Evaluating the Effect of Maine's 2019 Renewable Energy Legislation on Utility-Scale Solar

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Chapter 1

Introduction

Renewable energy policies in the United States have become a cornerstone in efforts to accelerate the transition to clean power, but their implementation and effectiveness have varied widely across the diverse array of contexts present in the country. Over the past two decades, many U.S. states have adopted Renewable Portfolio Standards (RPS) and other incentives to promote renewable generation (Barbose, 2024). RPS are state-level programs that require electric utility companies to source a specified percentage or absolute capacity of electricity from renewable sources. These standards typically establish mandatory targets with set deadlines and include various policy mechanisms to incentivize or mandate compliance with these goals (EIA, 2024a). RPS policies may also pursue more specific objectives in support of their overarching goals. Certain renewable technologies can be targeted to fulfill mandated requirements through mechanisms such as class distinctions or solar carve-outs, which explicitly require that a specific technology be used to meet renewable energy targets. These same mechanisms may also be used to influence the distribution and scale of projects. For example, they may prioritize rooftop solar over utility-scale installations, or encourage development in low-income communities. Structural changes may also be implemented to support growth, such as the creation of consistent and streamlined interconnection standards that define how generators connect to the larger transmission grid (EPA, 2021), or the adoption of net metering policies, which allow electricity to flow both to and from utility customers, especially important for distributed and rooftop solar systems (DSIRE, n.d.).

Early empirical studies on the efficacy of RPS found mixed results. Some detected no immediate increase in renewable electricity from RPS adoption (Carley, 2009), while others observed positive impacts, though only when accounting for policy stringency (Yin & Powers, 2010). These divergent findings suggested that context and details like the design and ambition of policies, as well as temporal lags in investment may play a large part in the policy outcomes. Subsequent research began to control for such heterogeneity. For instance, Shrimali et al. (2015) showed that more stringent RPS targets are indeed associated with greater in-state renewable capacity growth. Other research further highlighted the importance of complementary measures like net metering, interconnection standards, or solar carve-outs in enabling specific technologies such as solar to succeed (Steward & Doris, 2014). In general, the literature over the past 15 years indicates that the existence of a renewable energy policy does not necessarily guarantee a positive result on renewable energy capacity. However, ambitious and well-crafted renewable energy policies *do* have the potential to drive deployment, especially if combined with favorable socioeconomic and environmental factors both natural (e.g. solar resource availability, land suitability) and built (e.g. proximity to infrastructure like transmission lines and substations).

Within this broad national trend, Maine offers a compelling case study. By the late 2010s, Maine had developed an unusual renewable energy profile. It relied heavily on legacy hydropower and biomass and led New England in wind power, but utility-scale solar photovoltaics played almost no role in its energy mix (EIA, 2024b). Maine's solar resources remained modest throughout the 2010s, and state leadership during this time did little to prioritized solar development. In fact, under Governor Paul LePage (Republican, 2011 – 2018), policies were often unfavorable to all renewable energy. As a result, by 2018 Maine had only a handful of small solar farms, with virtually no large-scale solar projects online. The political landscape changed dramatically though in 2019, when newly elected Governor Janet Mills (Democrat, 2019 – Present) and the wider state administration passed three landmark clean energy policies:

1. Legislative Document 1679: An Act To Promote Clean Energy Jobs and To Establish the Maine Climate Council (2019)

2. Legislative Document 1494: An Act To Reform Maine's Renewable Portfolio Standard (2019)

3. Legislative Document 1711: An Act To Promote Solar Energy Projects and Distributed Generation in Maine (2019)

These bipartisan laws established a climate action council and emission targets (LD 1679), massively expanded the RPS (LD 1494), and removed barriers to distributed and community solar (LD 1711), and marked a major turning point in Maine's renewable energy policy environment. Together, the 2019 policies set some of the nation's most aggressive renewable targets and incentives, effectively guaranteeing a market for new solar projects in Maine. The confluence of stronger policy support, shifting political leadership, and rapidly improving solar economics created an exceptional opportunity to evaluate how these factors influence utility-scale solar deployment.

Stemming from the political and socio-economic context described above, alongside the uncertainty and gaps in the current body of literature, this thesis aimed to evaluate the impact of the 2019 renewable energy policies passed in Maine on the deployment of utility-scale solar power within the state, while accounting for relevant socio-political and geographic factors. More explicitly, this research aimed to answer the following question:

> *How did Maine's 2019 renewable energy policy package (LD 1679, LD 1494, and LD 1711) affect the deployment of utility-scale solar photovoltaic capacity (in megawatts) relative to areas which did not see similar policy, while accounting for hyper-localized geographic, environmental, and economic factors relevant to solar development?*

To address this question, I applied a quantitative methodology informed by past RPS policy evaluation literature. After constructing a counterfactual from national geospatial data using coarsened exact matching (CEM), the study employed an event-study framework to compare Maine's post-2019 solar capacity growth against its estimated trajectory absent the policy intervention. This approach was extended by including socio-political variables such as local political leanings and public opinion to capture the influence of community support, and included levelized cost of energy (LCOE) for solar versus wind to account for technology cost trends in various regions of the U.S. across time. By integrating these factors into the analysis, the effect of the 2019 policies is isolated while controlling for political context and market conditions.

The remainder of this thesis is structured as follows. Chapter 2 provides a literature review, summarizing the research methodologies and empirical findings of past research on renewable energy policy impacts. Chapter 3 presents the institutional background and policy context, detailing Maine's energy landscape and the specifics of the 2019 legislation. Chapter 4 describes the data used in the analysis and what specific pre-processing steps were taken. Chapter 5 details the methodology, including the econometric models and variables used to evaluate policy effects and to capture socio-political and economic influences. Chapter 6 reports the results for each empirical model. Chapter 7 provides a discussion of the implications of these results in the context of each research question and compares the results back to the findings of prior literature and Maine's unique context. Finally, Chapter 8 concludes the thesis, highlighting the main findings and their significance.

Chapter 2

Literature Review

In the early 2010s, as many RPS programs were just taking effect (Barbose, 2024), much of the literature used difference-in-difference (DiD) analyses to assess impacts on renewable capacity. Results were notably mixed. Carley (2009) examined RPS effects on renewable electricity generation across states. Using state fixed-effects models to analyze state-level data from 1998-2009, Carley found no significant immediate increase in renewable generation from RPS adoption, though each additional year under an RPS was associated with a slight uptick in renewable generation share (Carley, 2009). A dynamic treatment effect makes intuitive sense in this context, and it persists as a pattern in later literature. Given the development times associated with renewable energy projects, the results of Carley (2009) could suggest a growing effect caused by the completion of projects which were initiated shortly after RPS adoption. A year later though, Yin and Powers (2010) reported a positive effect of RPS on the share of non-hydro renewable capacity, but only when taking into account a measure of policy stringency, created by constructing an index of RPS targets. This suggested that while RPS requirements simply being present may not measurably impact renewable capacity, sufficiently stringent policies may (Yin & Powers, 2010). Other early studies also found somewhat similar results; Shrimali and Kniefel (2011) employed a similar state and time fixed effect model taking into account variations in not only RPS requirements, but also variables measuring other state level requirements. The resulting estimates aligned with the previous studies in that the effects of RPS are negligible or, in the findings of Shrimali and Kniefel (2011), even a negative effect on the share of capacity produced by renewables. These counterintuitive findings likely resulted from both heterogeneity in policies and lags in investment response (Shrimali & Kniefel, 2011). This conclusion aligns with the fact that renewable capacity, and especially utility-scale solar, was still developmentally young in many states around 2010, and RPS policies appear to have differed widely in design around this time.

Other studies at this time focused specifically on wind capacity, which was far more dominant than utility-scale solar due to the relative technological maturity of wind turbines. These studies too found no clear impact from RPS. Hitaj (2013) used county-level data from 1998 to 2007 to estimate the effect of state and federal incentives on wind capacity. Due to the size of his unit of observation, a tobit/probit model was first used to model the likelihood of existence of turbines within a county, then an instrumental variables (IV) approach to account for exogeneous variables. Again, the influence of the policies (including RPS) had no significant effect. Similarly, after utilizing Synthetic Controls Method to measure the impact of RPS on various early adopter states, Maguire & Munasib (2016) found very little evidence of renewable capacity gains attributable to RPS. Of the six states examined, only the Texas RPS was found to have a significant (and positive) effect on renewable capacity. These often inconclusive or statistically insignificant results reflect a common challenge shared by these early studies: a relative lack of longitudinal data, and difficulty in comparing a heterogenous body of policies labeled as RPS across areas which vary widely in characteristics that impact the viability of renewable energy. Within the heterogeneity of RPS and other renewable energy policy often lies policy specifically geared towards incentivizing or mandating solar development, such as solar carve-outs within RPS, or separate grants and incentives for solar. The effects of these more targeted policies have been studied as well. Steward and Doris (2014) find, unsurprisingly, that when solar development is mandated through solar carve-outs, it does have a significant positive effect on solar development, even in areas with less favorable conditions. The study also highlights the importance of foundational policies such as net metering and interconnection policies which enable easier development.

Shrimali et al. (2015) attempted to tackle the problem of policy heterogeneity by building a dataset to produce an indicator, so-called "Incremental Share Indicator", which provided a value to represent the relative stringency of a state's RPS requirements. As a result, they found that if controlling for policy heterogeneity, more stringent RPS requirements did appear to lead to more in-state renewable development. Specifically, a 1 percentage-point increase in an RPS's renewable energy target was associated with roughly a 0.28–0.29 percentage-point increase in the state's own renewable capacity share. Policy differences related to flexibility the extent to which states allowed renewable energy to be purchased from out-of-state was also highlighted as a significant source of heterogeneity across RPS designs. As expected, greater flexibility was associated with a negative impact on the amount of renewable capacity developed within a state's borders.

Similar to the earlier Maguire & Munasib (2016), Upton and Snyder (2017) used Synthetic Control Method to construct counterfactual groups for each RPS state using various measures of political leanings and gross state product values. In addition, similar to Shrimali et al. (2015), Upton and Snyder (2017) incorporated a measure of RPS stringency into their DiD analysis. Again though, just as Maguire & Munasib (2016) had, Upton and Snyder (2017) found that states with RPS did not experience a statistically significant increase in renewable generation relative to their counterfactual.

Alternatives to Synthetic Control Method have also been used in the existing literature. Wolverton et al. (2022) employed coarsened exact matching (CEM) to compare manufacturing plants in RPS states versus those in non-RPS states. After pre-matching manufacturing plants on domain-pertinent characteristics, then applying a DiD analysis, they found RPS adoption was a significant, although small influence on industrial electricity prices at manufacturing plants. The effect was especially small relative to earlier studies which also examined electricity prices (e.g. Greenstone & Nath, 2020; Upton & Snyder, 2017). By matching data at the manufacturing plant level, Wolverton et al. (2022) avoids bias caused by state-level aggregation and thus improves the precision of their estimate. This use of CEM, combined with an event study style analysis of high resolution, non-aggregated data, closely aligns with the methodological approach of this thesis.

In more recent research, econometric evaluations of renewable energy policies have focused on using newer causal inference methods to address biases inherent to traditional two-way fixed effects models like used in earlier studies (e.g. Shrimali & Kniefel, 2011; Upton & Snyder, 2017). Sun & Abraham (2021) describe issues with the standard DiD with two-way fixed effects and its ability to estimate effects on heterogenous and temporally dynamic treatments like RPS. Recent work explicitly adjusts for these issues. Consequently, following studies which use a DiD to estimate the effects of renewable energy policy use models which are robust to heterogenous treatment effects (e.g. Deschenes et al., 2023).

The most significant recent analysis of RPS on capacity investment comes from Deschenes et al. (2023). They assemble state-level data from 1990–2019 and address heterogeneous treatment effects using a DiD methodology outlined by Callaway & Sant'Anna (2021). This approach calculates year-by-year treatment effects for each "cohort" of adopters and then aggregates, avoiding the bias that can arise in two-way fixed effects models when effects change over time. Resulting, Deschenes et al. (2023) find robust causal impacts of RPS on wind power development, but do not on solar. On average, they found that an RPS policy caused an increase in wind capacity of about 600–1200 MW (a 44% jump relative to no policy), but no statistically significant effect on utility-scale solar capacity. This contrasting result is likely a reflection of the timespan of their data, as solar technology had only begun to become economically competitive with wind in the last year of the examined period (Seel et al., 2024; Wiser et al., 2024). Also notable were their findings on the speed of development after RPS implementation. Most of the wind capacity growth they observed only occurred more than five years after the policy was implemented. This pattern intuitively makes sense, especially given the long development time associate with utility scale wind energy, often taking between 3 and 8 years to complete (DOE, n.d.; Iberdrola, n.d.). It also helps explain why some earlier studies with shorter post-treatment windows found negligible effects.

Despite substantial research examining the impact of RPS on renewable energy capacity, notable gaps persist in the literature. Early studies using DiD models produced mixed results largely due to limited longitudinal data given the then recent RPS implementations and significant policy heterogeneity between states. More recent work has advanced their methodology, incorporating measures of policy stringency (e.g. Carley et al., 2018; Shrimali et al., 2015) and addressing heterogeneous treatment effects to better capture the dynamics of renewable capacity growth. However, many of the recent studies have predominantly focused on wind energy, leaving the distinct challenges and market dynamics of utility-scale solar underexplored. In addition, few studies utilize counterfactuals to estimate renewable capacity trajectory absent RPS policies for use in their analysis, instead opting to compare states while controlling for relevant features. Those which do construct a counterfactual, do so with data aggregated at the state level (e.g. Upton & Snyder, 2017), producing estimates based on less granular data that masks localized variation and introduces aggregation bias.

Chapter 3

Institutional Background and Policy Context

3.1 Solar Energy Development in the U.S. and Maine

Over the past two decades, the United States has experienced rapid growth in renewable energy generation, coinciding with both the implementation of RPS and significant technological advancements that have rendered new renewable energy solutions economically viable. These concurrent trends prompt a critical question to this research: to what extent can RPS policies be credited with driving the observed growth? RPS are state-level programs which contain policies that impose requirements on electric utility companies to supply energy from low or zero carbon sources. RPS policies vary widely state to state in structure, goals, enforcement mechanisms, and extent. The first RPS was introduced in Iowa in 1983, and they have since spread across the country. 11 states implemented their own RPS throughout the 1990s, and the proliferation of RPS continued into the 2000s. By 2019, 29 states and Washington D.C. had RPS programs (Barbose, 2024; EIA, 2024a).

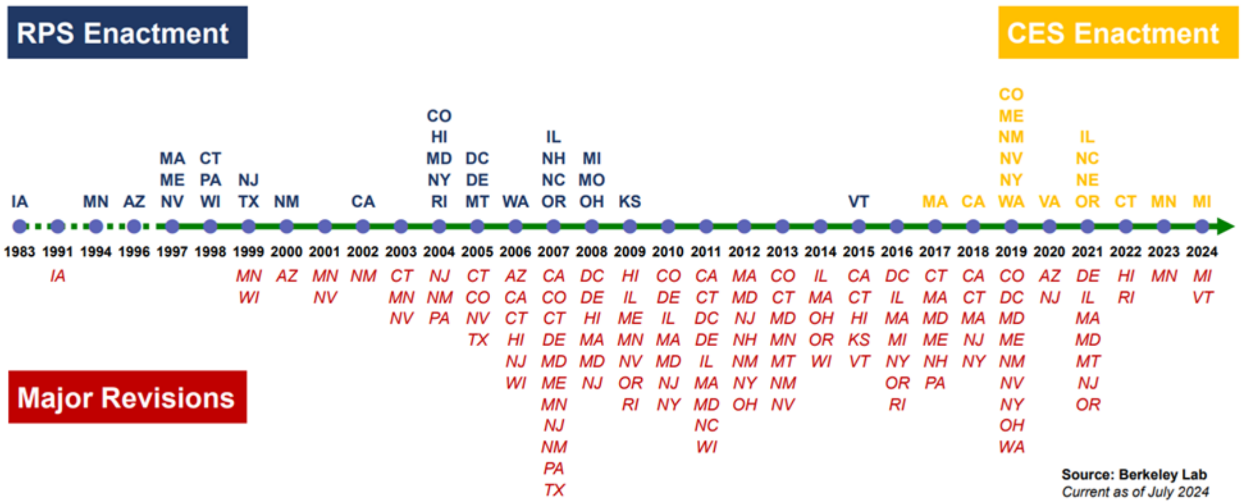

Figure 3.1: Timeline of Renewable Portfolio Standard (RPS) and Clean Energy Standard (CES) enactments and major revisions across the U.S.
Source: (Barbose, 2024)

Although roughly half of all renewable capacity added in the U.S. since 2000 is associated with state RPS requirements (Barbose, 2024), disentangling the direct impact of RPS from overlapping factors such as declining renewable levelized cost of energy (LCOE), federal policy, and technological advancements, is challenging. Early RPS policies in the 2000s were often aimed at relatively modest goals (e.g. 10–20% targets by 2015 or 2020), but over time many states raised their targets, especially in the late 2010s as concerns about climate change grew (Barbose, 2024). Significant to utility scale solar, many RPS policies have evolved to include specific carve-outs for certain technologies (such as solar), as discussed further below. In the absence of a federal RPS or other federal renewable mandates, states led the way in renewable energy policy, though federal incentives have played a supporting role. The Production Tax Credit (PTC) for wind and the Investment Tax Credit (ITC) for solar have provided crucial financial support, helping renewables compete with fossil fuels (Lips, 2024). The ITC was first implemented in 1979 and provided a tax credit worth 10% of the total value of the project, and has since been in place (with the exceptions of one month in 1990, and four months in 1992 when the policies were allowed to expire by congress), providing anywhere between 10-30% worth of tax credits to residential and commercial solar and wind projects (Lips, 2024). Overall, legislation enacted from the early 1990s to the early 2010s established the policy framework that formed the basis for RPS.

During this period, wind energy emerged as the dominant source of new renewable electricity. Improved turbine technology, economies of scale, and the PTC subsidy made wind farms increasingly economical. Wind power saw significant efficiency gains and capacity factor improvements from technological advances such as taller towers and longer blades, all while reducing costs roughly 50% over the 2000s. U.S. wind generation skyrocketed from only about 6 billion kWh in 2000 to roughly 300 billion kWh by 2019 (and has continued further to 434 billion kWh as of 2023)(Bowers, 2020; EIA, 2024a). By 2019, wind had even surpassed hydropower as the nation's largest source of renewable electricity (Francis, 2020).

This reflects both wind's rapid growth but also the stagnation of hydropower. Conventional hydroelectric capacity has changed little since the 1970s. Hydropower provided a substantial baseline of renewable generation throughout 2000–2019, but very little new hydropower capacity has been developed in the U.S. since the 1970s (EIA, 2024b).

Hydropower technology remained mature with incremental upgrades (e.g. turbine improvements) but no major capacity expansion. Overall, wind dominated new-build renewable capacity under RPS mandates in the 2000s and early 2010s, while hydropower largely maintained their legacy roles.

In the early 2000s, utility-scale solar power played only a negligible role in U.S. electricity. Solar photovoltaic (PV) technology at this time was still prohibitively expensive – median installed costs in 2010 were over 5 times higher per watt than a decade later, and most early solar development was in small-scale, distributed installations rather than large power plants (Bolinger et al., 2023). As a result, utility-scale solar contributed only a tiny fraction of U.S. renewable generation until about 2010 (EIA, 2024b). Many state RPS programs initially did not include special provisions for solar, and utilities often met RPS targets using cheaper resources (wind, existing hydro) before turning to solar (Barbose, 2024; EIA, 2024b). To kickstart solar markets, several states began to implement solar carve-outs (or set-asides) in their RPS: dedicated sub-requirements that a certain percentage of electricity comes specifically from solar energy. As of 2023, 15 states plus D.C. had solar-specific policy within their RPS (Barbose, 2024; NCSL, 2021). These carve-outs create assured demand for solar even when it was not the lowest-cost option.

Utility-scale solar installations began to appear in the late 2000s and began to slowly expand alongside an increasingly hospitable economic environment. Around 2010, the U.S. had only a few hundred megawatts of utility-scale solar, but by the end of the decade solar had become one of the fastest-growing electricity sources. It still trailed wind in absolute terms, but its growth rate was highest among renewables. In 2019, solar energy (including both utility-scale and distributed PV) was responsible for about 9% of U.S. renewable energy consumed – a relatively small share, but up sharply from near-zero a decade earlier (EIA, 2024b; Francis, 2020; Seel et al., 2024).

Maine entered the 21st century with an unusual renewable energy profile compared to most states. Thanks to long-standing hydropower dams and a sizable wood-products industry providing biomass fuel, Maine has historically generated a large share of its electricity from renewable sources. The state enacted its initial RPS in 1997 and began enforcement in 1999, requiring that at least 30% of each retail electricity provider's sales come from renewable resources, though the electric utility providers already surpassed 30% with existing hydroelectric and biomass generation (DSIRE, 2025; EIA, 2024c). To promote new projects, Maine designated a Class I RPS requirement, which mandated energy generation capacity on a schedule which ramped up 1% each year from 2008-2017 (DSIRE, 2025).

Starting around 2007, Maine experienced increased development of utility-scale wind projects, taking advantage of the wind resources on Appalachian ridgelines and the new RPS demand for renewable credits. By the mid-2010s, Maine had become New England's leader in wind generation, hosting large wind farms that helped Maine meet its Class I RPS (EIA, 2024b, 2024c). By 2018, approximately 19% of Maine's in-state utility scale electricity generation came from wind power, on top of roughly 15% from hydro and 10% from biomass (EIA, 2024b).

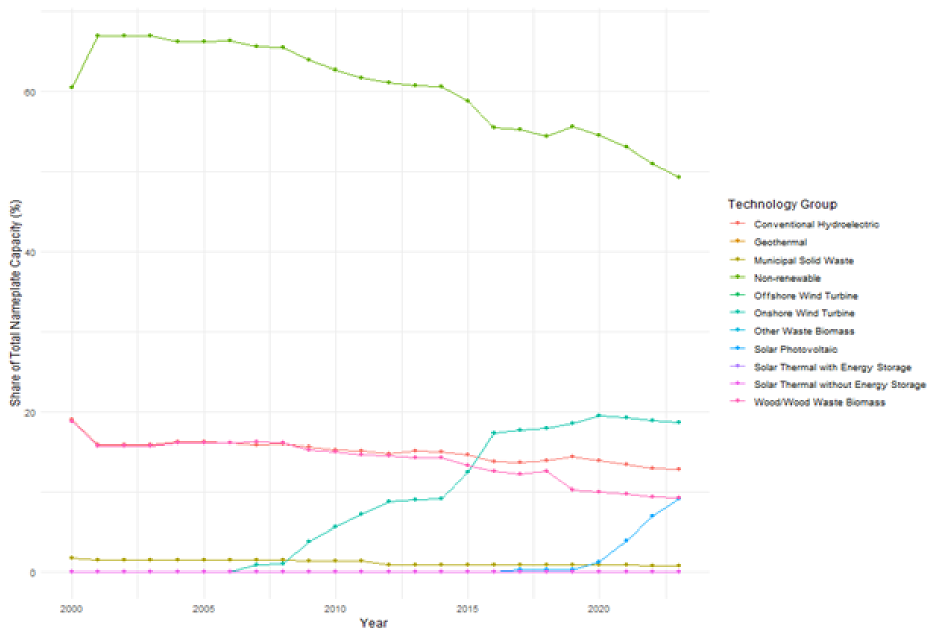

Figure 3.2: Share of total nameplate capacity (MW) in Maine by renewable technology group, and non-renewable technologies as a whole, 2000–2023. A steady decline in the share of non-renewable capacity can be seen as onshore wind and solar photovoltaic (PV) capacity being to claim a higher share.

However, solar energy played almost no role in Maine's pre-2019 energy mix. Maine's solar resource is low relative to most of the U.S. (but comparable to leading solar energy producers in Europe, such as The Netherlands) and the state had not implemented policies to aggressively promote solar development (CBS, 2024; Sengupta et al., 2018). There were no solar carve-outs in Maine's RPS, and under Republican Governor Paul LePage (2011–2018), state policies toward renewable energy were at times unfavorable. For example, Maine had a restrictive "gross metering" rule that rolled back net metering for rooftop solar in 2016 (Catherine Morehouse, 2019; Tux Turkel, 2016), and in 2018 LePage ordered a pause on wind turbine permits (An Order Establishing the Maine Wind Energy Advisory Commission, 2018). As a result, by 2018 Maine had only a handful of small solar farms. In fact, all of Maine's 99 utility-scale solar generators on record as of September 2024 were built in 2017 or later, and just three were operating before 2019 (EIA, 2024b), revealing how little solar development had been accomplished prior to the late 2010s.

3.2 Policy Changes in Maine (2019), and in the USA

In 2019, Maine enacted three landmark policies that together helped set the state's clean energy trajectory. These policies, signed by Governor Janet Mills in June 2019, received bipartisan support and marked a major shift in direction from Gov. Mills' predecessor's approach to renewable energy (Catherine Morehouse, 2019; Office of Gov. Janet T. Mills, 2019). First, Maine Legislative Document (LD) 1679 (2019) established a renewable energy and climate change plan and framework for the state. This law created the Maine Climate

Council to “assist Maine to mitigate, prepare for and adapt to climate change” and set greenhouse gas reduction targets: a 45% reduction below 1990 levels by 2030, and an 80% reduction by 2050, improving upon the original goal set in 2003 of 10% below 1990 levels by 2020(Maine DEP, 2019). It also committed Maine to achieve carbon neutrality by 2045. Though LD 1679 was primarily focused on greenhouse gas emissions and climate change mitigation, it also explicitly set goalposts for clean electricity that would be implemented through the state's RPS (An Act To Establish the Maine Climate Change Council To Assist Maine To Mitigate, Prepare for and Adapt to Climate Change, 2019; Office of Gov. Janet T. Mills, 2019).

The second and most directly related policy to renewable energy was LD 1494: An Act To Reform Maine's Renewable Portfolio Standard. This act expanded Maine's RPS in accordance with the goals set in LD 1679, increasing the required share of renewables in electricity supplied in Maine to 80% by 2030 (up from the previous requirement of 40% in 2019) and establishing a goal of 100% renewable electricity by 2050. Additionally, LD 1494 created a new “Class IA” resource category mandating a large increase in new renewable generation: an additional 40% of Maine's retail electric load must be met with new (post-2019) renewable resources by 2030 . This Class IA is in addition to the existing RPS classes (which had been 30% Class II (pre-2005 renewable capacity) existing and 10% Class I (post 2005)). To help achieve this, the law directs the Maine Public Utilities Commission to conduct long-term procurement of new renewable energy capacity by signing long-term contracts for renewable generation and energy storage totaling an amount needed to meet the Class IA targets (An Act To Reform Maine's Renewable Portfolio Standard, 2019a; An Act To Reform Maine's Renewable Portfolio Standard, 2019b; Office of Gov. Janet T. Mills, 2019). With LD 1494's passage, Maine moved from a non-effective requirement which mandated nothing more than the existing renewable capacity, to one of the most aggressive RPS requirements in the country. For comparison, as of 2022 only 15 states have a renewable energy capacity goal of 100% set, and only 7 of which have a shorter deadline than 2050 (NCSL, 2021). Thus, this 2019 RPS revision injects a much stronger demand for *new* renewables, effectively guaranteeing a market for utility-scale projects in Maine over the coming decade.

The third major policy change was LD 1711: An Act To Promote Solar Energy Projects and Distributed Generation in Maine. Though LD 1711 appears to aim for a facilitation of distributed and community solar, the incentives included in the bill overlap into the territory of utility scale solar, and in fact includes a directive aimed at procuring 125 MW of new distributed energy from “commercial or institutional customers”. Additionally, LD 1711 aimed to remove barriers that had stifled solar development in Maine. It authorized the procurement of at least 375 MW of new distributed generation, primarily solar PV, with separate programs for commercial/institutional solar and for community shared solar farms. The law also eliminated the prior cap on the number of customers who could participate in a community solar project and increased the size cap on eligible projects from 660 kW to 5 MW. In addition, LD 1711 includes provisions to ensure equitable access (e.g. requiring some community solar projects to benefit low- and moderate-income customers) (An Act To Promote Solar Energy Projects and Distributed Generation Resources in Maine, 2019; Office of Gov. Janet T. Mills, 2019).

Though LD 1711 in name appears to mainly impact distributed solar, a term generally used for installations like rooftop solar or other small capacity installations, the wide-reaching incentives provided by this bill represent a major boon to utility-scale solar, distributed solar, and community solar alike. By increasing the limit on maximum eligible project size to 5MW, it expands the support available for small utility-scale projects, now supporting projects that otherwise would not be tracked as utility scale by the EIA 860 (projects greater than 1 MW).

Maine's 2019 policy implementation occurred alongside broader trends in U.S. renewable energy policy in the late 2010s. In passing LD 1494, Maine became part of a group of states committing to 100% clean electricity by mid-century. A few examples in 2019 alone include New Mexico, which passed the Energy Transition Act (SB 489) mandating 100% carbon-free electricity by 2045, New York, which enacted the Climate Leadership and Community Protection Act, targeting 100% zero-emission electricity by 2040, and Nevada, which approved a law (SB 358) raising its RPS to 100% by 2050 (Barbose, 2024; NCSL, 2021). Thus, Maine's move to 80% by 2030 and 100% by 2050 was in line with this nationwide trend towards more ambitious climate and clean energy goals. Before the end of 2019, seven states plus D.C. and Puerto Rico had 100% clean energy commitments in place, and several others (e.g. Massachusetts in 2020) quickly followed suit (CESA, n.d.).

Chapter 4

Data and Descriptive Statistics

The goal of this section is to describe the data framework used, outline the variables employed in the analysis, and explain the rationale behind their selection. This paper consolidates various geospatial datasets into a unified raster grid. Although this approach introduces significant complexity and is far more computationally intensive than using an aggregated framework, utilizing a high-resolution grid to observe units on a highly localized level was critical to the construction of a valuable counterfactual.

Factors like land use, proximity to important infrastructure, and topography are all critical factors in solar siting, and can all vary significantly over short distances. Theoretically, two adjacent plots of land may be completely incomparable. One plot of land may have characteristics which make it very suitable for solar development (e.g. flat, near infrastructure, clear of obstructions such as trees or buildings). Meanwhile, its neighboring plot less than a kilometer away may be completely unsuitable (e.g. high slope, north facing, wetland). By using a fine-grained raster framework, the analysis captures these hyper-local differences, ensuring that the measured variations in solar capacity are reflective of the actual conditions in each area to a relatively accurate degree, avoiding aggregation bias.

To better contextualize Maine within the broader national landscape, Table 4.1 presents cell-level (for time-invariant variables) and state or region-level (for time-varying variables) differences between Maine and the rest of the contiguous United States for the continuous variables used in the analysis. Maine notably stands out in areas such as distances to important infrastructure, and average solar irradiance levels. These baseline differences highlight the structural differences that distinguish Maine from other states. These differences, along with the categorical variables used in the analysis will be discussed further in their respective subsections below.

Table 4.1: Means, Standard Deviations, and Differences (Maine – Rest of U.S.)

Variable	**Maine**		**Rest of U.S.**		**Difference**
	Mean	Std. Dev.	Mean	Std. Dev.	(Mean)
Time-Invariant Continuous Variables (Used in CEM)					
Slope (°)	3.77	2.93	4.41	5.54	-0.64
Powerline Distance (m)	22427.02	24621.73	9592.38	11854.55	12834.65
Substation Distance (m)	19819.00	19754.35	13838.66	13684.79	5980.34
GHI (kWh/m^2/day)	3.75	0.11	4.64	0.61	-0.90
Land Value (log 2017 USD/ha)	7.80	1.23	8.72	1.22	-0.92
Time-Varying Controls (Used in Models)					
LCOE Difference (2023 USD/MWh)	6.49	0.00	13.53	8.37	-7.04
Renewable Ener. Support (%)	86.45	0.00	82.83	2.46	3.62
Political Lean (%)	7.45	0.00	-6.45	18.63	13.90

Note: Time-varying control variables reflect values as of 2019, the base year used in the analysis.

The standardized raster framework used throughout the analysis has the following specifications: it spans the entire contiguous United States with 6054 rows and 9618 columns, and uses the NAD83 / Conus Albers projection (EPSG:5070). Each raster cell measures 480 meters by 480 meters. This grid serves as the foundation of the empirical analysis and allows the integration of variables from various data sources. The types of data include physical geography, land use, solar potential, energy infrastructure, and socio-political characteristics. Each dataset was reprojected, resampled, or aggregated as needed to match this spatial resolution and coordinate reference system. The specific variables selected are described below. Each variable inclusion was driven by their relevance to solar deployment and siting decisions, and will be explained in further detail in the following subsections.

4.1 Generator Data

The primary dataset used for tracking utility-scale power generation comes from the EIA-860M, a monthly supplement to the EIA-860 Annual Electric Generator Report. This dataset provides detailed information on every active and retired power generator in the United States with a nameplate capacity of at least 1 megawatt. It includes key attributes such as generator location (latitude/longitude), technology type, operational status, and nameplate capacity. The EIA updates this dataset monthly to estimate the current and near-term electric power generating capacity. However, because these updates rely on preliminary submissions and ongoing research, some reported values may be revised in subsequent releases (EIA, 2024b). The EIA-860M dataset was selected over the annual EIA-860 because it provides a comprehensive record of generators retired since 2002, whereas the annual EIA-860 dataset only includes generators retired within a given report's data cycle. As such, the EIA-860M dataset was instrumental in identifying existing and retired generators across the

United States. For the purposes of this study, only generators within the contiguous U.S. were considered.

The main variable used in the analysis from this dataset is megawatts (MW) of nameplate capacity for utility scale solar PV installations, a commonly used metric both in recent literature and in RPS legislation. It has been used in several previous studies as a main outcome variable (Deschenes 2023, Maguire & Munasib 2015, Greenstone & Nath 2019).

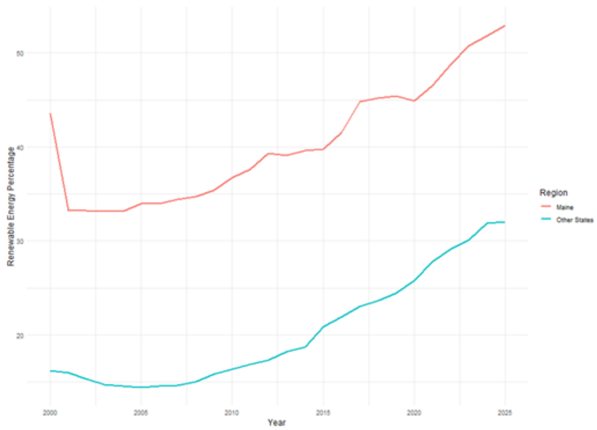

Figure 4.1: Share of renewable electricity generation in Maine vs. Rest of U.S. (2000–2024).

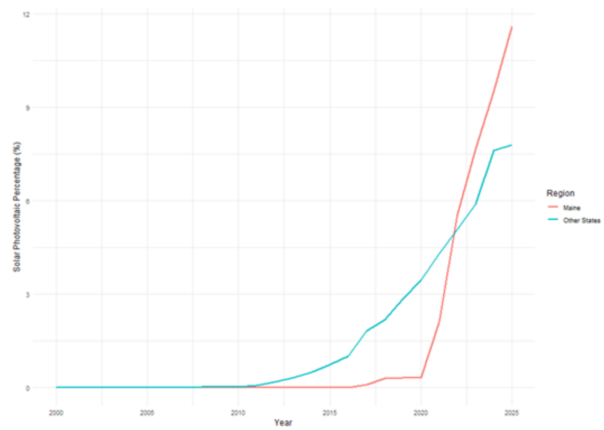

Figure 4.2: Share of solar photovoltaic electricity generation in Maine vs. Rest of U.S. (2000–2024).

As shown in Figure 4.1, Maine historically has not lagged behind national trends in renewable energy generation overall. However, as shown in Figure 4.2, while most states experienced steady growth in solar generation, Maine's solar share remained near zero until 2020, after which it rose rapidly to over 12% by 2024, overtaking the U.S. average which it had lagged behind for over a decade.

To ensure compatibility of the generator data with the framework of this study, several preprocessing steps were taken. First, generator operational periods were standardized by rounding start and retirement dates to the nearest year. Specifically, generators that began operation in the first half of the year were marked operational for that entire year, whereas those starting in the second half were counted operational from the subsequent year onward. Likewise, generators retiring in the first half of a given year were not considered as operational for that year, while those retiring in the second half were counted as operational for the full year.

Following the rounding to an annual temporal resolution, spatial filtering and standardization were performed. Generators located outside the contiguous United States were removed, and those lacking precise geographic coordinates (latitude or longitude) were excluded. The cleaned dataset was then converted into spatial point data, with each generator represented by a point placed on the map according to the generator's latitude and longitude. This data was then reprojected to align with the coordinate reference system (CRS) of the raster framework. This allowed the assignment of each generator to a raster cell according to the cell it's point overlapped with.

Lastly, the data was expanded to a generator-year panel dataset, so that every generator had a corresponding record for each year it was operational. In the final aggregation step, the generator capacities were summed by technology type within each raster cell for each year, resulting in a structured cell-year dataset. It is important to note here that this step introduced an unforeseen limitation, as 251 of the 10311 generators in the filtered dataset fell within cells that are outside of the study area due to the assumption that all build-able land would exist within the land value raster framework of Nolte (2020). Of the generators that were excluded, only 19 were solar PV, and none of the omitted solar installations are located in Maine.

4.2 Land Usage Data

Existing land usage plays a significant role in the costs associated with utility scale solar PV installation. The most cost-effective sites are generally large unshaded land areas, that do not require significant investment to achieve these characteristics. Because of this, agricultural land is predominantly favored by developers, as it is already flat and clear of large vegetation. In northeastern states such as Maine, where forest cover is extensive, including land use in this analysis is crucial when trying to compare effects across the country where there may be more suitable land to choose from. As illustrated in Table 4.2 and Figure 4.3 below, Maine's land cover profile is unique compared to the rest of the United States. In fact, according to this data, more than 75% of Maine's land area is classified as forest, compared to just 25.7% in the rest of the U.S., while land types typically more suited to utility-scale solar, like farmland and shrubland, are far less common than in the rest of the country, making up only 3.0% and 1.1% of its land area respectively, compared to 18.5% and 24.2% in the rest of the U.S.

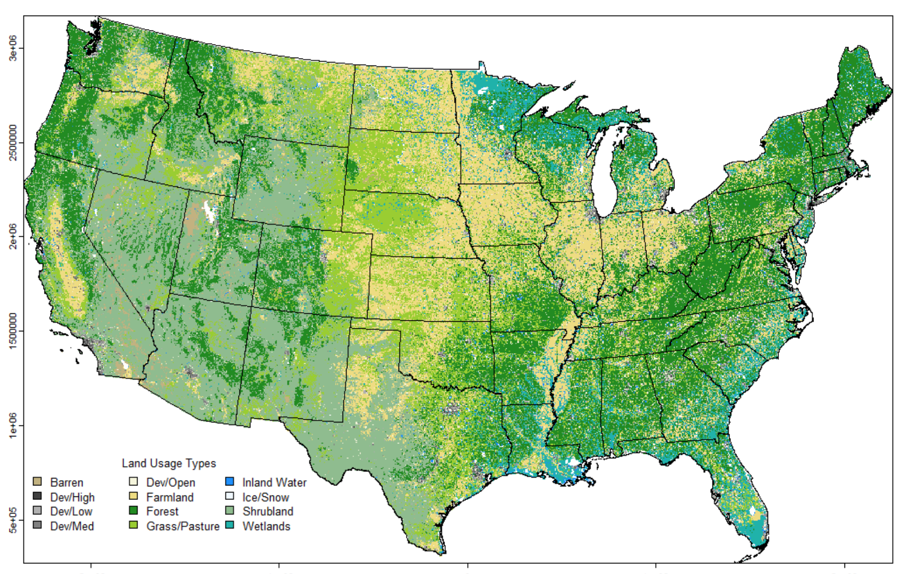

Figure 4.3: Land use classifications across the contiguous United States.

Table 4.2: Land Usage Category Percentages in Maine vs. Rest of US

Land Usage Category	Maine (%)	Rest of US (%)
Barren	0.14	1.00
Developed/High Intensity	0.18	0.38
Developed/Low Intensity	1.38	1.79
Developed/Med Intensity	0.67	1.08
Developed/Open Space	2.32	2.79
Farmland	3.04	18.46
Forest	75.24	25.72
Grassland/Pasture	1.45	17.47
Open Water	3.47	1.16
Shrubland	1.11	24.15
Wetlands	11.00	5.98
Perennial Ice/Snow	0.00	0.01

To take into consideration the relationship between land use and utility-scale solar development, this study utilizes land classification data from the 2024 USDA National Agricultural Statistics Service (NASS) Cropland Data Layer (CDL). The CDL is a high-resolution raster dataset that provides crop-specific land cover information across the contiguous U.S. using satellite imagery and agricultural reference data. This dataset has been produced annually since 1997, with full national coverage beginning in 2008.

The CDL is natively projected in the Conus Albers coordinate system and has a spatial resolution of 30 meters, making it well-suited for integration into the data framework of this analysis. The CDL raster initially contains general land use categories but breaks agricultural land out by crop. After cleaning, resampling and reprojection, the original land use classifications were categorized into broader categories.

4.3 Elevation, Slope, and Aspect

The topographic characteristics of a region, namely elevation, slope, and aspect, play a significant role in determining the economic feasibility of building solar PV and the efficiency of installations once built. Zero or near-zero slope sites are ideal for solar PV installations, and in practice, developers will generally consider sites with slopes greater than a 5 degree slope to be an untenable choice. Aspect (slope orientation) also plays an important role in siting. In the U.S. (and the rest of the northern hemisphere) a south-facing slope maximizes solar efficiency. South-facing slopes will typically be favored by developers, and in some cases allow for a higher acceptable limit on the steepness of the site (Farnaz et al., 2025; Habib et al., 2020; Islam et al., 2024). Elevation does not appear to have a major impact on siting decisions, though including elevation data does usually coincide with mountainous regions that are unsuitable due to their slope, aspect, remoteness, or otherwise.

As seen in Table 4.1, the average slope of a cell in Maine does not substantially differ from the national average, with a difference of just over half a degree. Similarly, aspect values (as shown in Table 4.3) show only minor differences in orientation between Maine and the rest of the U.S., suggesting that overall, aspect is relatively consistent across the country. However, inspection of the distribution of aspect categories reveals a notable pattern. North-facing slopes appear to be heavily underrepresented nationwide, with values close to zero in both Maine and the rest of the country.

Table 4.3: Aspect (Cardinal) Percentages in Maine vs. Rest of U.S.

Aspect (Cardinal)	Maine (%)	Rest of US (%)
E	9.50	6.97
N	0.01	0.00
NE	1.22	0.67
NW	1.20	0.60
S	34.70	40.82
SE	27.01	24.46
SW	19.38	20.59
W	6.98	5.89

This unusual distribution may stem from using only one method to calculate aspect values across a very large and topographically diverse area. The aspect raster in this study was derived using the eight-neighbor “queen” method, which incorporates elevation differences from all eight cells which neighbor any given cell. While this approach tends to perform better in rugged terrain, it may introduce classification bias in flatter regions, where slope orientation is less distinct. In areas with very low slope (flat or nearly flat) or only slight surface irregularities, the aspect calculation may be systematically predisposed to producing values which would be categorized as a southern cardinal direction. Importantly, this bias appears to be evenly distributed across the entire raster framework, as both Maine and the rest of the country show nearly identical underrepresentation of north-facing terrain. As such, while the distribution may not perfectly reflect real-world aspect orientations, it should not pose a significant threat to internal validity or the counterfactual comparison, since no region is disproportionately affected by the distortion. The elevation data used in this study was retrieved from the Shuttle Radar Topography Mission (SRTM). This dataset contains elevation data for the entire contiguous U.S. at a spatial resolution of 3 arc-seconds.

To create a continuous elevation dataset for the study area, 64 separate elevation tiles covering the contiguous U.S. were downloaded. These individual tiles were then merged into a single raster mosaic covering the entire contiguous United States. From this merged elevation raster, slope and aspect were derived. Slope, measured in degrees, represents the rate of elevation change between individual raster cell elevation values. Aspect, also measured in degrees (0° to 360° from north), indicates the direction a slope faces. Once elevation, aspect, and slope were determined for each cell, the raster was resampled and reprojected to the standard of this analysis. Additionally, aspect values were categorized into their cardinal and intercardinal directions, simplifying the analysis.

4.4 Infrastructure Distance (High-Voltage Power Lines and Substations)

The development and operational efficiency of utility-scale solar projects depend not only on geographic and environmental features, but also on proximity to electrical infrastructure such as high-voltage (HV) transmission lines and substations. The accessibility of grid infrastructure plays a crucial role in determining the feasibility and economic viability of solar energy projects. Additionally, transmission and distribution costs can impact the value of energy produced far from population centers (Greenstone & Nath, 2020).

Transmission infrastructure can be one of the costliest considerations to power plant developers when building a power plant. Grid connection costs rise dramatically with every additional foot of transmission needed – if a solar farm is sited far from the existing transmission grid, developers must build long interconnection lines, which can very quickly render the project financially unviable. As such, being near transmission infrastructure can significantly reduce upfront costs and line losses, improving a project's feasibility. Utility-scale solar farms are generally advised to locate within roughly one mile of a high-voltage transmission line, and within 2 miles of a suitable substation to keep interconnection costs manageable (Gorman et al., 2019; YSG Solar, 2020)

Historically, geospatial data on substations in the United States was publicly released by the U.S. Department of Homeland Security (DHS) through the Homeland Infrastructure Foundation Level Database (HIFLD). However, recent updates have restricted public access to this dataset. Fortunately, an archived version from 2020 is still available. This geospatial dataset contains information on approximately 80,000 substations across the contiguous United States. Unlike substation data, HV transmission line geospatial data remains publicly available through HIFLD. This dataset provides spatial information on electric power transmission lines across the U.S., including both overhead and underground lines.

From the data collected above, distance between the centroid of each raster cell and the nearest substation and nearest HV transmission line were calculated. First, the data in each dataset was filtered to only include active infrastructure within the contiguous U.S., and each were reprojected. The transmission line data was filtered to only include powerlines which were 69kV or higher, leaving only high voltage lines. The distances were then calculated and assigned to their respective cells.

4.5 Global Horizontal Irradiance (GHI)

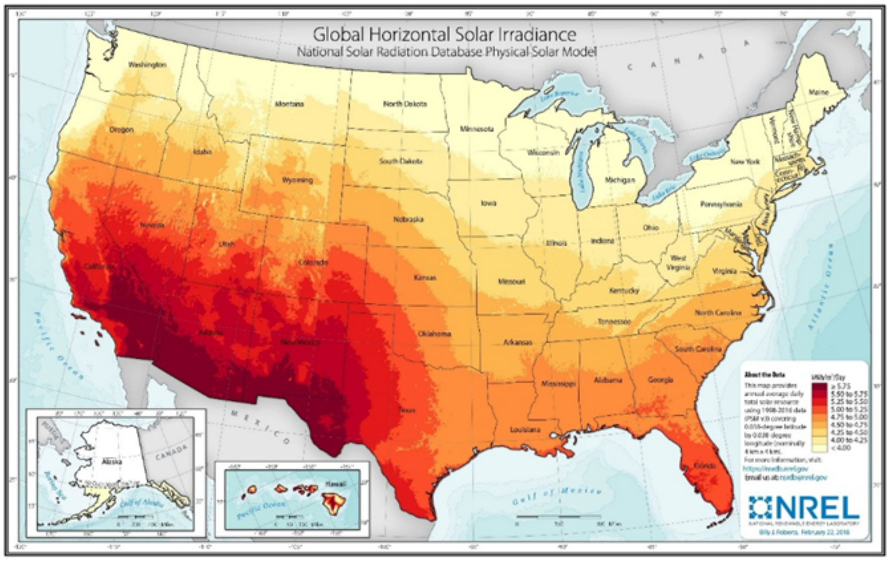

Figure 4.4: Global Horizontal Irradiance (GHI) across the United States, measured in average daily kilowatt-hours per square meter. The map illustrates the spatial distribution of solar potential, with higher irradiance concentrated in the Southwest and lower values in the Northeast and Pacific Northwest. GHI is a critical factor in assessing the technical viability of utility-scale solar photovoltaic (PV) development. *Source: National Renewable Energy Laboratory (NREL) (Sengupta et al., 2018)*

Solar resource availability is a fundamental determinant of the feasibility and efficiency of utility-scale solar energy development and is often used in RPS studies. GHI values represent the total amount of solar radiation received on a horizontal surface. Areas with greater GHI can generally achieve higher capacity factors (more kWh per kW installed), improving a project's cost-effectiveness (NREL, n.d.). To incorporate solar resource availability into the study, Global Horizontal Irradiance (GHI) data was obtained from the National Solar Radiation Database (NSRDB), a widely used (e.g. Deschenes et al., 2023; Upton & Snyder, 2017) dataset that provides long-term solar radiation estimates across the United States. The dataset contains annual average daily total GHI values (kWh/m^2/day) derived from 19 years of hourly model output (1998-2016). Maine has noticeably lower solar irradiance than most of the country. Figure 4.4 illustrates this disparity, with Maine appearing in the lighter yellow shades on the national GHI map (indicating roughly 4.0–4.5 kWh/m^2/day) compared to the deep red areas of the Southwest (exceeding 6 kWh/m^2/day).

The GHI data is originally high-resolution raster data, so it is easily incorporated into the raster framework of this study by resampling and reprojecting the data.

4.6 Land Value

Land value plays a critical role in determining the feasibility and economic viability of utility-scale solar development. Utility-scale projects require large areas, so high land prices can substantially increase project costs either through capital expenditure costs or land lease costs stretched over the life of a project, impacting a project's viability. Developers therefore gravitate toward lower-cost land to keep the levelized cost of energy competitive, and as such, many new solar farms are sited in rural or less-developed areas where land is inexpensive (Maguire et al., 2024; NREL, n.d.). To integrate land cost considerations into the study, high-resolution fair market value (FMV) estimates for private lands across the contiguous United States were obtained from a 2020 paper which used multiple datasets to create improved land value (Nolte 2020).

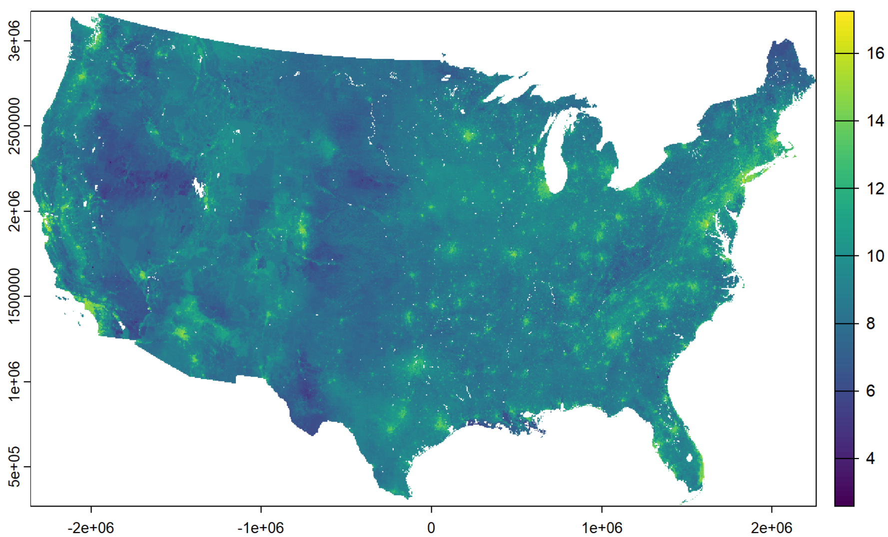

Figure 4.5: Log-transformed land value across the contiguous United States, measured in U.S. dollars.

As shown in Table 4.5, the average (log-transformed) land value in Maine is 7.80 ($2440 per hectare), compared to 8.72 ($6124 per hectare) in the rest of the United States. This difference of 0.92 log-points indicates that, on average, land in Maine is considerably less expensive than in many other parts of the country. Given the role of land cost in capital expenditure for utility-scale solar projects, lower land costs may provide an economic environment more suitable to solar development as compared to the rest of the United States.

The land value dataset was originally produced at a 480 × 480 meter resolution and utilized the NAD 83 / Conus Albers coordinate reference system (CRS). This raster framework serves as the framework which all other data collected was standardized to.

4.7 Political Leanings Data

Views on climate change and environmental protection are strongly split on partisan lines in the United States. Over the past two decades there has been a growing gap between the Democrat and Republican parties, through both a less pro-environmental shift in the Republican party, and a more pro-environment shift in Democratic attitudes(Smith et al., 2024). As of a 2020 Pew Research Center survey, Democrats are more than three times as likely as Republicans to say dealing with climate change should be a top priority (78% vs. 21%) (Kennedy & Johnson, 2020). In fact, in the case of Maine's 2019 RPS expansion, this appears to occur, with the passing of the RPS expansion coinciding with power shifting to the then recently elected Democratic Gov. Janet Mills. To account for political leanings in this study, similar to earlier studies (e.g. Carley et al., 2018; Deschenes et al., 2023; Upton & Snyder, 2017), a state-level dataset from the MIT Election Data and Science Lab was used (MIT, 2017). This dataset contains voter numbers by party for U.S. presidential elections from 1976 to 2020. For the 2024 election, data from The American Presidency Project was used (UCSB, 2024).

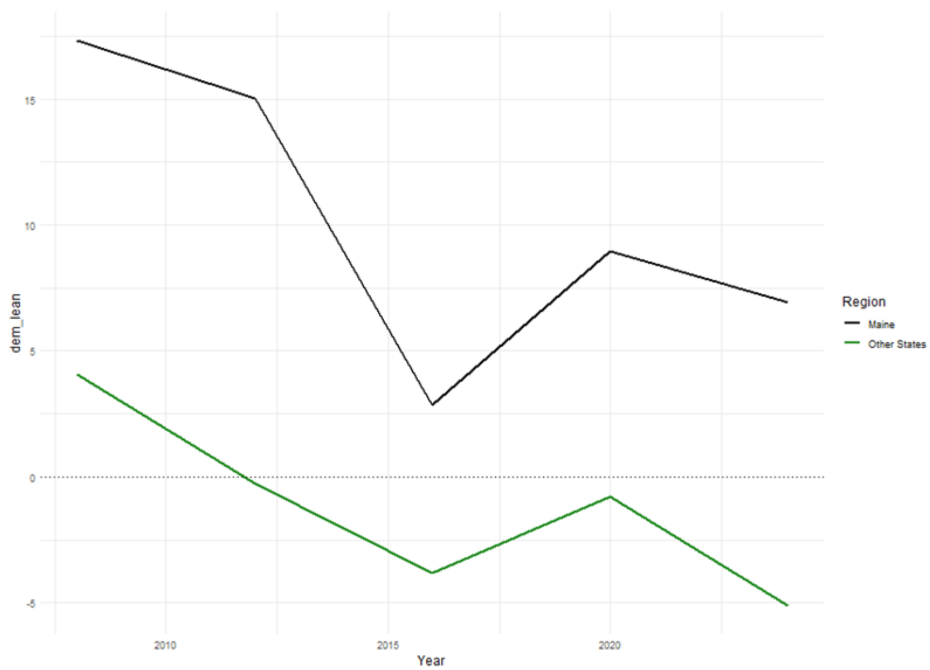

Figure 4.6: Average partisan lean based on presidential election voting, Maine compared to Rest of U.S., with a higher value indicating a higher percentage of Democratic voters.

Figure 4.6 presents the trend in political lean (measured as the difference between Democratic and Republican presidential vote share) for Maine and the rest of the contiguous United States from 2008 through 2024. The graph reveals that Maine has consistently leaned more Democratic than the national average, with values remaining above zero across all election cycles. In contrast, the average for other U.S. states dips below zero in multiple periods, indicating a modest Republican lean overall. As discussed, this difference in political climate could provide a very different environment for renewable energy development as compared to the average U.S. state, and is an important variable to control for in this analysis.

Values for non-election years were estimated using linear interpolation. To capture political lean in a single variable, the vote percentages for both major parties were calculated, and the difference between them was used to represent the partisan lean. These values were then assigned to each cell.

4.8 Renewable Energy Investment Support Data

Beyond formal politics, general public opinion and community attitudes toward renewable energy can potentially influence the success of utility-scale solar initiatives. Although opinions on environmental issues are generally divided on party lines, opinions specifically on energy efficiency and renewable energy are less polarized (Smith et al., 2024; Sydney O'Shaughnessy, 2020).

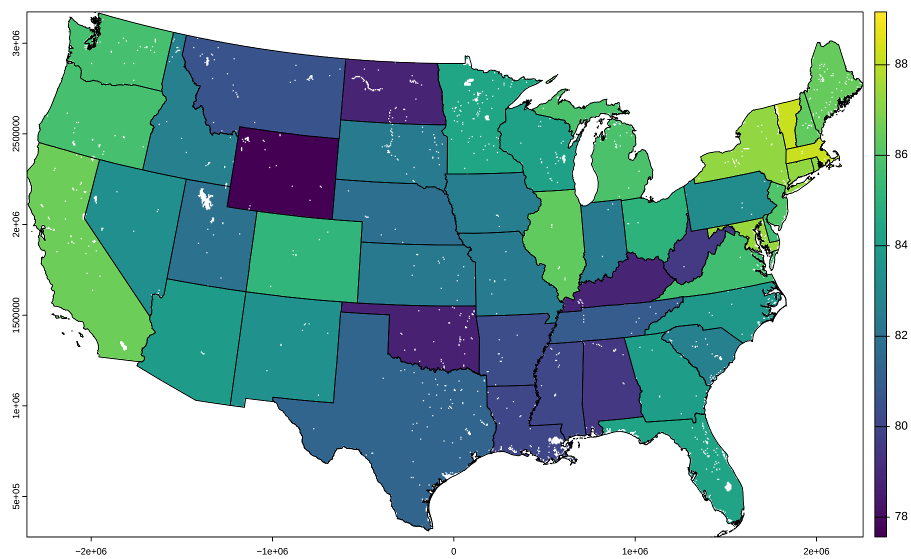

Figure 4.7: Estimated percentage who somewhat/strongly support funding research into renewable energy sources, by state. Estimates are based on survey responses from the Yale Climate Opinion Maps (YCOM) dataset.

To capture this, state-level longitudinal survey data on the support for renewable energy investment from the Yale Climate Opinion Maps (YCOM) was included (Howe et al., 2015; Marlon et al., 2022). Particularly, the variable which measures, "Estimated percentage who somewhat/strongly support funding research into renewable energy sources" is leveraged in this research. Figure 4.7 above shows the generally strong support for renewables in the United States. Nationwide, as of 2019, about 83% of Americans support investing into renewable energy research, and Maine generally trends inline or above this level.

4.9 Levelized Cost of Energy Data

The levelized cost of energy (LCOE) is a important economic indicator used to estimate the economic viability of different energy generation technologies and projects. LCOE represents the per-unit cost of electricity (usually measured in \$/MWh) over a project's lifetime, accounting for initial capital, operations and maintenance, financing, and fuel (which is zero for renewables like solar, wind and hydro) spread out over total energy generated. Incorporating LCOE into the analysis allows us to account for the economic attractiveness of solar energy. This is especially important in Maine, where wind energy has historically been the dominant new renewable, likely due to its more economically viable position. Several past studies (e.g. Greenstone & Nath, 2020; Wolverton et al., 2022), have included LCOE in their analyses, though they do critique LCOE in that it does not account for transmission and distribution costs. This shortcoming is addressed in this study by including infrastructure distance variables (section 4.4).

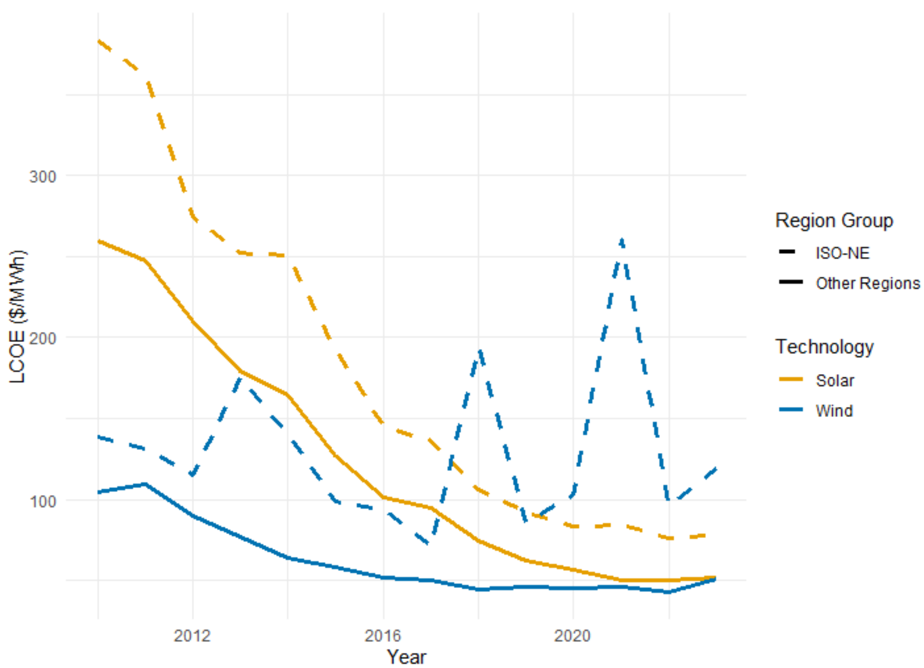

Figure 4.8: Estimated LCOE for utility-scale solar and wind across U.S. regions (2010–2023). ISO-NE (Maine's region) values are shown with dashed lines. The average value of all other regions are represented with solid lines.

The LCOE data from Lawrence Berkeley National Laboratory (LBNL) (Seel et al., 2024; Wiser et al., 2024) enables this study to reflect the significant decline in solar costs over the past two decades and the recent shift in economic competitiveness, with solar now emerging as a lower-cost option compared to wind. The LBNL datasets offers LCOE values by interconnection region from 2010 to 2023, although some regions lack data for certain years. To fill these gaps, the average percentage difference between each region and the national average was calculated and used to estimate missing values for those years. The difference between the LCOE of utility-scale solar and wind energy was calculated to create a single variable which captures the LCOE of both competing technologies relative to each other. These values were then assigned to each cell in the raster framework.

Chapter 5

Methodology

Utility-scale solar PV siting and development depends on several highly localized geographic and socioeconomic factors that can vary widely across locations. To avoid biased estimates of policy effects due to the underlying differences between Maine and control states, this study must first develop a comparable counterfactual using the spatially granular data described above. Sections 5.1 and 5.2 below describe how CEM is used to non-parametrically and efficiently construct a balanced treatment and control group prior to analysis. Leveraging the constructed groups, Sections 5.3 and 5.4 then discuss the two-way fixed effects event study framework used to estimate the growth of solar capacity growth in the treatment group which is attributable to the policy package (as compared to the counterfactual).

5.1 Coarsened Exact Matching (CEM) Approach

Coarsened Exact Matching (CEM) is a matching method that improves covariate balance between treated and control groups prior to estimation. In CEM, each continuous covariate is temporarily "coarsened" into bins, and observations are assigned a stratum based on the combination of bins their covariates fall into. Put otherwise, all treated and control observations are grouped into strata where they share identical bin values for all specified covariates. In sorting each observation into their respective stratum, each observation is matched to every other observation in the same stratum. By choosing the granularity of bins (determining bin cutpoints) the within-stratum covariate imbalance (and therefore the imbalance across treatment and control group) can be tightened or loosened. The result of CEM is a weighted dataset in which treated and control units have more balanced covariate distributions. In effect, CEM creates a subset of data which acts as a counterfactual by using prespecified covariates to pull data from a larger pool of control observations (Huffman, 2017; Iacus et al., 2022).

A major benefit of CEM is that it reduces selection bias by controlling for observed covariates in a non-parametric way (Iacus et al., 2022). Unlike propensity score matching (PSM), which most often rely on logistic regression models and balancing observations on a single score (Benedetto et al., 2018), CEM provides a simpler approach and directly balances covariate distributions through exact matching on the coarsened bins, and simply drops treated observations which do not have comparable control observations. Additionally, CEM is also computationally straightforward, an essential trait for the large dataset used in this study. These features give CEM a robustness in balancing covariates that is harder to guarantee with PSM alone.

Alternative approaches to constructing a counterfactual, such as Synthetic Control Method (SCM), have been used in RPS analyses at the state level (e.g. Upton & Snyder (2017) used SCM to match treated states with a weighted combination of control states). However, SCM is typically suggested for use with aggregate data and requires constructing a separate synthetic control for each treated unit, making it far less computationally feasible when dealing with a large number of observations (Abadie et al., 2011). Further, SCM matches units based on pre-trends of the outcome variable. Because Maine's utility-scale solar capacity trend was essentially flat and zero (or near zero) in the entire pre-treatment period, there would be insufficient information for SCM to identify matches and calculate proper weights. Additionally, given a constant pre-trend of zero, SCM would not be able to parse out what observed factors contribute most to changes in the outcome variable and would be unable to produce reliable covariate weights. As a result, SCM would likely produce a largely meaningless counterfactual. In the context of this research, where a single state's policy is analyzed using thousands of grid cells, CEM allows the usage of the large non-aggregated pool of potential control cells in other states that are available through the collected data, rather than condensing them into one synthetic index. Wolverton et al. (2022) provides a pertinent example of CEM to create a comparable control group in an RPS study. They match RPS state manufacturing plants to non-RPS state plants, then performing a DiD analysis, and note that, given a large dataset, "...we do not need to construct a synthetic control group. Instead, we use a Coarsened Exact Matching (CEM) algorithm to construct the control group.", which "...reduces the chances of significant omitted variable bias by controlling non-parametrically for observed pre-treatment differences." (Wolverton et al., 2022).

Following the same reasoning, CEM is implemented in this paper to control for observable and domain-relevant differences between Maine and other states, thereby improving the validity of our causal inference regarding the 2019 RPS expansion. CEM helps address potential selection bias where locations in Maine might systematically differ from locations elsewhere in ways that affect solar development, independent of the policy. CEM is well-suited to the fine-grained data of this study as it enables the retention of numerous control observations through many-to-many matching. Additionally, instead of depending on a regression model to adjust for extreme variance in covariate values, CEM creates comparable treatment and control groups, providing a solid foundation for a quasi-experimental analysis.

5.2 Coarsened Exact Matching Applied

The treatment group to be drawn from by the CEM in this study consists of all 480m $\times$ 480m grid cells in Maine. The control pool consists of cells in other contiguous U.S. states that did not undergo a major renewable energy policy change during the study period. To ensure that the observations in the control pool were truly "untreated", states that had RPS and/or CES policy expansions or adoptions between 2005 and 2020 were excluded prior to matching. After this filtering, the remaining control states include those with stable or no RPS policy changes in 2005–2020, providing a baseline with no treatment intervention.

Relevant matching covariates that capture factors influencing solar PV development were then selected for matching.

The following variables were included in the matching algorithm:

Table 5.1: Variables Used in CEM Matching

Variable	Description	Measurement Unit	Data Source
Land_usage_cat	Land cover classification indicating the predominant usage of the land within the cell	N/A	USDA NASS CDL
aspect_cardinal	The average primary cardinal or intercardinal direction which the slope of a cell faces	N/A	Hole-filled seamless SRTM data V4
slope	Average slope of the cell	Degrees (°)	Hole-filled seamless SRTM data V4
HVline_dist	Distance from the cell center to the nearest high-voltage (>69kV) transmission line	Meters (m)	HIFLD
substation_dist	Distance from the cell center to the nearest substation	Meters (m)	HIFLD
nsrdb3_ghi	Average daily Global Horizontal Irradiance	$kWh/m^2/day$	NREL NSRDB
landval_ln	Natural logarithm of average estimated land value in the cell	log(2017 USD/ha)	Nolte (2020)

Each continuous variable is coarsened into categorical bins designed to capture variation that would meaningfully affect siting decisions for utility-scale solar projects. The bin thresholds are informed by previous solar suitability studies (Aly et al., 2017; Majumdar & Pasqualetti, 2019) that use multi-criteria analysis to define suitability ratings based on the same or similar variables. By adopting a similar structure, the CEM ensures that matched cells are comparably suitable for utility-scale solar development. Choosing more granular bins would differentiate values which are not practically different (e.g. a slope of 1° versus 2°), and would tighten the matching requirements, unnecessarily limiting the number of matched cells left for use in the following analysis. Both GHI and land values were cut into four categories based on the quartile values of Maine's distributions for each. The slope and both infrastructure distance variables were cut into 5 categories:

Slope: <3° (ideal), 3°–5° (very suitable), 5°–8° (moderately suitable), 8°–10° (less suitable), >10° (unsuitable)

HVline_dist & substation_dist: <1km (ideal), 1–5km (very suitable), 5–7km (moderately suitable), 7–10km (less suitable), >10km (unsuitable)

After defining cut-points for coarsening, the CEM algorithm is executed, sorting each cell into their respective stratum. The resulting treatment and counterfactual groups are illustrated in Figure 5.1 below.

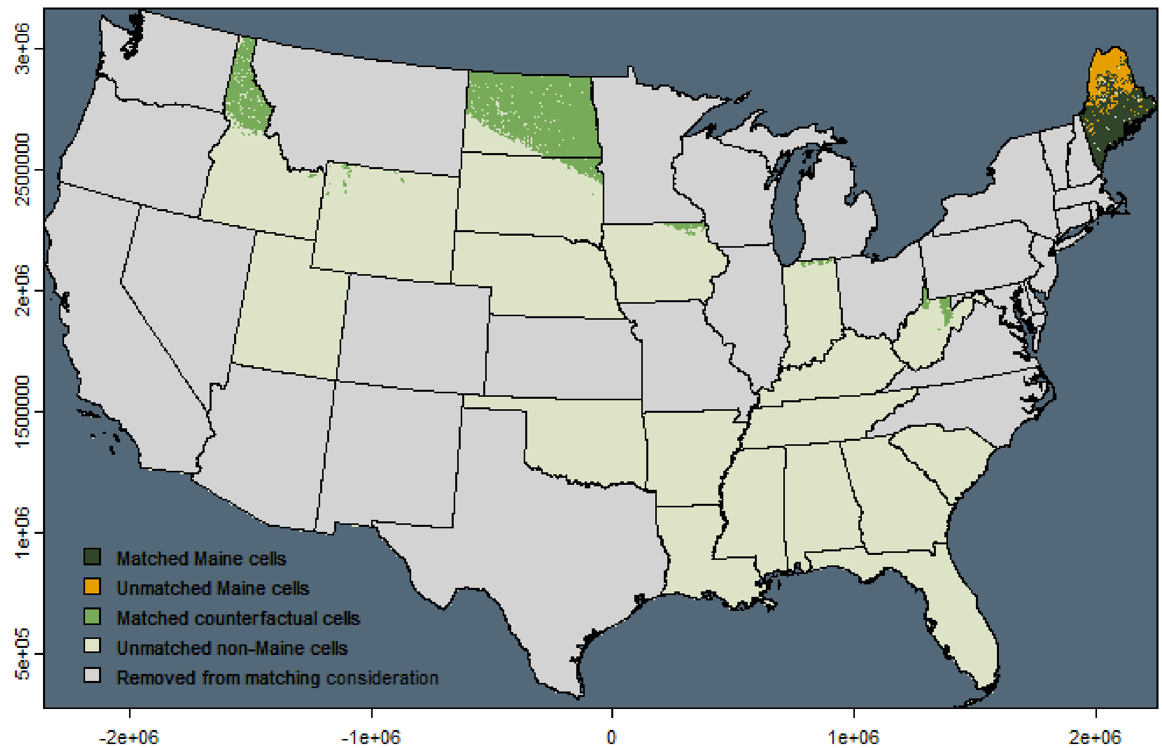

Figure 5.1: Geographic distribution of matched and unmatched cells produced by the CEM. States shown in grey are those which had a similar renewable energy policies enacted between 2005-2020, and were therefore removed from the matching pool.

Any cell with a perfectly unique set of characteristics falls into a stratum with no other cell and is therefore dropped (weighted as 0). In total, the CEM created 7949 stratum, matching 235,543 of the possible 357,339 cells in Maine (65.91%) and 927,759 of the possible 12,323,558 cells outside of Maine (7.52%). Matched control cells can clearly be seen clustered in areas that are environmentally similar to Maine. The influence of average GHI is particularly apparent, constraining matches to more northerly latitudes and following the same pattern that can be seen in Figure 4.4. This study employs the many-to-many match, retaining multiple control cells for each treated cell (and vice versa if applicable), weighted appropriately. A k-to-k (one-to-one) method was considered to avoid weighting, where each treated cell is paired with an equal number of controls, however, the weighted many-to-many matching achieved acceptable balance, and the full weighted sample maximizes statistical power.

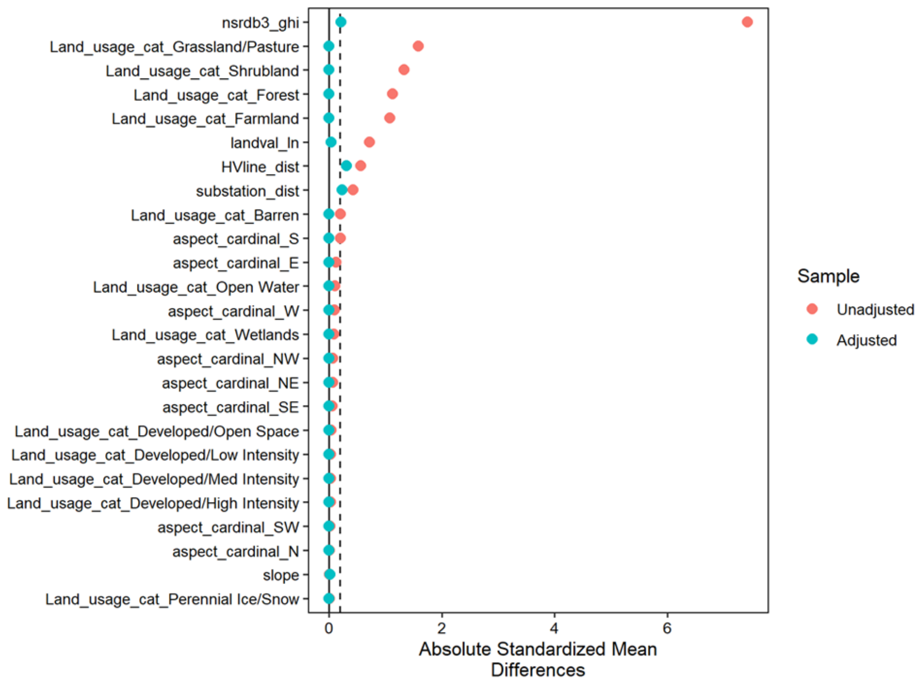

Figure 5.2: Covariate balance before and after matching using coarsened exact matching (CEM).

Figure 5.2 illustrates the standardized differences for each matching variable before and after CEM. The orange points show the absolute mean differences between Maine and control cells in the unmatched data, while the blue points show the differences between the treatment and control groups produced by the CEM. Although there is no universally accepted limit defined, standardized differences below 0.2 are safely considered sufficiently balanced (Andrade, 2020; Austin, 2011). As shown in the figure, all variables were significantly imbalanced before matching. After matching, however, the differences in all variables were brought below or nearly below the threshold of 0.2. Only nsrdb3_ghi (0.21), HVline_dist (0.30), and substation_dist (0.23) failed to achieve and absolute standardized mean difference of less than 0.2. Despite slight remaining imbalance, the CEM ensures that the variation is confined within the same categorical "suitability ratings" used in the coarsening process. In other words, while the treatment and control groups may differ slightly in these three variables, these differences are not large enough to shift observations so significantly that they would meaningfully affect solar development potential. As a result, the matched control group should still be considered a valid and comparable counterfactual for evaluating treatment effects.

Following the balance check, this CEM-weighted sample is used to estimate the causal effect of Maine's RPS expansion on solar PV capacity deployment. Any remaining imbalance should be minimal, and the regression will adjust for time trends and provide an estimate of the treatment effect that is both robust (due to matching on observables) and efficient (due to use of regression on all matched data). Matching can only account for observed variables; therefore, the analysis relies on the assumption that no significant unobserved differences exist that could bias the estimated treatment effect (assumption of no omitted variable bias)

(Iacus et al., 2022). While this assumption cannot be directly verified, its plausibility is strengthened by the extensive set of variables used in the matching process.

5.3 Two-Way Fixed Effects Difference-in-Differences (Event Study) Analysis

To estimate the causal effect of Maine's RPS expansion over time, a two-way fixed effects difference-in-differences (TWFE DiD) method in the form of an event study. Though concerns about TWFE bias exist in settings with staggered treatment adoptions, this study avoids such issues as the treatment occurred simultaneously across all treated cells. Difference-in-differences is a quasi-experimental technique that compares the change in outcomes over time between a treated group and a control group. By differencing across groups and time, it removes biases from time-invariant differences between the groups and from common temporal shocks. In a TWFE specification, fixed effects for each unit and each time period are included, consistent with past RPS studies (e.g. Carley, 2009; Carley et al., 2018; Greenstone & Nath, 2020; Shrimali & Kniefel, 2011; Upton & Snyder, 2017).

The simple DiD equation can be written as:

$$Y_{it} = \beta\,(\text{Treated}_i \times \text{Post}_t) + \gamma_i + \lambda_t + \epsilon_{it} \tag{5.1}$$

where Y_{it} is the dependent variable for unit i at time t. γ_i are unit fixed effects and λ_t are time fixed effects. The term $Treated_i \times Post_t$ is an indicator that unit i is in the treated group and time t is after the policy implementation; the coefficient β on this interaction is the DiD estimator of the treatment effect. A simple DiD model would compare Maine vs. other cells before and after 2019 to get an average treatment effect. This basic setup is equivalent to the model used in other state-level RPS studies (with state and year fixed effects) where the coefficient on an RPS policy dummy measures the average policy impact (e.g. Carley et al., 2018; Upton & Snyder, 2017). However, this formulation yields only a single averaged "post" effect, effectively deeming the treatment effect as constant over time after the policy.

To provide a more detailed understanding, an event study version of the TWFE model is used. An event study extends the DiD by allowing a separate coefficient for each time period relative to the policy change. In practice, this approach estimates several lead and lag effects, capturing how the outcome changes in each year both before and after the policy assuming a constant effect across all post-treatment years.

The TWFE event-study (for a homogenous treatment time) can be written as:

$$Y_{it} = \sum_{k \neq k_0} \beta_k \,\mathbf{1}\{t = k\} \times \text{Group}_i + \gamma_i + \lambda_t + \epsilon_{it} \tag{5.2}$$

where $Group_i$ is a dummy indicator for the treated group and $\mathbf{1}\{t = k\}$ is an indicator for year $t = k$. k_0 is the reference period and is therefore omitted in this model. Each β_k

coefficient measures the difference in the outcome between treatment and control groups in period k, relative to their difference in the reference period.

Given the context of this thesis, β_{2018} would capture any pre-policy difference in 2018 (one year before the RPS expansion), β_{2020} is the effect in the first year after the expansion, β_{2021} the second year after, and so on. Estimating these year-specific effects allows us to observe the trajectory of the treatment effect: whether there were pre-existing trends (statistically significant positive or negative trends in β_k for $k < 2019$) and how the effect evolves in the years following the policy ($k > 2019$). The inclusion of unit fixed effects γ_i means that we are always comparing each cell to itself over time (accounting for time-invariant cell characteristics), and the year fixed effects δ_t accounts for any universal changes in year t.

A critical assumption for DiD is the parallel trends assumption, where in the absence of the treatment, the treated group would have followed the same trend as the control group. We cannot test this directly, but by checking the pre-2019 values of our outcome variable (as seen in Figure 5.3 below) and the lead coefficients (pre-treatment β_k) for any systematic differences, we can estimate the existence of parallel pre-trends.

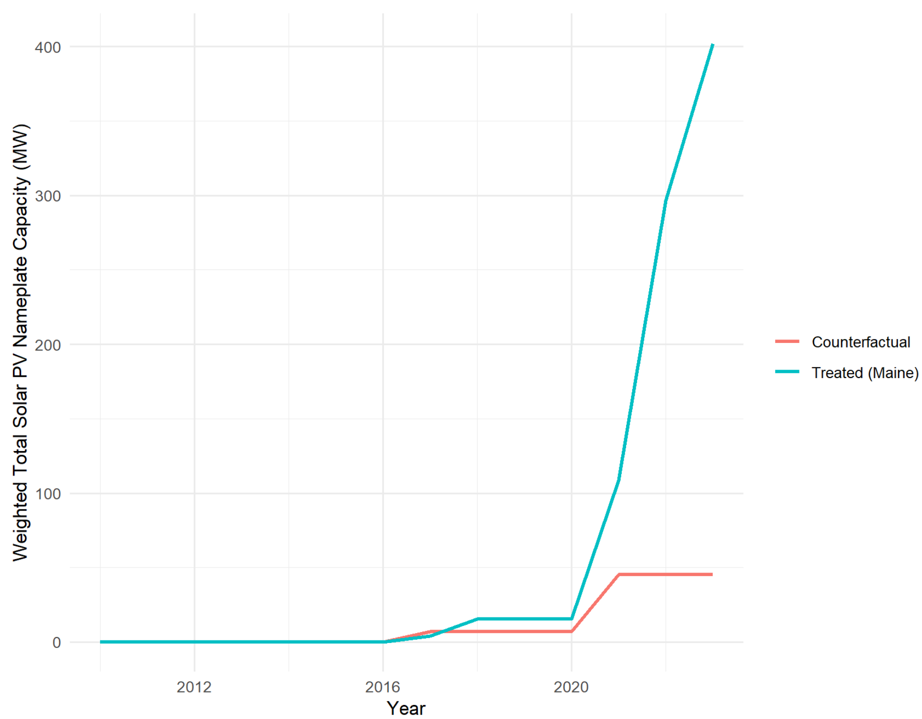

Figure 5.3: Total weighted utility-scale solar PV nameplate capacity (MW) for matched treated cells in Maine and matched control cells, 2010–2023.

An event study design also helps address the concern of treatment effect heterogeneity over time. Standard TWFE DiD can produce biased or misleading estimates when treatment effects vary across cohorts or over time (Sun & Abraham, 2021). In this analysis, there is only one treated cohort (matched Maine cells in 2019), so staggered adoption bias is not an issue. However, concern that the magnitude of the RPS effect could grow or change each year after implementation remains. Again, an event study captures that dynamic pattern rather than averaging it out. Deschenes et al. (2023) emphasizes the importance of examining dynamic effects for renewable energy policies, finding, for example, that, at least in the case of wind energy "most of the capacity additions occur 5 years after RPS implementation". This event study will similarly allow us to observe if Maine's solar capacity response was delayed or immediate.

5.4 TWFE DiD Event Study Applied

Two models are specified: Model 1 is the event study with no additional covariates, and Model 2 includes time-varying covariates as controls.

Model 1 can be written as:

$$\text{Solar\_PV}_{it} = \sum_{k \neq 2019} \beta_k \left[1\{t = k\} \times Maine_i\right] + \gamma_i + \lambda_t + \epsilon_{it} \tag{5.3}$$

where $1\{t = k\} \times Maine_i$ is an indicator for cell i being in Maine and year $t = k$ (with 2019 omitted) as described above. γ_i are cell fixed effects and δ_t are year fixed effects. This analysis uses raster cell-year level (as described in section 4). The dataset is a balanced panel of cell observations from 2010 through 2023, where each observation $Solar\_Photovoltaic_{it}$ represents the nameplate utility-scale solar PV capacity (in MW) located in cell i in year t. Simply put, this value represents the total installed capacity accumulated in a given cell for a given year. For treated (Maine) cells, $\text{Maine}_i = 1$ and the treatment begins in 2019 (so for $t > 2019$ those cells are "treated"). The control group, produced by the CEM, (where $Maine_i = 0$), did not experience an RPS expansion in 2019 and thus remain "untreated" throughout. In essence, the model is a TWFE event study with a homogeneous treatment time across all treated cells.

Following guidance from Abadie et al. (2023), standard error is clustered at the state level. Clustering by state accounts for correlation between cells which are in the same state, given the state-level nature of the RPS impacts and other unobserved influences that are common to cells in the same state. Clustering on this level avoids overly optimistic estimation confidence.

Model 2 augments Model 1 with three covariates:

$$\text{Solar\_PV}_{it} = \sum_{k \neq 2019} \beta_k \left[1\{t = k\} \times Maine_i\right] + \beta_1\, dem\_lean_{it} + \beta_2\, YCOM_{it} + \beta_3\, LCOE\_diff_{it} + \gamma_i + \lambda_t + \epsilon_{it} \tag{5.4}$$

Here, dem_lean_{it} is a measure of political leanings in the state of cell i in year t. $YCOM_{it}$ is the Yale Climate Opinion metric for renewable energy research support; specifically, "Estimated percentage who somewhat/strongly support funding research into renewable energy sources" (Howe et al., 2015; Marlon et al., 2022), in year t. $LCOE\_diff_{it}$ represents the difference in levelized cost of energy between solar energy and its major competitor, wind energy.

Including $LCOE\_diff_{it}$ accounts for the fact that Maine's solar energy growth could be influenced by falling costs, specifically in relation to wind energy. A negative value indicates that solar energy became cheaper than wind energy, a trend in many regions (Seel et al., 2024; Wiser et al., 2024). By adding these covariates (denoted by the θ coefficients), Model 2 controls for other factors that vary over time and could affect solar capacity independent of the RPS policy. If public opinion or cost trends in Maine differed from other states, those are accounted for, so that β_k in Model 2 isolates the impact of the RPS expansion net of those influences. Essentially, Model 2 aims to answer the question: controlling for political context, public support, and cost competitiveness, did Maine see a greater increase in solar capacity after 2019?

As Maine's RPS expansion was enacted in 2019, any impact on solar deployment is expected to begin from that year onward (with some lag likely for project development). In the model, 2019 serves as the baseline period – all β_k are relative to 2019, so by construction $\beta_{2019} = 0$. Both models are estimated using ordinary least squares (OLS) on the weighted matched sample, with fixed effects and cluster-robust standard errors applied as described. The coefficient estimates β_k where $k < 2019$ will inform us if Maine had any pre-policy trend relative to controls, and β_k where $k > 2019$ will tell us the size of the policy's effect in each subsequent year.

Chapter 6

Results

This chapter presents the empirical findings of the event study analyses described in Section 5.4, which evaluate the impact of Maine's 2019 renewable energy legislation on the deployment of utility-scale solar photovoltaic nameplate capacity (MW). First, Model 1 implements a two-way fixed effects event study without additional covariates, estimating separate year-specific coefficients for each period before and after 2019 to trace the policy's trajectory (Equation 5.3). Model 2 expands and improves upon Model 1 by including three covariates: political lean (dem_lean_{it}), public support for renewable energy research ($YCOM_{it}$), and the levelized cost of energy difference between solar and wind ($LCOE\_diff_{it}$) (Equation 5.4). The inclusion of the three additional covariates intend to reduce ommited variable bias and allow a more accurate estimation of the policy effects.

The results of Model 1 are plotted in Figure 6.1:

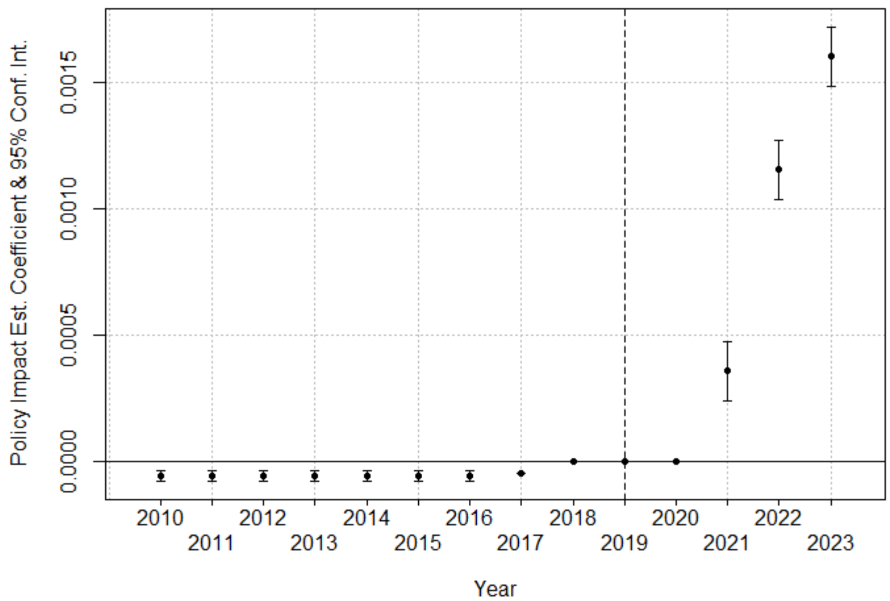

Figure 6.1: Event-study coefficient plot for Model 1, showing the estimated treatment effects of Maine's 2019 renewable energy policy package on utility-scale solar PV deployment with a 95% confidence interval shown by the error bars (2010-2023). The dashed vertical line marks the policy enactment year (2019). No coefficient is calculated for 2019.

Each point in Figure 6.1 represents the estimated coefficient β_k for a given year k, along with a 95% confidence interval. The estimates for years prior to the RPS expansion are all clustered near zero, and show a continually flat trend prior to the treatment period. This reflects the pre-trends of the utility-scale solar capacities of the counterfactual and treatment groups shown in Figure 5.3, and provides additional evidence supporting the parallel trends assumption. Around the time periods after the policy enactments though, the coefficients begin to change.

Table 6.1: Event Study Results

Dependent Variable:	Utility-Scale Solar PV Nameplate Capacity (MW)	
Model:	(1)	(2)
Variables		
2010	$-5.85 \times 10^{-5***}$	0.0002
	(8.97×10^{-6})	(0.0003)
2011	$-5.85 \times 10^{-5***}$	0.0002
	(8.97×10^{-6})	(0.0003)
2012	$-5.85 \times 10^{-5***}$	0.0001
	(8.97×10^{-6})	(0.0002)
2013	$-5.85 \times 10^{-5***}$	-2.96×10^{-5}
	(8.97×10^{-6})	(6.61×10^{-5})
2014	$-5.85 \times 10^{-5***}$	4.01×10^{-5}
	(8.97×10^{-6})	(0.0001)
2015	$-5.85 \times 10^{-5***}$	6.96×10^{-5}
	(8.97×10^{-6})	(0.0001)
2016	$-5.85 \times 10^{-5***}$	-6.86×10^{-6}
	(8.97×10^{-6})	(6.35×10^{-5})
2017	$-4.84 \times 10^{-5***}$	3.8×10^{-5}
	(2.9×10^{-14})	(9.38×10^{-5})
2018	-2.32×10^{-14}	-0.0002
	(2.8×10^{-14})	(0.0002)
2020	-2.32×10^{-14}	-5.41×10^{-5}
	(2.8×10^{-14})	(5.78×10^{-5})
2021	0.0004^{***}	2.38×10^{-5}
	(5.06×10^{-5})	(0.0004)
2022	0.0012^{***}	0.0011^{***}
	(5.06×10^{-5})	(8.43×10^{-5})
2023	0.0016^{***}	0.0015^{***}
	(5.06×10^{-5})	(0.0001)
dem_lean		7.19×10^{-6}
		(8.34×10^{-6})
YCOM_value		4.08×10^{-6}
		(5.33×10^{-6})
LCOE_difference		-1.98×10^{-6}
		(2.16×10^{-6})
Fixed-effects		
cell	Yes	Yes
year	Yes	Yes
Fit statistics		
Observations	16,286,228	16,286,228
R^2	0.18269	0.18269
Within R^2	3.25×10^{-5}	3.27×10^{-5}

Clustered (State) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

In the first full year after 2019 policy implementation, the point estimates continue to remain near zero, showing that immediately after the RPS increase, there was not yet a detectable increase in solar capacity in Maine relative to the control. This outcome aligns with expectation and is plausible given development time for new utility-scale projects that were catalyzed by the policies. Starting around 2021 (approximately 2 years after the policy) however, the coefficients become positive and statistically significant. Model 1 estimates that $\beta_{2021} \approx 0.0004$ MW and is highly significant, and by 2023 the effect grows to $\beta_{2023} \approx 0.0016$

MW. These numbers, though they appear to be miniscule, represent the additional solar capacity per matched grid cell attributable to the policy. Aggregated over many cells though, they translate into meaningful capacity. Given the number of cells in the treatment group, the 2023 estimate of 0.0016 MW per cell across 235,543 treatment cells would amount to approximately 361 MW of added capacity. In the context of the 642 MW of utility-scale solar nameplate capacity that has been added in Maine since 2019 (EIA, 2024b), this result is substantial.

The upward trend from 2020 to 2023 aligns with the expectation of a lagged policy effect, where little impact is initially seen, but the effects become more apparent a few years later as projects begin to come online. This pattern is consistent with findings in other RPS studies that effects on capacity tend to materialize with a multi-year lag (e.g. Deschenes et al., 2023). By 2023, Maine's solar capacity in the treated cells is clearly higher than it would have been without the RPS expansion, according to Model 1. Turning to Model 2, which includes covariates (shown in Figure 6.2 below), we see a very similar trend with some differences in magnitude and confidence.

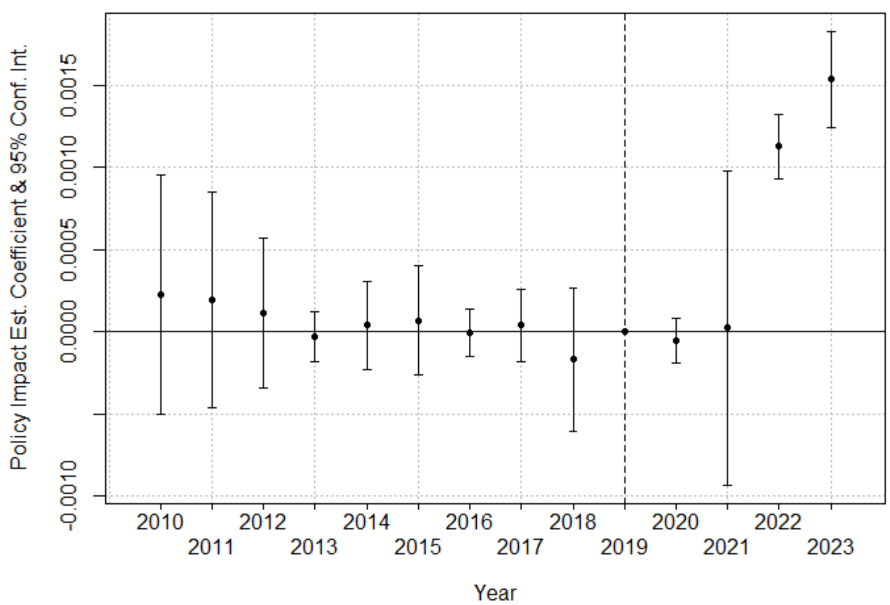

Figure 6.2: Event-study coefficient plot for Model 1, showing the estimated treatment effects of Maine's 2019 renewable energy policy package on utility-scale solar PV deployment with a 95% confidence interval shown by the error bars (2010-2023). The dashed vertical line marks the policy enactment year (2019). No coefficient is calculated for 2019.

The inclusion of political lean, public opinion, and LCOE difference controls does not massively change the shape of the estimated impact trajectory, but does introduce some differences. While a few of the pre-2019 coefficients deviate from zero and are statistically significant in Model 2, the overall pattern does not suggest a systematic violation of parallel trends, especially considering the small magnitudes and the absence of any consistent upward or downward pattern prior to treatment.

Interestingly, In Model 1, without covariates, a treatment effect appears to emerge slightly earlier in the post-treatment years (with a statistically significant coefficient in 2021). However, when including covariates to control for potential confounders, the treatment effect does not become statistically significant until 2022. Despite this change in β_{2021}, the estimates for β_{2022} and β_{2023} are very similar across both models. This could suggest that the β_{2021} estimate produced by Model 1 may have been distorted by omitted variable bias, while the somewhat consistent effects observed from 2022 onward likely reflect the true impact of the treatment. Both the 2022 and 2023 effects are highly significant in Model 2.

Intuitively, utility-scale solar nameplate capacity appears to be positively impacted by falling solar costs and a shift toward more democratic political conditions, though direct opinions on renewable energy research did not appear to have a statistically significant impact on capacity. The coefficients of the added controls reflect this. β_1 for dem_lean was positive and the β_3 for $LCOE\_diff$ was negative and significant, indicating that as solar becomes cheaper relative to the alternative of wind energy, solar capacity increases. On top of providing valuable information on the impact of these variables, by accounting for these, the policy coefficients can be more accurately estimated.

Chapter 7

Discussion

This section interprets and situates the empirical results of the analysis, connecting the observed results with the broader literature on renewable energy policy, and discusses potential implications for future policymaking. Subsection 7.1 focuses on the magnitude, timing, and robustness of the policy effect observed in both model specifications. Particular attention is paid to the event-study coefficients and the consistency between Model 1 and Model 2, which together reinforce the credibility of a causal relationship between Maine's 2019 policy package and the substantial increase in utility-scale solar capacity through 2023. This discussion also explores the role of political, social, and economic contextual factors in influencing solar deployment, as revealed through the inclusion of the covariates.

The second subsection compares these findings to existing empirical literature, particularly studies that have evaluated the effectiveness of RPS and related clean energy policies across U.S. states. Building on this, subsection 7.3 identifies several key policy implications that emerge from the analysis. These include the importance of setting ambitious and credible targets, designing mechanisms to stimulate new capacity rather than credit existing resources, and aligning complementary policies that lower barriers to project development. Finally, the last subsection acknowledges the various limitations of the study and outlines promising avenues for future research. By reflecting on these limitations and identifying directions for continued inquiry, this section aims to contextualize the contribution of the study within the broader landscape of renewable energy research and policy evaluation.

7.1 Interpretation of Key Findings

The results indicate that Maine's 2019 renewable energy policies had a clear and significant positive effect on utility-scale solar PV capacity in the state. Both Model 1 (without covariates) and Model 2 (controlling for covariates) provide similar results which show that Maine's 2019 renewable energy policies had a significant causal impact on utility-scale solar capacity deployment. According to both models, by 2023, Maine's solar capacity was considerably higher than it likely would have been without the policy, as represented by the counterfactual. Furthermore, this effect increased in magnitude each year after 2019.

Notably, the magnitude of the estimated effect grew over time. The policy's impact was negligible in the immediate aftermath of implementation but became pronounced in the subsequent years. This temporal pattern is evident in the event-study coefficients. During the pre-policy period, coefficient estimates consistently hovered near zero, reflecting that Maine and the control regions exhibited no divergent trends in solar capacity prior to 2019. In the first year after the policies (2019–2020), the estimated treatment effect remained near zero, indicating no instantaneous jump in capacity was caused by the policy implementation. This outcome aligns with expectations, considering the development timelines of utility-scale solar projects, which, despite generally being shorter than those of other technologies, still span several years from initiation to completion. Starting in 2021 though, the policy's influence appears to begin to take effect. The first signs of the effect appeared for Model 1 where the 2021 coefficient turned positive, and by 2022 and 2023 the effects became both statistically significant and progressively larger for both Model 1 and 2. By 2023, both models suggest that a large fraction of Maine's recent solar expansion can be attributed to the 2019 policy package. Aggregating the estimated impact of the policy across every matched treatment cell makes this effect apparent.

The steadily rising coefficients through 2023 further imply that the policy-driven growth may not have yet plateaued, with the effect still trending upwards in the latest year of data. Importantly, the inclusion of the controls in Model 2, *dem_lean* (the balance between republican and democrat votes in a state, reflecting political values), $YCOM$ (the percentage of people who support renewable energy research funding, reflecting social support), and *LCOE_diff* (the difference in levelized cost of energy between solar and wind, reflecting solar's cost-competitiveness) enhances the validity of these findings. Model 2's results follow a very similar post-2019 trajectory to Model 1, reinforcing the robustness of the positive policy impact even after accounting for differing political, social, and economic contexts. As mentioned though there are slight differences between the two models in the timing of the effect's emergence. Without covariates, Model 1 estimates a relatively small, but statistically significant uptick in policy impact on utility-scale solar capacity as early as 2021. In Model 2, the coefficient for 2021 is no longer significant and the first statistically significant increase appears in 2022. This suggests that the modest 2021 increase observed in the simpler model may have been influenced by underlying local conditions. It is possible that areas in Maine which were already politically inclined toward renewables or had more favorable economics might have seen earlier growth. Once those influences are held constant in Model 2, it appears that it took about two years for the policies' effect to fully materialize in new capacity installed and online. Again though, by 2022 and 2023 both models converge to very similar (and statistically significant) estimates of the policy effect. The agreement of the two specifications in the magnitude and significance of the 2022–2023 impact reinforces confidence that the identified increase in solar capacity is indeed driven by the policy intervention rather than other variables.

For the most part, the estimates of the control covariates in Model 2 further corroborate the logic of their inclusions. The positive coefficient of *dem_lean*, indicates that, all else equal, areas with stronger Democratic voting tendencies saw greater solar capacity growth, staying consistent with the notion that pro-environment political environments are more conducive to renewable development. The *LCOE_diff* variable is estimated with a negative and significant coefficient, again fitting the expected outcome. A lower (or negative in particular) LCOE difference value here indicates that utility-scale solar energy is cheaper than wind, the main (and historically dominant) competitor to filling new renewable energy goals. Unsurprisingly, all else equal, the coefficient shows that a drop in this relative cost of utility-scale solar energy is correlated with an increase in an area's utility-scale solar capacity. In contrast, the measure of renewable energy research funding support does not show a significant independent effect on utility-scale solar capacity after controlling for the other factors. This could imply that more general public support is less directly translated into utility-scale project deployment than are concrete economic and political factors, or it may simply be that YCOM is correlated with *dem_lean* such that its unique contribution is hard to disentangle. Regardless, by including these granular controls, Model 2 accounts for key local determinants of solar investment – political inclination, community support, and cost competitiveness – and therefore isolates the policy's impact more cleanly. The consistency of the main policy coefficients between Model 1 and Model 2 (especially in 2022 and 2023) suggests that any omitted-variable bias in the simpler model was fairly minor, and that the matching procedure was effective in creating a credible counterfactual.

Taken all together, the outcomes provide strong evidence of a causal link between Maine's 2019 policy trio and the accelerated growth of utility-scale solar capacity in the state. The combination of the highly granular matching to create a representative counterfactual, along with an event-study which controls for time-varying covariates lends credibility to this inference. While some differences emerged in the precise timing of the effect's onset, both models converge by 2022 to show a large, statistically significant policy-driven increase in solar capacity, that is robust to political, economic, and social contextual factors and consistent with expectations based on solar development timelines. Following, the next sections compare these findings to the outcomes of prior studies, explore their implications for future policy design, and reflect on the study's limitations and directions for future research.

7.2 Comparison with Existing Literature

The results of this thesis both confirm and expand upon the findings from previous studies on renewable energy policy over the past two decades. A significant portion of the literature has focused on the implications of the heterogeneity of RPS implementation, the impact of project development on effect lag, and the ability of utility companies to effectively meet RPS requirements through economically viable resources.

As noted, early empirical evaluations (Carley, 2009; Shrimali & Kniefel, 2011; Yin & Powers, 2010) often found weak or no immediate impacts of RPS on renewable generation. Due likely to the examination of a later period and a strong policy implementation (especially in relation to early RPS), this study provides an outcome counter to those early studies. Later studies acknowledge the importance of these conditions as well (Carley et al., 2018; Deschenes et al., 2023; Greenstone & Nath, 2020; Maguire & Munasib, 2016; Shrimali et al., 2015). Throughout these papers, various features like in-state requirements, solar carve-outs and renewable energy credit trading rules are discussed as impactful to a meaningful analysis. Carley et al. (2018) goes so far as to develop a measure of RPS stringency to explicitly control for the heterogeneity. Maine's 2019 policies act as a case study of a stringent, well-designed policy, incorporating several best-practice elements: effectively enacting in-state requirement for new generation via Class IA and state procurement of community solar, and supportive policies like net metering and streamlined permitting to complement the

RPS. This multifaceted approach in Maine reflects the idea that a combination of policy instruments often works best. The importance of this is particularly exemplified by Maguire & Munasib (2016), who despite concluding that RPS generally did not influence renewable energy capacity, indicated that one state at that time, Texas, succeeded partly due to its transmission investments, properly complementing the RPS. In Maine, the already ambitious RPS update (LD 1494) was complimented by the facilitation of distributed and community solar (LD 1711) to help meet RPS goals, and the establishment of the Maine Climate Council (LD 1679) to keep broad support and planning in place. The results of this paper cannot parse out the effect of each act individually, but the overall effect indicates the synergy of these policies.

As previously noted, an important contribution of this research is its focus on a more recent period which captures key policy and technological advances that earlier studies, which were limited to earlier time frames, did not observe. The significance of this limitation is exacerbated by the lagged nature of renewable policy effects. Deschenes et al. (2023) found that (for wind energy), most capacity came about 5 years after RPS adoption due to project development times. This thesis similarly indicates that Maine's solar capacity ramped up over a few years, and it's plausible that even more capacity will come online in 2024–2025 as a result of the 2019 policy. The trends shown in the coefficients of Model 1 and Model 2 (see Figure 6.1 and Figure 6.2) suggest the impact was still growing through 2023, and that the full effect may yet be seen. Evaluations of RPS (or any renewable policy) should consider a sufficiently long horizon. Using the September 2023 EIA-860M caught only approximately four years of data post-policy, though fortunately; given the relatively short development runway of solar, it was still possible to observe some policy effect.

Though there is some limitation shared with past literature regarding the temporal scope of the data used, this study also improves on past literature by implementing a highly granular raster framework. This approach improves spatial resolution and captures characteristic variation far beyond the state-level analyses seen in previous literature. Only Hitaj (2013) used more granular data, opting for county-level observations. This granularity enhances the ability to construct a credible counterfactual. While several previous studies (e.g. Maguire & Munasib, 2016; Upton & Snyder, 2017) developed counterfactuals using highly aggregated data, this analysis leveraged CEM to match treatment and control cells on relevant characteristics at a small scale. By doing so, this study more precisely develops a counterfactual and minimizes heterogeneity between treatment areas substantially. As a result of an improved counterfactual, the proceeding causal inference is strengthened.

In summary, the findings of this thesis largely align with past literature, while providing up-to-date and highly granular data that highlights the importance of policy design and political and economic context. Maine's case adds evidence that under the right conditions renewable energy policy can create significant impact on renewable energy within a state. It validates arguments like those made by Shrimali et al. (2015) that RPS can work when tailored properly, and it offers a successful case to compare against the less successful ones documented in literature. This kind of case study approach was even recommended by Shrimali et al. (2015) as a follow-up to their work, and indeed Maine appears to serve as a valuable case to study how a combination of factors yields a positive outcome.

7.3 Policy Implications

The outcomes of this research carry several implications for energy policy makers and conscientious voters aiming to support renewable energy growth, both within and outside of Maine.

The clearest implication of the results is that specific renewable energy policy design may have a large impact on the policy's effect. Though this study cannot isolate the effect of any individual policy component, Maine's experience suggests that setting ambitious targets (80% by 2030, 100% by 2050) and including provisions for new capacity (Class IA) may stimulate capacity growth. Policymakers should consider raising RPS targets to levels that truly challenge the market rather than enacting easy-to-meet (or already met, like initially done in Maine) targets that credit existing facilities. Furthermore, incorporating carve-outs or sub-targets for new projects help prevent simply reallocating old resources and instead ensure that additional capacity is built. Again, Maine's renewable energy class distinctions create a guaranteed market for new renewable projects. However, when designing such stringent command-and-control type policies, there must be consideration taken for a realistic implementation timeline. Maine's target is aggressive but provided a more than 10-year runway for utility companies to hit the set goal.

In addition to the RPS expansion, Maine's success may have been aided by complementary measures that systematically alter the energy production and transmission environment (e.g., net metering expansion, removal of size caps, procurement of community solar). For solar specifically, facilitating grid interconnection and financing for projects is crucial. States governments can implement standardized interconnection rules, offer financing support, and update land use regulations to accommodate utility-scale renewables. The overarching point here is that a systemic approach to policy that aligns renewable portfolio standards, utility regulations, and local incentives may yield better results than any single policy in isolation.

Lastly, one of the more unique insights of this study relates to the role that small or community utility-scale solar plays. Like done through Maine's LD 1711, which focuses on incentivizing solar projects smaller than 5 MW, actively cultivating small renewable projects may have significant impact. An extraordinary 87 of the 96 solar farms built since the implementation of the policies have been 5 MW or less, accounting for approximately 54% of all new solar capacity (EIA, 2024b). This suggests that community-scale projects can be rapidly deployed and may better suit energy needs in a context similar to Maine's. The localized nature of such projects may also mitigate potential opposition related to land use and visual impacts, as community members are more likely to support projects from which they can derive direct benefits. This idea aligns with prior research (e.g. Steward & Doris, 2014; Taminiau et al., 2022) which describes how policies emphasizing smaller-scale, community-focused renewable projects tend to generate higher local acceptance and drive significant capacity additions. Therefore, the policy implication here is to design incentives and lower regulatory barriers for small-scale utility solar development, not just large-scale.

7.4 Limitations and Directions for Future Research

The findings should be interpreted with caution given the following limitations. The use of high-resolution data and CEM is a strength, as it addresses many observable differences between treated and control areas. However, focusing on a single state limits generalizability. Maine has certain unique characteristics (considerable forested land, a relatively small population, a history of high renewable usage from hydro and biomass, etc.) that may impact results for a more urbanized state attempting a similar solar expansion. In addition, the use of CEM necessarily excludes some treated cells that cannot be adequately matched to a comparable control, resulting in an analysis based on a subset of Maine that is similar to the constructed counterfactual. While the results remain informative for assessing the causal impact of the policy, they truly reflect outcomes for a "matched Maine" rather than the state in its entirety. Future research could apply a similar methodology to multiple other states that implemented renewable energy policies, to see if the results seen for Maine hold.

Another limitation is the time frame of analysis. Only roughly 4 years of post-policy data was examined. While this captures the immediate impact, the longer-term effects remain uncertain. It's possible that Maine experienced a short explosion in solar development as "low-hanging fruit" projects were built, and that growth could plateau afterward if the most economically viable sites have been taken. If, for example, LD 1711 was responsible for a significant amount of the solar development due to its procurement mandates which expired in July of 2024, future development may start to flatten. Alternatively, the development already seen could be the start of a steady climb towards the 100% goal in 2050. Only further years of data can distinguish between an initial burst and a sustained trend. Therefore, future research should look at a longer horizon to assess longer-run outcomes. This would also allow the examination of whether any backlash or saturation occurs.

This study also did not explicitly account for spillover effects. Though the Maine policies do explicitly legislate for in-state renewable energy development, as considered by Carley et al. (2018), it's possible that Maine's policy had regional effects, or that other state policies had effects on Maine's solar capacity. Including the difference in LCOE between wind and solar for each region may provide some control for this effect given the potential impact of state policies on LCOE, but this certainly does not negate spillover.

Another limitation to acknowledge is the assumption that the CEM and TWFE DiD fully accounted for potential confounders. It is certainly possible that some unobserved factors changed in and around 2019 in Maine which could bias results. The covariates used, focused on political lean, renewable energy attitudes, and cost-competitiveness, which were central to the research questions. However, other socio-economic factors could also be important and may have helped better answer these questions. Additional covariates which may impact treatment assignment, or the magnitude of the treatment effect could improve the precision of the results. Likewise, (natural and built) environmental variables like land values, solar irradiation, or proximity to transmission lines are critical drivers of solar project siting. While the CEM does control for these factors, future studies which explicitly examine land suitability and availability across the United States using multi-criteria analysis (similar to that of Majumdar & Pasqualetti (2019)) would be of great value.

Additionally, the scope was limited to utility-scale solar nameplate capacity as the outcome. This was appropriate given the policy focus (L.D. 1711 targeting 660 kW - 5 MW community solar, L.D. 1494 and 1679 aimed at utility-scale renewables). However, these policies almost certainly also had effects on other outcomes such as distributed rooftop solar adoption or wind energy development. Taking these into account in some way may have been prudent, as even if not considered as an outcome during the analysis, another level of "spillover" could have been taken into account by considering the level of energy demand or RPS requirements fulfilled by other sources. Future work could broaden the lens to examine a larger group of outcomes. How did the policies impact the broader renewable energy mix, or what was the effect on greenhouse gas emissions? How did the cost to consumers change after implementation?

Lastly, the CEM provides a suitable counterfactual, but can be administered with many different cutpoints and variables, creating some uncertainty in the matching process. Alternative binning methods, both data driven and theory driven, (including automatic binning rules such as Sturges' rule, Freedman-Diaconis' rule etc.) were considered and basic balance checks were used to evaluate the match, but given ample time and computing power, a sensitivity analysis could likely provide valuable information on the robustness of the analysis to different matching specifications, enhancing the credibility of the estimates.

Chapter 8

Conclusion

In conclusion, this study finds that Maine's 2019 renewable energy policies triggered a substantial expansion of utility-scale solar capacity in the state. In the years immediately following the policy changes, solar development accelerated far beyond historical trends and beyond what would be expected without the policy interventions. By comparing Maine's growth to a no-policy counterfactual, the analysis shows a clear effect between the three 2019 policies passed in Maine are linked with a substantially higher amount of solar capacity than would have occurred otherwise.

This outcome directly answers the question this paper set out to answer, demonstrating that the new policies had a large and significant effect on utility-scale solar PV nameplate capacity growth. The state's updated aggressive Renewable Portfolio Standard and the solar-specific incentives created a strong environment for project development. This finding aligns with past literature suggesting that stringent, well-designed renewable policies can have a significant impact on renewable energy deployment (Shrimali et al., 2015). In Maine's case, what had been one of the slowest states to adopt solar energy quickly became a regional leader, indicating that policy commitments like those made in LD 1679, LD 1494, and LD 1711 can rapidly change the trajectory of renewable energy adoption.

The role of political preferences and renewable energy opinions emerged in the context and results of this paper as well. The inclusion of political, social, and economic control variables helped to isolate the effect of Maine's 2019 renewable energy policies and provided additional insight into the broader conditions that shape solar development. The results revealed that areas with stronger political leanings towards the Democratic Party were positively associated with the level of utility-scale solar capacity, suggesting that local political opinions may play a role in the realization of state-level policy goals related to solar and potentially other renewable energy sources. Maine's political environment appears on the surface to support the idea that political ideologies are related to renewable energy development. The political shift from a governor who opposed many renewable initiatives to one who championed them was seemingly a critical enabling condition. The bipartisan nature of the passage of the 2019 bills indicates a broader political will, but the analysis confirms that a partisan alignment does exist with renewable energy goals. This is consistent with broader studies that emphasize government ideology and leadership as drivers of renewable outcomes (Carley et al., 2018; Upton & Snyder, 2017). In contrast, the measure of attitudes toward renewables given by the Yale Climate Opinion Map survey did not show any significant relationship with utility-scale solar deployment in the model, potentially suggesting that there may be some level of systemic misrepresentation or disconnect stemming from the limitations of a two-party system, where opinions like renewable energy preferences are marginalized due to structural polarization and are therefore more isolated from general societal actions than expected. While general public support for clean energy might be relatively high, it is the concrete actions of political actors which translate public support into change. Given the change in governors and therefore the controlling party, the socio-political landscape in Maine proved mostly supportive.

The economic context also proved to be an important underlying factor. Over the 2010s, the cost of solar photovoltaics plummeted, and by around 2019 the LCOE of utility-scale solar had become consistently competitive with or lower than that of onshore wind in many markets, including New England, where Maine is located. The analysis confirmed that this cost-competitiveness has a significant relationship with the solar deployment in Maine. This outcome was unsurprising, and suggests that developers may have reacted to favorable market conditions. As solar became cheaper relative to the previously dominant new renewable energy source in Maine, onshore wind, the state also began to see additional solar capacity being built. These parallel trends cannot draw a causal relationship between the two factors, but does align with the expectation that mandated renewable energy development would be met with the most economically cost-efficient method. In Maine, the timing was fortuitous for solar, as the 2019 policies came into effect just as solar prices fell and efficiency improved, pulling the economic context towards conditions correlated with more utility-scale solar development.

For policymakers in Maine and beyond, these findings carry several important implications. Maine's 2019 effective renewable energy strategy can serve as a model for other states seeking to boost their clean energy sectors. Although the results are not without limitations, and cannot parse out the individual effects of each piece of legislation, it does suggest that the multi-faceted policy approach used in Maine was effective in achieving its goal. Combining mandated long-term targets with enabling measures (such as procurement plans for new projects, and removal of barriers to community solar development) appear to have created a strong environment for investment. States aiming to replicate Maine's progress should consider not only raising their renewable targets but also adopting complementary policies that address common bottlenecks in development, often related to permitting, power grid capacity and connection limitations, as well as financing options for both utility-scale and distributed projects. Additionally, Maine's surge in solar capacity was substantially driven by projects in the 1–5 MW range. These could have been motivated by the incentives and facilitation of LD 1711, indicating that smaller and community solar can scale up rapidly when given the opportunity. Thus, policy designs that encourage a mix of project sizes (rather than focusing solely on large utility-scale solar farms) may achieve faster and more broadly distributed gains.

For future research, an extended post-treatment timeframe and continual monitoring of Maine's solar trajectory in the coming years would provide even more valuable results. As more data become available, researchers can assess whether the initial surge is sustained, and how various other emerging trends and challenges (e.g., grid congestion or evolving net metering rules) might affect the growth trend. Additionally, another valuable avenue would be to apply the high-resolution data and methodological framework of this study to multiple other states, like done so often in earlier literature. Such comparative studies could employ CEM like used here to build counterfactual scenarios and test the generalizability of Maine's outcomes. A wider focus on multiple power generation technologies would also offer even more information and bolster the results of this study. Continued study of Maine's and other state's clean energy transitions can not only benefit state policymakers but also enrich the broader understanding of how climate and energy policies can be designed to achieve specific and effective results.

In closing, Maine's deployment of utility-scale solar power since 2019 stands as a great example of effective policy-driven change. This thesis has shown that the trio of 2019 renewable energy laws passed, along with a favorable socio-political climate and accelerating technological progress resulted in a substantial increase in solar capacity in a short time. By systematically evaluating the outcome of this case, the study contributes evidence that a detailed and multi-faceted policy coupled with supportive context can unlock rapid growth even in a technology which had severely lagged in development. As governments hopefully continue to strive to meet climate goals, the lessons from Maine highlight the power of ambitious targets, supportive policy, and market-ready mature technologies working in tandem. Maine's progress as of 2023 is encouraging, but the ultimate measure of these policies' impact on utility-scale solar will be the ability to sustain and build on these gains in the coming years.

Declaration

I acknowledge the use of ChatGPT (https://chat.openai.com/) and Writefull (https://writefull.com/) to improve my understanding of complex topics, improve the quality and flow of the text, debug R and LaTeX code, and assist in creating data visualizations and tables.

Code Availability

All R code for data collection, cleaning, matching, analysis, and figure generation can be accessed at https://github.com/CRwag/WURthesis.

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