H_0 : \alpha_2 = \alpha_3$, $H_a : \alpha_2 \neq \alpha_3$

4. Small and Medium Rooftop Space: $H_0 : \theta_{32} = \theta_{33}$, $H_a : \theta_{32} \neq \theta_{33}$

The first likelihood ratio test compares the fit of a null model in which there is no heterogeneity in preferences across the distribution of housing values to the fit of the full model. I reject the null hypothesis in favor of the full model for all specifications.[3] The second likelihood ratio test compares the fit of a null model where there is no heterogeneity in preferences across the distribution of rooftop space to the fit of the full model. I reject the null hypothesis in favor of the full model for all specifications.[4] The third likelihood ratio test compares the fit of a null model in which preferences for prices are the same across households in the top two terciles of the housing value distribution to the fit of the full model. I reject the null model in favor of the full model for all specifications.[5] The fourth likelihood ratio test compares the fit of a null model where household preferences for efficiency rates are the same across the bottom two terciles of the rooftop space distribution to the fit of the full model above. In all specifications, I reject the null model in favor of the full model.

I report choice probabilities in Table 6.7 by specification and time period. The first column of the table identifies the specification of the model that corresponds with the choice probabilities. The first row of probabilities are the empirical choice probabilities from the CEC dataset. The next three rows are the simulated choice probabilities for each specification of the model. The choice probabilities are small with the largest, in the last period, equaling a half of one percent probability of purchase. This is a result of the low number of purchases during the sample period relative to the market size. I find that all three dynamic specifications fit the empirical choice probabilities closely. The model over-predicts the choice probabilities during the first two periods where the least amount of purchases occur, but as the number of purchases increase the simulated probabilities match the empirical probabilities closer. Also, I find small differences in the simulated choice probabilities between the specifications of the dynamic model.

---

[3]The perfect foresight model rejects the null hypothesis with a likelihood ratio statistic of 251.16, the pessimism model rejects the null with a likelihood ratio statistic of 250.33, and the auto-renewal case rejects the null with a likelihood ratio statistics of 245.82 with 2 degrees of freedom.

[4]The perfect foresight model rejects the null hypothesis with a likelihood ratio statistic of 4892.92, the pessimism model rejects the null with a likelihood ratio statistic of 4880.48, and the auto-renewal case rejects the null with a likelihood ratio statistics of 4886.10 with 2 degrees of freedom.

[5]The perfect foresight model rejects the null hypothesis with a likelihood ratio statistic of 76.21, the pessimism model rejects the null with a likelihood ratio statistic of 77.95, and the auto-renewal case rejects the null with a likelihood ratio statistics of 76.26 and 1 degree of freedom.

In Table 6.8, I present choice probabilities by specification, time, and capacity bin. The first column of the table identifies the specification associated with the choice probabilities, and the second column identifies the capacity bin. The simulated choice probabilities in general fit closely with the empirical probabilities across capacity bins. In capacity bin 1, the model under-predicts in 2003 and 2003.5 following the subsidy regime change, and over-predicts in the last period before the regime change. Similarly, the model over-predicts the simulated choice probabilities in capacity bin 4 in the first two periods prior to the regime change, and under-predicts in the final period. The instances of larger differences between the empirical and simulated choice probabilities are correlated with time periods close to the regime changes.

6.4 Elasticities

I present short-run and long-run price elasticities in Table 6.9.[6] The short-run price elasticities are calculated as a 1% temporary price increase across all products for one period. Households have full information about the duration of the price increase and form expectations about future prices knowing that the price change is not persistent. The price increase is unknown to the households until the beginning of the period it occurs. I find that simulated price elasticities, on average, are elastic in the short run. The average short-run price elasticity is -1.387 in the perfect foresight case, -1.310 in the pessimism case, and the average price elasticity is -1.390 in the auto-renewal case.

In the perfect foresight case, I find that medium housing value households are the most price elastic with an average elasticity of -1.447 followed by the high housing value households at -1.379, and the low housing value households with an elasticity of -1.354. In the pessimism case, I find that low housing value households are the most price elastic with an elasticity measure of -1.350 followed by the high housing value households at -1.296, and medium value homes being the least price elastic with -1.276. In the autorenewal case, I find that low housing value households are least price elastic at -1.231 followed by medium value homes at -1.415, and high value homes being the most price elastic with an elasticity of -1.515.

[6] The price elasticities presented in Table 6.9 are taken from middle of the sample period, the first six-month period of 2004, and averaged over 50 simulations.

	Choice Probabilities (Empirical vs Simulated) in %									
	2002	2002.5	2003	2003.5	2004	2004.5	2005	2005.5	2006	2006.5
Data	**0.0973**	**0.0898**	**0.3016**	**0.3116**	**0.2358**	**0.1784**	**0.1409**	**0.2999**	**0.4271**	**0.4667**
PF	0.1483	0.1640	0.1985	0.2429	0.2132	0.1967	0.2073	0.2613	0.4682	0.4309
Pes	0.1475	0.1687	0.1965	0.2399	0.2115	0.1957	0.2062	0.2595	0.4612	0.4437
ARe	0.1485	0.1626	0.1993	0.2442	0.2136	0.1968	0.2073	0.2614	0.4694	0.4286

Table 6.7: Empirical vs Simulated Choice Probabilities

	Capacity	Choice Probabilities (Empirical vs Simulated) in %									
		2002	2002.5	2003	2003.5	2004	2004.5	2005	2005.5	2006	2006.5
Data	**1**	**0.0371**	**0.0354**	**0.0818**	**0.0912**	**0.0442**	**0.0329**	**0.0266**	**0.0473**	**0.1154**	**0.0836**
PF		0.0352	0.0383	0.0458	0.0543	0.0512	0.0462	0.0480	0.0615	0.1177	0.1367
Pes		0.0351	0.0394	0.0454	0.0537	0.0508	0.0461	0.0478	0.0612	0.1161	0.1398
AR		0.0352	0.0380	0.0459	0.0545	0.0512	0.0461	0.0480	0.0614	0.1180	0.1364
Data	**2**	**0.0245**	**0.0213**	**0.0899**	**0.0886**	**0.0771**	**0.0631**	**0.0438**	**0.0888**	**0.1083**	**0.1074**
PF		0.0384	0.0439	0.0514	0.0624	0.0550	0.0515	0.0534	0.0670	0.1254	0.1057
Pes		0.0382	0.0452	0.0509	0.0617	0.0545	0.0512	0.0531	0.0667	0.1232	0.1091
AR		0.0385	0.0436	0.0517	0.0628	0.0552	0.0515	0.0534	0.0671	0.1257	0.1051
Data	**3**	**0.0219**	**0.0194**	**0.0832**	**0.0880**	**0.0689**	**0.0445**	**0.0342**	**0.0713**	**0.0898**	**0.1272**
PF		0.0399	0.0413	0.0501	0.0644	0.0549	0.0513	0.0550	0.0682	0.1171	0.1005
Pes		0.0395	0.0425	0.0496	0.0635	0.0545	0.0509	0.0547	0.0678	0.1152	0.1037
AR		0.0400	0.0409	0.0503	0.0648	0.0550	0.0514	0.0551	0.0684	0.1174	0.0998
Data	**4**	**0.0136**	**0.0136**	**0.0465**	**0.0437**	**0.0454**	**0.0377**	**0.0362**	**0.0924**	**0.1134**	**0.1484**
PF		0.0347	0.0403	0.0511	0.0616	0.0520	0.0476	0.0507	0.0644	0.1079	0.0877
Pes		0.0345	0.0414	0.0504	0.0608	0.0515	0.0473	0.0505	0.0639	0.1065	0.0909
AR		0.0347	0.0399	0.0513	0.0620	0.0521	0.0476	0.0507	0.0645	0.1082	0.0870

Table 6.8: Empirical vs Simulated Choice Probabilities by Capacity Bin

Specification	Housing Value	Short Run	Long Run
Static	All	-1.854	-
Perfect Foresight	All	-1.387	-1.290
	High	-1.379	-1.291
	Med	-1.447	-1.373
	Low	-1.354	-1.229
Pessimism	All	-1.310	-1.198
	High	-1.296	-1.213
	Med	-1.276	-1.164
	Low	-1.350	-1.205
Autorenewal	All	-1.390	-1.128
	High	-1.515	-1.417
	Med	-1.415	-1.333
	Low	-1.231	-1.089

Table 6.9: Price Elasticity Given a 1% Increase in Price

I present simulated long-run price elasticities in Table 6.9 by permanently increasing prices across capacity by 1%. The price increase is persistent from the period it is initialized onwards. Households in the market have full information regarding the persistence of the price increase, but are not aware of the price increase until the period it begins. Simulated price elasticities indicate that households are price elastic, with an average long-run price elasticity of -1.198 in the pessimism case and -1.128 in the autorenewal case. The difference between short-run and long-run price elasticities suggest that households are price elastic in the solar panel system market and are willing to substitute demand intertemporally in the presence of higher prices.

The marginal effect of a change in efficiency rates on the probability of purchase are presented in Table 6.10. The table consists of three columns representing the model specification, households, and long-run marginal effect. The results indicate that a permanent 1% increase in efficiency rates increases the probability of purchase by an average of 6.46% across all specifications. The consistency across specifications is not surprising given the estimates from the model.

Specification	Roof Size	Long Run
PF	Market	6.46
No Future	Market	6.45
Auto-renewal	Market	6.48

Table 6.10: Marginal Effect of a 1% Increase in Efficiency Rates

CHAPTER 7

COUNTERFACTUALS

In the first counterfactual, I simulate the solar panel system market without subsidies. I report the results for each specification of the dynamic model below. For each specification, I present two tables of results. In the first table I present the simulated number of purchases from the full model, simulated purchases without government intervention, and the percent change in purchase attributed to removing the subsidies. In the second table, I report the percent change of purchase due to the removal of subsidies by capacity bin over the sample period. For the counterfactuals, I assume that suppliers are perfectly price elastic so prices do not vary with respect to changes in subsidies.

I present the results from the counterfactual simulation for the pessimism case in Table 7.1 and Table 7.2.[1] In the first row of Table 7.1, I report the simulated number of purchases with subsidies. In the second row, I present the number of simulated purchases without subsidies, and in the third row I report the percentage change in purchase. I find the largest percentage loss of purchase, -68.04%, occurs during the early periods of the sample. Also, I find that over the sample period the percentage loss of purchase decreases reaching a minimum level of 38.73% in 2006. There are two main factors driving the decrease in percentage loss over time. First, households can intertemporally substitute demand and forgo purchase until a later period. Second, the removal of subsidies increases the price households face in earlier periods of the model. This occurs for two reasons. First, prices are higher in earlier periods relative to later in the sample. Second, subsidies are larger in earlier periods of the sample. Lastly, I find that in the absence of subsidies the total

	2002	2002.5	2003	2003.5	2004	2004.5	2005	2005.5	2006	2006.5	Total
Data	492	454	1522	1568	1183	893	704	1496	2124	2311	12747
Simulated	746.4	856.41	987.42	1204.91	1068.86	986.31	1035.05	1295.9	2303.01	2203.15	12687.42
No Subsidy	260.9	273.7	354.85	437.42	530.65	528.23	581.76	773.23	1411.02	1290.81	6442.57
%Δ Purchase	-65.05	-68.04	-64.06	-63.7	-50.35	-46.44	-43.79	-40.33	-38.73	-41.41	-49.22

Table 7.1: Change in Purchase without Government Intervention (Pessimism)

Capacity	2002	2002.5	2003	2003.5	2004	2004.5	2005	2005.5	2006	2006.5
Small	-60.76	-63.72	-59.60	-58.60	-46.70	-42.90	-39.32	-36.24	-39.44	-47.21
Medium	-65.03	-68.92	-64.20	-63.82	-49.81	-46.00	-43.62	-40.13	-40.18	-40.43
Large	-67.59	-69.37	-65.63	-65.73	-52.81	-48.50	-46.03	-42.37	-38.30	-39.00
X-Large	-66.52	-69.81	-66.44	-65.98	-51.96	-48.14	-45.73	-42.33	-36.73	-36.48

Table 7.2: Change in Purchase (%) without Government Intervention by Capacity (Pessimism)

number of solar panel system purchases decrease by 49.22% from 12,687.42 to 6442.57.

In Table 7.2, I simulate the number of purchases by capacity bin and report the percent change in purchase after the removal of government subsidies. The first column identifies the capacity of the solar panel system. For each capacity, I report the percentage change in purchase for each period in the sample. I find a pattern of decreasing percentage loss of purchase over time similar to Table 7.1. Additionally, I find the largest percentage loss of purchase for most periods in the sample occurring for large and extra-large capacity solar panel systems. Part of the result could be driven by reasons discussed in the previous paragraph: intertemporal demand substitution and the percentage reduction in price over time. Additionally, the higher percentage of loss of purchase could be a result of households substituting between capacity levels. Policy makers are interested in the impact of subsidies on the number of residential installations of solar panel systems. Also, policy makers are interested in the total amount of capacity (kW) of solar generation installed from policy intervention.

I find that 49.57% of the total capacity installed during the sample period is directly attributable to the subsidy program.[2] In Table 7.3, I present the additional amount of capacity installed for each system size and over the sample period with the subsidy. In all periods, I find that the large and extra-large solar panel systems makeup the majority share of capacity installed. Overall, large and extra-large solar panel systems contribute 69.73% of the total solar capacity installed for purchases directly attributable to the subsidy program. The total capacity installed by households that only purchase with subsidies is shown in Figure 7.1. Of the total capacity installed, I find that 41.23% is due to extra-large capacity installations, 28.5% is due to large capacity installations, 18.69% is due to medium capacity installations, and 11.58% come from small capacity installations. The finding suggests that the subsidy program is both incentivizing households to purchase solar panel installations and importantly larger capacity installations.

I extend the analysis beyond the removal of subsidies and simulate purchases for different

[1] I present results from the counterfactual simulations for the perfect foresight case in Tables C.4 and C.5 and the auto-renewal case in Tables C.7 and C.8. The results are similar across all three specifications.

[2] In the case where subsidies are removed that total capacity in the market reduces by 23,545.44 kW.

	2002	2002.5	2003	2003.5	2004	2004.5	2005	2005.5	2006	2006.5	Total
Small	195.26	228.96	246.01	286.02	217.64	179.59	168.44	199.8	418.12	587.77	2727.61
Medium	340.16	428.89	449.24	538.18	372.29	320.74	316.42	366.38	670.24	597.15	4399.68
Large	560.68	623.82	679.25	864.80	605.56	517.62	526.28	592.81	907.03	831.48	6709.33
X-Large	758.61	957.95	1085.02	1313.98	873.38	750.99	756.85	870.91	1264.24	1076.88	9708.82
Total	1854.72	2239.61	2459.51	3002.98	2068.86	1768.95	1767.99	2029.9	3259.63	3093.28	23545.44

Table 7.3: Additional Capacity (kW) Installed with Government Intervention (Pessimism)

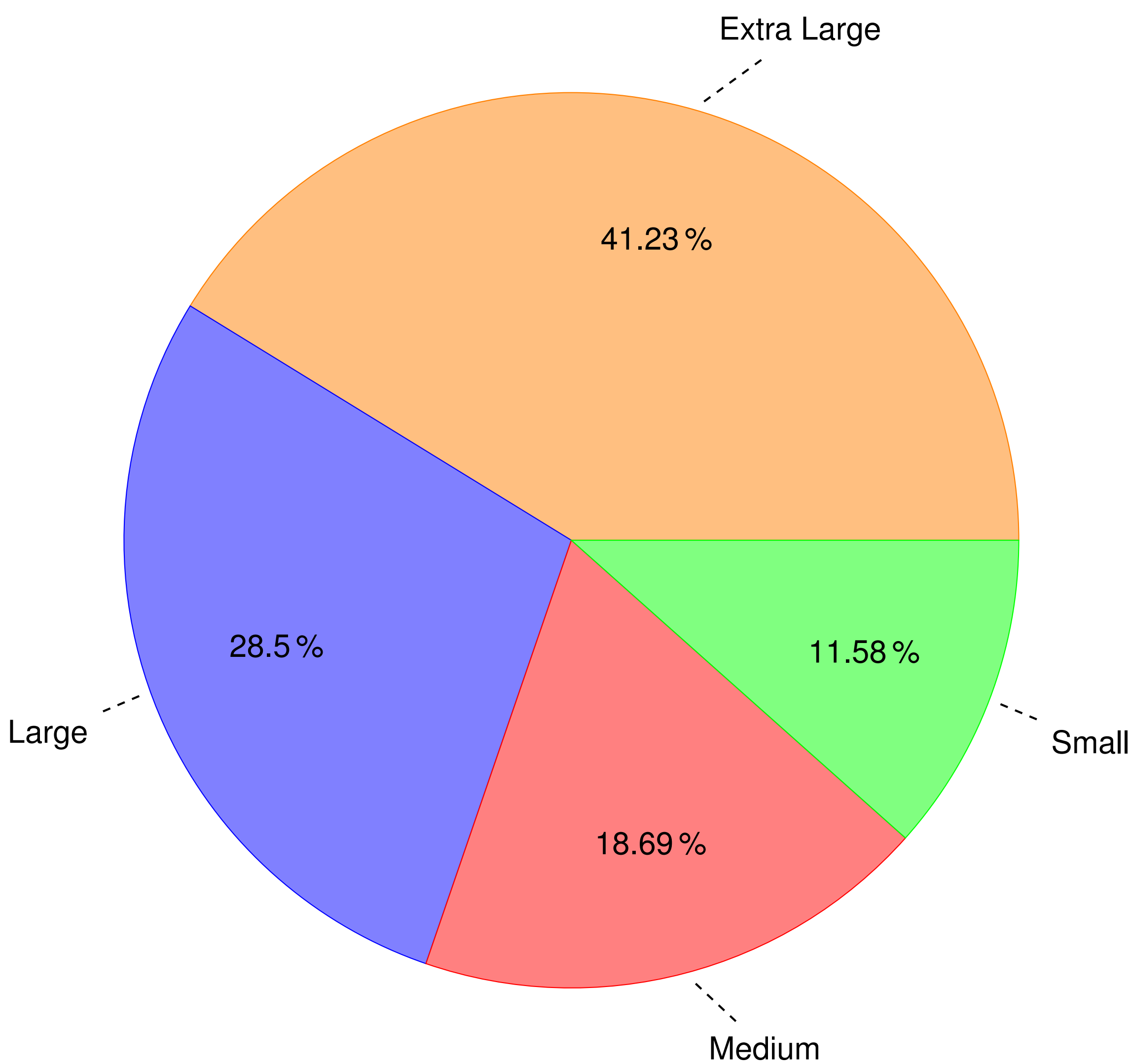


Figure 7.1: Additional Capacity Installed with Subsidy by Capacity Bin

percentage levels of the subsidy. In Figure 7.2, I represent the number of installations as a function of the percentage of subsidy rates offered during the sample. The vertical axis represents the number of installations aggregated over the sample period, and the horizontal axis represents the percentage of the subsidy rate. The horizontal axis is discretized into 10% bins ranging from 0% to 120%. I simulate purchases by setting the subsidy rates to the chosen percentage of the original subsidy rate and run the counterfactual. Then, I aggregate the number of purchases across capacity bin and time and report it as a black dot on the figure. The vertical dashed line represents 100% of the subsidy and the horizontal dashed line represents the number of simulated purchases with the actual subsidy rates. I find that at any percentage below 100% of the subsidy rate the number of purchases is below the horizontal line.

In Table 7.4, I calculate the marginal increase in the number of installations per 10% increase. The columns are separated into bins that match the horizontal axis in Figure 7.2. The first row in each column represents the total number of installations given the percentage of the subsidy rate. In the second row, I calculate the percentage change in the number of installations with respect to the 10% increase in the subsidy rate. In the third row, I calculate the change in the level of installations given the 10% increase in the subsidy rate. For example in the 30% column, I report a percentage change of 5.87% in the number of installations and a level increase of 420.49 installations. The values are calculated using the difference in the number of installations from 20% to 30% subsidy rates.

I find that there are increasing returns to the subsidy rate. In Table 7.4, I show that the percentage increase in purchases becomes larger with each additional 10% of the subsidy added. At the point where the subsidy is increased beyond the rate offered in the sample the percentage increase in purchase is greater than the percentage increase in the subsidy.

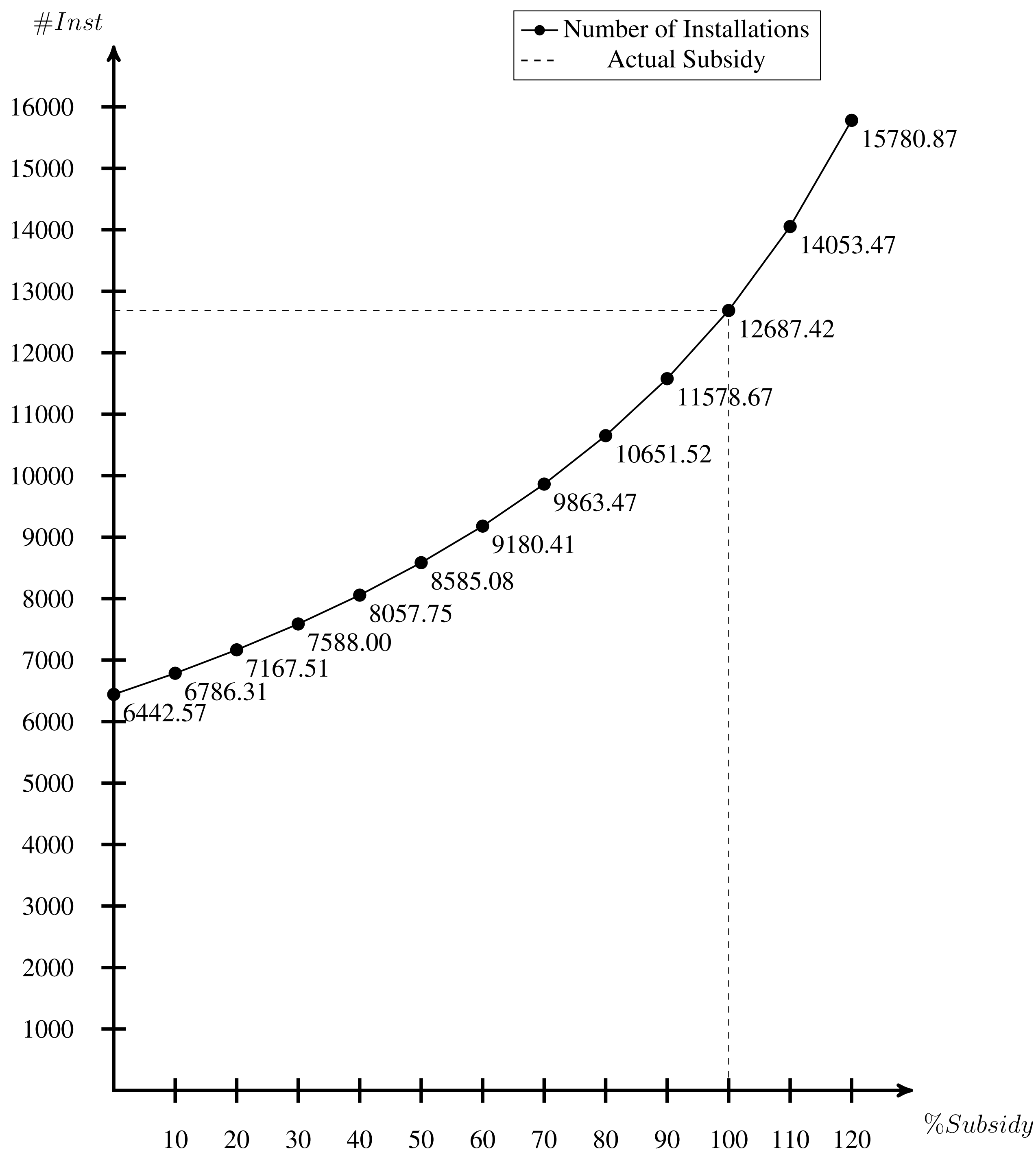


Figure 7.2: Number of Installations as a Function of % of Subsidy

	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%	110%	120%
#	6786.31	7167.51	7588.00	8057.75	8585.08	9180.41	9863.47	10651.52	11578.67	12687.42	14053.47	15780.87
%Δ	5.34	5.62	5.87	6.19	6.54	6.93	7.44	7.99	8.7	9.58	10.77	12.29
Level Δ	343.74	381.2	420.49	469.75	527.33	595.33	683.06	788.05	927.15	1108.75	1366.05	1727.4

Table 7.4: Marginal Increase in Installations given a 10% Increase in the Subsidy (Pessimism)

	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%	110%	120%
#	7324.92	7693.04	8094.4	8543.08	9043.04	9593.28	10217.28	10927.18	11731.84	12687.42	13775.22	15102.18
%Δ	4.91	5.03	5.22	5.54	5.85	6.08	6.5	6.95	7.36	8.15	8.57	9.63
Level Δ	342.56	368.12	401.36	448.68	499.96	550.24	624	709.9	804.66	955.58	1087.8	1326.96

Table 7.5: Marginal Increase in Installations given a 10% Increase in the Subsidy (Autorenewal)

	2002	2002.5	2003	2003.5	2004	2004.5	2005	2005.5	2006	2006.5
Purchase w/ Uncert	746.4	856.41	987.42	1204.91	1068.86	986.31	1035.05	1295.9	2303.01	2203.15
Purchase w/out Uncert	748.86	810.48	990.46	1204	1079.6	984.78	1041.3	1321.84	2308.68	2034.9
%Δ Purchase	0.33	-5.36	0.31	-0.08	1	-0.16	0.6	2	0.25	-7.64

Table 7.6: Number of Installations under Pessimism without Uncertainty

	2002	2002.5	2003	2003.5	2004	2004.5	2005	2005.5	2006	2006.5
Purch w/ Uncert	753.52	819.88	1002.3	1231.06	1077.52	988.94	1040.7	1303.38	2333.78	2119.44
Purch w/out Uncert	756.14	821.7	1008.18	1230.86	1091.96	991.1	1047.54	1331.5	2357.48	2069.36
%Δ Purchase	0.35	0.22	0.59	-0.02	1.34	0.22	0.66	2.16	1.02	-2.36

Table 7.7: Number of Installations under Auto-renewal without Uncertainty

CHAPTER 8

CONCLUSION

In this dissertation, I analyze households' decisions to purchase a residential-level solar panel system. The solar panel system market is characterized by large upfront costs, differentiated products, technological innovation, decreasing prices, and uncertainty regarding future government subsidies. I use a newly assembled dataset to estimate demand for solar panel installations that cover a sample period from 2002 through 2006.

The first result is directly related to the uncertainty inherent in the use of short-lived subsidy regimes. I find no evidence that household behavior is affected by the uncertainty regarding future subsidy regimes. Further, I do not observe evidence of anticipatory behavior occurring in the solar panel market during the sample period. These findings suggest that short term solar policies can be used with minimal loss to the number of purchases or the total capacity installed.

Second, I find that households in the solar panel market are price elastic with short-run elasticities greater in magnitude relative to long-run elasticities. I find that price elasticities vary across the distribution of housing values. This suggests that there are potential efficiency gains through income-based subsidy targeting. Also, I find that technological innovation in the form of increasing efficiency rates is significant. The marginal effect of a 1% increase in efficiency rates increases the probability of purchase by 6.4%. This value is large given that efficiency rates increase by 30% during the sample period.

Third, I find that the subsidy regimes during the sample period incentivize household purchase of solar panel systems. I find that 49.5% of solar panel system installations from 2002 through 2006 are directly attributable to subsidies. Also, I find that within the set of purchases related to subsidies that larger capacity systems provide 70% of the total capacity installed.

APPENDIX A

ASSUMPTIONS AND COPULAS

A.1 Assumptions

In the full model, households simultaneously choose their consumption of electricity and purchasing decision during each period. The electricity consumption decision is not modeled due to constraints on data availability for electricity use and plan information at the household level. Instead, two assumptions separate the decision of electricity consumption and purchase.

Assumption 1: *Electricity is a homogeneous good.*

Assumption 1 suggests that households are indifferent about the source of electricity. Specifically, utility from consuming electricity is not differentiated between solar and traditional sources, (i.e., the grid).

Assumption 2: *Households face average electricity prices,* $p^e_{it}(q) = \bar{p_{it}}^e$.

Assumption 2 restricts the model's ability to capture the effect of the purchasing decision on the marginal price of electricity for households. In a tiered-pricing environment, the decision to generate solar electricity potentially decreases the marginal price of traditional electricity from the grid. The reduction in marginal price of electricity, holding everything else constant, would increase the quantity demanded of total electricity consumption.[1] Without data on household pricing plans and use information, considering this effect is difficult. Instead, the average price of electricity within each region is assumed to be the price that households care about when making an electricity consumption decision.

These assumptions reduce the explanatory power of the model in two ways. First, an electricity consumption decision is independent of the purchasing decision. This is potentially restrictive when thinking about the change in total electricity consumption after purchasing solar panels due to a change in the marginal price of electricity. Second, estimating the effect electricity consumption at the household level has on the decision to purchase is impossible. These assumptions allow

[1] In the baseline tiered pricing scheme households are charged higher prices as consumption increases.

estimation of the model without access to electricity use data while accounting for the monetary benefit of installing solar panels.

A.2 Brief Summary of Copula Functions

The purpose of this appendix is to provide the reader with a detailed description of the process used to simulate households that were not included in the CEC dataset. These households are needed to fill the population of nonpurchasers during the sample period and to be used for counterfactual simulations. The goal is to simulate a dataset of households for each zip code in the state of California.

To simulate the population of households, marginal distribution data was obtained from Dataquick. The data includes marginal distribution measures for housing value, number of bedrooms, number of stories, square footage, and year built for single family dwellings at the zip code level. For each characteristic the data includes the following information about the marginal distribution:

- Count
- Mean
- Median
- Standard Deviation
- Quintiles

Theses measures provide information about the first two moments of the distribution and a coarse look at the shape of the distribution using the quintiles. Additional to the data regarding the individual marginal distributions, the data include correlation measures between each of the housing characteristics. This allows for a covariance-variance matrix to be constructed for houses in each zip code.

1. **Copulas**

   - Let a function C :$[0,1]^d \to [0,1]$ be a copula if there is a probability space (Ω, F, P) supporting a random vector $(U_1, \ldots, U_d)$ such that $U_k \sim U[0,1]$ for all $k = 1, \ldots, d$

and

$$C\left(u_{1,}\ldots,u_d\right)=P(U_1\leq u_1,\ldots,U_d\leq u_d),\ u_{1,}\ldots,u_d\in[0,1]$$

- Let $F_1(x_1),\ldots,F_d(x_d)$ be the marginal distributions for the random variables
- The copulas are functions that connect multivariate distributions to their one-dimensional margins with a dependence parameter θ.

$$H\left(x_1,\ldots,x_d\right)=C\left(F_1\left(x_1\right),\ldots,F_d\left(x_d\right);\theta\right)$$

2. **Gaussian Copula**

- Let $(X_1,\ldots,X_d)$ be a normally distributed random with joint distribution function

$$\begin{aligned}F\left(x_1,\ldots,x_d\right) &= \\ \int_{\times_{i=1}^{d}(-\infty,x_i]} & (2\pi)^{-\frac{d}{2}}\,det\left(\Sigma\right)^{-\frac{1}{2}}\quad exp\left(-\frac{1}{2}\left(s-\mu\right)\Sigma^{-1}\left(s-\mu\right)'\right)ds\end{aligned}$$

- Σ is a symmetric positive definite matrix with the diagonal entires representing the variances
- μ is a mean vector
- The copula of $(X_1,\ldots,X_d)$ is called the Gaussian copula and is given by

$$C_{\Sigma}^{Gauss}\left(u_{1,}\ldots,u_d\right)=H\left(F_1^{-1}\left(u_1\right),\ldots,F_d^{-1}\left(u_d\right)\right)$$

3. **Algorithm to Simulate Observations**

(a) Pull observations from a multivariate normal distribution $(y_1,\ldots,y_d)\sim MN(0,\Sigma)$ where Σ is a matrix consisting of variance equal to one on the diagonal and the correlation coefficients off diagonal.

(b) Retrieve the probabilities associated with the observations from step 1 by running them through a univariate normal CDF with mean 0 and variance 1: $(u_1, \ldots, u_d) = G(y_1), \ldots G(y_d) \sim N(0,1)$

(c) Generate observations by taking the inverse of the marginal distributions with the probabilities as inputs: $\left(F_1^{-1}(u_1), \ldots F_d^{-1}(u_d)\right) = (x_1, \ldots x_d)$

APPENDIX B

ADDITIONAL DATA CONSIDERATIONS

The purpose of the appendix is to provide the reader with additional information regarding the dataset used in estimation. The appendix includes summary statistics, a figure that represents monthly installations over the sample period, the California Solar Initiative subsidy schedule, an example of a solar panel specification sheet, and two examples of a CEC public guidebook. The first public guidebook discusses the details of the first subsidy regime during the sample period. The second public guidebook details the second subsidy regime in the sample period. I include the table of contents from each guidebook to provide the reader with a summary of the information available to households at the beginning of a regime. Also, I provide the summary portion of the guidebook that gives an overview of the program and the subsidy rates available.

Variable	Mean	Std. Dev	Min	Max
Capacity	3.78	1.94	0.095	9.99
System Price	36,794	18,437	1,073	158,012
Capacity-based Subsidy	12,718	7,161	213	52,043
Tax Credits	2,313	1,302	79	16,658
Electricity Rate	14.01	0.43	11.02	14.86
Solar Irradiation	4.99	0.26	3.87	5.83
Price per Watt	9.97	1.79	4.52	28.90
# of Installations	1386.17	901.64	7	2951

Table B.1: Summary Statistics

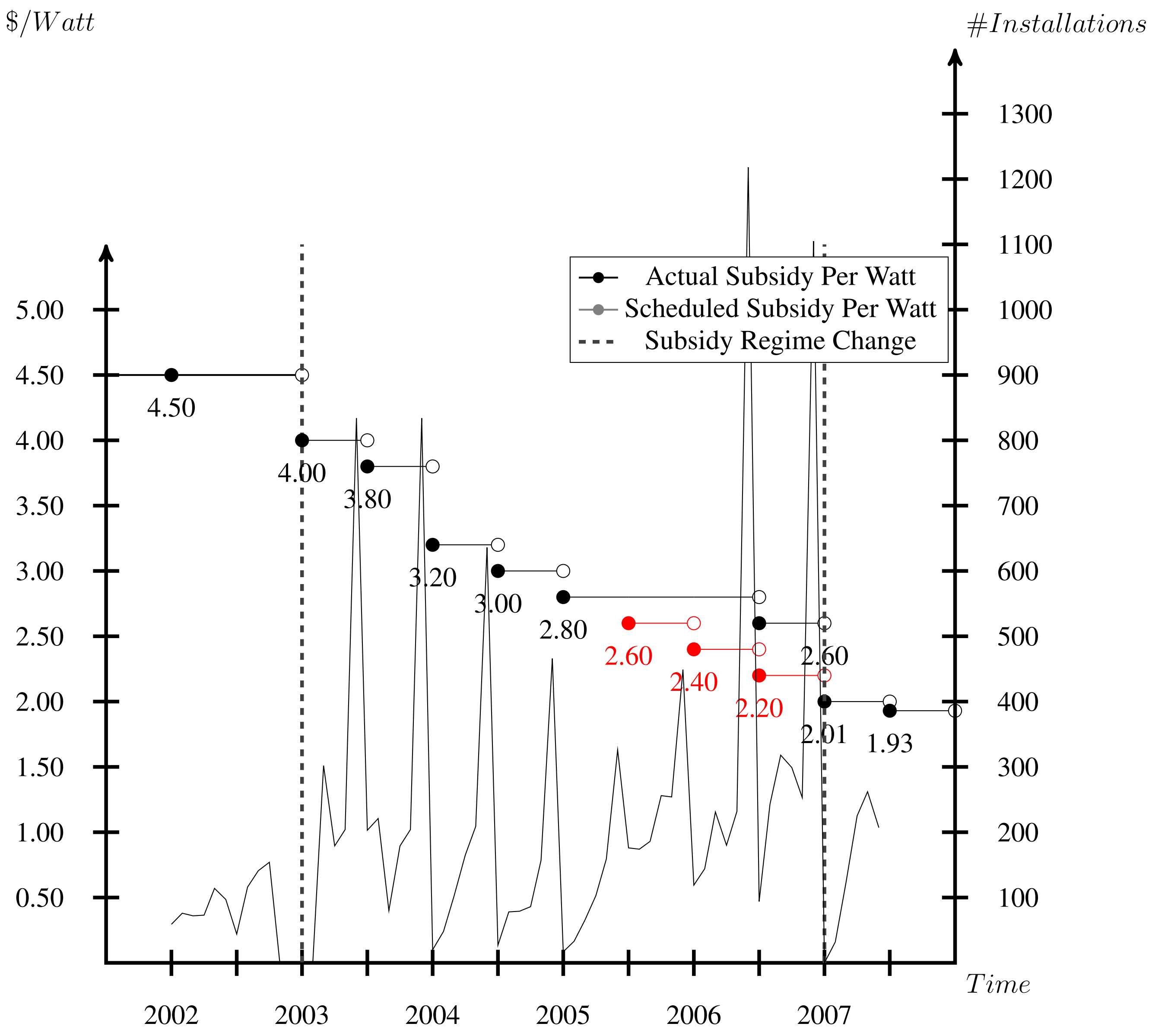


Figure B.1: Number of Installations Per Month and Subsidy Rate

CSI Step table: CSI Rebate Levels by Incentive Step and Rebate Type

		EPBB Payments (per Watt)			PBI Payments (per kWh)		
			Non-Residential			Non-Residential	
Step	Statewide MW in Step	Residential	Commercial	Government/ Non-Profit	Residential	Commercial	Government/ Non-Profit
1	50	n/a	n/a	n/a	n/a	n/a	n/a
2	70	$2.50	$2.50	$3.25	$0.39	$0.39	$0.50
3	100	$2.20	$2.20	$2.95	$0.34	$0.34	$0.46
4	130	$1.90	$1.90	$2.65	$0.26	$0.26	$0.37
5	160	$1.55	$1.55	$2.30	$0.22	$0.22	$0.32
6	190	$1.10	$1.10	$1.85	$0.15	$0.15	$0.26
7	215	$0.65	$0.65	$1.40	$0.09	$0.09	$0.19
8**	250	$0.35	$0.35	$1.10	$0.05 (a)/$0.044 (b)	$0.05 (a)/$0.044 (b)	$0.15 (a)/$0.139 (b)
9**	285	$0.25	$0.25	$0.90	$0.03 (a)/$0.032 (b)	$0.03 (a)/$0.032 (b)	$0.12 (a)/$0.114 (b)
10**	350	$0.20	$0.20	$0.70	$0.025	$0.025	$0.088

bp solar

BP 175B

175 Watt Photovoltaic Module

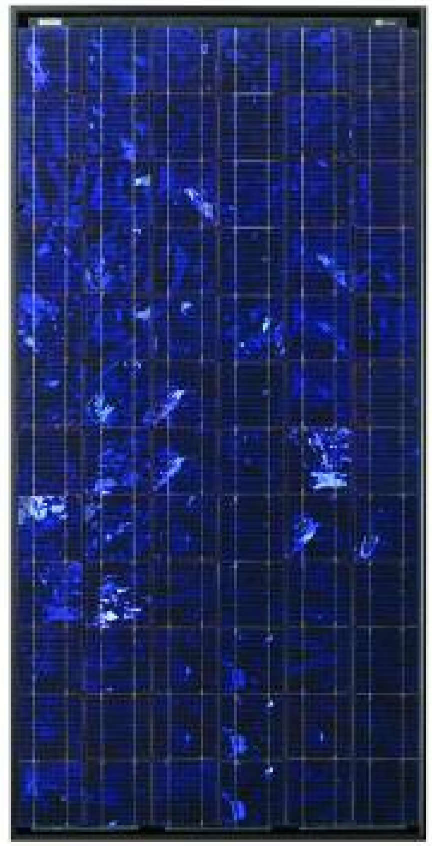
High-efficiency photovoltaic module using polycrystalline silicon cells

Performance

Rated power (P_{max})	175W
Power Tolerance	±5%
Nominal voltage	24V
Limited Warranty[1]	25 years

Configuration

B	Bronze frame with output cables and polarized Multicontact (MC) connectors



Electrical Characteristics[2]	BP 175B
Maximum power (P_{max})[3]	175W
Voltage at P_{max} (V_{mp})	35.8V
Current at P_{max} (I_{mp})	4.9A
Warranted minimum P_{max}	166.3W
Short-circuit current (I_{sc})	5.47A
Open-circuit voltage (V_{oc})	43.6V
Temperature coefficient of I_{sc}	(0.065±0.015)%/°C
Temperature coefficient of V_{oc}	-(160±20)mV/°C
Temperature coefficient of power	-(0.5±0.05)%/°C
NOCT (Air 20°C; Sun 0.8kW/m^2; wind 1m/s)	47±2°C
Maximum series fuse rating	15A
Maximum system voltage	600V (U.S. NEC rating)

Mechanical Characteristics

Dimensions	Length: 1593mm (62.8") Width: 790mm (31.1") Depth: 50mm (1.97")
Weight	15.4 kg (34 pounds)
Solar Cells	72 cells (125mm x 125mm) in a 6x12 matrix connected in series
Output Cables	RHW-2 AWG# 12 (4mm^2), cable with polarized weatherproof DC rated Multicontact connectors; asymmetrical lengths — 1250mm(-) and 800mm(+)
Diodes	***IntegraBus™*** technology includes Schottky by-pass diodes integrated into the printed circuit board bus
Construction	Front: High-transmission and anti-reflective 3mm (1/8th in) tempered glass; Back: Black Polyester; Encapsulant: EVA
Frame	Anodized aluminum Universal frame; Color: Black

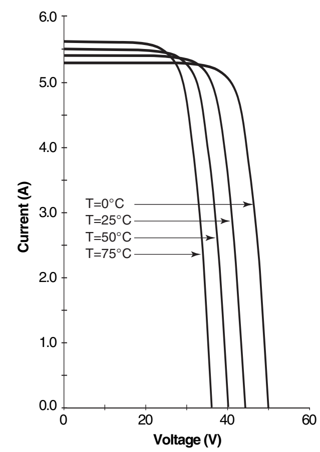
1. Warranty: Power output for 25 years. Freedom from defects in materials and workmanship for 5 years. See our website for full terms of these warranties.
2. This data represents the performance of typical BP Solar products, and are based on measurements made in accordance with ASTM E1036 corrected to SRC (STC.)
3. During the stabilization process that occurs during the first few months of deployment, module power may decrease by approximately 1% from typical P_{max}.

6802.0006-v1 09/09

Quality and Safety

ESTI	Module power measurements calibrated to World Radiometric Reference through ESTI (European Solar Test Installation at Ispra, Italy)
UL	Listed by Underwriter's Laboratories for electrical and fire safety (Class C fire rating)

BP 175B I-V Curves

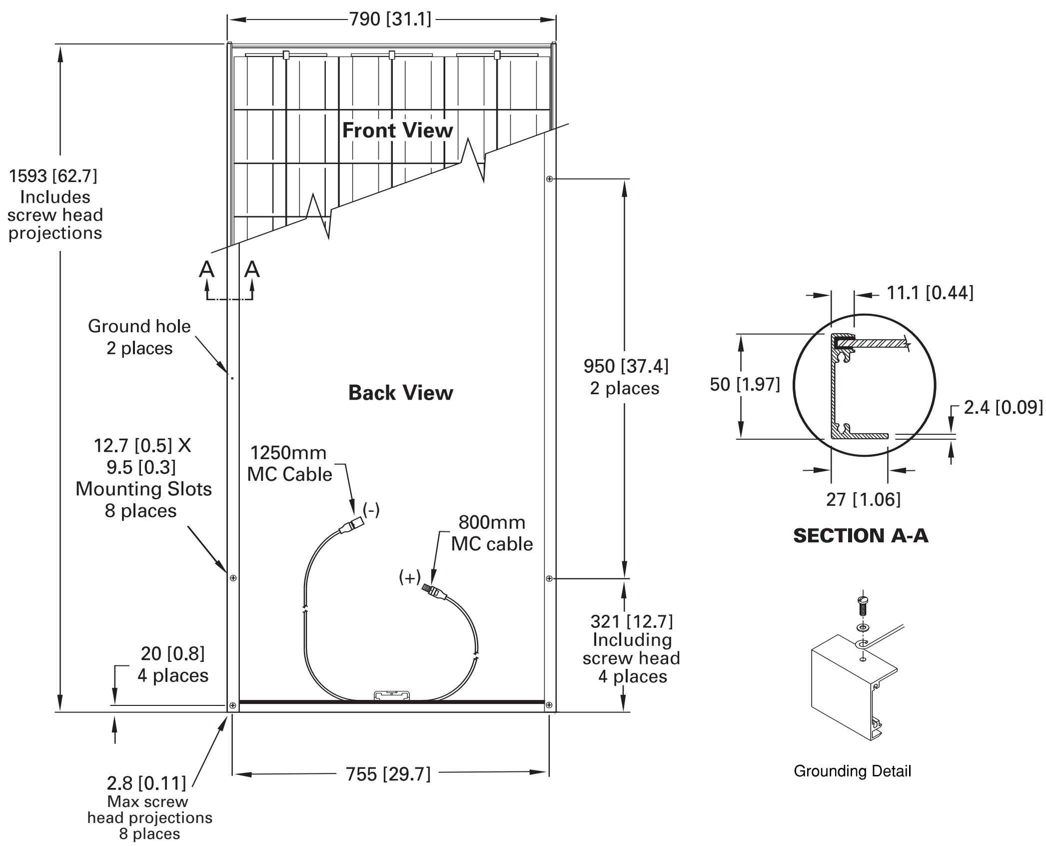


Qualification Test Parameters

Temperature cycling range	-40°C to +85°C (-40°F to 185°F)
Humidity freeze, damp heat	85% RH
Static load front and back (e.g. wind)	45psf (2160Pa)
Hailstone impact	25mm (1 inch) at 23 m/s (52 mph)

Module Diagram

Dimensions in brackets are in inches. Un-bracketed dimensions are in millimeters. Overall tolerances ±3mm (1/8").



Included with each module: self-tapping grounding screw, instruction sheet and warranty documents.

Note: This publication summarizes product warranty and specifications, which are subject to change without notice.
Additional information may be found on our web site: **www.bpsolar.us**

6802.0006-v1 09/09

bp solar

INTRODUCTION **1**
SUMMARY OF BUYDOWN PROGRAM 3
WHAT TYPES OF FINANCIAL ASSISTANCE WILL THE PROGRAM PROVIDE? . **7**
WHO CAN RECEIVE THE BUYDOWN PAYMENT? **7**
WHAT GENERATING SYSTEMS ARE ELIGIBLE FOR BUYDOWNS? **7**
APPROVED TECHNOLOGIES 8
CERTIFIED COMPONENTS OR SYSTEMS 8
CONTRACTORS AND INSTALLATION CODES AND STANDARDS 10
GRID CONNECTED 10
WARRANTIES 11
WHAT COSTS OF A GENERATING SYSTEM ARE ELIGIBLE FOR THE BUYDOWN? **12**
HOW BIG CAN MY SYSTEM BE? **13**
HOW MUCH IS THE BUYDOWN? **15**
DO FINANCIAL INCENTIVES FROM OTHER SOURCES AFFECT THE AMOUNT OF BUYDOWN I CAN RECEIVE? **16**
WHAT IS THE MAXIMUM BUYDOWN AMOUNT ANY SINGLE PROJECT CAN RECEIVE? **16**
HOW LONG DOES MY RESERVATION LAST? **17**
CAN MY INSTALLED SYSTEM BE DIFFERENT THAN MY RESERVATION? **17**
SUBSTANTIVE CHANGES 17
HOW A CHANGE AFFECTS THE BUYDOWN AMOUNT 18
HOW DO I RESERVE A BUYDOWN? **21**
INSTRUCTIONS FOR COMPLETING CEC 1890C-1 RESERVATION REQUEST FORM 25
INSTRUCTIONS FOR COMPLETING STD-204, VENDOR DATA RECORD 29
SUBMITTING THE RESERVATION REQUEST FORM 30
HOW DO I REQUEST A BUYDOWN PAYMENT? **30**
SUBMITTING A CLAIM FORM 32
DEFINITIONS **34**
FORMS AND SAMPLES **37**

technologies that utilize renewable fuels, and wind turbines of not more than ten kilowatts (kW) rated electrical capacity per customer site. The law further states that these four technologies are only eligible to participate in the program if they meet the emerging technology eligibility criteria contained in the Commission's March 1997 ***Policy Report on AB 1890 Renewables Funding.***

Based on Commission staff research (e.g., Energy Technology Status Report, Targeted RD&D studies), docketed information, and testimonials by various interested parties and stakeholders at public workshops and hearings held during the AB 1890/SB 90 process, the Commission finds that photovoltaic, small wind systems (not more than 10 kW), fuel cells using renewable fuel and solar-thermal technology all meet the qualifying criteria for eligibility contained in the Commission’s Policy Report. These eligibility criteria were applied to individual systems representing each of the four technology categories. At least one or more systems in each of the four technology categories was found to satisfy the eligibility criteria. Therefore, technologies from all four categories are eligible to receive funding from the Emerging Renewables Resources Account.

To qualify for funding, however, individual systems in the four eligible technology categories must meet the requirements contained in this guidebook. The Commission recognizes that there may be individual systems employing each of the four technologies that may not be able to meet these requirements because of the system’s stage in its research, development and demonstration, and therefore will not qualify for funding despite the eligibility of their underlying technology.

Those who wish to receive funding from the Emerging Renewable Resources Account under the Buydown Program must purchase an electrical generating system that employs an emerging renewable technology and meets certain eligibility requirements, and follow the reservation and claim procedures outlined in this guidebook. If after reading this guidebook, you require additional information about the Buydown Program please contact the Commission Call Center at (800) 555-7794 or send e-mail to renewable@energy.state.ca.us.

Summary of Buydown Program

The Buydown Program is a multi-year program that provides funding in the form of rebates (also referred to herein as “buydown payments”) for eligible electricity generating systems that are powered by emerging renewable resources. Funding from the Buydown Program is intended to substantially reduce the current costs of generating equipment using emerging renewable technologies. The intent is to reduce the net cost to the end user of such generating systems and, thereby, stimulate substantial sales of such systems during a period of at least four years beginning in 1998. These increased sales of generating equipment are expected to encourage manufacturers, sellers and installers to expand their operations and reduce their costs. In addition, the Buydown Program is intended to foster the siting of small, reliable generating systems throughout California at locations where the electricity produced is needed and consumed. This is known as “distributed generation.”

Under the program, buydown payments may be made either directly to the retailer of a generating system, to the purchaser, or to the lessor in a leasing arrangement. It is expected that most purchasers of these systems will find it preferable to have the buydown payment paid directly to the retailer, and thereby deducted from the price the purchaser will pay. Purchasers of these systems can be any class of utility customer, including residential, commercial, agricultural or industrial customers. This program, however, is open only to customers of the California electrical corporations contributing to this fund and to customers of local publicly owned electric utilities pursuant to Assembly Bill 29x (AB 29x). (See “Who Can Receive the Buydown Payment?” below.) The electrical load served by the generating systems must be connected to the electrical grid of such utilities.

Additionally, the generating system must be installed on the premises of eligible customers and be sized so that the electricity produced is expected to primarily offset part or all of the customer's electrical needs at these premises. All electricity generating system components must be new and unused, and must not have been previously placed in service in any other location or for any other application, and major system components must be approved by the Commission. It is expected that systems receiving rebates from this program will remain at the original service location during their useful life. If a system is removed for any reason, you must notify the Commission in writing. To help maintain minimum standards of quality, the program also requires:

1) a minimum of a full five year warranty on the entire generating system if installed by a licensed contractor, or a limited five year warranty if installed by the owner;
2) installation by an appropriately licensed contractor, or the system owner, and in compliance with appropriate electrical codes; and
3) certain key system components, or the entire generating system, certified to meet certain established standards as described herein.

The amount of the buydown payment an eligible system will receive is dependent on:

1) the \$/watt rebate level available to pay buydowns at the time an eligible system is purchased and a buydown is reserved;
2) the size or rated electrical output of the system in comparison to the customer’s estimated annual electrical load or usage; and
3) the total eligible costs of the system.

Table 2 provides the rebate levels available. These rebate levels will be reviewed on an annual basis and may be decreased if reasonable, consistent with the intent of SB 90 that rebate levels decline over the term of the program. Sellers and purchasers of generating systems may want certainty at the time their system is ordered of the rebate amount they are eligible to receive once their system is installed. To provide this certainty, purchasers or retailers can reserve a rebate amount using the Reservation Request Form (CEC-1890C-1). Submitting this form to the Commission along with the supporting documentation (see "How Do I Reserve a Buydown") will allow purchasers or retailers to reserve a specified rebate amount for a period of 9 months for generating systems of 10 kW or smaller and for 18 months for all systems larger than 10 kW. A group of reservations in one location, such as for multiple homes in a new residential development, or for one customer at several locations, such as for multiple retail store in one retail chain, which totals 30 kW or greater in aggregate capacity, will receive an 18 month reservation period and may request an extended reservation period, which may be granted at the Commission's discretion.

When the system is installed and in service the purchaser or retailer may request a buydown payment by submitting the Reservation Confirmation and Claim Form (CEC 1890C-2) along with the other required documentation. (See "How Do I Request a Buydown Payment?" below.) If the Reservation Confirmation and Claim Form is complete and submitted with the required documentation, the Commission will then issue a check for the buydown, typically within 30 days of receiving the claim form.

Table 2
Buydown Program Parameters

BUYDOWN PROGRAM FUNDS	Rebate
All systems	The lesser of $4.50 /watt or 50% of total installed costs

To be eligible for this increased rebate level, the funding must be reserved and the system must be installed on or after February 8, 2001.[7] In this context, "reserved" means the date the Commission's Accounting Office receives an application for funding for a proposed system.

The Buydown Program is open to generating systems of all sizes, subject to certain conditions and restrictions. The program, however, is intended to favor small generating systems, such as those typically used by residential or small commercial and agricultural customers. Pursuant to SB 90, at least 60 percent of the program funds must be awarded to systems of 10 kW or smaller in rated output, and at least 15 percent of the program funds must be awarded for systems rated at 100 kW or less. The Commission applied this awarding requirement to the initial $54 million allocated to the program. It also applied this requirement to the $16.2 million (September 2001) and the $13 million (September 2002) in rollover

[7] Systems not meeting the date criteria but otherwise meeting all other eligibility criteria contained in this Guidebook were eligible to receive 1) the lesser of $3/watt or 50% of total costs for 10kw or less systems or 2) the lesser of $2.50/watt or 40% of total costs for systems larger than 10kw.

funds reallocated to this program from other accounts within the Renewable Resource Trust Fund.

In September 2001, the Commission created two subcategories of medium systems: those systems larger than 10kW but smaller than 30 kW, and those systems that are 30 kW or larger, up to 100 kW. The rollover funds reallocated to this program for medium systems in September 2001 were distributed 75 percent to the 10 to 30 kW subcategory and 25 percent to the 30 to 100 kW subcategory.[8] All of the funds reallocated to this program for medium systems in September 2002 were distributed to the 10 to 30 kW subcategory.[6] These subcategories and allocations are intended to ensure that systems in the 10 to 30 kW subcategory have sufficient funds available for the remainder of 2002. These systems do not have the option of applying for funding under the CPUC-approved Self Generation program, which is limited to systems 30kW and larger in size.

Pursuant to AB 29x, an additional $30 million in program funds was allocated to systems 10 kW or smaller in size. These funds may not be distributed to medium or large systems. Under AB 29x, $8 million of the $30 million in new program funding must be used to fund eligible systems 10 kW and smaller located in the service territories of local publicly owned electric utilities. Customers of local publicly owned electric utilities are eligible for funding under the Buydown Program for systems purchased and installed after December 19, 2001, provided the systems meet the requirements specified herein.

Pursuant to Interagency Agreement No. R500-02-006 between the Commission and the California Power Authority, an additional $1.25 million from the Attorney General's Alternative Energy Retrofit Account (AGAERA) was provided to the Buydown Program to fund photovoltaic electricity generating systems for eligible K -12 public schools. This initial contribution from the AGAERA may be increased up to $ 25 million under the Interagency Agreement. To qualify for these funds schools must satisfy special requirement discussed herein as part of the Solar Schools Program.

For generating systems placed in service (i.e., installed and generating) that are eligible for this program, there is a maximum payment amount of $2,500,000 overall for any single project as defined herein.

The Energy Commission will conduct random audits of systems which have received buydown payments to ensure that the systems were properly installed, are properly functioning and are in accordance with the information provided in the reservation request and buydown claim forms. The Energy Commission will also

---

[8] Of the $2.43 million in rollover funds reallocated in September 2001 to the program for medium systems ($16.2 million x 15 percent), $1.82 million will be distributed for systems in the 10 to 30 kW subcategory and the $0.61 million will be distributed for systems in the 30 to 100 kW subcategory.
[6] $3 million of the $13 million in rollover funds reallocated to the Emerging Renewable Resources Account in September 2002 will be distributed for systems in the 10 to 30 kW subcategory. $10 million will go to systems 10kW and smaller in size.

I - INTRODUCTION **1**
A. PURPOSE 1
B. OVERVIEW 2
II - WHAT ARE THE ELIGIBILITY REQUIREMENTS **4**
A. SYSTEM OWNERSHIP 4
B. GRID INTERCONNECTION 4
C. SYSTEM COMPONENTS 4
D. NEW EQUIPMENT 5
E. SYSTEM SIZED TO OFFSET ON-SITE ELECTRICITY LOAD 5
F. SYSTEM INSTALLATION 5
G. FIVE-YEAR WARRANTY REQUIREMENTS 6
H. SYSTEM PERFORMANCE METER 6
I. RETAILERS 6
J. AUDITS AND INSPECTIONS 7
III - INCENTIVES OFFERED THROUGH THIS PROGRAM **8**
A. REBATES OFFERED 8
B. OTHER INCENTIVES MAY AFFECT YOUR REBATE AMOUNT 9
C. PERFORMANCE-BASED INCENTIVES FOR PHOTOVOLTAIC SYSTEMS 30 KW OR GREATER 9
D. AVAILABLE FUNDS 9
E. ADJUSTMENT OF REBATE LEVELS 9
IV - RESERVATION PROCESS **10**
A. RESERVING A REBATE 10
1. Reservation Request Form 11
2. Evidence of Agreement to Purchase 11
3. Itemized Cost of Major Equipment and Labor 12
4. Evidence that Site Electricity Load is Supplied by Eligible Utility 12
5. Payee Data Record (Form STD-204) 12
6. Submitting Your Complete Reservation Application 12
V - PAYMENT PROCESS **14**
A. CLAIMING A REBATE PAYMENT 14
1. Payment Claim Form 14
2. Documentation Confirming Final Payment and System Installation 14
3. Building Permit and Final Inspection Sign Off 15
4. Five-year Warranty 15
5. Utility Interconnection Application 15
B. SUBMITTING A PAYMENT CLAIM 15
C. CLAIMING A REBATE PAYMENT WITHOUT A PRIOR RESERVATION 16
D. ASSIGNMENT OF REBATE PAYMENT 16
E. CAN MY INSTALLED SYSTEM BE DIFFERENT THAN MY RESERVATION? 16
1. How do Changes Effect the Rebate Amount 17
2. Extension Requests and Other Substantive Changes 17
VI - ELIGIBLE SYSTEM COSTS **19**
A. WHAT SYSTEM COSTS ARE ELIGIBLE? 19
B. WHAT COSTS ARE NOT ELIGIBLE? 19

VII - SPECIAL FUNDING **21**
A. SOLAR SCHOOLS PROGRAM 21
B. SPECIAL FUNDING FOR AFFORDABLE HOUSING PROJECTS 21

APPENDIX 1 - FORMS AND WORKSHEETS

APPENDIX 2 - TIPS FOR CONSUMERS
A. CHOOSING A CONTRACTOR
B. CHOOSING A RETAILER
C. HOW MUCH ENERGY DOES A SYSTEM PRODUCE?

APPENDIX 3 - CRITERIA FOR LISTING COMPONENTS AS ELIGIBLE
A. PHOTOVOLTAIC MODULES
B. SOLAR THERMAL
C. FUEL CELLS
D. SMALL WIND
E. INVERTERS
1. Changes to the Eligible Inverter List
F. METERING CRITERIA
G. OTHER TECHNOLOGIES

APPENDIX 4 - MAXIMUM SYSTEM SIZE CALCULATIONS
A. MAXIMUM SYSTEM SIZE CALCULATIONS
1. New or expanded site electrical load
2. Peak load capacity option

APPENDIX 5 - ATYPICAL INCENTIVE APPLICATIONS
A. NEW HOUSING DEVELOPMENT
B. SYSTEMS INSTALLED BY SELLERS OR CONTRACTORS FOR THEIR OWN PERSONAL OR BUSINESS USE
C. ADDING TO EXISTING SYSTEMS
D. SPECIAL REQUIREMENTS FOR LEASED SYSTEMS

III - Incentives Offered Through This Program

A. Rebates Offered

The rebates offered through this program vary by system size, technology, and type of installation. The rebates offered for professionally installed new systems are identified below in Table 1. Lower rebates, 15 percent less, are also available for owner or self installed systems. Additionally, special rebates are available for systems installed for “affordable housing,” and may be available at a later date for public schools. Because these special rebates target specific groups or classes of customers, they are discussed separately in Chapter VII of this guidebook.

Table 1 lists the rebate levels available by size category and technology type at the beginning of the ERP; these rebate levels are expected to decline over time as described below.

Table 1: Rebates Available for Emerging Renewable Systems

Technology Type	Size Category	Rebate Offered*
Photovoltaic, Solar Thermal Electric Fuel Cells using a renewable fuel**	<30 kW	$4.00 per Watt
	=>30 kW	Future Performance Incentive
Wind	First 7.5 kW	$2.50 per Watt
	Increments above 7.5 kW up to 30 kW	$1.50 per Watt
	=> 30 up to 50 kW	Future Performance Incentive

* Rebates for owner installed systems are discounted by 15 percent.
** Fuel cells that operate on non-renewable fuels and are used in combined heat and power applications may be eligible for rebates at a later date when funds from other sources are no longer available.

B. Other Incentives May Affect Your Rebate Amount

Incentives received from sources other than the ERP that lower the cost of a generating system may affect the rebate amount you receive from the Energy Commission. No system may be issued a reservation or receive payment from the ERP if the system is also participating in the California Public Utilities Commission approved Self Generation Incentive Program. Fifty percent (50%) of incentives received or expected must be subtracted from the rebate amounts listed in Table1 if the incentives are from a utility incentive program, a State of California sponsored incentive program, or a federal government sponsored incentive program, other than tax credits. For example, under no circumstance will the incentive from the ERP exceed the net purchase price of the system (before ERP incentives).

See Chapter VII of this guidebook for information regarding rebate levels for affordable housing.

C. Performance-Based Incentives for Photovoltaic Systems 30 kW or Greater

This portion of the program will be developed at a later date.

D. Available Funds

As discussed in the *Overall Program Guidebook*, at least $118,125,000 in funding is available for the ERP. Of this amount, $10 million is allocated to performance-based incentives for systems 30 kW or larger.

E. Adjustment of Rebate Levels

The rebate levels for all technology types will be reduced by 20 cents per watt every six months beginning July 1, 2003 (and every January 1st and July 1st thereafter). In addition, the rebate level for photovoltaic systems will be reduced an additional 40 cents per watt beginning January 1, 2004.

APPENDIX C

ADDITIONAL RESULTS AND COUNTERFACTUAL SIMULATIONS

C.1 Additional Count Regression Results

This section describes additional count regression results using the number of purchases every six-months as the dependent variable in Table C.1. I find similar estimation results to the estimates shown in Table 6.3. I find that the number of purchases are negatively correlated with the subsidy rate and a 10% increase in the subsidy rate results in a reduction of 4.6% in the number of purchases.

	Poisson	Neg. Binomial	Poisson	Neg. Binomial
Subsidy Rate	-0.157	-0.366	-0.614***	-0.614***
	(0.089)	(0.437)	(0.019)	(0.070)
% Change in Installations	-1.5%	-0.4%	-4.6%	-4.6%
Constant	6.962***	6.346**	9.350***	9.350***
	(0.456)	(2.239)	(0.062)	(0.281)
6-month Effects	N	N	Y	Y
Year Effects	Y	Y	N	N
LL	-228.142	-67.604	-44.252	-44.252
Observations	10	10	10	10

Table C.1: Models for Semi-Annual Installations

C.2 Estimation Results

In Table C.2, I present the estimates from the three specifications of the dynamic model in a market that is reduced to 20% of the full model's market size. The difference in the estimated parameters across the specifications are larger relative to the full model. This shows the importance of choosing the correct market size for the model.

In Table C.3, I present the estimates for the three specifications of the dynamic model that includes an additional regime change. An additional regime change is included for the second six month period in 2005. This coincides with the unscheduled change in the subsidy rate. There is a small change in the magnitude of the estimates on the present value and net price variables from the estimates in Table 6.6.

Sub Belief Solar Price	PF -	Pes State	AR State
ln PV ($)	0.876***	0.677***	0.926***
	(0.065)	(0.068)	(0.074)
Efficiency (%)	0.798***	0.750***	0.793***
	(0.016)	(0.015)	(0.017)
Eff*Small Roof	0.193***	0.187***	0.194***
	(0.002)	(0.003)	(0.003)
Eff*Med Roof	0.093***	0.089***	0.093***
	(0.002)	(0.001)	(0.002)
ln Net Price ($)	-1.018***	-0.795***	-1.074***
	(0.0.071)	(0.074)	(0.081)
Price*Med Value	0.042***	0.0415***	0.042***
	(0.003)	(0.003)	(0.003)
Price*High Value	0.019**	0.018**	0.019**
	(0.003)	(0.003)	(0.003)
Constant	-10.270	-10.065	-10.121
MSA FE	Y	Y	Y
LL	-79025.87	-79044.49	-79013.56
# Of Obs	101110	101110	101110
Escalation Rate	2.2%	2.2%	2.2%
Halton Draws	-	50	50

Table C.2: Second Stage Estimation Results (Reduced Sample)

Sub Belief Solar Price	PF -	Pes State	AR State
ln PV ($)	1.180***	1.117***	1.203***
	(0.048)	(0.074)	(0.074)
Efficiency (%)	0.659***	0.643***	0.659***
	(0.011)	(0.015)	(0.015)
Eff*Small Roof	0.163***	0.162***	0.164***
	(0.002)	(0.002)	(0.002)
Eff*Med Roof	0.074***	0.073***	0.075***
	(0.001)	(0.001)	(0.002)
ln Net Price ($)	-1.359***	-1.288***	-1.386***
	(0.052)	(0.080)	(0.08)
Price*Med Value	0.041***	0.0413***	0.0419***
	(0.002)	(0.002)	(0.002)
Price*High Value	0.019**	0.0190***	0.0195***
	(0.002)	(0.002)	(0.002)
Constant	-11.346	-11.272	-11.311
MSA FE	Y	Y	Y
LL	-100041.87	-100062.95	-100033.75
# Of Obs	505558	505558	505558
Escalation Rate	2.2%	2.2%	2.2%
Halton Draws	-	50	50

Table C.3: Second Stage Estimation Results with an Additional Regime Change

C.3 Counterfactual Simulations

I present the results of counterfactual simulations for the perfect foresight case and the auto-renewal case in the tables below. I find the results of the counterfactuals are similar across the three specifications.

	2002	2002.5	2003	2003.5	2004	2004.5	2005	2005.5	2006	2006.5	Total
Data	492	454	1522	1568	1183	893	704	1496	2124	2311	12747
Simulated	750.96	815.14	999.38	1220.58	1088.28	989.36	1046.1	1331.16	2356.28	2069.44	12666.68
No Subsidy	296.2	310.66	405.52	504.46	571.86	562.22	631.34	834.56	1513.02	1393.14	7022.98
$\%\Delta$ Purchase	-60.56	-61.89	-59.42	-58.67	-47.45	-43.17	-39.65	-37.31	-35.79	-32.68	-44.56

Table C.4: Change in Purchase without Government Intervention (Perfect Foresight)

Capacity	2002	2002.5	2003	2003.5	2004	2004.5	2005	2005.5	2006	2006.5
Small	-57.03	-58.24	-55.57	-53.54	-44.42	-39.45	-34.68	-33.41	-35.54	-35.53
Medium	-60.53	-62.24	-59.29	-58.3	-47.34	-43.06	-39.58	-37.18	-35.46	-31.47
Large	-62.95	-62.45	-60.56	-60.4	-48.6	-44.99	-41.88	-38.98	-35.9	-31.83
X-Large	-61.43	-64.38	-61.93	-61.78	-49.36	-44.89	-41.9	-39.41	-36.32	-30.67

Table C.5: Change in Purchase (%) without Government Intervention by Cap (Perfect Foresight)

	2002	2002.5	2003	2003.5	2004	2004.5	2005	2005.5	2006	2006.5	Total
Small	183.49	199.04	230.98	264.42	209.05	163.19	148.82	188.57	376.96	420.66	2385.18
Medium	320.74	369.32	420.24	496.02	363.07	303.93	291.64	348.92	609.99	434.71	3958.58
Large	525.61	531.33	635.66	807.55	564.86	483.14	484.38	559.31	875.28	632.67	6099.79
X-Large	702.69	844.87	1025.33	1248.62	848.64	703.34	702.17	836.27	1290.02	846.04	9047.99
Total	1732.54	1944.56	2312.2	2816.61	1985.62	1653.6	1627.01	1933.08	3152.24	2334.08	21491.54

Table C.6: Additional Capacity (kW) Installed with Government Intervention (Perfect Foresight)

	2002	2002.5	2003	2003.5	2004	2004.5	2005	2005.5	2006	2006.5	Total
Data	492	454	1522	1568	1183	893	704	1496	2124	2311	12747
Simulated	753.52	819.88	1002.3	1231.06	1077.52	988.94	1040.7	1303.38	2333.78	2119.44	12670.52
No Subsidy	294.06	308.88	403.1	502.3	565.6	557.96	623.74	821.06	1494.96	1410.7	6982.36
%Δ Purchase	-60.98	-62.33	-59.78	-59.2	-47.51	-43.58	-40.07	-37.01	-35.94	-33.44	-44.89

Table C.7: Change in Purchase without Government Intervention (Auto-Renewal)

Capacity	2002	2002.5	2003	2003.5	2004	2004.5	2005	2005.5	2006	2006.5
Small	-57.46	-58.56	-55.91	-54.06	-44.39	-39.89	-35.07	-32.94	-35.71	-36.19
Medium	-61.01	-62.66	-59.59	-58.8	-47.37	-43.53	-39.97	-37.01	-35.7	-32.31
Large	-63.29	-62.97	-60.94	-60.99	-48.78	-45.37	-42.39	-38.63	-35.95	-32.63
X-Large	-61.85	-64.85	-62.33	-62.25	-49.4	-45.22	-42.26	-39.17	-36.47	-31.45

Table C.8: Change in Purchase (%) without Government Intervention by Cap (Auto-Renewal)

	2002	2002.5	2003	2003.5	2004	2004.5	2005	2005.5	2006	2006.5	Total
Small	185.29	200.95	232.67	268.67	206.6	164.66	149.47	181.87	374.87	438.84	2403.9
Medium	324.71	374.44	423.61	505	360.07	307.31	293.11	340.27	609.66	457.5	3995.68
Large	530.75	538.86	642.11	823.45	562.05	487.53	488.52	543.09	867.08	664.22	6147.65
X-Large	709.2	856.33	1035.74	1269.06	839.79	708.03	704.12	813.75	1282.34	887.31	9105.67
Total	1749.95	1970.58	2334.14	2866.17	1968.51	1667.52	1635.22	1878.98	3133.95	2447.88	21652.90

Table C.9: Additional Capacity (kW) Installed with Government Intervention (Auto-Renewal)

REFERENCES

AGUIRREGABIRIA, V. AND A. NEVO (2013): "Recent Developments in Empirical IO: Dynamic Demand and Dynamic Games," in *Advances in Economics and Econometrics: Tenth World Congress*, Cambridge University Press, vol. 3, 53.

AYOMPE, L., A. DUFFY, S. MCCORMACK, AND M. CONLON (2010): "Projected costs of a grid-connected domestic PV system under different scenarios in Ireland, using measured data from a trial installation," *Energy Policy*, 38, 3731–3743.

BARBOSE, G. (2011): "Tracking the Sun III; The Installed Cost of Photovoltaics in the United States from 1998-2009," *Lawrence Berkeley National Laboratory*.

BARBOSE, G., N. DARGHOUTH, R. WISER, AND J. SEEL (2011): "Tracking the Sun IV: An Historical Summary of the Installed Cost of Photovoltaics in the United States from 1998 to 2010." Tech. rep., Lawrence Berkeley Laboratory, USA.

BASS, F. M. (1980): "The relationship between diffusion rates, experience curves, and demand elasticities for consumer durable technological innovations," *Journal of Business*, S51–S67.

BAUNER, C., C. CRAGO, ET AL. (2013): "Adoption of residential solar power under uncertainty: Implications for renewable energy incentives," in *Proceedings of 2013 Annual Meeting*.

BECK, F. AND E. MARTINOT (2004): "Renewable energy policies and barriers," *Encyclopedia of energy*, 5, 365–383.

BERRY, S., J. LEVINSOHN, AND A. PAKES (2004): "Differentiated Products Demand Systems from a Combination of Micro and Macro Data: The New Car Market." *Journal of Political Economy*, 112, 68.

BHANDARI, R. AND I. STADLER (2009): "Grid parity analysis of solar photovoltaic systems in Germany using experience curves," *Solar Energy*, 83, 1634–1644.

BLACK, A. J. (2004): "Financial payback on California residential solar electric systems," *Solar energy*, 77, 381–388.

BLUNDELL, R., M. FRANCESCONI, AND W. VAN DER KLAAUW (32): "Anatomy of policy reform evaluation: Announcement and implementation effects," Tech. rep.

BOLLINGER, B. AND K. GILLINGHAM (2012): "Peer effects in the diffusion of solar photovoltaic panels," *Marketing Science*, 31, 900–912.

BORENSTEIN, S. (2008): "The market value and cost of solar photovoltaic electricity production," *Center for the Study of Energy Markets*.

——— (2009): "To what electricity price do consumers respond? Residential demand elasticity under increasing-block pricing," .

BROWN, R. E. AND J. G. KOOMEY (2003): "Electricity use in California: past trends and present usage patterns," *Energy Policy*, 31, 849–864.

BURR, C. (2012): "Subsidies, Tariffs and Investments in Solar Power Market," Working Paper.

CARRANZA, J. E. (2007): "Estimation of demand for differentiated durable goods," Unpublished manuscript, University of Wisconsin.

CARROLL, C. D. (2011): "Solution methods for microeconomic dynamic stochastic optimization problems," .

CONLON, C. T. (2010): "A Dynamic Model of Costs and Margins in the LCD TV Industry," *Unpublished manuscript, Yale Univ*.

DARGHOUTH, N. R., G. BARBOSE, AND R. WISER (2011): "The impact of rate design and net metering on the bill savings from distributed PV for residential customers in California," *Energy Policy*, 39, 5243–5253.

DASTRUP, S. R., J. G. ZIVIN, D. L. COSTA, AND M. E. KAHN (2012): "Understanding the solar home price premium: electricity generation and green social status," *European Economic Review*, 56, 961–973.

DAVIS, L. W. (2008): "Durable goods and residential demand for energy and water: evidence from a field trial," *The RAND Journal of Economics*, 39, 530–546.

DUBÉ, J.-P., J. T. FOX, AND C.-L. SU (2012): "Improving the numerical performance of static and dynamic aggregate discrete choice random coefficients demand estimation," *Econometrica*, 80, 2231–2267.

DUBIN, J. A. AND D. L. MCFADDEN (1984): "An econometric analysis of residential electric appliance holdings and consumption," *Econometrica: Journal of the Econometric Society*, 345–362.

DUKE, R., R. WILLIAMS, AND A. PAYNE (2005): "Accelerating residential PV expansion: demand analysis for competitive electricity markets," *Energy Policy*, 33, 1912–1929.

ESTEBAN, S. AND M. SHUM (2007): "Durable-goods oligopoly with secondary markets: the case of automobiles," *The RAND Journal of Economics*, 38, 332–354.

FAIERS, A., M. COOK, AND C. NEAME (2007): "Towards a contemporary approach for understanding consumer behaviour in the context of domestic energy use," *Energy Policy*, 35, 4381–4390.

FERNANDEZ, V. P. (2001): "Observable and unobservable determinants of replacement of home appliances," *Energy Economics*, 23, 305–323.

FÉVRIER, P. AND L. WILNER (2012): "Do Consumers Correctly Expect Price Reductions? Testing Dynamic Behavior," Tech. rep., Institut National de la Statistique et des Etudes

Economiques, DESE.

FISCHER, C. AND R. G. NEWELL (2008): "Environmental and technology policies for climate mitigation," *Journal of environmental economics and management*, 55, 142–162.

GILLINGHAM, K. AND J. SWEENEY (2010): "Market failure and the structure of externalities," *Harnessing Renewable Energy in Electric Power Systems: Theory, Practice*, 69–92.

GORDON, B. R. (2009): "A dynamic model of consumer replacement cycles in the PC processor industry," *Marketing Science*, 28, 846–867.

GOWRISANKARAN, G., S. S. REYNOLDS, AND M. SAMANO (2011): "Intermittency and the value of renewable energy," Tech. rep., National Bureau of Economic Research.

GOWRISANKARAN, G. AND M. RYSMAN (2012): "Dynamics of Consumer Demand for New Durable Goods," *Journal of Political Economy*, 120, 1173–1219.

HECKMAN, J. J. AND S. NAVARRO (2007): "Dynamic discrete choice and dynamic treatment effects," *Journal of Econometrics*, 136, 341–396.

HENDEL, I. AND A. NEVO (2006): "Measuring the implications of sales and consumer inventory behavior," *Econometrica*, 74, 1637–1673.

HIGGINS, A., C. MCNAMARA, AND G. FOLIENTE (2014): "Modelling future uptake of solar photo-voltaics and water heaters under different government incentives," *Technological Forecasting and Social Change*, 83, 142–155.

HORBACH, J., E. FEESS, J. HEMMELSKAMP, J. HUBER, R. KEMP, M. LEHMANN-WAFFENSCHMIDT, A. P. MOL, AND F. STEWARD (2007): "Sustainability and Innovation," .

ISLAM, T. (2014): "Household level innovation diffusion model of photo-voltaic (PV) solar cells from stated preference data," *Energy Policy*, 65, 340–350.

ISLAM, T. AND N. MEADE (2013): "The impact of attribute preferences on adoption timing: The case of photo-voltaic (PV) solar cells for household electricity generation," *Energy Policy*, 55, 521–530.

JAGER, W. (2006): "Stimulating the diffusion of photovoltaic systems: A behavioural perspective," *Energy Policy*, 34, 1935–1943.

JENNINGS, C. E., R. M. MARGOLIS, AND J. E. BARTLETT (2008): *A Historical Analysis of Investment in Solar Energy Technologies (2000-2007)*, National Renewable Energy Laboratory.

KAENZIG, J. AND R. WÜSTENHAGEN (2010): "The effect of life cycle cost information on consumer investment decisions regarding eco-innovation," *Journal of Industrial Ecology*, 14, 121–136.

KAHN, M. E. (2007): "Do greens drive Hummers or hybrids? Environmental ideology as a determinant of consumer choice," *Journal of Environmental Economics and Management*, 54, 129–145.

LEE, E. H. (2009): "Copula analysis of correlated counts," .

LOBEL, R. AND G. PERAKIS (2011): "Consumer Choice Model For Forecasting Demand And Designing Incentives For Solar Technology," .

MAGNAC, T. AND D. THESMAR (2002): "Identifying dynamic discrete decision processes," *Econometrica*, 70, 801–816.

MELNIKOV, O. (2013): "Demand for differentiated durable products: The case of the US computer printer market," *Economic Inquiry*, 51, 1277–1298.

MILLS, B. F. AND J. SCHLEICH (2009): "Profits or preferences? Assessing the adoption of residential solar thermal technologies," *Energy Policy*, 37, 4145–4154.

NEVO, A. (2011): "Empirical Models of Consumer Behavior," *Annual Review of Economics*, 3, 51–75.

NEWELL, R. G., A. B. JAFFE, AND R. N. STAVINS (2006): "The effects of economic and policy incentives on carbon mitigation technologies," *Energy Economics*, 28, 563–578.

PEREZ, R., L. BURTIS, T. HOFF, S. SWANSON, AND C. HERIG (2004): "Quantifying residential PV economics in the US—-payback vs cash flow determination of fair energy value," *Solar Energy*, 77, 363–366.

PRINCE, J. T. (2009): "How do households choose quality and time to replacement for a rapidly improving durable good?" *International Journal of Industrial Organization*, 27, 302–311.

REISS, P. C. AND M. W. WHITE (2005): "Household electricity demand, revisited," *The Review of Economic Studies*, 72, 853–883.

——— (2008): "What changes energy consumption? Prices and public pressures," *The RAND Journal of Economics*, 39, 636–663.

RUST, J. (1987): "Optimal replacement of GMC bus engines: An empirical model of Harold Zurcher," *Econometrica: Journal of the Econometric Society*, 999–1033.

——— (1994): "Structural estimation of Markov decision processes," *Handbook of econometrics*, 4, 3081–3143.

SARZYNSKI, A. (2009): "The impact of solar incentive programs in ten states," *George Washington Institute of Public Policy, Washington, DC*.

SCHEUERMANN, K., D. BOLEYN, P. LILLY, AND S. MILLER (2004): "Measured Performance of California Buydown Program: Residential PV Systems," *California Energy Commission,* *Consultant Report*.

SONG, I. AND P. K. CHINTAGUNTA (2003): "A micromodel of new product adoption with heterogeneous and forward-looking consumers: Application to the digital camera category," *Quantitative Marketing and Economics*, 1, 371–407.

TAYLOR, J. AND P. VAN DOREN (2007): "Energy Myth Five–Price Signals are Insufficient to induce Efficient Energy Investments," in *Energy and American Society–Thirteen Myths*, Springer, 125–144.

TAYLOR, L. D. (1975): "The demand for electricity: a survey," *The Bell Journal of Economics*, 74–110.

TAYLOR, M. (2008): "Beyond technology-push and demand-pull: Lessons from California's solar policy," *Energy Economics*, 30, 2829–2854.

TRIVEDI, P. K. AND D. M. ZIMMER (2006): "Copula Modeling: An Introduction for Practitioners," *Foundations and Trends® in Econometrics*, 1, 1–111.

VAN BENTHEM, A., K. GILLINGHAM, AND J. SWEENEY (2008): "Learning-by-doing and the optimal solar policy in California," *The Energy Journal*, 131–151.

VAN DER KLAAUW, W. AND K. I. WOLPIN (2008): "Social security and the retirement and savings behavior of low-income households," *Journal of Econometrics*, 145, 21–42.

VOLLEBERGH, H. R. AND C. KEMFERT (2005): "The role of technological change for a sustainable development," *Ecological Economics*, 54, 133–147.

WISER, R., M. BOLINGER, P. CAPPERS, AND R. MARGOLIS (2006): "Letting the sun shine on solar costs: An empirical investigation of photovoltaic cost trends in California," *Lawrence Berkeley National Laboratory*.