

FACTORS INFLUENCING THE DEPLOYMENT OF UTILITY SCALE SOLAR POWER IN  
THE UNITED STATES

by

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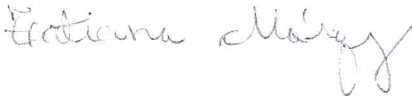
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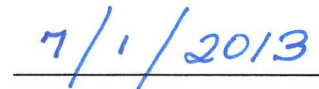
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## Abstract

In the last decade, the United States (U.S.) has experienced robust growth in the renewable energy sector. A variety of economic, political and environmental factors have been studied as possible drivers of solar energy adoption. This study examines the factors influencing the deployment of utility scale solar by using first a cross sectional model that measures solar adoption as of 2012 followed by an event history analysis that measures how long it takes for a utility in a state to first build a large solar plant. Three policies are found to be effective (both in the static and dynamic models) at encouraging the development of the first utility scale solar project. The first is a mandated solar carve-out (also known as a set-aside), which requires utilities to obtain a portion of their energy from solar technologies. The second is the presence of a credit multiplier which enables utilities to obtain additional renewable energy credits for either trading or if kept to meet their own renewable energy obligation. The third effective policy is the availability of tax subsidy schemes that provide tax relief to developers when renewable energy technology is adopted. One market and one regulation variable were also found to influence the deployment of solar power: growth in electricity demand relative to existing capacity and lower air quality in the form of ozone levels above national ambient air quality standards. Additionally two other factors are found to influence how long it takes for a utility to first integrate solar into their electricity portfolios: (1) having a Renewable Portfolio Standard (RPS) in effect which requires a certain percentage of the state's electricity to be derived from renewable sources and (2) resource endowment that provides higher solar technical potential in comparison to other renewable energy sources. As the visibility of large-scale solar power increases and states become interest in deploying solar technologies, the findings in this thesis may assist policy makers in choosing the most effective policy tools that support the still fragile solar industry.

## Introduction

In the last decade, the United States (U.S.) has experienced robust growth in the renewable energy sector. Solar power is perceived by many to offer some respite to the problems of environmental degradation, depletion of non-renewable resources, national dependence on imported fuels and other problems associated with conventional energy production. Of all renewable energy resources available in the U.S., utility scale solar has a generation potential that far exceeds all other renewables technical potentials combined and over 100 times the current U.S. national energy demand (Lopez *et al.* 2012). Although solar electricity generation has grown at historical rates since the mid-2000s, it still only represents about 0.2% of overall U.S. electricity generation (Gelman, 2013). Without clear leadership from the federal government, a number of states have started to actively encourage the deployment of large-scale solar projects. The objective of this thesis is to determine the state level factors that have influence the deployment of utility scale solar power.

A variety of economic, political and environmental factors have been studied as possible drivers of solar energy adoption (Shrimali and Kniefel, 2011; Sarzynski *et al.*, 2012; Timilsina *et al.* 2012). One possible explanation is that states will naturally gravitate towards technologies that utilize the natural resources most readily available to them. Another factor that may influence the deployment of large scale solar is the adoption of state legislation that regulates electricity generation. The availability of state-level financial incentives and high or volatile conventional energy prices may also improve the attractiveness of investing in solar technologies. Although a growing body of research has considered the effectiveness of renewable energy policies, very little attention has been given specifically to solar power, that is, factors that influence the market penetration of solar power technologies at the state level.

Furthermore, previous studies have focus on the renewable energy cumulative adoption rate or capacity at the state level (Shrimali and Kniefel, 2011; Sarzynski *et al.*, 2012). An alternative approach is explored in this thesis using first a cross sectional model that measures solar adoption as of 2012 followed by an event history analysis that measures how long it takes for a utility in a state to first build a large solar plant.

Three policies are found to be effective (both in the static and dynamic models) at encouraging the development of the first utility scale solar project: a mandated solar carve-out (also known as set-aside) which requires utilities to obtain a portion of their energy from solar technologies, the presence of a credit multiplier which enables utilities to obtain additional renewable energy credits for either trading or if kept to meet their own renewable energy obligation, and the availability of tax subsidy schemes that provide tax relief to developers when renewable energy technology is adopted. One market and one regulation variable were also found to influence the deployment of solar power: growth in electricity demand relative to existing capacity and lower air quality in the form of ozone levels above national ambient air quality standards. Additionally two other factors are found to influence how long it takes for a utility to first integrate solar into their electricity portfolios: (1) having a Renewable Portfolio Standard (RPS) in effect which requires a certain percentage of the state's electricity to be derived from renewable sources and (2) higher solar technical potential in comparison to other renewable energy sources.

The solar carve-out and solar credit multiplier are policy instruments that are sometimes included in RPS legislation. An RPS is a command and control policy that sets a goal requiring a certain amount of renewable energy to come from renewable resources. The tax subsidies can take the form of income, sales, property, equipment, investment, and/or production tax

exemptions. The designation of an area with ozone levels above national ambient air quality standards mandates states to develop and implement plans to reduce pollution levels.

The econometric results obtained in this thesis support the conclusions from previous studies with respect to the effect of the policy variables and reinforce the notion that renewable energy policies have a different impact on the solar market than they do on other renewable energy technologies. Moreover, the results presented here, unlike previous studies provide a bigger picture of factors on top of financial incentives that influence large scale solar and confirm the developers claim that tax breaks are an influential tool in promoting the adoption of solar technologies.

## **Outline**

Section two provides pertinent background on the growth of solar power. An introduction to the solar sector is provided followed by a background on the policy changes, restructuring of the sector and the different financial instruments that have been used to promote the adoption of renewable energies.

Section three reviews the relevant literature concerning renewable energy state policies. The literature review focuses on five studies that used quantitative analysis to determine which state policies have a statistically significant effect on the development of renewable energy, with two studies specifically focusing on solar power.

Section four outlines the analytical framework and describes the data used in this thesis; a discrete choice model and an event history analysis are used to identify the factors that influence the deployment of utility scale solar power. Data was drawn from the Solar Energy Industries Association (SEIA), the Database of State Incentives for Renewable Energy (DSIRE), the U.S. Energy Information Administration (EIA), NASA's Atmospheric Science Data Center, the U.S.

Environmental Protection Agency (EPA), the National Renewable Energy Laboratory (NREL) and the U.S. Census Bureau.

Section five presents the results of this research. First, it provides the regression results from the SAS and STATA calculations, compares the results from the different models including marginal effects for the logit and complementary-log-log specifications and finally proceeds to relate the relationships of each of the policies to state solar power deployment.

Section six provides the relevant conclusions to this research. In this chapter, results are compared to those from previous studies and points out the differences especially to the studies included in the literature review. The section concludes with suggestions for further work.

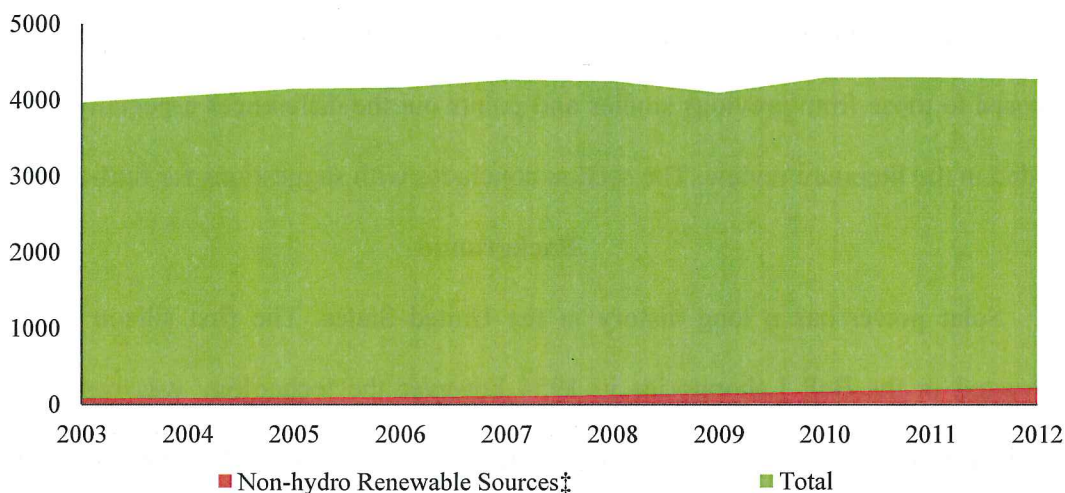
### **Background**

Solar power has a long history in the United States. The first silicon solar cell was constructed in the Bell Laboratories in 1954 however the technology was costly and highly inefficient (DOE EERE, 2002). A lot of interest and support for the development and commercialization of solar was experienced in the 1970s following the Oil Crisis. Significant federal support including the dedication of the National Renewable Energy Laboratory occurs in this decade. A few solar demonstration projects were constructed in the early 1980s in California culminating with the construction of the 354-megawatt (MW) LUZ Solar Energy Generating Systems (SEGS I-IX) that was gradually expanded starting in 1984 and reaching completion in 1990. Due to a variety of factors including cheap conventional energy prices and lack of continuous policy support, the fragile solar industry buckled in the 1990s (Timilsina *et al.* 2012).

With renewed energy security and environmental concerns associated with an over reliance on conventional energy sources, the solar industry reported new signs of activity starting in the early 2000s. Introduction of federal climate change legislation combined with a lack of a

federal energy strategy incited state governments to come up with a variety of policies that aimed to diversify electricity industry energy sources. At a first glance, it would appear as if renewable energy is starting to become an important contributor to the overall national energy portfolio. National non-hydro renewable sources (biomass, geothermal, wind and solar) cumulatively rose from generating 2% of overall energy generated in 2003 to over 5% in 2012.

**Figure 1. U.S. Electricity Generation (Thousands MWh)**

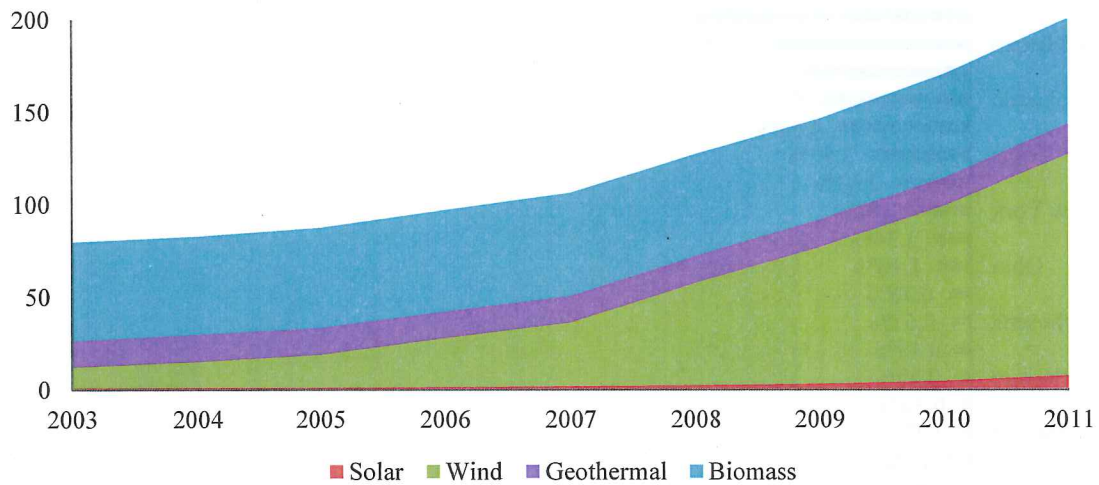


‡Non-hydro Renewable Sources include wood, black liquor, other wood waste, biogenic municipal solid waste, landfill gas, sludge waste, agriculture byproducts, other biomass, geothermal, solar thermal, photovoltaic energy, and wind.

Source: Energy Information Administration – Net Generation by Energy Source, 2003-February 2013

However, under closer inspection, it is clear that the growth in the solar sector is overshadowed by the substantial growth of the wind industry sector. Please refer to Figure 2 for a comparison of renewable electricity growth from 2003-2012 by sector. Of the non-hydro renewable electricity sources, only wind and solar have experienced any significant growth over the last decade with wind increasing over 18 fold between 2000 and 2011 and solar increasing over 9 fold over this same period (Gelman, 2013). Even with this growth rate by the end of 2012, solar represented about 0.2% of overall U.S. electricity generation, a negligible amount by most accounts.

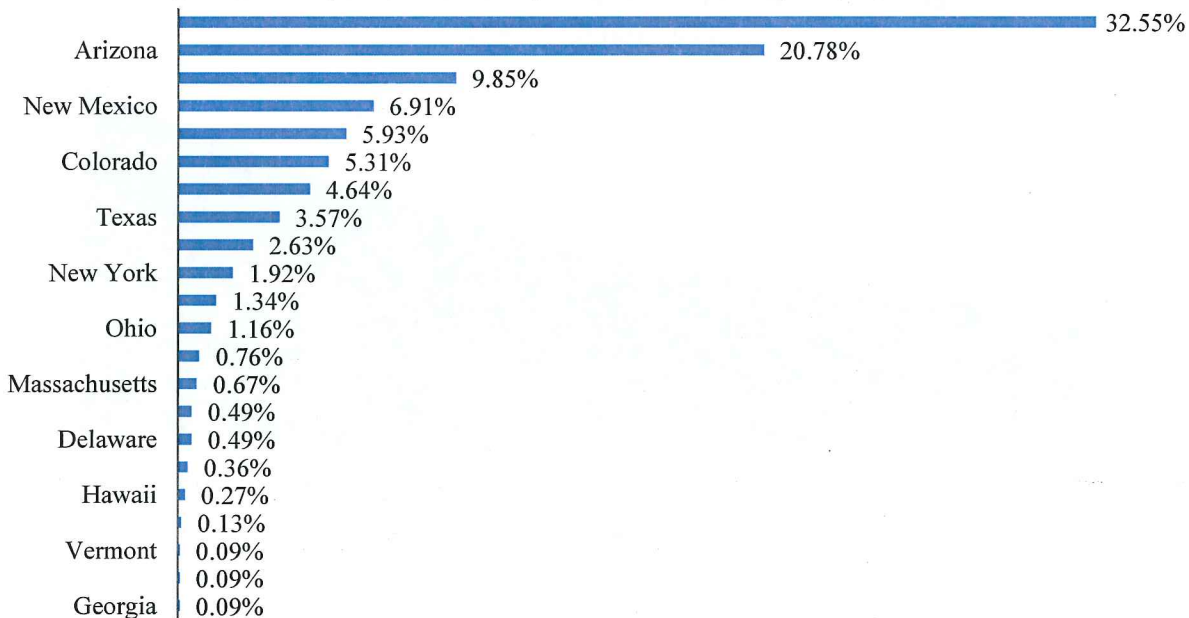
**Figure 2. U.S. Renewable Electricity Generation by Sector  
(Thousands MWh)**



Source: Gelman, 2013. "2011 Renewable Energy Data Book (Revised)".

As indicated in Figure 3, the growth in the solar sector has been led by a few major actors in the industry and geographically the southwest has experienced most of the growth with California, Arizona, Nevada and New Mexico accounting for over 70% of national utility scale solar capacity added since 2003. Cumulative capacity of large-scale solar projects ranges widely, from 2 MW in Vermont, Kentucky and Georgia to 730 MW in California.

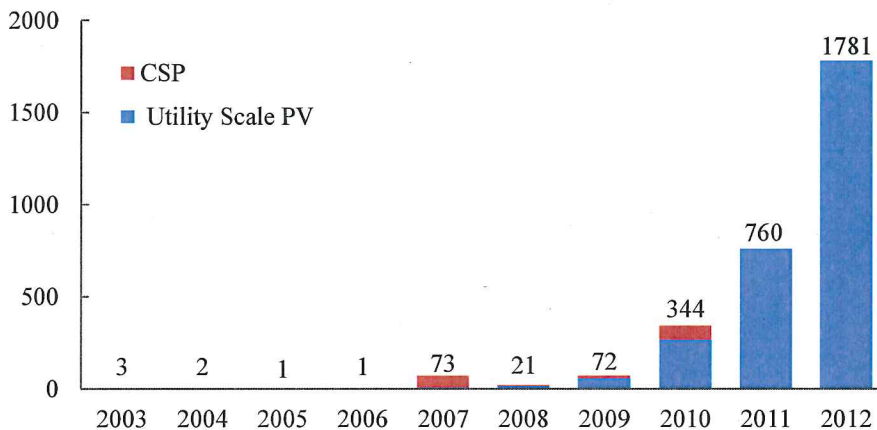
**Figure 3. Utility Scale Solar Projects Cumulative Capacity by State - 2012**



Source: Solar Energy Industries Association (Jan. 2013)

With this background in mind, it is important to point that the large scale solar industry has made great strides in the last decade, especially in the last four years when the industry has year over year surpassed its historical installation levels (SEIA, 2013). The newly installed capacity in 2012 is nearly sixty percent of all the capacity added between 2003 and 2011.

**Figure 4. Utility Scale Solar Installations (MW)**

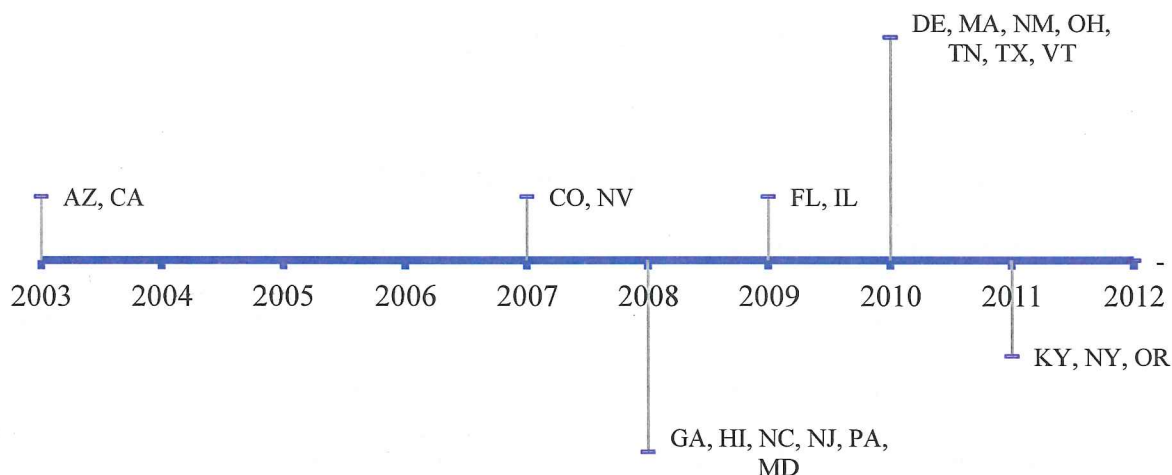


Source: Solar Energy Industries Association; Interstate Renewable Energy Council



Furthermore, new large-scale solar projects are being deployed in states where only a few years ago the market had seemed unwelcoming. As illustrated in Figure 5, by the end of 2012, 22 states had already deployed at least one utility scale solar project with year 2010 being the most active deployment year thus far.

**Figure 5. Deployment of Utility Scale Solar Projects in the United States**



Source: Solar Energy Industries Association (2013); U.S. Energy Information Administration

### **Determinants of solar power deployment**

The growth of the solar industry may be attributed to various technical, political, and economic factors. Research and development of solar technologies have enabled solar cell efficiencies to improve steadily with substantial improvements achieved since the mid-1990s (NREL, 2013). Lawrence Berkeley National Laboratory reports that utility scale PV prices declined from a “\$6.2/W [average] for projects installed during 2004-2008 to \$3.4/W for projects installed in 2011” with the downward trend in prices expected to continue (Barbose *et al.* 2012) Federal legislation has probably also influenced the rate of development of the utility scale solar market. Such legislation includes the *Energy Policy Act (EPAct) of 1992* that restructured the electricity industry thus allowing the renewable energy sector access to the grid and providing new tax incentives for renewable energy facilities; the *EPAct of 2005* that

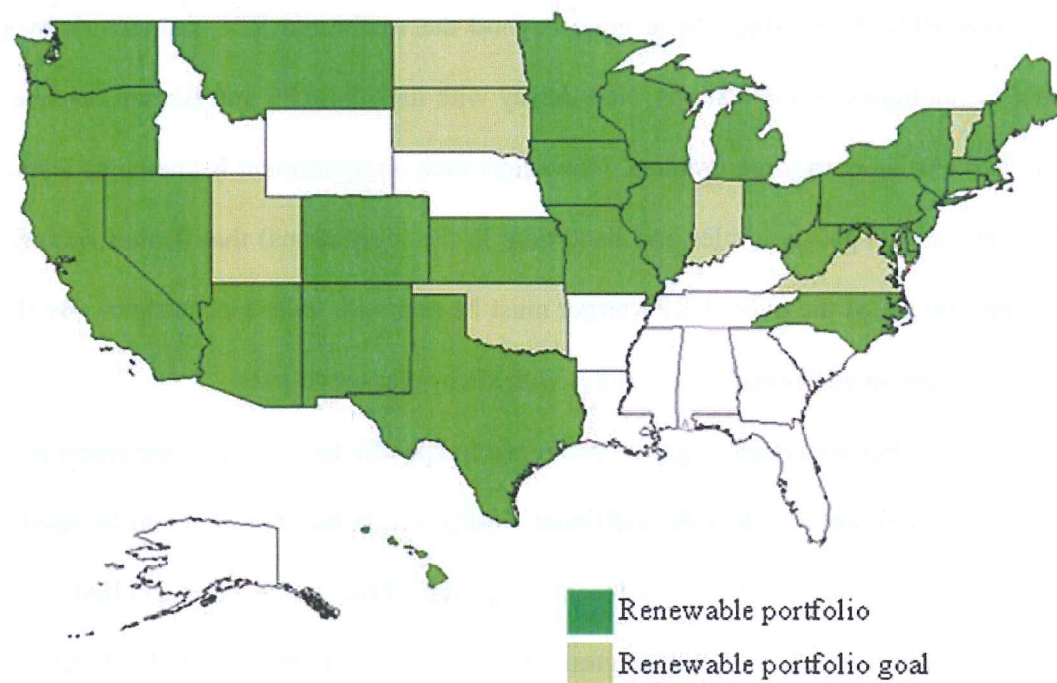
“established Clean Energy Renewable Bonds (CREBs) as a financing mechanism for public sector renewable energy projects” (DOE, 2013); and the *American Recovery and Reinvestment Act of 2009* that authorized loan guarantees for renewable energy including solar (DOE Loan Programs Office, 2013).

Another relevant federal policy spearheaded in the late 1990s under the Clean Air Act is the establishment of the National Ambient Air Quality Standards (NAAQS) for 8-hour ozone (i.e. smog). Ozone itself is not emitted into the air instead it is a byproduct of the reaction between nitrogen oxides and volatile organic compounds (EPA, 2012). An area in compliance with the national ground-level ozone standard is said to be in “attainment” while those areas above this level are classified as “nonattainment” areas. This policy is of particular interest to the electricity sector as they are major contributors of sulfur dioxide and nitrogen oxides, the precursors in the formation of ozone and other fine particles (EPA, 2007). According to the Environmental Protection Agency (EPA), “in 2006, the power industry accounted for seventy percent of total nationwide sulfur dioxide emissions and twenty percent of total nationwide nitrogen oxides emissions”. Due to this, under NAAQS the power sector has been required to reduce emissions and address the interstate transport of ozone. For older plants, this has meant installing emission controls using best available retrofit technology while more stringent controls are applied to new electricity sources (EPA, 2007).

At the state level, governments have adopted an array of policies and offered different financial incentives to encourage the development of renewable energy technologies. The most common regulatory policy known as a Renewable Energy Portfolio (RPS) mandates utilities to gradually increase the overall electricity generating capacity that comes from renewable energy sources. Iowa lead the way on this front with its 1983 Alternative Energy Production

law requiring its two investor-owned utilities to cumulatively provide 105 megawatts (MW) from renewable energies (DSIRE AEL, 2013). Although a few other states including Arizona, Connecticut, Maine and Wisconsin also implemented RPS policies in the 1990s, these policies were more widely enacted by states and became effective after the year 2000. As of December 2012, thirty states had passed mandatory renewable energy portfolio standards and an additional seven states had adopted voluntary renewable energy goals.

**Figure 6. States with Renewable Portfolio Standards or Goals - 2012**



Source: Database of State Incentives for Renewable Energy (DSIRE) 2013

Common eligible RPS technologies include wind, solar, geothermal, biomass and hydropower however other resources such as municipal solid waste and tidal and wave energy have also have been known to be included. While RPS policies share several important features, including a binding target, specificity on eligible technologies and tracking system, the final design and ultimate targets vary widely among states. One particular state, West Virginia is

classified in this thesis as a state with an RPS even though the Interstate Renewable Energy Council categorizes it as a voluntary RPS state. The law was written so that alternative resources such as coal technology, and natural gas among other resources may be used to satisfy the state's Alternative and Renewable Energy Portfolio Standard. Even though it is feasible to meet the standard using solely alternative resources, provisions that favor renewable resources are included in the legislation. Therefore, given that this is a binding target and there is great heterogeneity among what qualifies as a renewable resource in other states, WV policy is treated as a regular RPS. Some states have gone beyond the traditional RPS framework by favoring specific technologies or applications. New Jersey with its 2004 RPS amendment became the first state to add a solar energy requirement. Nowadays such a requirement is known as a solar carve-out (or set-aside in policy circles and band/tiers in the legislations) that further specifies that a certain percentage of the overall RPS target must be met with solar technologies. By the end of 2012, there were an additional twelve states with such solar carve-outs.

Another policy tool used to grant preference to specific technologies are credit multipliers, which as the name implies provide additional credits within the RPS that can be used to fulfill the electricity supplier's RPS compliance obligation. Five states have explicit solar credit multipliers while Arizona and Washington have a distributed generation (DG) multiplier that favors the development of small-scale solar facilities. Additionally, Texas has a multiplier for non-wind renewable energy facilities. Nearly all solar credit multipliers apply solely to in-state electricity generation and are usually only available the first few years of an RPS. Solar multipliers generally double or triple the renewable energy credits associated with a new solar energy plant. For example, the state of Oregon whose RPS became effective in 2011 is currently offering double renewable energy credits for all solar PV installed before 2016. Various states

have granted credit multipliers for other renewable energy technologies including wind, methane, fuel cells and technologies using waste tires as a fuel source. Please refer to Table 1 for details on state variance of RPS targets, timeframes and application of solar carve-out and multipliers.

With the exception of Delaware, Illinois and Maryland, all other RPS states allow free trade of renewable energy credits (also known as certificates). A renewable energy credit (REC) is separate product from the energy generated and it usually represents one megawatt-hour of renewable energy, however a few states like Colorado provide credits for each kilowatt-hour of eligible electricity generate in-state (DSIRE CO, 2013). The purpose of renewable energy credits is twofold. First, RECs supplement the generators revenue as credits may be traded separately from the electricity generated. Second, RECs served as a tracking mechanism that allows generators to demonstrate compliance (Wiser *et al.*, 2007). Trading of renewable energy credits provide flexibility to the utilities when they are mandated to meet RPS standards since the cost of generating renewable energy may vary across generators due to their location (i.e. access to the renewable resource). The REC market is driven by RPS policies, which establish whether utilities can meet their RPS obligations using this mechanism, and whether there are geographical restrictions associated with the RECs. More specifically this means being able to use RECs that were generated in neighboring states to meet RPS obligations or only being able to use RECs that were generated in-state. Furthermore, states without an RPS are able and in fact many have joined regional REC tracking systems that technically allows them to participate in this market without hindrance. There are currently seven major regional REC tracking systems operating in the U.S.: NEPOOL, PJM-GATS, WREGIS, M-RETS, MIRECS, NVTREC and NC-RETS. For the purpose of this thesis, states belonging to any of these seven regional tracking

systems are considered REC trading states. There are a total of thirty seven states that can technically participate in REC trading with a few states belonging to more than one regional tracking system. Please refer to Appendix A for a Figure depicting the regional extent for each of these trading systems.

**Table 1. Renewable Portfolio Standards Design Details**

State	Original Start Date	Current Target	Solar carve-out	Solar Multiplier
Arizona	1999	15% (2025)		
California	2003	33% (2020)		
Colorado	2007	20% (2020)		✓
Connecticut	2000	23% (2010)		
Delaware	2007	20% (2019)	✓	✓
Hawaii	2005	20% (2020)		
Iowa	1983	105MW (1999)		
Illinois	2008	25% (2025)	✓	
Kansas	2011	20% (2025)		
Maine	2000	40% (2017)		
Maryland	2006	15% (2020)	✓	
Massachusetts	2003	15% (2020)	✓	
Michigan	2012	10% (2015)		✓
Minnesota	2002	25% (2020)		
Missouri	2011	15% (2021)	✓	
Montana	2008	25% (2025)		
Nevada	2001	20% (2015)	✓	✓
New Hampshire	2008	24% (2025)	✓	
New Jersey	2001	22.5% (2021)	✓	
New Mexico	2002	20% (2020)	✓	
New York	2006	24% (2013)		
North Carolina	2010	12.5% (2021)	✓	
Ohio	2009	25% (2025)	✓	
Oregon	2011	25% (2025)	✓	✓
Pennsylvania	2001	18% (2020)	✓	
Rhode Island	2007	16% (2020)		
Texas	2002	5,880MW (2015)		
Washington	2012	15% (2020)		
West Virginia	2011	25% (2025)		
Wisconsin	2000	10% (2015)		

Source: DSIRE (accessed April 2013)

At the state level, financial incentives for renewable energy usually take the form of tax credits, rebates, loan, and grant programs that are often financed through public benefit funds (PBFs). Most PBFs were started in the 1990s after the restructuring of the electricity market with the aim of continuing research and development (R&D) as well as deployment of renewable energy technologies. PBFs are supported by a surcharge on electricity consumption. Alternatively, a few other PBFs have been created after reaching settlements with electric utility companies (Shrimali & Kniefel, 2011). States with notable financial support for the development of the renewable energy sector include: (1) California's 10-year, \$3 billion *Go Solar California* campaign launched in 2007, (2) New Jersey's solar rebate program which at its peak in 2006 provided \$78 million in support of solar installations and (3) the \$100 million *Pennsylvania Sunshine Solar Rebate Program* launched in 2009 (Sherwood, 2012). The latest policy measure being advocated to accelerate the renewable energy sector are feed-in tariffs (FITs) which have been in practiced since the 1990s in Europe and are meant to create certainty in the market while "providing a reasonable rate of return for investors" (Cornfeld & Sauer, 2010). FITs offer a long term premium based on the cost of electricity production therefore technologies such as solar which are typically more expensive are offered a higher price that reflect the higher upfront investment cost. Many states have now incorporated FITs to their renewable energy policy toolbox.

Finally on a technical note, electricity generating solar technologies can be classified as either photovoltaic (PV) or concentrated solar power (CSP). PV is the most readily known and available technology. In the utility scale sector, PV represents almost 95% of all cumulative new installations since 2003. CSP refers to a technology that concentrates solar heat that is then channeled to a conventional steam generator. This is unlike PV that converts sunlight directly to

electricity. Concentrated solar is mainly used at the utility scale. For the purposes of this research, utility scale solar includes both PV and CSP projects.

### **Literature Review**

Several recent econometric studies have examined the effect of state renewable energy policies on the adoption of renewables. Up to a couple of years ago, studies had grouped all renewable energy technologies together (Carley, 2009; Yin and Powers, 2010) with an underlying assumption that policies and factors affected the development of different renewable energy technologies in the same manner. However, only wind and solar have experienced any significant growth in the past two decades and wind by far leads the renewable energy sector, accounting for over eighty percent of all new non-hydro renewable installations since 2001 (Gelman, 2013). I was able to identify only three studies that either concentrate on the effect of policies in promoting solar power or differentiate effects among the different renewable energy technologies. While most of the growth in the utility scale solar sector has occurred in the West, there are many other states across the country that have integrated large scale solar power to their energy portfolio mix. With the kind of growth experienced by the solar industry in the last few years and given that most of the growth has occurred in states that appear to have surpassed the experimenting and learning phase, it is important to understand the factors that facilitate the entrance to this market. As solar power becomes more visible and concerns with the environmental impacts of conventional energy grow further it is important to quantitatively measure the effect of the different dynamics that make the adoption of solar power attractive and feasible. This thesis adds to the growing body of literature that tries to accomplish just this. Please refer to Table 1 for a list of the relevant empirical studies that will be discussed in this section.



Table 2. Relevant empirical studies

	Timeframe	Technology-specific?	Dependent variable	Key policy variables
Carley (2009) <sup>1</sup>	1998-2006	No	% renewable energy (RE), total annual RE generation	RPS, % regional RPS, tax index, subsidy index, deregulation
Yin and Powers (2010)	1993-2006	No	% renewable generation	incremental share RPS, REC trading, mandatory green power options (MGPO), public benefits fund (PBF), net metering (NM), interconnection standards
Shrimali and Kneifel (2011)	1991-2007	Wind, biomass, geothermal, solar	% renewable capacity	RPS, green power purchasing (GPP), MGPO, PBF
Murray (2011) <sup>2</sup>	2005-2009	Solar	Photovoltaic purchases	Solar carve-out (SCO), solar credit multipliers (SCM), tax rebates and credits, property and sales tax exemptions, PBF, NM
Sarzynski <i>et al.</i> (2012)	1997-2009	Solar	Annual amount of grid-tied PV capacity installed	financial incentives, RPS, SCO, NM
This study	2003-2012	Utility scale solar	Deployment of at least one utility scale solar power plant in a state	RPS, voluntary RPS, SCO, SCM, four groups of financial incentives, renewable energy credits trading

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<sup>1</sup> Sample consisted of 48 U.S. states

<sup>2</sup> Sample consisted of 40 U.S. states

The most relevant and recent studies that econometrically estimate the effects of state renewable energy policy on energy capacity are Sarzynski *et al.* (2012), Murray (2011) and Shrimali and Kniefel (2011). All these studies use a different dependent variable from the one used in this thesis. As shown in Table 2, dependent variable choice ranges from grid-tied photovoltaic capacity, photovoltaic purchases to nameplate installed capacity. Sarzynski *et al.* conduct a throughout examination of the impact of U.S. state-level financial incentives on the market deployment of grid-tied solar capacity for the period 1997 to 2009. Four types of financial incentives are studied including income tax, cash, sales tax and property tax incentives. The authors use a fixed effects model to account for heterogeneity across states. Their study indicates that cash incentives such as rebates and grants are important to market deployment while property and sales taxes do not appear to spur PV market deployment. Additionally RPS is found to be an important policy that promotes solar development. As pointed out by the authors, a drawback from this study is that “states with multiple incentives of the same type are treated the same as states with just one” and their analysis ends with the year 2009, right before the solar market experienced substantial growth and other states incorporated solar into their energy portfolios. This thesis will further Sarzynski *et al.* research by accounting for the difference in the number of incentives available by state and including up-to-date developments of the solar market. In addition, Sarzynski *et al.* consider only the PV solar market in aggregate, combining residential, commercial and large scale installations. In contrast, this thesis focuses on the utility scale solar market including both PV and CSP solar.

Murray (2011) uses a fixed effects model to examine the effects of solar set asides, credit multipliers, tax rebates, personal tax credits, sales and property tax exemptions, net metering, and public funds on photovoltaic purchases for the period 2005-2009. Murray finds that only solar

set asides and property tax exemptions have a significant effect of solar energy development. Unlike Sarzynski *et al.* RPS policies without solar set asides and credit multipliers are not included in the study and the timeframe of the study is narrow with a total of 197 observations. The choice of some independent variables in this thesis such as the inclusion of solar credit multipliers and separating different financial incentives are inspired by Murray's research findings.

Shrimali and Kniefel (2011) analyze the effects of state policies on the penetration of four emerging electricity sources using a fixed effects model. Although solar is not the focus of their research, the authors distinguish between solar and the other three emerging electricity sources. A panel data that include the 50 U.S. states covering the years 1991 through 2007 is constructed by the authors using data from the Energy Information Administration (EIA), DSIRE and the League of Conservation Voters (LCV). Variables in the study include state level renewable energy nameplate capacity, RPS, state government green power purchasing, mandatory green power option (MGPO), clean energy fund, electricity prices (as an economic variable) and a couple of political variables. In this study, it is found that overall, economic and political factors do not significantly influenced the deployment of renewable energy. Policy variables (RPS and MGPO) are found to be significant drivers of renewable energy development. While this study acknowledges the separation of impact of different policies on the penetration of a renewable energy source, the study is limited by focusing on factors and policies that are common to all renewables. This thesis narrows down Shrimali and Kniefel's study by concentrating on utility scale solar instead of renewable energy capacity as a whole.

Although the following studies analyze the effectiveness of renewable energy policy in general, they are important as these were some of the first studies to empirically estimate the

factors affecting renewable energy development and their findings set the stage for discussion in policy circles. Early non-econometric case studies including Petersik (2004) and Brown and Busche (2008) found a significant correlation between RPS policies and renewable generation in a state. In 2009, with one of the first econometric studies on overall renewable energy policies Carley finds no strong evidence that RPS policies were obtaining their stated objective of increasing the percentage of renewable energy generation. She uses a fixed-effects vector decomposition (FEVD) model with state level data for 1998 to 2006 using a total of fifteen variables that fall under these categories: RPS, political and environmental institution factors, socioeconomic factors, electricity market trends, and natural resource endowment variables. Other than rebutting earlier claims of RPS effectiveness, Carley finds that subsidy programs are found to be positively associated with renewable energy deployment while the opposite effect is found for tax incentives. Carley' study is one of the most comprehensive studies on the overall effect of renewable energy policies in the deployment of renewables in general however it lumps all renewables into one category, it is now outdated and it makes no distinction between RPS policies. Furthermore, Greene (2011) has shown that the FEVD estimator as was used by Carley does not provide a correct estimation for parameters on time-invariant variables and the gains in efficiency attributed to FEVD model are illusory.

Yin and Powers (2010) estimate the effectiveness of an RPS in promoting renewable energy development. Using state level data from 1993 to 2006 that include the presence of policies usually enacted as part of RPS legislation such as Public Benefit Funds, net metering, interconnection standards, mandatory green power option, and alternative compliance payments, the authors explore whether the heterogeneity in the design of the RPS policy makes a difference in the achieving the stated intent of the policy of promoting non-hydro renewable energy

technologies. The authors find that by ignoring the heterogeneity of RPS policies, the RPS variable indeed appear to be ineffective in accelerating renewable energy deployment. However when accounting for the differences in RPS policy design, having a mandatory green power option and having a higher state import electricity rate influence the strength of an RPS. It is this study's conclusion that inspired the inclusion of specific RPS policy designation including solar carve-outs and set asides in the models for this thesis.

A general drawback from the studies previously discussed is that they have all used some form of fixed effect (FE) models while including time invariant variables in their model specification. It is well known that parameters for variables that either change very slowly or do not change at all over time cannot be estimated using the FE model approach. Beck (2001) and Beck and Katz (2001) provide insightful discussion on the problematic use of FE for binary time-series-cross-section (TSCS) data. As will be discussed later, TSCS data with time invariant variables will be used for second part of the analysis in this thesis.

Overall, the research conducted on the factors influencing renewable energies has found mixed results and the couple of studies that focus on solar have not reached the same conclusion on the effect of financial incentives. Considering that solar constitutes such a small percentage of the overall renewable energy sector and an even smaller fraction of the nation's total energy production, it is surprising that no other studies have attempted to analyze the effect of the different factors that may influence the deployment of the solar power development using a binary variable as the dependent variable. In addition, with the significant growth the solar energy market has experienced in the last few years alone, and as most authors have pointed out, there is a continued need to update the empirical results as data becomes available and the solar market with related policies mature.

### **Analytical Framework**

This thesis considers the state factors that influence the deployment of large scale solar projects. Variables included in the analysis are informed by previous research but the focus on the utility sector, a large and up to date sample, and modeling approach make this study unique in discerning the effect of state renewable energy policies on the deployment of pioneering utility scale solar projects. The binary dependent variable utility scale solar projects (hereon referred as *USSP*) represents whether at least one utility scale solar power plant of one megawatt (MW) capacity or larger operates in a state and is used both in the cross sectional and survival analysis conducted for this research.

As previously mentioned, California deployed its first utility scale solar project in the mid-1980s however no other large scale solar project came online until the early 2000s. Data for the event history analysis model starts in 2003 which coincides with the beginning of a new momentum for the solar energy markets and extends up to 2012 covering a period of historically unprecedented rate of newly installed solar energy capacity in the U.S. Following the survival analysis framework, as will be further explained later in this section, states that experience deployment of large scale solar fall out of the data set the year following this event. Therefore the survival analysis models in this research will cover a span of ten years for a total of 425 observations. The cross sectional models use data aggregated by state for the period 2003-2012 for a total of 50 observations. Data was drawn from the Solar Energy Industries Association (SEIA), the Database of State Incentives for Renewable Energy (DSIRE), the U.S. Energy Information Administration (EIA), the U.S. Environmental Protection Agency (EPA), NASA's Atmospheric Science Data Center, the National Renewable Energy Laboratory (NREL) and the U.S. Census Bureau (USCB).

## Description of the Data

The deployment data for the utility scale solar projects in the U.S. comes from the Solar Energy Industries Association (SEIA). SEIA publishes a monthly report tracking utility-scale solar projects that are operating, under construction, or under development. It is based on the SEIA reports that utility scale solar is defined as those projects with one MW capacity or more. The information for these reports is compiled from public announcements and through contacts with individual developers. As SEIA forthrightly discloses, their list is not a comprehensive database of all utility-scale solar projects and it may underrepresent smaller projects located outside of California that are built on a short time-scale and/or are not publicly announced. To the best of my knowledge, this is the most comprehensive utility scale solar dataset covering deployment across all active states in the solar market. SEIA data was to the extent possible cross referenced with the EIA *Operable Generating Units 2001-2011* database. SEIA reports usually include the date the solar plant came online. However, the online date reported does not necessarily represent the date the plant came online. Large scale solar power plants are built in stages and are often turned online as stages are completed although the usual online date is the date the whole plant goes online. This could mean an up to six month lagged in reported online dates for some plants. Due to discrepancies in the timing of projects online date, the analysis is conducted on an annual timescale. The dependent variable USSP represents whether at least one utility scale solar power plant of one MW capacity or larger operates in a state.

The following table summarizes the variables that are included in this thesis and that will be further discussed in this section:

Table 3. Description of model variables

	Variable	Definition	Variable type	Time variation
Dependent Variable	<b>USSP</b>	State has at least one utility scale solar project	Binary	Variant; as soon as one utility scale solar project is deployed in a state, the state is dropped from sample
RPS & Related Policies	<b>RPS_eff</b>	State has RPS policy and it is effective/enforced	Binary	Variant
	<b>VRPS</b>	Voluntary RPS	Binary	Variant
	<b>REC</b>	State permits use and trading of renewable energy credits - no restrictions	Binary	Variant
	<b>SCO</b>	Solar carve-out	Binary	Variant
	<b>SCM</b>	Solar credit multiplier	Binary	Variant
Constraints	<b>OZNA</b>	State has at least one partial ozone non-attainment area	Binary	Variant
Financial Policies	<b>pop_dens</b>	Population per land area in square miles	Continuous	Variant
	<b>FI_TC</b>	No. of financial incentives in the form of tax credits available in a given year	Discrete	Variant
	<b>FI_BD</b>	No. of financial incentives in the form of buy downs available in a given year	Discrete	Variant
	<b>FI_LOAN</b>	No. of financial incentives in the form of loan programs available in a given year	Discrete	Variant
	<b>FI_PBI</b>	No. of financial incentives in the form of performance based incentives available in a given year	Discrete	Variant
Natural endowment - renewables	<b>SI_NASA</b>	Solar insolation levels in kWh/m <sup>2</sup> /day	Continuous	Invariant
	<b>SRC</b>	Ratio of solar energy potential per wind, bio and geo potential combined	Continuous	Invariant
Market	<b>EP_Totald</b>	State average energy prices (in 2010 dollars) lagged 2 years; cents per kWh	Continuous	Variant
	<b>PopEC</b>	Share of population with respect to state electricity capacity lagged two years; person per MW	Continuous	Variant
Time trend	<b>t</b>	Time (in years)	Discrete	Variant
	<b>t_sq</b>	Time squared	Discrete	Variant
	<b>t_cube</b>	Time cubed	Discrete	Variant



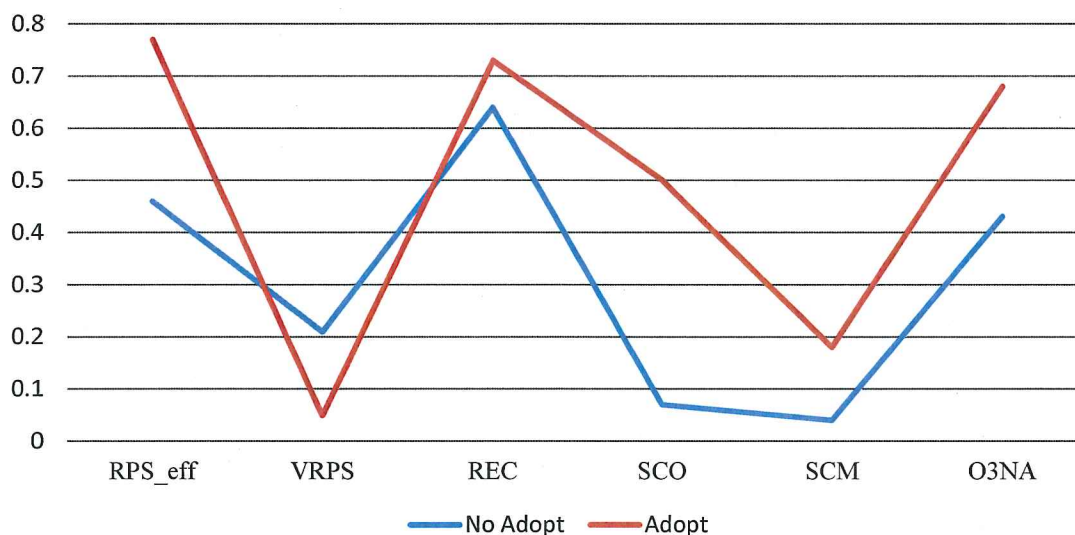
Information on the renewable energy policies that follow was obtained from DSIRE, a project of the Interstate Renewable Energy Council and the U.S. Department of Energy that is currently operated by North Carolina State University. DSIRE is also the largest and best known database providing summary of financial incentives and policies established by the federal, state and local governments specifically for renewables. This database compiles information from different sources that are disclosed in each policy description.

The most studied, controversial and ambiguous variable in regards to its effectiveness is the presence of a Renewable Portfolio Standard (*RPS*). This variable captures the effect of operating in a state with an established RPS. An RPS is a legally binding state-mandated program that requires a specified percentage or amount of the state's total electricity generation to be derived from renewable sources. For example, Maine's RPS ultimate target is for electricity providers to supply at least 40% of their total electric sales with renewable energies by the year 2017 while Texas's RPS calls for 5,880 MW of renewables to be installed by 2015 (DSIRE, 2013). There is often a lag between the year RPS legislation is enacted and the year it becomes effective. For the purpose of this research, the binary RPS binary variable kicks in the first year of regulatory compliance that is it takes the value of 1 along with the following years and is 0 otherwise. To illustrate the designation of this variable, consider Colorado where an RPS policy was approved in 2004 but the first compliance year was 2007. In this case the *RPS\_eff* variable takes the value of 0 up to 2006 and 1 starting in 2007 and the following years.

Inspired by Yin and Powers (2010) additional RPS subtleties that have been specifically added to support solar were included in the dataset. Dummies for solar carve-outs (*SCO*), solar credit multipliers (*SCM*) and renewable energy credits (*REC*) were included to capture the effect of these provisions within the RPS. These dummies take the value of 1 for the years in which the

provisions were in place and are 0 otherwise. The presence of a solar carve-out, a credit multiplier, or both is expected to have a strong influence on the deployment of solar power. The ability to buy renewable energy credits may substitute for plant construction. Figure 7 plots the average variation of the dummy variables by states with utility scale solar projects and states without large scale solar projects over the period 2003-2012.

**Figure 7. Binary variables comparison by adoption (%)**



A separate variable was included for states with voluntary RPS goals (*VRPS*) to account for the difference in legal requirements. As the name implies, voluntary RPS goals structured in a similar way as RPS policies however they are not legally binding and there are no financial penalties imposed for noncompliance. The theory behind distinguishing *VRPS* from an RPS is that although this policy may have an influence on the deployment of solar, it is likely that the effect of a legally binding RPS would be stronger. Please refer to Table 4 for the descriptive statistics of RPS & related policies.

**Table 4. Descriptive statistics for RPS & related policies**

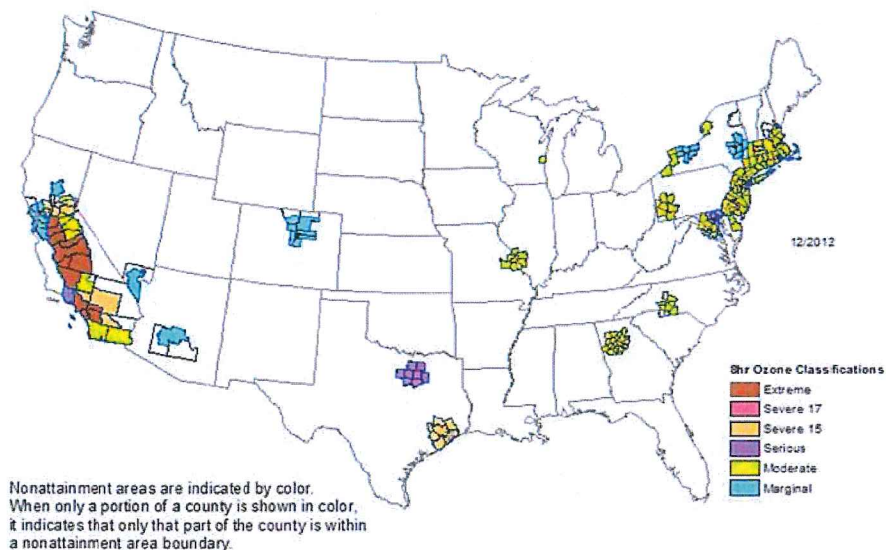
Variable	n=50		n=425		all	
	%	Std. dev.	%	Std. dev.	Min	Max
RPS_eff	60%	0.49	30.35%	0.46	0	1
VRPS	14%	0.35	10.12%	0.30	0	1
REC	68%	0.47	42.82%	0.50	0	1
SCO	26%	0.44	10.82%	0.31	0	1
SCM	10%	0.30	5.65%	0.23	0	1

To pick up the effects of environmental conditions in a state that may restrict the kinds of new utility projects that may be approved, I included the presence of an 8-hour ozone nonattainment area within a state.<sup>3</sup> There are currently two 8-hour ozone standards: 1997 and 2008 however this last one was designated after the range of this study in 2012. Therefore the 8-hour ozone nonattainment areas referred from here on are those from the 1997 standard. Information from the EPA *Pollutant Nonattainment Areas 1990-present* database was used to construct this variable. The binary variable *O3NA* (for ozone nonattainment area) represents whether at least one partial or entire county is designated an ozone nonattainment area in a state. Data for the 8-hour ozone nonattainment counties are not available for the year 2003 as the EPA designated the standard in 2004. Through personal communication with the EPA Office of Air Quality and Standards, it was advised to assume that the 2003 nonattainment designation was same as the first year the standard became effective in 2004. Thus the 2003 and 2004 states with ozone nonattainment areas are the same for these two years. Please refer to Figure 8 for a geographical reference on the distribution of the ozone nonattainment areas at the end of 2012.

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<sup>3</sup> Initially sulfur dioxide nonattainment areas were also included in the model but after finding that this variable was irrelevant to the model it was removed.

**Figure 8. 8-hour Ozone Nonattainment Areas as of 12/2012 (1997 Standard)**



Source: U.S. Environmental Protection Agency 12/14/2012

A possible barrier to large scale solar is the need for significant amounts of land. A variable accounting for population density was included with the idea that there would be less resistance by the local population and more potential sites available for large solar projects in states with low population density. This variable is measure in population per square mile. Data for this variable was obtained from multiple reports published by the USCB. Please refer to Table 5 for the descriptive statistics of ozone nonattainment areas and population density variables.

**Table 5. Descriptive statistics for restriction variables**

Variable	n=50				n=425			
	Mean (or %)	Std. dev.	Min	Max	Mean (or %)	Std. dev.	Min	Max
OZNA	54%	0.50	0	1	50.12%	0.50	0	1
pop_dens	194.7955844	260.66	1.28	1185	179.63	250.02	1.14	1185

Historically incentives have been an important policy instrument used to promote new technologies in the early stages of deployment. Financial incentives can be subdivided into four categories: (1) tax credits (*FI\_TC*) such as income, investment and property tax exemptions, (2)

buy downs (*FI\_BD*) which generally covers funds that are conditional upon making an investment but do not need to be paid back and are claimed either at the time of purchase or shortly afterwards– this would include grants and any other cash subsidy that is not tax related (3) loan programs (*FI\_Loan*) which generally are tailored for the renewable energy industry – this would include loans with interest below-market rate, and (4) performance based incentives (*FI\_PBI*) such as feed-in tariffs that were discussed earlier. Count variables were created for the four types of financial incentives. While the absolute number of policies is not a measurement of overall policy strength, it may be argued that it is a measurement of regulatory activity and an indicator of how much policy activity takes place in a state. It is difficult to know a priori which financial incentives may have a significant impact on the development of large scale solar power but it is hypothesized that states with a higher policy activity that combine different types of financial incentives may be more successful in encouraging the deployment of renewables in general. Data on currently offered financial incentives with initial adoption date can be found in DSIRE however this database does not include historical financial incentives that have expired. Various other sources including DOE’s Tax Credits, Rebates and Savings webpage, old EPA States Incentives publications, DOE’s Open Energy Info wiki and state energy websites were used to fill in the data gaps.

It is important to note that other financial incentives are offered by other entities including the federal and local governments as well as non-profit organizations. Such incentives were not included in the financial incentives variables following the rationale that (1) federal incentives are the same for all states therefore all projects are equally eligible to use them and (2) financial incentives from local government and non-profit organizations are relatively small especially for utility scale projects that they are considered not to significantly influence activity

in this sector. On the other hand, incentives offered by utilities that seemed to encourage large scale projects were included in these count variables. For example, the Tennessee Valley Authority (TVA) is currently offering up to 20 year price contracts for renewable energy generators with systems capacity between 50kW and 20MW that are sited in the TVA power service area (i.e. Alabama, Georgia, Kentucky, Mississippi, North Carolina, Tennessee and Virginia). Manufacturing and R&D incentives have also been known to be offered by some states but were not included in the count variables. Thus the financial incentives captured in these variables are restricted to those offered directly to utilities or investors for the deployment of large scale renewables.

**Table 6. Summary statistics of financial incentives variables**

Variable	n=50				n=425			
	Mean	Std. dev.	Min	Max	Mean	Std. dev.	Min	Max
FI_TC (tax credits)	1.66	1.42	0	5	1.21	1.35	0	6
FI_BD (buy downs)	0.48	0.84	0	4	0.34	0.67	0	4
FI_LOAN	0.5	0.68	0	2	0.36	0.59	0	3
FI_PBI (performance based)	0.54	0.71	0	3	0.28	0.53	0	3

State electricity prices were included with the assumption that solar power may be more economically attractive in states already experiencing higher energy prices. Electricity providers in such states may be more willing to invest in long-term energy supplies that guarantee energy prices. However it may also be that given high energy costs already in place, utilities may be less willing to deploy the more expensive solar power technologies (Shrimali and Jenner, 2012). Average total energy prices are based on the EIA's "1990-2011 Average Price by State by Provider (EIA-861)" data and were lagged two years with the assumption that the decision to build a new electricity plant is schedule at least this far in advanced. Prices were deflated to 2010 dollars using the U.S. Department of Labor Consumer Price Index for All Urban Consumers

(CPI-U). Annual average electricity price ( $EP\_totald$ ) is measured in cents per kilowatt-hour (kWh).

Growth in electricity demand relative to existing state electricity capacity was included with the hypothesis that as demand outstrips supply there will be incentives to build new electricity plants in general. In a scenario where electricity demand outstrips supply solar power would have the advantage that it can be deployed on a relatively shorter time scale when compared to conventional energy sources. This variable is measured in population per kWh. Data from the EIA's "1990-2011 Existing Nameplate and Net Summer Capacity by Energy Source, Producer Type and State (EIA-860)" and the USCB were used to construct this variable. Similarly to electricity prices, electricity capacity is lagged two years.

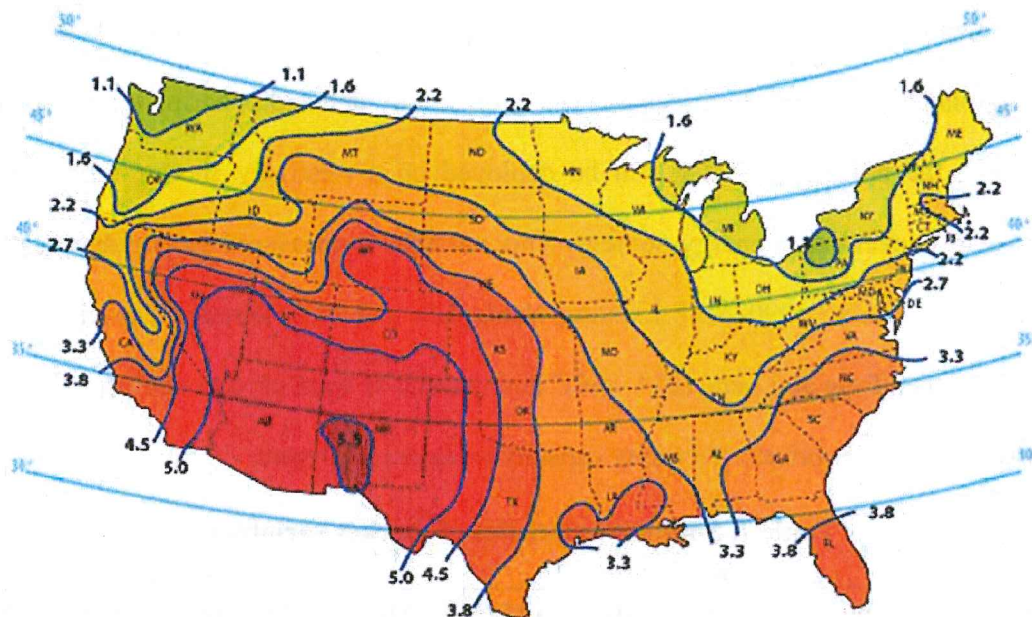
**Table 7. Summary statistics of market variables**

Variable	n=50				n=425			
	Mean	Std. dev.	Min	Max	Mean	Std. dev.	Min	Max
EP_total	10.04	3.55	6.20	25.12	7.31	2.80	3.44	19.16
Pop_EC	280.32	115.61	68.79	564.99	285.23	115.22	68.79	772.42

Although the U.S. has a large natural endowment of solar energy, it is not evenly distributed among the states. The southwest in general enjoys higher levels of solar insolation than any other region in the country including Hawaii. Solar insolation refers to the amount of solar radiation reaching a given surface and recorded during a given time. This measure is influenced by atmospheric conditions such as dust and cloud coverage and the angle at which solar radiation strikes a surface including altitude (Stickler and Kyle, 1999). Please refer to Figure 9 for a depiction of the solar insolation levels throughout the United States. Data for this variable is based on the National Aeronautics and Space Administration (NASA)'s Surface Meteorology and Solar Energy estimates and is an annual average of solar insolation level measured at the highest populated areas of a state. The solar insolation variable  $SI\_NASA$  is

measured in kWh/m<sup>2</sup>/day with a mean of 4.5, standard deviation of 0.56 and a range of 2.87 to 6.11 kWh/m<sup>2</sup>/day.

**Figure 9. Geographic distribution of solar insolation levels in the U.S.**



Please note that this map shows the amount of solar energy in hours, received each day on an optimally tilted surface during the worst month of the year.

Source: solarinsolation.org

An alternative way of measuring solar endowment is by consider solar potential with respect to the potential of other non-hydro renewable sources. As previously discussed solar insolation is a direct measure of the amount of solar energy reaching a surface and in the U.S. the higher insolation levels happen to occur where there are also significantly higher levels of available land (i.e. the Southwest) – a necessary but not sufficient condition for the deployment of large scale solar power. Lacking better variables other studies have relied on the solar insolation data as the measure of a state’s natural solar energy endowment. NREL data became available last year that included the technical potential by state in gigawatts for all renewables. Technical potential estimates for each of the renewable energy technologies takes into account



the availability and quality of the resource, the technical system performance, topographic limitations, as well as environmental and land use constraints. One can hypothesize that states with low solar insolation but a relatively higher solar energy potential than wind, geothermal and biomass may be more likely to experience deployment of solar power. The variable SRC measures the technical potential of utility scale solar with respect to the technical potential of wind, geothermal and biomass combined. Although the technical potential for each of the renewable resources was originally measured in gigawatts (GW), the final variable is unitless as it is a simple ratio. Data from NREL's U.S. Renewable Energy Technical Potential report was used to construct this variable. Please refer to NREL's report for a throughout discussion on the assumptions made for each of the renewable resources technical potential. Please refer to Table 8 for summary statistics of natural endowment variables.

**Table 8. Summary statistics of natural endowment variables**  
**n=50** **n=425**

Variable	Mean	Std. dev.	Min	Max	Mean	Std. dev.	Min	Max
SI_NASA	4.52	0.56	2.87	6.11	4.48	0.53	2.87	6.11
SRC	127.74	284.78	0.04	1232.52	118.72	279.02	0.04	1232.52

On a final note on the data, information for non-renewable competing resources including coal, natural gas and petroleum (reserves were used as proxy for technical potential as this information is not available) was also collected and tried in the models but after finding that these variables were irrelevant they were all dropped from the study.

### **Model Specification**

The present study has a cross-sectional (CS) and a time-series-cross-section (TSCS) component (TSCS). Ignoring time-varying factors, the cross-sectional study determines the conditions that make it more economically conducive to solar energy production while the TSCS

study measures the time it takes a utility in a state to first built a solar plant in the study period of 2003-2012. A detailed discussion on model specification follows below.

The cross sectional model serves to estimate the independent effects of the political, economic and natural endowment characteristics on the adoption of large scale solar in a state and can be expressed as

$$y_i = \alpha + x_i\beta + \varepsilon_i$$

Given the binary nature of the dependent variable, this model can be estimated as a logit or probit regression. The choice of model in such a case is considered by many a matter of taste. For instance, Johnston and DiNardo (1997, pg. 430) conclude on their discussion of the correct functional form that these two specifications “seem to produce similar answers in most empirical applications” and advice to adhere to “what is convenient in a particular application”. Today’s computational advancements allow for the estimation of both models without imposing any additional hardship to the modeler. Therefore, both logit and probit specifications are estimated for this thesis.

The probit and logit models estimate the probability of deploying a utility scale solar project at the state level. These models provide an estimation of the likelihood that a given state will experience a utility scale solar project deployment. The binary response model is specified as follows:

$$P(USSP_i = 1) = F(x_i\beta)$$

where USSP is the binary dependent variable.  $X_i$  is the set of exogenous independent variables that explain the deployment of a utility scale solar project in a state, and F is the distribution function, which is standard normal for the probit and logistic for the logit.

As previously mentioned, the cross sectional model ignores dynamics, specifically when a solar plant is first built. The modeling approach that follows centers around the idea that the deployment of the first large scale solar project is a watershed event that reduces general uncertainty in the industry as it paves the way by navigating the “system” and it is therefore worthy of analysis in its own right. Weitzman *et al.* (1981) provide an insightful analysis behind this issue of sequential decision-making. Duration analysis, which allows the timing of an event to be explored in a dynamic framework, is used in this thesis to model explicitly the time to the first deployment of a large solar power for individual states. Survival analysis better known as duration modeling in the economics field, roots from the biometrics field but the approach has been widely applied to political science problems such as studies on militarized conflict (Enterline, 1997) and policy diffusion (Mooney, 2001). Duration analysis attempts to empirically identify the factors or characteristics that have a significant effect on the length of a spell. For this thesis, an event is the deployment of a large scale solar project in a state, with the spell being the time it takes for a utility in a state to first build a solar plant. The start of the spell is the time when the first event took place; traditionally only one event occurs for each subject after which the subject (state in this case) exits the study. To be more specific, for the purpose of estimation the relevant states in a given year are those that had not experienced a utility scale solar project deployment at the beginning of the year. Again, once a utility scale solar project is deployed in a state, the state is no longer in the sample.

For as long as the subject has not experienced an event, there is a probability that in the future it will experience such an event. This probability of how likely a subject is to experience an event within a given time interval is known as the hazard rate. The most common duration

model is the Cox (1975) proportional hazard model. As Beck, Katz and Tucker (1998) have pointed out, in this model the hazard rate is

$$h(t|x_{it}) = \underbrace{h_0(t, t^2, t^3)}_{\text{baseline hazard}} \exp(x_{it}\beta)$$

where  $x_{it}$  is the vector of independent variables measured at  $t$ , which in this case are intervals of one year. In this setup, the hazard of an event occurring depends both on the independent variables via the  $\exp(x_{it}\beta)$  term and the length of time the unit has been at risk which is represented by the  $h_0(t, t^2, t^3)$  term also known as the baseline hazard. Beck, Katz and Tucker (1998) have proven that a discrete time version of a Cox hazard proportional model is analogous to a complementary log-log (cloglog) model with dummy variables measuring intervals between events. Unlike logit and probit that are symmetrical about  $P=0.5$ , the response curve for cloglog models depart slowly from  $P=0$  and approaches  $P=1$  very rapidly (Box-Steffensmeier and Jones, 2004). Due to this asymmetry, the cloglog function form is frequently used when the probability of an event is very small or very large and in such cases the results may differ from the logit model. The cloglog model is

$$\text{cloglog}(P) = \log(-\log(1 - P))$$

and can be restated as

$$P(y_{it} = 1|x_{it}, k_{it}) = 1 - \exp(-\exp(x_{it}\beta + k_{it}\alpha))$$

where  $k_{it}$  is the vector of time dummy values and  $\alpha$  is the vector of coefficients associated with the time dummies. The inclusion of temporal dummies allows the baseline hazard to change so that the model shows duration dependence. However the use of time dummies can induce estimation problems due to quasi-complete separation. Carter and Signorino (2010) have proven that a cubic polynomial approximation that consists of including  $t$ ,  $t^2$  and  $t^3$  can trace out the path

of duration dependence and smooth out the time dummies while avoiding the problem of quasi-complete separation. Therefore the cubic polynomial approximation to the baseline hazard will be used for this thesis.

Sueyoshi (1995) has shown that logit and probit models can be derived from other complicated time duration models. Beck, Katz and Tucker (1998) contend that logit is about the same as cloglog, but due to its familiarity logit is easier to estimate and interpret. King and Zeng (2001) argue that logistic regression sharply underestimates the probability of rare events which are defined as cases where the binary dependent variable has significantly fewer events than nonevents (i.e. zeros) and therefore penalized logistic regression should be performed in such cases to reduce bias. Known as the Firth method, after its inventor David Firth, penalized likelihood reduces small sample bias by removing the first-order term from the asymptotic bias of maximum likelihood estimates by a suitable modification of the score function (Firth, 1993). The four functional forms to be compared in this thesis for the duration analysis are: logit, probit, cloglog and penalized. The model to be estimated is

$$y_{it} = \alpha + X_{it}\beta + Z_{it}\gamma + W_i\delta + T_i\theta + \varepsilon_{it}$$

where  $i$  is the state, and  $t$  is the year of the specific observation. The dependent variable is defined the same way as in the cross sectional model;  $X_{it}$  is the set of market and environmental constraint variables,  $Z_{it}$  is the set of the binary policy variables,  $W_i$  are the natural endowment variables and  $T_i$  is the set of time variables included to approximate the baseline hazard.

## Results

Because many of the variables used in this thesis are part of what may be considered an overall state “green energy portfolio “ where some states deploy all of these policies to incentivize the adoption of renewables, it was important to check that the data was not weakened

from the presence of perfect multicollinearity. The correlation between model variables was assessed to determine whether the analysis is limited by multicollinearity. As demonstrated in Table 8 (n=50) and Table 9 (n=425) no two variables are perfectly correlated. The strongest correlation in the cross sectional data is between average total energy prices (EP\_Total) and share of population with respect to state electricity capacity (popec) with a correlation of 0.6973. As expected the time trend variables added to the panel data set are highly correlated with each other. Other than these, the strongest correlation in the panel data set is between the deflated energy prices (EP\_totald) and performance based incentives (FI\_PBI) with a Pearson correlated coefficient of 0.4826. From these results it is concluded that multicollinearity was not a problem in the statistical analysis. Regression results are presented first for the CS data followed by the survival analysis results.

Table 9. Pearson Correlations Coefficients, N=50

	USSP	RPS_eff	VRPS	REC	SCO	SCM	OZNA	FI_TC	FI_BD	FI_LOAN	FI_PBI	SI_NASA	SRC	EP_To	pop_dens	popec
USSP	1															
RPS_eff	0.313	1														
VRPS	-0.242	-0.4942	1													
REC	0.09	0.6651	0.153	1												
SCO	0.485	0.484	-0.239	0.407	1											
SCM	0.242	0.2722	-0.135	0.229	0.258	1										
OZNA	0.252	0.1474	-0.206	0.055	0.273	0.04	1									
FI_TC	0.271	0.1217	0.138	0.261	0.014	-0.014	-0.109	1								
FI_BD	0.167	0.2261	-0.094	0.138	0.207	0.128	0.147	0.071	1							
FI_LOAN	0.12	0.2434	-0.215	0.192	0.51	-0.149	0.09	-0.074	0.3231	1						
FI_PBI	0.122	0.1636	-0.064	0.162	-0.067	-0.067	0.082	0.39	0.0358	-0.192	1					
SI_NASA	0.186	0.0295	-0.039	-0.077	-0.127	0.217	0.196	-0.039	-0.067	-0.2681	-0.1235	1				
SRC	0.126	-0.3378	-0.113	-0.383	-0.164	-0.025	-0.027	0.063	-0.071	-0.1	0.0808	-0.0538	1			
EP_Total	0.302	0.3598	-0.185	0.009	0.112	-0.037	0.159	0.021	0.1749	0.1371	0.2736	0.2198	-0.195	1		
pop_dens	0.275	0.3194	-0.177	0.188	0.33	-0.059	0.403	0.128	0.2016	0.2936	0.2574	-0.1036	-0.163	0.528	1	
popec	0.377	0.3048	-0.008	0.209	0.134	-0.02	0.126	0.196	0.2757	0.2031	0.3518	0.1876	-0.259	0.697	0.5573	1





Four specifications were run to observe the effect of the different variable groups on the baseline and to confirm the robustness of results against model specification bias. Additionally, this step helps in pairing down the variables that will be used in further comparisons. A baseline Specification (1) was run using the natural endowment, market, and restriction variables previously described in the data section. The variables included in the baseline model are those that were considered to be outside of a state's control. On that note, even though states often regulate electricity distribution and utilities' rates of return for use and upkeep of the distribution system (EPSA, 2013), it is assumed that the underlying price of electricity is not set by the states. Specification (2) includes the legally binding RPS and the voluntary RPS variables. This specification ignores the heterogeneity of RPS policies. Specification (3) adds depth to the RPS policies while Specification (4) includes all variable groups. Please refer to Table 11 for a summary of results.

**Table 11. Logit model in stages, N=50**

<i>USSP</i>	(1)	(2)	(3)	(4)
<b>Intercept</b>	-3.87***	-4.66***	-5.18**	-7.90**
<b>SRC</b>	0.0021*	0.0031**	0.0035**	0.0038*
<b>EP_Total</b>	0.030	-0.058	-0.092	-0.078
<b>OZNA</b>	1.08	1.03	1.04	2.07
<b>pop_dens</b>	-0.0002	-0.0010	-0.0016	-0.0028
<b>poppec</b>	0.0087*	0.012**	0.015**	0.021**
<b>RPS_eff</b>		1.445543	2.837689	2.918205
<b>VRPS</b>		-1.23811	1.447664	0.137522
<b>REC</b>			-3.19	-4.71
<b>SCO</b>			3.13***	5.15**
<b>SCM</b>			1.76	2.01
<b>FI_TC</b>				1.11**
<b>FI_BD</b>				0.015
<b>FI_LOAN</b>				-0.94
<b>FI_PBI</b>				-0.70
<i>Pseudo R Sq.</i>	0.1939	0.2727	0.4467	0.5692

\* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$

For this analysis, a regression coefficient that is statistically significant at the 10% level for all specifications will be considered robust. Based on this definition, from the baseline model the amount of solar potential with respect to other renewables (SRC also expressed as solrencomp) and the share of population with respect to state electricity capacity (popec) are the only robust results. From the additional three specifications, the presence of solar carve-outs and tax credits (or breaks) are found to be significant predictors of utility scale solar projects. Additionally the results show that the pseudo  $R^2$  (McFadden's) of the regression with the baseline variables amounts to only 0.19. It increases to 0.57 when all variable groups are included. From these results, it can be concluded that most of the variation is explained by the subtleties within an RPS policy and the availability of tax credits. Both of these are time variant policies. Next, results are compared for both probit and logit using the two different measures of natural endowment. Since the financial incentives variables in the form of buy downs, loans and performance based incentives were statistically insignificant in the model specifications, these three variables will not be compared any further.

One of the concerns with the model was its robustness that depended both on the specification of the model and the choice of natural endowment variable. The former in this case is simply addressed by including both the logit and probit functional forms. For the latter, I am able to compare results by using an alternative measure of solar potential in a state as previously discussed in the data section. Please refer to Table 12 for a comparison of results using the two functional forms and the different measures of natural endowment. Although the magnitudes of the estimates between the logit and probit are not comparable, the direction of effect (i.e. sign) should be consistent. According to these results, solar carve-outs, the presence of tax credits and a higher share of population with respect to electricity capacity have a positive effect on the

deployment of large scale solar projects. Even though the typical RPS policy is not significant in any of the model specifications, solar carve-outs can only occur within an RPS. Therefore the statistical significance of solar carve-outs implies that an RPS with a solar carve-out has a significant impact on the adoption of solar power. This result is not surprising as a solar carve-out means an explicit mandate for utilities to adopt solar power. Another unsurprising result is the insignificance of having a voluntary RPS. This weak policy instrument, more aptly described as a statement of interest in renewables from the part of states does not provide any carrots or sticks for the utility sector. It is therefore expected to have no effect on the status quo. The results from the static model provide a line of comparison for the survival results. Therefore further examination of the significance and interpretation of the other variables will be discussed in the survival analysis results.

**Table 12. Comparison of Results – all specifications, N=50**

	SRC		Solar Insolation	
	Logit	Probit	Logit	Probit
<i>USSP</i>				
<b>Intercept</b>	-7.40***	-4.37***	-11.44**	-6.78**
<b>RPS_eff</b>	4.02	2.25	2.18	1.19
<b>VRPS</b>	1.62	0.87	0.78	0.37
<b>REC</b>	-5.79	-3.28	-4.75	-2.71
<b>SCO</b>	4.38***	2.55***	4.83***	2.83***
<b>SCM</b>	2.74	1.58	2.67	1.54
<b>OZNA</b>	2.02	1.15	1.81	1.01
<b>FI_TC</b>	1.04**	0.60**	1.22**	0.71***
<b>SRC or SI</b>	0.0036*	0.0021*	1.32	0.77
<b>EP_Total</b>	-0.15	-0.077	-0.15	-0.0772
<b>pop_dens</b>	-0.0028	-0.0016	-0.0021	-0.0011
<b>popec</b>	0.02***	0.01***	0.014**	0.0084**
<i>LR Test</i>	37.85***	38.26***	35.83***	36.30***
<i>Pseudo R Sq.</i>	0.5518	0.5577	0.5224	0.5292
<i>Adj. Count R Sq.</i>	0.7273	0.6364	0.6818	0.5455

\* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$

Marginal effects for the cross sectional model with the SRC variable were calculated and are compared in Table 13. For the rest of the discussion on the cross sectional results, only specifications with the SRC variable are discussed as the functional forms with this variable provided slightly better results than its counterpart the solar insolation variable. The marginal effects for the continuous variables are calculated at their mean with the dummy variables set at their mode to reflect a “typical” case scenario. Since 60% of all states had an RPS in effect in 2012, the RPS variable was set at 1. Only 14% of all states have a voluntary RPS therefore VRPS is set at 0. About 2/3 of all states participate in regional REC tracking programs therefore in the typical case the REC variable takes the value of 1. Solar carve-outs and credit multipliers are offered in thirteen states or less, therefore both of these variables are set at 0. Twenty seven states have ozone nonattainment areas; therefore OZNA is set at 1. Finally, the average number of financial tax breaks is 1.66 so the FI\_TC is set at 2 for the typical case scenario. Marginal effects are obtained by computing the derivation of the conditional mean function with respect to  $x$  given by

$$\begin{aligned}\frac{\partial E[y|x_i]}{\partial x_i} &= \left\{ \frac{dF(x_i\beta)}{d(x_i\beta)} \right\} \beta \\ &= f(x_i\beta) \beta\end{aligned}$$

Where  $f(\cdot)$  is the density function that corresponds to the cumulative function  $F(\cdot)$ . The marginal effects are nonlinear functions of the parameter estimates and levels of the explanatory variables. The marginal effects due to dummy variables were approximated by taking the difference of estimated probabilities between the different levels of dummy covariates. Letting  $x_k$  denote the dummy explanatory variable and  $x^*$  denote the other covariates at their means, the effect due to a change of  $x_k$  on the predicted probabilities of  $y$  is

$$\Pr[y = 1|x_k = 1, x^*] - \Pr[y = 1|x_k = 0, x^*]$$

The resulting marginal effects are presented in Table 13.

**Table 13. Marginal Effects using SRC, N=50**

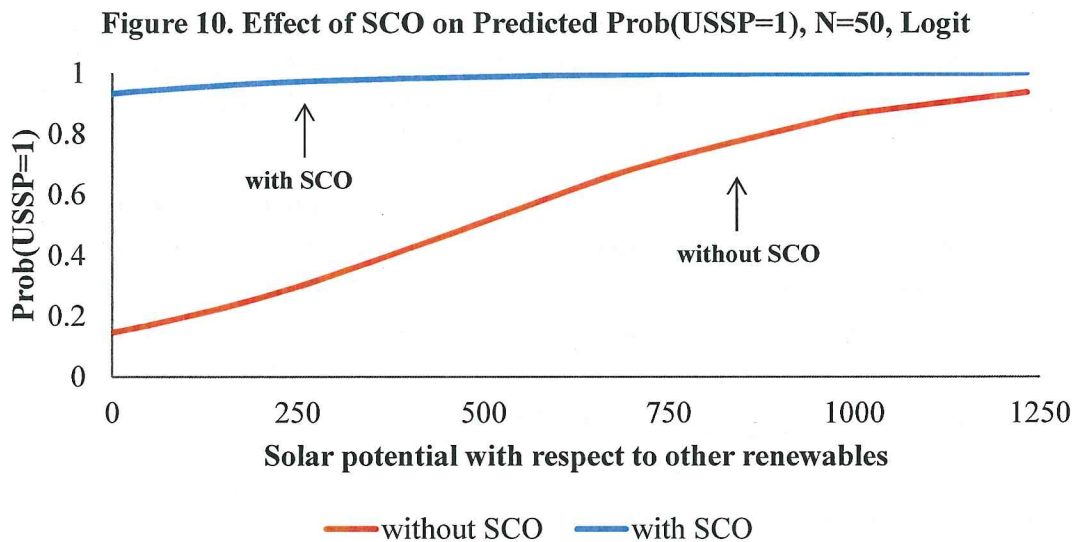
	<b>Logit</b>	<b>Probit</b>
<b>SRC<sup>‡</sup></b>	7.69E-04	4.46E-04
<b>EP_Total</b>	-3.17E-02	-1.66E-02
<b>pop_dens</b>	-5.88E-04	-3.38E-04
<b>popec<sup>‡</sup></b>	4.05E-03	2.38E-03

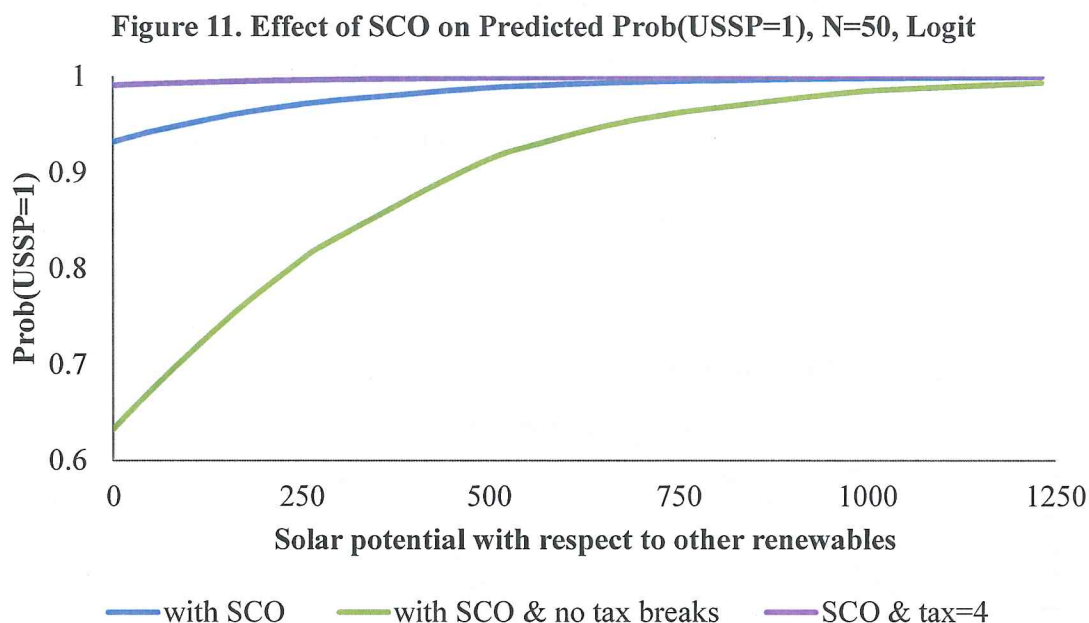
Starting from a typical case where RPS=1, VRPS=0, REC=1, SCO & SCM=0, OZNA=1, FI\_TC=2 and cont= $\mu$  the marginal effects for the dummy variables are as follows:

	<b>Logit</b>	<b>Probit</b>
<b>Scenario 1. carve-out included</b>	0.743	0.745
<b>Scenario 2. SCO &amp; tax=4</b>	0.781	0.782
<b>Scenario 3. SCO &amp; no tax breaks</b>	0.519	0.498
<b>Scenario 4. typical (no SCO) &amp; tax=5</b>	0.645	0.629
<b>Scenario 5. no policies (i.e. no tax breaks)</b>	-0.180	-0.193

The marginal effects estimated for both the logit and probit specifications are nearly identical meaning that for this particular application either one of the two specifications is appropriate. Given this similarity, for the rest of this section I will concentrate on discussing the marginal effects estimated for the logit specification only. Furthermore since solar carve-outs and financial incentives in the form of tax breaks were the only statistically significant policies in the cross sectional model, I concentrate on graphing these two policy variables to elucidate their impact on the two baseline variables that are also significant in the model (i.e. solar potential with respect to other renewables and population with respect to energy capacity).

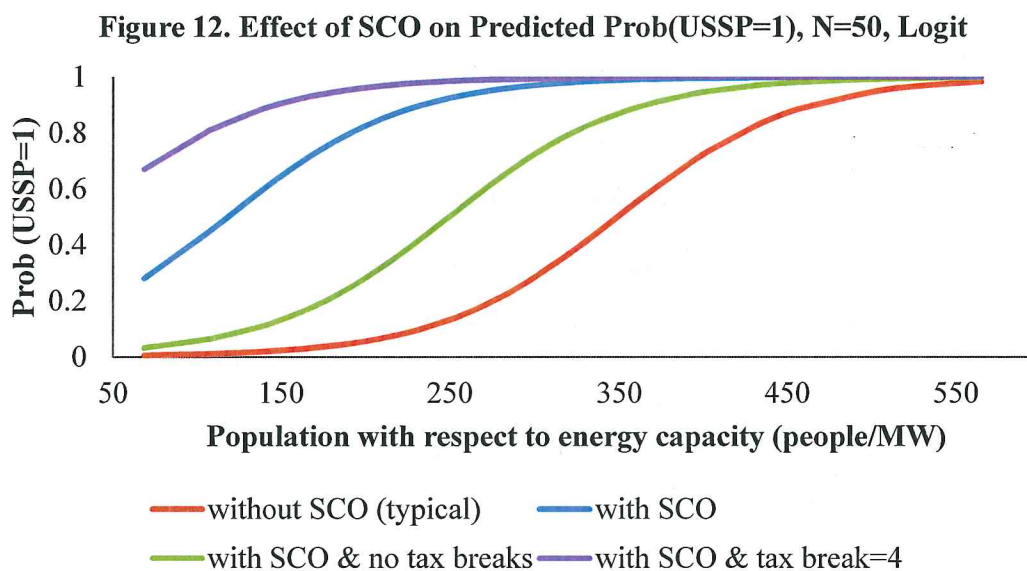
The effect of a solar carve-out on the predicted probability of adopting large scale solar project is presented on Figure 10. This shows that the probability that a state will experience deployment of a utility scale solar project after enacting an RPS with a solar carve-out is far greater for states with low solar potential with respect to other renewables than those with high solar potential with respect to wind, biomass and geothermal. At the typical case previously described, the effect of a solar carve-out on the probability is 0.743. Clearly the typical case scenario does not show the wide range of differences displayed in Figure 10.





Another scenario of interest is the effect of tax breaks given that a solar carve-out is already in place. Since a solar carve-out is a strong command and control policy, it is difficult to predict a priori how tax breaks will further influence the probability of adoption. Offering an additional two tax breaks once a carve-out is in place results in a 3.8% increase in probability of adoption (0.743-0.781) while going from the typical case of two tax breaks to no tax breaks decreases the probability by 22.4% (0.743-0.519). These effects are presented in Figure 11. From these results, one could interpret that the first few tax break programs have a bigger impact in the probability of adoption and there is diminishing marginal returns as more tax breaks are offered. Another way to consider the effect of a solar carve-out is by switching from natural endowment to a proxy for electricity demand in states. Figure 12 presents those results. This graph shows that the probability that a state will experience deployment of a utility scale solar project after enacting an RPS with a solar carve-out is greater for states with a medium number of people per MW. A possible interpretation for this result is that states with a high number of persons per MW were already more likely to have adopted large scale solar power by 2012 as there are more

incentives to build new electricity plants in general given demand outstrips supply while on the lower end states are just less likely to build any new electricity plants in general. It is therefore in this mid-range where a solar carve-out has the greatest impact on the probability of adoption. As with the natural endowment variable, the same scenarios of interest were plotted to visualize the effect of solar carve-outs with different levels of tax breaks.



To start the duration modeling, a similar procedure as for the cross sectional model was applied by adding to the baseline one variable group at the time. The baseline and specifications (2) through (4) remain the same as in the cross sectional model. Specification (5) was added to observe the effect of the time trend variables. Please refer to Table 14 for a summary of these results. Similar to the cross sectional estimates, the results for SRC are robust. On the other hand, the variable *poppec* is statistically significant in specification (3) to (5) only. Electricity prices, which had previously not been statistically significant in any of the specifications, are significant in specification (1) through (3). Finally from the baseline model, population density is statistically significant at the 10% level in specifications (4) and (5). Having an RPS in effect



was statistically significant in specifications (2) and (5). The results for these last four variables (popec, electricity prices, population density and RPS\_eff) will be treated as potentially affecting the deployment of large scale solar. The effect of a solar carve-out and availability of tax credits were again found to be robust. Additionally the time trend variables are statistically significant at the 1% level meaning there is duration dependence, that is, the baseline hazard is not constant.

The results show that the pseudo  $R^2$  (max-rescaled  $R^2$ ) of the regression with the baseline variables amounts to 0.13 while going up to 0.49 when all variable groups are included. Next results are compared for the four functional forms. As in the cross sectional model, the solar insolation variable did not perform as well as the SRC variable therefore all following discussions will center on the SRC variable. Comparison of the results for the four functional forms using solar insolation is included as Appendix B. And again since the financial incentives variables in the form of buy downs, loans and performance based incentives were irrelevant to the model these three variables will not be compared any further.

Table 14. cloglog model in stages, N=425

<i>USSP</i>	(1)	(2)	(3)	(4)	(5)
<b>Intercept</b>	-6.31***	-6.60***	-7.82***	-9.37***	-5.98**
<b>SRC</b>	0.0015**	0.0023***	0.0028***	0.0031***	0.0035***
<b>EP_Total</b>	0.22***	0.12*	0.13*	0.1284	-0.0087
<b>OZNA</b>	0.88	0.54	-0.13	0.46	0.84
<b>pop_dens</b>	-0.00121	-0.00134	-0.00121	-0.0022*	-0.0022*
<b>popec</b>	0.0035	0.0040	0.0075**	0.008**	0.011***
<b>RPS_eff</b>		1.96***	1.1244	1.1428	2.00**
<b>VRPS</b>		0.39	-0.17	-0.38	-0.01
<b>REC</b>			0.20	-0.71	-0.83
<b>SCO</b>			2.15***	2.82***	2.69***
<b>SCM</b>			0.11	0.03	0.93
<b>FI_TC</b>				0.69***	0.59***
<b>FI_BD</b>				0.06	-0.06
<b>FI_LOAN</b>				0.39	0.13
<b>FI_PBI</b>				0.33	0.02
<b>t</b>					-4.72***
<b>t_sq</b>					1.09***
<b>t_cube</b>					-0.066***
<i>Pseudo R Sq.</i>	0.1334	0.2029	0.309	0.3974	0.4908

\* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$

Based on the results presented in Table 15, the four different functional forms generally identify the same significant variables. As previously mentioned, estimates from these models cannot be compared with each other straightforwardly. Before the models are compared by means of the marginal effects, the direction of some of the estimates will be further discussed. In the duration model, unlike the cross sectional model, an RPS policy that is a basic RPS policy without additional incentives that promote solar power has positive and significant effect on the deployment of large scale solar at the state level. One theory as to why an RPS is a significant

predictor of *USSP* in a dynamic model but not in a static model is that it takes years for an RPS to have an effect in renewable energy deployment in general. Not surprisingly a voluntary RPS is not a significant predictor of large scale solar power. Trading of renewable energy credits has the expected negative sign implying that being able to trade credits substitutes for plant construction however this result is not statistically significant. Credit multipliers have statistically no effect on the predicted probability of deploying large scale solar. Murray (2011) found a similar result for this variable. This result is interesting as multiplier have been discussed as possible alternatives for solar carve-outs. In fact in 2010 Colorado replaced its solar energy carve-out for a combination of “distributed generated” requirement and a solar credit multiplier (Galbraith, 2010). The presence of an ozone nonattainment area does not statistically have an effect on large scale solar power. On a side note, this is one of two additional variables that were found to be statistically significant at the 10% level when using the solar insolation variable. Regarding the market variables, in one hand electricity prices are not significant predictors of solar power while demand for new electricity plants is. One may hypothesize that states with high energy prices may not be as willing to ask their electricity generators to adopt the more expensive solar technologies while states with low energy prices have no incentive to find alternative means of electricity production therefore the effect of prices may be lost by these two extremes. Finally population density is potentially affecting the development of solar power (the results do not hold for all functional forms) and has the opposite sign of what was expected. No speculation will be made about the ambiguity of this result. Next marginal effects for the different function forms will be compared. From here on only the cloglog and penalized regressions will be considered as these two functional forms fitted the data well and predicted better than logit and probit.

Table 15. Summary of Results for SRC Var, N=425

<i>USSP</i>	Logit	Probit	cloglog	Penalized
<b>Intercept</b>	-6.09**	-2.97**	-5.95**	-5.06**
<b>t</b>	-5.09***	-2.59***	-4.72***	-4.20***
<b>t_sq</b>	1.19***	0.61***	1.09***	0.97***
<b>t_cube</b>	-0.07***	-0.038***	-0.067***	-0.059***
<b>RPS_eff</b>	2.09**	1.02**	1.92**	1.73**
<b>VRPS</b>	-0.10	0.01	-0.07	0.16
<b>REC</b>	-1.07	-0.78	-0.74	-0.98
<b>SCO</b>	3.17***	1.69***	2.76***	2.74***
<b>SCM</b>	0.71	0.34	0.79	0.63
<b>OZNA</b>	0.99	0.62	0.84	0.84
<b>FI_TC</b>	0.66***	0.35***	0.57***	0.56***
<b>SRC</b>	0.0035***	0.0016***	0.0035***	0.0030***
<b>EP_Totald</b>	-0.01	-0.003	-0.01	-0.002
<b>pop_dens</b>	-0.0023*	-0.0012*	-0.0021*	-0.0019
<b>popec</b>	0.012***	0.0055**	0.012***	0.01***
<i>Pseudo R Sq.</i>	0.4339	0.4354	0.4904	0.7485
<i>Adj. Count R Sq.</i>	0.1579	0.1579	0.2105	0.2105

\* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$

The marginal effects estimated for both the cloglog and penalized specifications are presented in Table 16. Similar marginal effects are provided by the cloglog and penalized regression. The marginal effects for the continuous variables are calculated at their mean with the dummy variables set at their mode to reflect a “typical” case scenario. Since 30% of all states had an RPS in effect in the study period of 2003-2012, the RPS variable was set at 0. About 10% of all states have a voluntary RPS therefore VRPS is set at 0. Less than half of all states participated in regional REC tracking programs during the study period therefore in the typical case the REC variable takes the value of 0. Similarly solar carve-outs and credit multipliers are

set at 0. A little bit more than 50% of the observations have an ozone nonattainment area therefore OZNA is set at 1. The average number of financial tax breaks is 1.21 so the FI\_TC is set at 1 for the typical case scenario. Finally the midpoint for the study period is 5 (year 2007) and the marginal effect is measured at year 10 (that being 2012 and also the last year in this study). Similar to the marginal effects calculated for the cross sectional data, these are nonlinear functions of the parameter estimates and levels of the explanatory variables. Resulting marginal effects are presented in Table 16.

**Table 16. Marginal Effects using SRC, N=425**

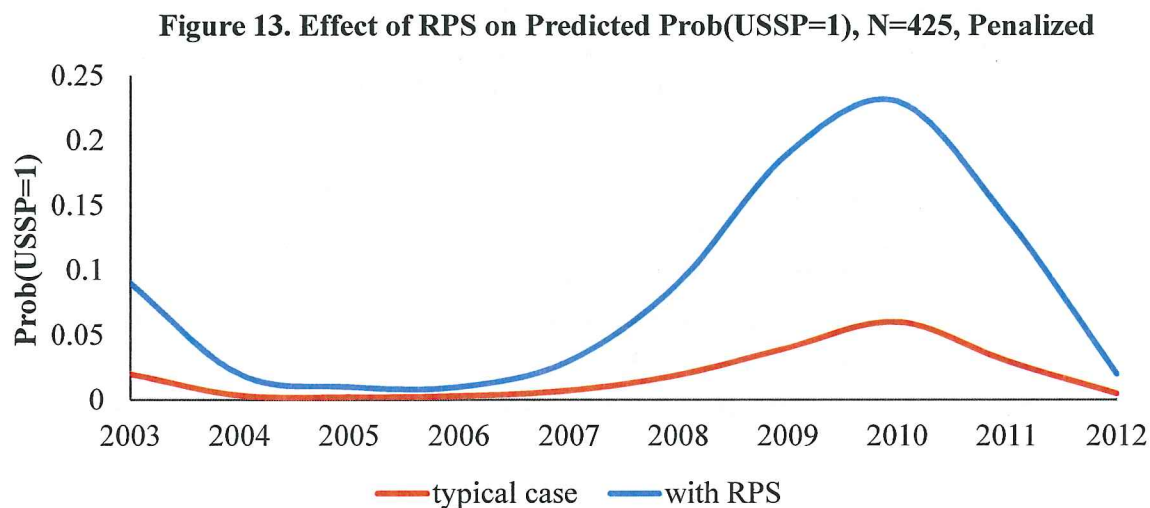
	<b>cloglog</b>	<b>penalized</b>
<b>solrencomp</b>	8.05E-06	1.83E-05
<b>EP_Total</b>	-2.99E-05	-1.23E-05
<b>pop_dens</b>	-4.87E-06	-1.18E-05
<b>popec</b>	2.67E-05	6.21E-05

Starting from a typical case where  $t=5$ ,  $RPS=0$ ,  $VRPS=0$ ,  $REC=1$ ,  $SCO$  &  $SCM=0$ ,  $OZNA=1$ ,  $FI\_TC=1$  and  $cont=\mu$  the marginal effects for the dummy variables by  $t=10$  are as follows:

	<b>cloglog</b>	<b>penalized</b>
<b>Scenario 1. RPS in effect</b>	0.01	0.02
<b>Scenario 2. RPS and SCO in place</b>	0.30	0.26
<b>Scenario 3. RPS &amp; SCO=1, tax breaks =4</b>	0.85	0.66
<b>Scenario . RPS and SCO=1, no tax breaks</b>	0.18	0.17
<b>Scenario 5. typical but FITC=3</b>	0.01	0.01
<b>Scenario 6. no policies (i.e. no tax breaks)</b>	-0.004	-0.004

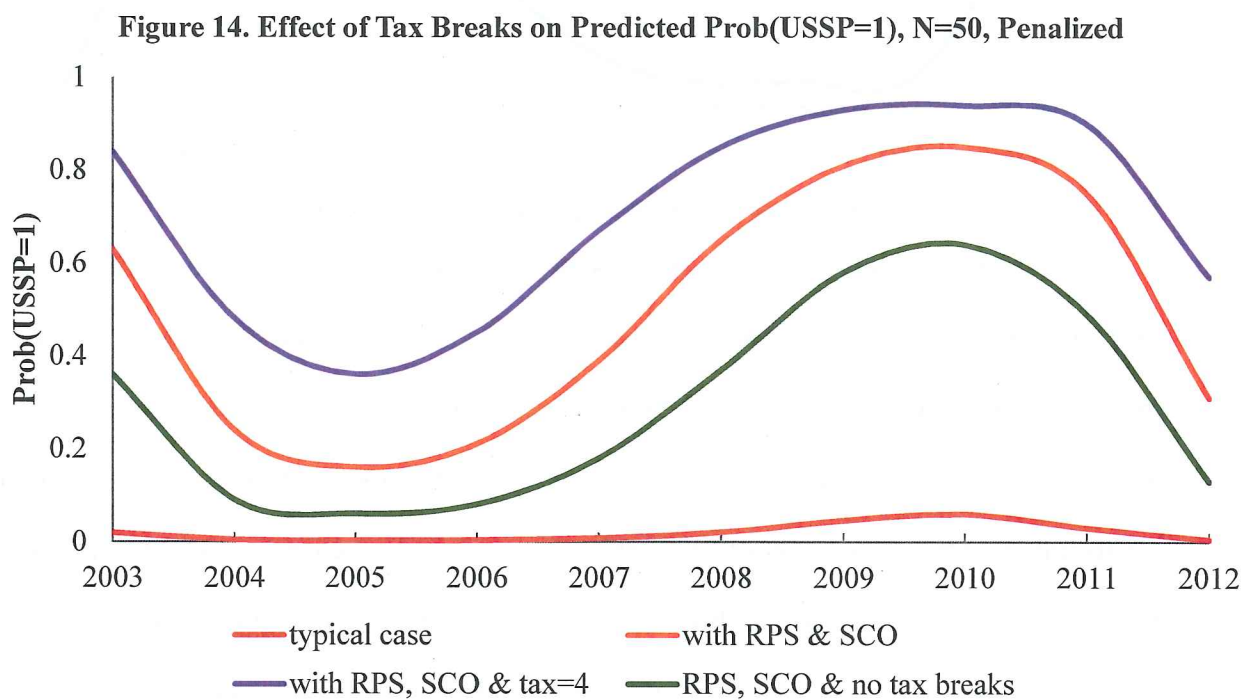
A drawback from the typical case scenario is that it measures the effect of these policies in a 5 year period. To better illustrate the effect of these policies a few scenarios of interest were plotted (Figures 13-15) and will be used as the basis for discussion. Given the similar marginal effects estimates for both cloglog and penalized only the penalized results were graphed.

The effect of an RPS on the predicted probability of adopting large scale solar project is presented on Figure 13. Having an RPS in effect shifts the probability of adoption upwards at all times during the study period. The upward shift is especially evident between 2008 and 2012. The significant higher levels of solar adoption between 2008 and 2010 may be explained by higher levels of funding for renewable projects starting with the Economic Stimulus Act of 2008 that was continued with the American Recovery and Reinvestment Act of 2009 but ran out by the end of 2011. One could theorize that electricity generators in states with RPS policies had experience with renewables prior to this infusion of capital however may not have deployed solar earlier due to its high costs. The theory goes that when funding became available, the generators within these states were better equipped to adopt large scale solar power. The marginal effect from 2007 to 2012 in a typical case scenario is 2% highly underestimating its effect at different points in the study period.



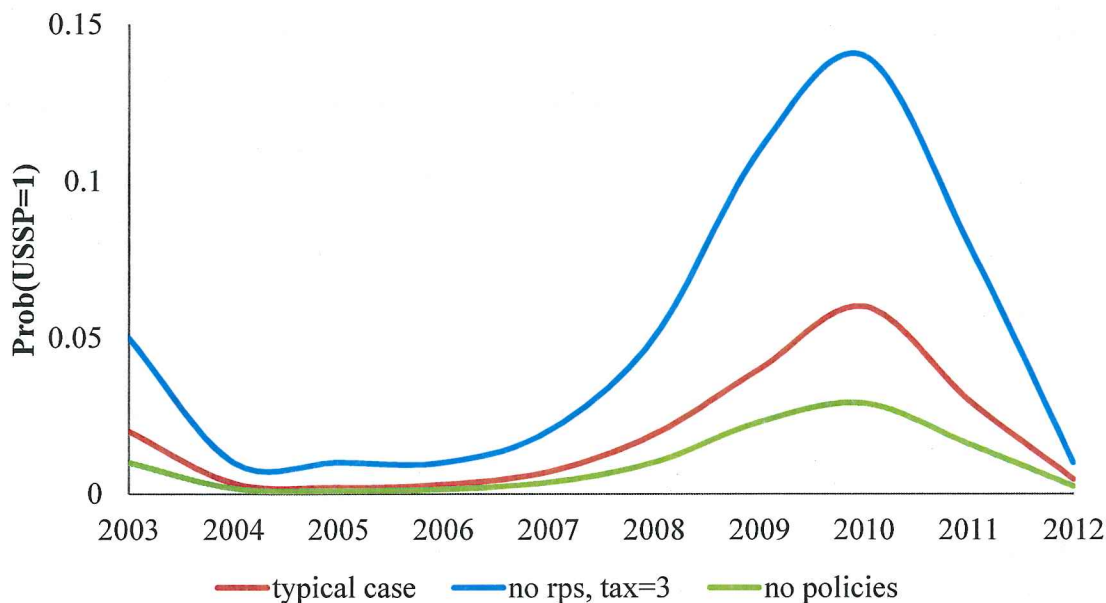
Similarly as in the cross sectional model, the effect of solar carve-outs and a few different level of tax credits are presented in Figure 14. The expected shifts are observed for the different scenarios. For example going from a typical case to then having an RPS in effect with a solar

carve-out significantly increases the probability of deploying a large scale solar project. If there is an RPS with a solar carve-out but no tax breaks the probability of adoption is still higher than that of a typical case but lower than if one tax break is offered. Along these lines if instead of offering no tax credits, four times the usual number of tax credits is provided then the probability increases even further becoming almost the perfect environment for solar deployment in the years 2008 through 2011.



Finally a few peculiar scenarios are considered and plotted in Figure 15. One of them includes not enacting an RPS policy while offering three times the average number of incentives. In such a case, the probability of adopting solar power at the peak of solar adoption in 2010 increases from about 5% to almost 15%. The last scenario models an otherwise typical state except it offers no tax incentives for solar or renewable energy technologies.

**Figure 15. Interesting Scenarios, N=425, Penalized**



In summary through duration analysis, the probability of deploying the first large scale solar project at the state level was modeled while controlling for time dependence. Unlike the cross sectional model, it is found that RPS has a positive impact on the probability of solar power deployment. In the cross sectional and survival analysis, the presence of solar carve-outs and tax credits influence the deployment of large scale solar while only one market variable – people per MW capacity installed – makes a difference. Lastly the variable measuring solar potential with respect to other renewables available in a state is found to be a better predictor of solar deployment than the more popularly used solar insolation measure.

### Discussion

Motivation for this research came from the observation that some states with relatively lower natural solar energy endowment had succeeded in promoting the deployment of utility scale solar projects especially compared to other states with relatively high solar energy resources. Such is the case of New Jersey in the northeast which has become a leader in the region for solar development while there are states like Utah that enjoys high levels of solar



insolation but it is yet to deploy its first large scale solar plant. It was expected that policies would have an important effect in promoting renewables in general while the market would provide additional incentives to adopt these technologies. In general it appears as if policies are indeed a driving force behind the deployment of large scale solar projects while the need for new electricity plants in general enhance the probability of solar being adopted. The finding of a strong effect of a solar carve-out is in line with the previous conclusion reach by Murray in 2011. That an RPS policy is significant even without a solar carve-out reinforces the notion that RPS has a different effect on the different renewable energy sectors. It has been a long way since 2009 when the first empirical report (i.e. Carley 2009) measuring the impact or renewable energy policies contended that RPS policies were not fulfilling their intended purposes. As new data becomes available and different policy tools and mechanisms are adopted by states, it would be interesting to continuing the assessment of the policy effects on the development of renewables in general and its subset sectors. Additionally if more refined data became available that would allow to measure the magnitude of incentives instead of the simple count used for this thesis, it would allow for a better understanding of their impacts on the renewable energy market. Other policies such as mandatory green power options that were not considered for this study but may also influence the deployment of solar energy may be included in future analysis.

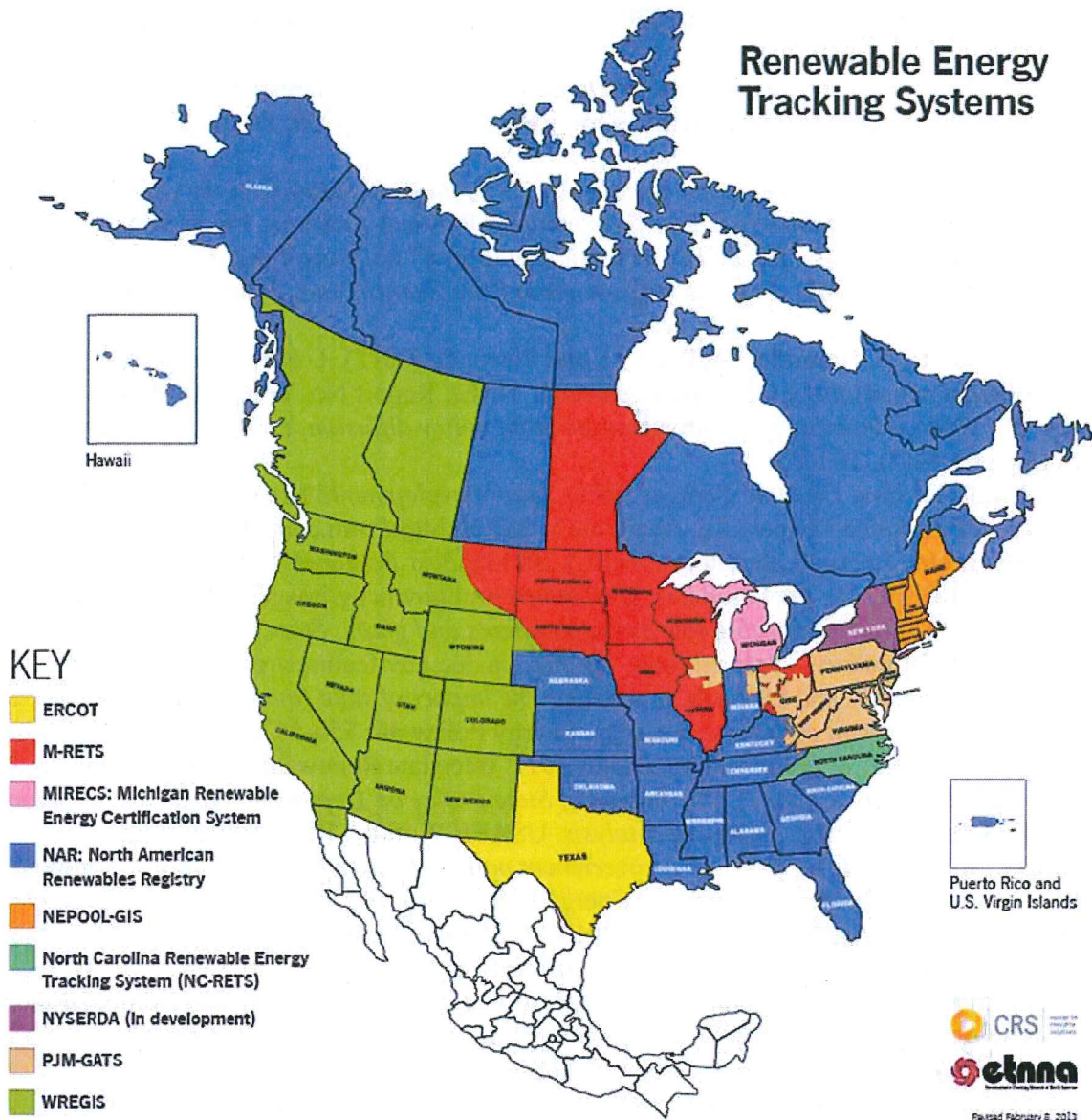
This study contributes to the literature by conducting the first econometric analysis on the utility scale solar sector. Its significance is further amplified by including up to date data that covers the years when the solar sector experienced its historically record breakings growth marks. The implications of the findings are of especially interest to policymakers and the solar energy industry.

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Appendix A



Source: U.S. DOE Energy efficiency & Renewable Energy  
<http://apps3.eere.energy.gov/greenpower/markets/certificates.shtml?page=3>

## Appendix B

## Summary of Results for Solar Insolation Var, N=425

<i>USSP</i>	Logit	Probit	cloglog	Penalized
<b>Intercept</b>	-6.9**	-3.67**	-5.97*	-6.19**
<b>t</b>	-5.14***	-2.70***	-4.32***	-4.31***
<b>zt_sq</b>	1.20***	0.63***	1.00***	0.99***
<b>t_cube</b>	-0.074***	-0.039***	-0.061***	-0.06***
<b>RPS_eff</b>	1.51*	0.79*	1.31*	1.30*
<b>VRPS</b>	0.34	0.15	0.32	0.52
<b>REC</b>	-1.41	-0.88*	-1.04	-1.21
<b>SCO</b>	2.96***	1.62***	2.58***	2.60***
<b>SCM</b>	0.47	0.21	0.55	0.43
<b>OZNA</b>	1.30*	0.69*	1.09*	1.12*
<b>FI_TC</b>	0.66***	0.35***	0.57***	0.57***
<b>SI_NASA</b>	0.80	0.44	0.56	0.71
<b>EP_Totald</b>	-0.08	-0.04	-0.08	-0.07
<b>pop_dens</b>	-0.001	-0.001	-0.001	-0.001
<b>popec</b>	0.0074*	0.004*	0.001*	0.001**
<i>Pseudo R Sq.</i>	0.3949	0.4037	0.4386	0.6189
<i>Adj. Count R Sq.</i>	0.05	0.05	0.05	0.05

\* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$

**Appendix C**

**Data**

Gross sectional data

Stat e	USS P	RPS_eff	VRP_S	RE_C	NTR_EC	SC_O	SC_M	SC_A	OZN_A	SO2_NA	FL_T_C	FL_T_D	FL_B_AN	FL_LO_AN	FL_P_BI	SI_NA_SA	EP_To_tal	pop_de_ns	solrenco_mp	popec
AK	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	4.62	14.76	1,2818	18.1786	323.50
AL	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	2.87	8.89	95.211	1232.52	136.64
AR	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	4.59	7.28	56.675	247.635	171.04
AZ	1	1	0	1	0	0	0	1	1	1	2	0	0	0	0	5.89	9.69	48.509	715.080	221.22
CA	1	1	0	1	0	0	0	1	0	0	0	0	0	0	2	5.43	13.01	226.30	9.65666	524.20
CO	1	1	0	1	0	0	1	1	0	0	3	0	0	0	0	5.29	9.15	46.350	19.6236	333.00
CT	0	1	0	1	0	0	0	1	0	0	4	0	0	0	3	4.29	17.39	741.44	2.34207	399.37
DE	1	1	0	1	1	1	1	1	0	0	0	1	0	0	0	4.3	11.97	461.79	11.6272	260.98
FL	1	0	0	0	0	0	0	0	0	0	3	1	0	0	1	5.02	10.58	347.83	251.483	285.00
GA	1	0	0	0	0	0	0	1	0	0	1	0	0	0	0	4.62	8.87	165.26	51.1099	250.09
HI	1	1	0	0	0	0	0	0	0	0	1	0	0	0	0	6.11	25.12	207.42	0.03756	501.55
IA	0	1	0	1	0	0	0	0	0	0	3	0	0	1	0	4.3	7.66	55.036	7.02697	195.09
ID	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	5.14	6.54	19.308	158.216	397.63
IL	1	1	0	1	1	1	0	1	0	0	1	2	2	0	0	4.24	9.13	231.28	18.6531	257.03
IN	0	0	1	1	0	0	0	1	0	0	2	0	0	0	1	4.24	7.67	182.47	20.4584	211.37
KS	0	1	0	1	0	0	0	0	0	0	1	0	1	0	0	4.56	8.35	35.297	10.3352	212.19
KY	1	0	0	0	0	0	0	0	0	0	3	0	0	0	1	4.23	6.73	110.59	1017.41	180.24
LA	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	4.62	7.8	106.51	7.07601	147.64
MA	1	1	0	1	0	1	0	1	0	0	4	0	1	1	1	4.21	14.26	841.43	0.33729	432.18
MD	1	1	0	1	1	1	0	1	0	0	3	0	0	1	1	4.22	12.7	606.20	7.27084	432.33
ME	0	1	0	1	0	0	0	0	0	0	0	0	0	0	2	4.2	12.84	43.095	4.14889	279.59







Panel

Year	State	US SP	RPS_enact	RPS_eff	VR_PS	RE_C	NT_RE_C	S_C	S_C	OZ_NA	SO_2N_A	FL_TC	FL_BD	FLL_OAN	FL_PBI	SIN_ASA	EP_Totaid	pop_dens	solren_comp	t_sq	t_cube	popec
2003	A	0	0	0	0	0	0	0	0	0	0	0	0	1	0	4.62	8.560	1.136	18.17	1	1	284.
2003	K	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4.62	342	291	867	1	1	6418
2003	AL	0	0	0	0	0	0	0	0	1	0	0	0	0	0	2.87	4.548	88.92	1232.	1	1	177.
2003	A	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4.59	189	214	52	1	1	1076
2003	R	0	0	0	0	0	0	0	0	1	0	0	0	0	0	4.59	4.913	52.36	247.6	1	1	256.
2003	AZ	1	0	1	0	0	0	0	0	1	1	2	0	0	0	5.89	669	458	359	1	1	5257
2003	C	1	0	1	0	0	0	0	0	1	0	0	0	0	2	5.43	525	925	803	1	1	300.
2003	C	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5.29	9.112	226.3	9.656	1	1	612.
2003	O	0	0	0	0	0	0	0	0	0	0	1	0	0	0	4.889	622	021	664	1	1	5019
2003	C	0	0	1	0	0	0	0	0	1	0	0	0	0	0	4.29	4.889	43.69	19.62	1	1	484.
2003	T	0	0	0	0	0	0	0	0	1	0	1	0	0	0	4.29	304	596	361	1	1	0457
2003	D	0	0	0	0	0	0	0	0	1	0	0	0	0	0	4.3	7.813	719.5	2.342	1	1	412.
2003	E	0	0	0	0	0	0	0	0	1	0	0	1	0	0	4.3	14	533	079	1	1	836
2003	E	0	0	0	0	0	0	0	0	1	0	0	0	0	0	4.3	5.522	419.8	11.62	1	1	315.
2003	E	0	0	0	0	0	0	0	0	1	0	0	0	0	0	4.3	801	03	721	1	1	7094
2003	FL	0	0	0	0	0	0	0	0	0	0	1	0	0	0	5.02	6.229	317.0	251.4	1	1	358.
2003	G	0	0	0	0	0	0	0	0	0	0	1	0	0	0	5.02	395	939	836	1	1	1089
2003	A	0	0	0	0	0	0	0	0	1	0	0	0	0	0	4.62	5.189	149.9	51.10	1	1	272.
2003	HI	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4.62	809	264	992	1	1	83
2003	IA	0	0	0	0	0	0	0	0	0	0	1	0	0	0	6.11	11.41	194.8	0.037	1	1	490.
2003	IA	0	0	1	0	0	0	0	0	0	0	1	0	1	0	4.3	108	04	568	1	1	2641
2003	ID	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4.3	4.986	52.67	7.026	1	1	300.
2003	IL	0	0	0	0	0	0	0	0	0	0	1	0	0	0	4.3	765	007	979	1	1	5106
2003	IL	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4.3	3.995	16.49	158.2	1	1	414.
2003	IN	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5.14	909	72	162	1	1	9057
2003	IN	0	0	0	0	0	0	0	0	1	0	0	0	0	0	4.24	5.604	226.1	18.65	1	1	280.
2003	K	0	0	0	0	0	0	0	0	1	1	0	0	0	0	4.17	019	572	316	1	1	5373
2003	S	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4.17	4.304	172.9	20.45	1	1	230.
2003	K	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4.56	536	643	842	1	1	7443
2003	K	0	0	0	0	0	0	0	0	0	0	1	0	0	0	4.56	5.067	33.30	10.33	1	1	245.
2003	Y	0	0	0	0	0	0	0	0	1	1	0	0	0	0	4.23	983	536	523	1	1	4041
2003	Y	0	0	0	0	0	0	0	0	1	1	0	0	0	0	4.23	3.443	104.2	1017.	1	1	206.
2003	LA	0	0	0	0	0	0	0	0	1	0	0	0	0	0	4.62	629	682	414	1	1	1471
2003	MI	0	0	0	0	0	0	0	0	1	0	0	0	0	0	4.62	5.652	104.6	7.076	1	1	183.
2003	MI	0	0	1	0	0	0	0	0	1	0	0	0	0	0	4.62	75	443	014	1	1	5583
2003	A	0	0	0	0	0	0	0	0	1	0	3	1	1	1	4.21	9.380	823.3	0.337	1	1	495.
2003	MI	0	0	0	0	0	0	0	0	1	0	0	0	0	0	4.22	641	994	297	1	1	1862
2003	MI	0	0	0	0	0	0	0	0	1	0	0	0	0	0	4.22	5.360	566.2	7.270	1	1	435.



























08 C	241	617	703	6	857
20 S	6,194	10,54	6,719	3	255.
08 D	372	1	606	6	3928
20 T	6,443	151.5	971.0	3	271.
08 N	996	078	983	6	5557
20	9,559	93.05	13.01	3	221.
08 TX	673	547	095	6	6643
20 U	5,537	32.40	272.0	3	376.
08 T	954	892	37	6	3999
20 V	6,342	198.3	11.82	3	320.
08 A	297	661	23	6	8477
20	10,51	67.71	12.03	3	570.
08 VT	194	987	378	6	0009
20 W	5,676	98.74	7,590	3	231.
08 A	634	621	699	6	4638
20	7,516	104.1	17.41	3	332.
08 WI	454	585	266	6	8218
20 W	4,659	76.55	16.64	3	106.
08 V	647	77	156	6	0942
20 W	4,872	5,623	8,715	3	77.0
08 Y	29	909	5	6	4854
20 A	12,62	1,224	18.17	4	323.
09 K	75	754	867	7	1137
20	7,198	93.94	1232.	4	143.
09 AL	054	623	52	7	182
20 A	6,618	55.67	247.6	4	175.
09 R	026	053	359	7	9715
20 C	15,64	735.5	2,342	4	416.
09 T	174	519	079	7	0503
20 D	10,79	457.6	11,62	4	252.
09 E	233	401	721	7	973
20	9,822	347.8	251.4	4	295.
09 FL	444	364	836	7	3938
20	6,494	54.29	7,026	4	226.
09 IA	414	692	979	7	5195
20	4,820	18.80	158.2	4	441.
09 ID	89	906	162	7	853
20	8,044	230.4	18,65	4	263.
09 IL	325	94	316	7	0159
20	6,180	180.2	20,45	4	214.
09 IN	628	966	842	7	9526
20 K	6,503	34,64	10,33	4	232.
09 S	922	712	523	7	1889















