# Policy Uncertainty, Market, Political Polarization, and Utility-scale Solar in the United States

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## Abstract

We examine the effects of economic policy uncertainty (EPU), market deregulation, and political polarization on the utility-scale solar electricity generation in the United States. Using state-level data from 2000 to 2023 and a negative binomial fixed effects model, we find a significant negative relationship between EPU and annual solar electricity generation. On average, a one-unit increase in the EPU index is associated with a 716.51 megawatt-hours (0.14%) decline in expected solar electricity generation annually, likely due to investor risk aversion. While existing studies are on the national level, this study is the first one documenting the impact of EPU at the state-level. Conversely, states with a 1% higher percentage of voters for the Democratic Senate nominees is associated with a 29,990.92 megawatt-hours (5.86%) higher solar electricity generation annually, reflecting the party's strong support for renewable energy. Finally, deregulated electricity markets are linked to a 211,778.91 megawatt-hours (41.38%) increase in annual solar electricity generation compared to regulated markets. Based on these findings, we suggest that policymakers should prioritize reducing policy uncertainty, foster bipartisan support, and encourage market deregulation to boost investments in utility-scale solar electricity generation.



**Keywords:** Economic policy uncertainty; market deregulation; political polarization; solar energy.

**JEL Codes:** D81, P48, Q42.

## 1 | Introduction

The urgency of clean energy transition in the United States (US) has driven by the need to achieve net-zero carbon goals by 2050 (Li & Gou, 2024). To achieve this target, the utility-scale solar has become economically attractive for the US as a solution to clean energy transition due to its technological improvements and declining costs (Benalcazar et al., 2024). Large investments like utility-scale solar thrive on a country's overall stability. Investors seek predictable policies, unhindered market access, and a politically harmonious environment (Zvezdanovic, 2024). However, the US has witnessed growing economic policy uncertainty (EPU), evolving electricity markets, and deepening political polarization (Baker et al., 2022; Chen, 2019; Comnes et al., 1996; Marlow & Makovi, 2023; Tsai & Tsai, 2018). Understanding how these factors influence the solar energy industry is crucial for outlining the future of renewable energy in the country with significant policy implications. Thus, we examine the association between EPU, electricity market deregulation, and political polarization with utility-scale solar electricity generation in the United States. We choose solar electricity generation variable as our main outcome variable of interest because it directly quantifies the extent to which solar energy has been integrated into the energy mix, providing a clear metric for assessing progress.

While previous studies have examined the relationship between EPU and renewable energy investment at global and national levels including the US (Deschenes et al., 2023; Pata et al., 2023; Sendstad & Chronopoulos, 2020), there remains a gap in research at the U.S. state level. A state-level analysis is crucial for several reasons. First, given the significant variation in state-level policies and solar electricity generation across the US, this approach allows us to quantify the solar industry's sensitivity to varying levels of economic policy uncertainty (EPU) in different states. Fig. A1 and Fig. A2 show the distribution of utility-scale solar energy generation at the national

and state-level, respectively. Second, amid increasing political polarization regarding renewable energy subsidies across states, it helps us understand how political differences influence state-level solar development. Finally, as the U.S. electricity market has undergone substantial deregulation, a state-level analysis enables us to examine the extent to which market deregulation accounts for variations in solar electricity generation across U.S. states.

Existing research consistently demonstrates—both theoretically and empirically—a negative correlation between uncertainty and investment (Ghosal & Loungani, 2000). Likewise, increased EPU can hinder utility-scale solar generation in several ways. Firstly, the large upfront costs and long-term payback periods of solar projects make them vulnerable to policy uncertainty. For instance, unpredictable changes in energy policies, tax incentives, or regulations can deter investors from committing capital. Secondly, EPU raises perceived risks for lenders and investors, leading to higher borrowing costs or tighter lending conditions. This can make solar projects financially unviable. Lastly, EPU can disrupt global supply chains, affecting the availability and cost of crucial materials like solar panels and batteries. This can slow down the deployment of utility-scale solar projects.

The empirical findings on the relationship between EPU and solar industry development remains inconclusive. While some studies suggest a negative association, others indicate a positive or neutral impact. For instance, Shafiullah et al. (2021) find that higher EPU reduces renewable energy consumption in the US. This means higher EPU lowers renewable energy consumption. Conversely, Chu & Le (2022) and Wei et al. (2021) report positive relationships between EPU and renewable energy consumption and production, respectively. Second, using cross-country data, Yi et al. (2023) find that increased EPU hinders renewable energy production capacity. Doğan et al. (2023) further support the negative impact of EPU on renewable energy investments, particularly

for utility-scale solar projects. Given the significant capital investment and long-term nature of solar projects, as well as the need for community support and land acquisition, increased EPU can deter investment and hinder solar development. Therefore, we hypothesize that states with higher EPU will experience lower utility-scale solar electricity generation.

Historically, the electricity market in the US has been dominated by large, vertically integrated, and heavily regulated utilities until recent decades (Tsai & Tsai, 2018). In the late 1990s, massive market deregulation took place in both wholesale and retail electricity market by gradually moving to competitive market. Fig. A5 shows that more than a dozen states and the District of Columbia have partially or fully deregulated their electricity markets. Does market deregulation affect solar energy generation? Existing literature explores the implications of market deregulation on the energy sectors' performance, including distribution costs, retail prices, and overall customer well-being (Ajayi & Weyman-Jones, 2021; Joskow & Schmalensee, 2024; Ohler et al., 2020; Tsai & Tsai, 2018). However, no study examines the impact of electricity market deregulation on utility-scale solar electricity generation. Market deregulation can significantly impact solar electricity generation. First, by removing or simplifying rules, it allows more solar companies to enter the market and reduces regulatory hurdles for developers. This streamlined process accelerates project approvals, leading to quicker construction and operation. Second, market deregulation also attracts private capital by offering more investment flexibility and reducing regulatory risks. A more predictable investment climate encourages greater financial support for solar initiatives. Finally, by lowering regulatory barriers, deregulation fosters innovation in the solar sector, leading to advancements in technology, business models, and storage solutions. Based on these factors, we hypothesize that states with deregulated electricity markets will experience increased utility-scale solar electricity generation.

Besides increasing EPU and market deregulation, the US has also experienced a growing political divide and societal polarization, as documented by numerous studies (Marlow & Makovi, 2023). While the technical, economic, and policy drivers of solar energy transitions in the US have been extensively researched, the political dynamics of solar development have received less attention (Stokes & Breetz, 2018)**.** Political polarization can both promote and hinder solar industry development. Pro-renewable administrations can support solar energy through policies, tax incentives, and federal investments, while administrations prioritizing fossil fuels may reduce support. At the state level, polarization can lead to diverse regulatory environments. Progressive states may adopt renewable portfolio standards, while conservative states may prioritize traditional energy sources. Additionally, public opinion influenced by polarization can affect solar development. Conservative regions may exhibit skepticism towards renewable energy, leading to resistance and obstacles in the approval and permitting process. As Marlow & Makovi (2023) found, Republicans may be less supportive of policies like expanding tax credits for renewable energy. Based on this evidence, we hypothesize that states with a higher proportion of Democratic voters will have greater support for renewable energy, including solar, compared to states with a higher proportion of Republican voters.

All data for this study is sourced from publicly available databases. For instance, data for the solar electricity generation and average retail electricity price is collected from the U.S. Electricity Information Administration. We collect data on the RPS from the Lawrence Berkeley National Laboratory. For EPU, we collect the aggregate index compiled by Baker et al. (2016). Data for gross domestic product is collected from the U.S. Bureau of Economic Analysis. We collect the voter percentages for democratic party senate nominee from MIT Election data. Climate variables are sourced from the PRISM Climate Group. States with retail choices are collected from

National Renewable Energy Laboratory (NREL) publications. Finally, demographic data is collected from U.S. Census. The unit of observation is U.S. states and the temporal framework of our dataset is 2005-2020.

We use Negative Binomial Fixed Effect (NBFE) to estimate our regression parameters. We use NBFE for several reasons. First, it is particularly useful when there is overdispersion in the data, which is the case of our study. Second, this distribution allows greater flexibility in modeling the variance, making it suitable for the count data with more variability than other distributions, such as Poisson distribution. Last, this fixed-effect model allows for the control of time-invariant state-specific characteristics.

Results show that for every unit increase in the EPU is associated with, on average, 716.51 megawatt-hours (0.14%) reduction in the expected utility-scale solar electricity generation. This suggests that states with higher EPU are likely to experience lower utility-scale solar electricity generation. While existing literature shows this negative relationship at the national level, this study is the first one to document this relationship using state-level data. Based on our results, we can infer that stable economic policies are favorable to the solar industry, and this is true for both national and state-level policy uncertainty. We also find that a positive association between the higher voters' percentages for democratic party senate nominees and solar electricity generation. In fact, a 1% increase in the voters for democratic party senate nominee in a state is associated with, on average, an increase of 29,990.92 megawatt-hours (5.86%) in the expected solar electricity generation. To the best of our knowledge, no empirical study explores the impact of this political polarization on state-level solar electricity generation. This finding aligns with recent surveys indicating that Democrats are increasingly united in their support for renewable energy development across the country. Finally, we also find a positive association between deregulated

electricity market and solar electricity generation. For instance, the utility-scale solar electricity generation is 41.38% higher in deregulated markets compared to regulated ones, which corresponds to 211,778.91 megawatt-hours annually.

This research makes several key contributions to the existing literature. First, we establish a negative and statistically significant association between EPU and utility-scale solar electricity generation in the U.S. This novel finding, conducted at the state level, sheds new light on the impact of policy uncertainty on solar energy generation going beyond the national level analysis. Policymakers can leverage this insight to create a more stable regulatory environment, fostering investment in solar energy and reducing reliance on fossil fuels. Second, we demonstrate a positive association between Democratic voter support and solar electricity generation. States with a higher proportion of Democratic voters exhibit greater utility-scale solar development compared to Republican-leaning states. This finding underscores the importance of political will and public support in driving renewable energy adoption in the US. Finally, we uncover a positive relationship between deregulated electricity markets and solar electricity generation, but with a diverse impact based on ownership structure. While deregulated markets may not significantly influence solar power generated by independent power producers (IPPs), they have a significant positive effect on utility-scale solar electricity produced by electric utilities. This suggests that policymakers should consider the role of market structure in shaping solar energy development and tailor policies accordingly.

## 2 | Data and methodology

The unit of observations of this study is the individual states in the US and the temporal framework of our dataset is 2005-2020. Table 1 presents the summary statistics for key variables.

### 2.1 | Response variables

The primary response variable in this study is the utility-scale solar electricity generation by state per year. We select this variable as it directly measures solar energy production at the utility scale, reflecting the industry's primary output. Additionally, this variable exhibits significant spatial and temporal variations across U.S. states. Fig. A1 and Fig. A2 present the temporal and spatial distribution of utility-scale solar electricity generation in the US, respectively. This solar electricity data is measured in megawatt-hours (MWh), and we obtained historical data from the U.S. Energy Information Administration (EIA).

To check robustness, we collected data on how much of the annual utility-scale solar electricity is produced by the independent power producers (IPPs) and public electric utilities. Solar electricity generation by IPPs, also measured in MWh, focuses on private sector contributions to solar energy production while electricity generation by utilities shows the public sector contributions. IPPs play a significant role in competitive markets and can reflect different regulatory and market dynamics compared to public utilities. Analyzing generation from IPPs separately helps understand how economic policy uncertainty, market structures like deregulation, and political polarization influence solar energy production. It also provides a comparison between public utility performance and private sector-driven solar development. Including these variables for robustness checks ensures that our findings are not solely driven by public or private contributions but reflect broader trends in solar electricity generation across different ownership structures.

### 2.2 | Key explanatory variables

We collect the EPU index constructed by Baker et al. (2022) following the approach of Baker et al. (2016). This index is based on local newspaper coverage frequency of articles that discuss uncertainty related to the economic policies for each state in the US. Particularly, the authors

consider nearly 3,500 local newspapers and count the number of articles that contain terms referring to three categories: the economy (E), policy (P), and uncertainty (U) to construct the monthly indexes for EPU. They also include each state-specific policy term set to measure the index including energy and utilities. For instance, for Alabama, they include Alabama House of Representatives, Alabama Senate, Alabama Attorney General, Alabama Department of Labor, Alabama Department of Environmental Management, Alabama Department of Conservation and Natural Resources, and other state specific agencies that can be a source of policy news and uncertainty. [1]

After counting the number of articles that contain these terms, they then scale the raw count by the total number of articles in the same newspaper by month. Finally, the authors standardize the monthly series of scaled counts and average them across the newspapers they consider obtaining the monthly EPU index. EPU has three monthly indexes for each state: one that captures state and local sources of policy uncertainty (EPU-S), one that captures national and international sources (EPU-N), and a composite index that captures both (EPU-C). Although the authors have constructed these three distinct EPU indexes, we have chosen to use only the state and local index (EPU-S) in our analysis. Our decision is primarily driven by the need to avoid multicollinearity issues that can arise when multiple correlated predictors are included in a regression model. The composite index, EPU-C, is designed to cover both state, local, and national uncertainties. Thus, it should show a strong positive correlation with EPU-S. Moreover, since EPU-N captures broader national and international uncertainties, it may exhibit a positive correlation with EPU-S. This

[1] A full list of state specific terms can be found using the following link: https://www.policyuncertainty.com/state_epu_terms.html

means that periods of high national uncertainty might coincide with increased state and local uncertainty. Thus, we use only EPU-S in our study.

Secondly, to measure the political polarization, we used the "U.S. Senate statewide 1976–2020" dataset from the Massachusetts Institute of Technology (MIT) Election Data.[2] This dataset represents the number of voters for both democratic and republican nominee for the U.S. senate in the general elections. We calculate the percentage of voters for the democratic party for each state by simply dividing democratic votes by the total number of voter turnout. One challenge with this dataset is that the general elections take place every four years and our other variables are annual. We address this issue by filling in the non-election years with the data from the election years. For instance, we have voter turnout data for the years 2016 and 2020. However, we do not have data for the years 2017, 2018, and 2019. We assign the voter turnout values for 2017 equal to the voter turnout in 2016, as 2016 is the closest election year to 2017. Meanwhile, for the year 2019, we allocate the voter turnout values recorded in 2020. Finally, the voter turnout for 2018 is determined by calculating the average of the turnouts observed in 2016 and 2020, ensuring a balanced representation of the electoral landscape. This methodology allows us to fill in the missing values with a thoughtful and reasoned approach. Fig. A4 illustrates the percentage of voters for democratic party nominee for the U.S. senate in the last four general elections:2008, 2012, 2016, and 2020 across states.

Finally, we collect the information on the U.S. states with deregulated electricity market from the Electric Choice website.[3] This website has information on when a particular state adopted

[2] This data file contains constituency (state-level) returns for elections to the U.S. Senate from 1976 to 2020. This dataset is publicly available and can be downloaded using the following link: https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/PEJ5QU.

[3] https://www.electricchoice.com/map-deregulated-energy-markets/

market deregulation. We also used other sources to confirm the years when the states became deregulated such as National Renewable Energy Laboratory (NREL).

### 2.3 | Other control variables

Our other control variables include renewable portfolio standard (RPS), residential electricity price, and weather variables. Firstly, we collect the RPS data from the Lawrence Berkeley National Laboratory (LBNL) website. The unit of RPS in in Terawatt-hours (TWh). To control for the electricity price in each state, we collect the residential electricity retail prices (¢/kilowatt hours) from the U.S. EIA website. To control for the climatic conditions of each state, we collect two weather variables including precipitation and temperature from PRISM Climate Group.[4] For this study, we use the state-level annual means of these variables. The precipitation is in inches and the temperature is in Fahrenheit (°F). In addition, we collect gross domestic product (GDP) and population density data as additional explanatory variables for robustness check. Data for gross domestic product is collected from the U.S. Bureau of Economic Analysis. The unit of GDP is billions of 2012 dollars. Moreover, we collect the education data from the Federal Reserve Bank of St. Louis website. This variable represents the percentage of people with 25 years and over who have completed an advanced degree by state. Finally, we collect the population and land area by state data from the U.S. Census website. Based on this, we calculate the population density which represents thousands of persons per square mile land area for each state.

## 3 | Model specification

[4] The PRISM Climate Group is a popular source for quality weather data. PRISM gathers climate observations from a wide range of monitoring networks, applies sophisticated quality control measures, and develops spatial climate datasets. Historical data can be downloaded using the following link: https://prism.nacse.org/explorer/

Let the response variable $Y_{it}$ be the random variable representing the solar electricity generation in megawatt-hours (MWh) for each state $i$ in year $t$ and can be written as a function of the following explanatory variables and the stochastic error term:

$$Y_{it} = \beta_0 + \beta_1 \cdot EPU_{\text{it}} + \beta_2 \cdot DemoVote_{\text{it}} + \beta_3 \cdot DeMKT_{\text{it}} + \boldsymbol{\beta_3 \cdot X_{it}} + \tau_t + \alpha_i + \varepsilon_{it} \quad (1)$$

where $EPU$, $DemoVote$, and $DeMKT$ represents our key explanatory variables representing economic policy uncertainty, percentage of votes for democratic party senate nominee, and deregulated electricity market, respectively. The term $\boldsymbol{X_{it}}$ represents other control variables. Finally, the terms $\tau_t$ , $\alpha_i$ , and $\varepsilon_{it}$ represents the time trend, state fixed effect, and the error term, respectively.

The vector $\boldsymbol{X_{it}}$ includes five control variables including renewable portfolio standard (RPS), residential retail electricity price, annual total precipitation, annual average temperature, and two-year lagged per capita gross domestic product (GDP). First, we include RPS because these state-level policies mandate that a certain percentage of electricity generation comes from renewable sources like wind, solar, and hydro, encouraging investment in renewable energy infrastructure which potentially affects energy costs, market dynamics, and employment in the renewable energy sector. Therefore, including RPS as a control helps account for differences in renewable energy policy across states, ensuring that any effect observed in our model is not simply due to policy differences regarding renewable energy among U.S. states. Second, we include residential electricity price as a control because these prices affect both consumer behavior and business decisions. Higher prices could reduce electricity consumption, alter investments in energy efficiency, or influence economic activity in the residential and commercial sectors. Thus, controlling for residential retail electricity prices helps isolate the effect of our key explanatory

variables, as fluctuations in energy prices might influence investments in the utility-scale solar. Third, we include two-year lagged per capita GDP as a control variable because it is a proxy for economic well-being and development. Lagged GDP captures the long-term effects of state-level economic performance on a state's current conditions, reflecting how previous economic conditions influence a state's current investments, energy use, and market dynamics. Therefore, using a two-year lag helps us to control for the time it takes for changes in a state's economic performance to impact other variables in our model, such as renewable energy consumption including solar or policy implementation, avoiding simultaneity bias.

Finally, we include two weather variables as controls: annual total precipitation and average temperature. We include precipitation because it influences water availability, energy use, and economic activity, especially in sectors like farming and energy. Consequently, state-level variations in precipitation may affect solar energy generation. Thus, controlling for annual total precipitation allows us to capture the impact of precipitation patterns on utility-scale solar energy generation. We also include temperature as a control because it affects solar panel performance, energy demand (heating and cooling), and overall economic activity. Extreme temperatures, either hot or cold, increase electricity demand for climate control. Including average annual temperature as a control accounts for climate variation, ensuring that the effects of other factors are not conflated with temperature-driven fluctuations in utility-scale solar energy generation.

To estimate the regression coefficients in equation (1), we initially consider both Poisson and negative binomial (NB) regression models. However, our response variable $Y_{it}$ contains a lot of zero values revealing that there are several U.S. states having zero solar electricity generation for many beginning years, leading to overdispersion in the data. We know that, to fit a response variable using Poisson model, it requires that the mean and variance of that response variable must

be equal, such that $E(Y_{it}) = \text{Var}\ (Y_{it})$. Since our response variable does not meet this assumption of the Poisson specification, we choose the negative binomial specification for this study.

We include a time trend $\tau_t$ and state fixed effects $\alpha_i$ in the model to account for the impact of technological advancements in the solar energy sector and the influence of time-invariant characteristics of U.S. states on utility-scale solar electricity generation. For instance, states with higher solar irradiance (e.g., southwestern states) are naturally better suited for solar energy due to abundant sunlight. Conversely, states with mountainous or heavily forested terrain may have fewer suitable locations for large-scale solar development. Additionally, states with abundant fossil fuel resources may have a historical dependence on traditional energy sources, while states lacking such resources might be more inclined to develop renewable alternatives like solar energy. Finally, states with robust electricity transmission networks are better equipped to support utility-scale solar energy development by facilitating the transportation of solar-generated electricity to population centers. The presence (or absence) of infrastructure, such as transmission lines and substations, can significantly affect a state's capacity to integrate large-scale solar projects.

Finally, since the expected value of the response variable $E(Y_{it})$ is a linear combination of our explanatory variables, it may yield both positive and negative values. However, $E(Y_{it})$ must not produce negative values because the expected value of the solar electricity generation cannot be negative. To ensure $E(Y_{it})$ remains positive, we link our explanatory variables to the parameter of the negative binomial distribution, $\lambda_{it}$, using a log-link function, such that $\log(\lambda_{it}) = E(Y_{it})$. This avoids negative values for $\lambda_{it}$ because $\lambda_{it} = \exp[E(Y_{it})]$ Therefore, the regression coefficient, $\beta$, represents the log-change in $\lambda_{it}$ for a one-unit change in the explanatory variable, keeping all other variables constant.

## 4 | Empirical results and discussion

In this section, we present and discuss the results of our main regression estimations and the results from the robustness checks. Table 2 presents the estimates of the impact of key explanatory variables on the utility-scale solar energy in the US, based on the annual solar electricity generation data from 2005-2020, and using negative binomial fixed effect (NBFE) model. Moving from left to right, we estimate the regression parameters with a linear time trend while progressively adding key explanatory variables and a richer set of control variables. For example, model (1) is our base specification where we only include the EPU and a linear time trend. In model (2) and (3), we include the percentage of voters for democratic party senate nominee in the U.S. general election (representing political polarization) and the dummy variable representing the deregulated electricity market, respectively. Although the electricity market can be divided into three types of market structures: deregulated, partially deregulated, and regulated, we have divided the market into two categories either deregulated or regulated for simplicity, treating the later one as the reference group. From model (4), we keep adding relevant control variables that can influence the utility-scale solar electricity generation in a state. For instance, in model (4), (5), and (6), we include RPS, residential retail electricity price, and two-periods lagged per capital GDP, respectively. Finally, model (7) represents our fully specified (and preferred) model including the climate variables (e.g. annual total precipitation and average temperature).

We find a significant negative association between EPU and the utility-scale solar electricity generation in the US. This indicates that states with higher EPU tend to have lower solar generation. Our preferred model (Model 7) reveals that a one-unit increase in the EPU index (mean: 88.02) is associated with a 0.144% decrease in expected solar electricity generation, which is equivalent to 736.98 MW hours annually. This finding aligns with previous research by Ozarslan

et al. (2023) and Pata et al. (2023), who observed a negative connection between EPU and renewable energy investments in G7 countries. However, our study differs by employing state-level EPU, providing a more granular perspective on economic policy uncertainty's impact on the solar industry. Additionally, our results corroborate those of Shafiullah et al. (2021), who found a negative relationship between EPU and renewable electricity consumption. Collectively, our research not only contributes to the existing literature but also delves into local-level EPU to uncover its specific influence on the utility-scale solar sector.

We also find a positive and statistically significant impact of the percentage of voters for the democratic party senate nominee in a state on the utility-scale solar electricity generation. In fact, a 1% increase in the voters for the democratic party senate nominee in a state is associated with, on average, a 5.86% increase in the expected solar electricity generation, which is equivalent to 29,990.92 MW hours per year. This means states with a more democratic party voters tend to have a higher utility-scale solar electricity generation compared to the states with more republican voters. This finding aligns with several surveys conducted by Pew Research Center revealing Republicans' less support for renewable energy development (Kennedy & Spencer, 2021).

In addition, we find a significant positive impact of deregulated markets on utility-scale solar electricity generation. In fact, the utility-scale solar electricity generation is 41.38% higher in deregulated markets compared to regulated ones, which corresponds to 211,778.91 MW hours annually. This could be because deregulated markets offer more competitive pricing structures, increased investment incentives, and greater flexibility for solar developers to enter the market without the constraints of traditional utility monopolies. As a result, utility-scale solar projects in these states may experience fewer regulatory barriers and faster development timelines, leading to higher overall electricity generation.

Interestingly, we find three out of five control variables statistically insignificant in our preferred model (7) including RPS, residential retail electricity price, and two-year lagged per capital GDP. Historically, RPS has been found to have a positive impact on utility-scale solar electricity generation (Deschenes et al., 2023; Wiser et al., 2011), we, however, do not find a statistically significant impact. On the other hand, we find statistically significant association between climate variables and utility-scale solar generation. For instance, we find a negative association between annual total precipitation and utility-scale solar electricity generation. To be more exact, we find that, with one unit increase in the mean of annual precipitation (mean: 1,006 inches), the expected utility-scale solar electricity generation decreases by 0.107%, which is equivalent to 547.62 MW hours per year. This finding supports the existing literature. For example, Simsek et al. (2021) finds that increasing rainfall can decrease the performance of the solar panels. Moreover, a recent study led by NREL found that while rainfall washes away some pollen or dust from solar panels, but it fails to raise the panels' performance to their original levels, leading to a performance decrease of up to 15% (Bessa et al., 2024). Nevertheless, we find a positive association between annual average temperature and utility-scale solar electricity generation. In fact, we find that, with one unit increase in the annual total temperature (mean: 11.79 Fahrenheit), the expected utility-scale solar electricity generation increases by 9.39%, which corresponds to 48057.13 MW hours annually. One possible explanation for finding this positive relationship in our study is that higher temperatures are often associated with sunny weather and clearer skies, leading to more solar electricity generation. This means that when temperatures rise, solar panels get more sunlight to convert into electricity.

## 5 | Robustness Check

To verify the strength and consistency of our model parameter estimates, we conducted several robustness checks. First, to assess the sensitivity of our regression parameters, we included two additional control variables: education and population density. The inclusion of these variables is justified as they are critical factors that can influence both economic outcomes and political behavior, potentially influencing the development of renewable energy sectors and solar electricity generation. Table 3 illustrates the results from this analysis. Model 1 and Model 2 show the results of adding each variable separately, while Model 3 presents the outcomes of incorporating both additional controls into our preferred Model 7 (Table 2). Our findings indicate that the coefficients for EPU and the percentage of voters for the democratic party senate nominee remain robust across all models. This robustness implies that our primary results are reliable and not overly dependent on the initial model specification. However, we observe a notable shift regarding the coefficient for deregulated electricity markets. Initially significant in our preferred Model 7 (Table 2), it becomes statistically insignificant upon the addition of the new control variables. This suggests that while deregulated markets may have some influence on the utility-scale solar electricity generation, their effect could be confounded by factors such as education and population density. This also highlights that further research is needed to fully understand how these factors interact in various contexts.

Second, given that over 87% of U.S. solar electricity is generated by Independent Power Producers (IPPs), we separately analyzed the impact of our key explanatory variables on IPP-generated and utility-generated solar electricity. IPPs, as private entities focused solely on production, are more susceptible to market factors than public utilities. As shown in Tables 4 and 5, the coefficients for EPU and democratic vote share remain robust across both models, confirming the reliability of our primary findings. However, the coefficient for deregulated

electricity markets exhibits different results: it becomes statistically insignificant when IPP-generated solar electricity is the response variable but significant when utility-generated solar electricity is the response variable. This suggests that while deregulated markets may not directly influence utility-scale solar development by IPPs, they have a positive impact on utility-scale solar projects undertaken by electric utilities.

Finally, to further validate the robustness of our model estimates, we employed a bootstrapping technique, resampling the data 500 times and estimating the regression parameters for our preferred Model 7 of Table 2. The results, presented in Table 6, indicate that most of the bootstrapped coefficients fall within the 95% confidence intervals. For example, the bootstrapped coefficients for EPU, Democratic vote share, and deregulated electricity markets are -0.139, 5.824, and 0.438, respectively, with 95% confidence intervals of (-0.230, -0.048), (3.553, 8.095), and (-0.032, 0.907), respectively. This confirms the reliability of our model estimates.

Overall, our key findings regarding the relationship between our explanatory variables and solar electricity generation remained consistent across various model specifications and sample compositions. These robustness checks strengthen the credibility of our conclusions. While our model proves robust, further exploration of specific relationships, particularly those involving deregulated electricity markets, may yield additional insights.

## 6 | Policy Implications

The findings of this study offer several policy implications. First, given the detrimental impact of economic policy uncertainty on utility-scale solar electricity generation, policymakers should strive to create stable and predictable policy environments, including consistent interest rates and renewable energy incentives. This involves reducing regulatory uncertainty, providing clear

guidelines for renewable energy projects, and ensuring long-term policy consistency. Such measures would not only encourage solar investments but also mitigate the adverse effects of policy uncertainty.

Second, the significant positive relationship between the percentage of Democratic party voters and solar generation underscores the need for bipartisan support for renewable energy policies. While states with more Democratic voters are currently driving solar adoption, policymakers must bridge the political divide. Encouraging bipartisan legislation and fostering greater Republican support for renewable energy initiatives could help broaden solar energy development across all states.

Third, deregulated electricity markets have been shown to significantly boost utility-scale solar generation. States with regulated markets might consider deregulation as a strategy to unlock greater solar energy potential. By adopting more competitive market structures, states could attract more solar developers, increase investments, and expedite project approvals. Deregulated markets provide flexibility and incentives that can lead to a more dynamic and responsive solar energy sector.

Finally, the inclusion of weather variables in the model and the discovery of opposing relationships for precipitation and temperature yield intriguing policy implications. For example, the negative association between annual precipitation and solar electricity generation suggests the need for weather-resilient solar technologies and infrastructure. Policymakers should promote investment in advanced solar technologies, such as water-resistant and self-cleaning solar panels, that can mitigate the negative effects of rainfall. Conversely, the positive relationship between annual average temperature and solar electricity generation indicates that states or regions with warmer climates can strategically benefit from higher solar capacity. Policymakers should

encourage the expansion of solar farms in hotter, sunnier states to capitalize on these natural advantages. Additionally, solar energy investments in high-temperature states should be prioritized as part of broader climate adaptation strategies, especially where temperatures are expected to rise further due to climate change.

## 7 | Conclusion

Electricity generation using renewable sources such as solar at the utility-scale has become a major contributor to the renewable energy landscape in the US. With the tremendous growth in the last decade, stakeholders are becoming increasingly interested in the sensitivity of this industry to the broader economic factors such as economic policy uncertainly, to social factors such as political polarization, and to the changes in the electricity market structure such as deregulation. In this article, we provide empirical support for three important hypotheses related to these socio-economic factors. Therefore, the overarching objective of this research is to investigate the impacts of economic policy uncertainty, political polarization, and electricity market deregulation on the utility-scale solar electricity generation in the US.

Our empirical results show that for every unit increase in the EPU is associated with, on average, 0.213% reduction in the expected utility-scale solar electricity generation. This suggests that states with higher EPU are likely to experience lower solar electricity generation. We also find that RPS becomes negatively associated with the solar electricity generation for the states having partially retail choice option for their customers compared to the states having no retail choice option. In fact, with a unit increase in RPS, the expected utility-scale solar electricity generation in the partial retail market reduces by 4.91%, on average. According to the existing literature, RPS usually has a positive impact on electricity generation. There can be many reasons for this deviation including increasing competition in the partial retail market which leads to a reduction

in electricity prices and, eventually, less solar electricity generation. Finally, our results show a positive impact of higher voters' percentages for democratic party senate nominees on solar electricity generation. In fact, a 1% increase in the voters for democratic party senate nominee in a state is associated with, on average, an increase of 633.8% in the expected solar electricity generation. In other words, states with major republican voters experience less solar electricity generation. Through this research, we bring contributions to several strands of existing literature by revealing the sensitivity of the utility-scale solar industry to uncertainty, market, and political factors.

Our findings indicate several directions for future research. Firstly, on a few occasions, we find mixed impact (both positive and negative) of RPS on solar electricity generation in partially retail market and fully retail market. Authors can reinvestigate these relationships controlling different wholesale electricity markets. Secondly, instead of using economic policy uncertainty which covers broader policy issues, authors could apply machine learning to get policy uncertainty directly related to the renewable energy industry (i.e. solar or wind) and can use it as an explanatory variable. This will allow the researchers to delve deeper into the impact of energy policy uncertainty on the utility-scale solar electricity generation in a more subtle way. Finally, authors could also explore the impact of other electricity market related aspects on the utility-scale solar electricity generation such as grid operators' characteristics, transmission coverage, and others.

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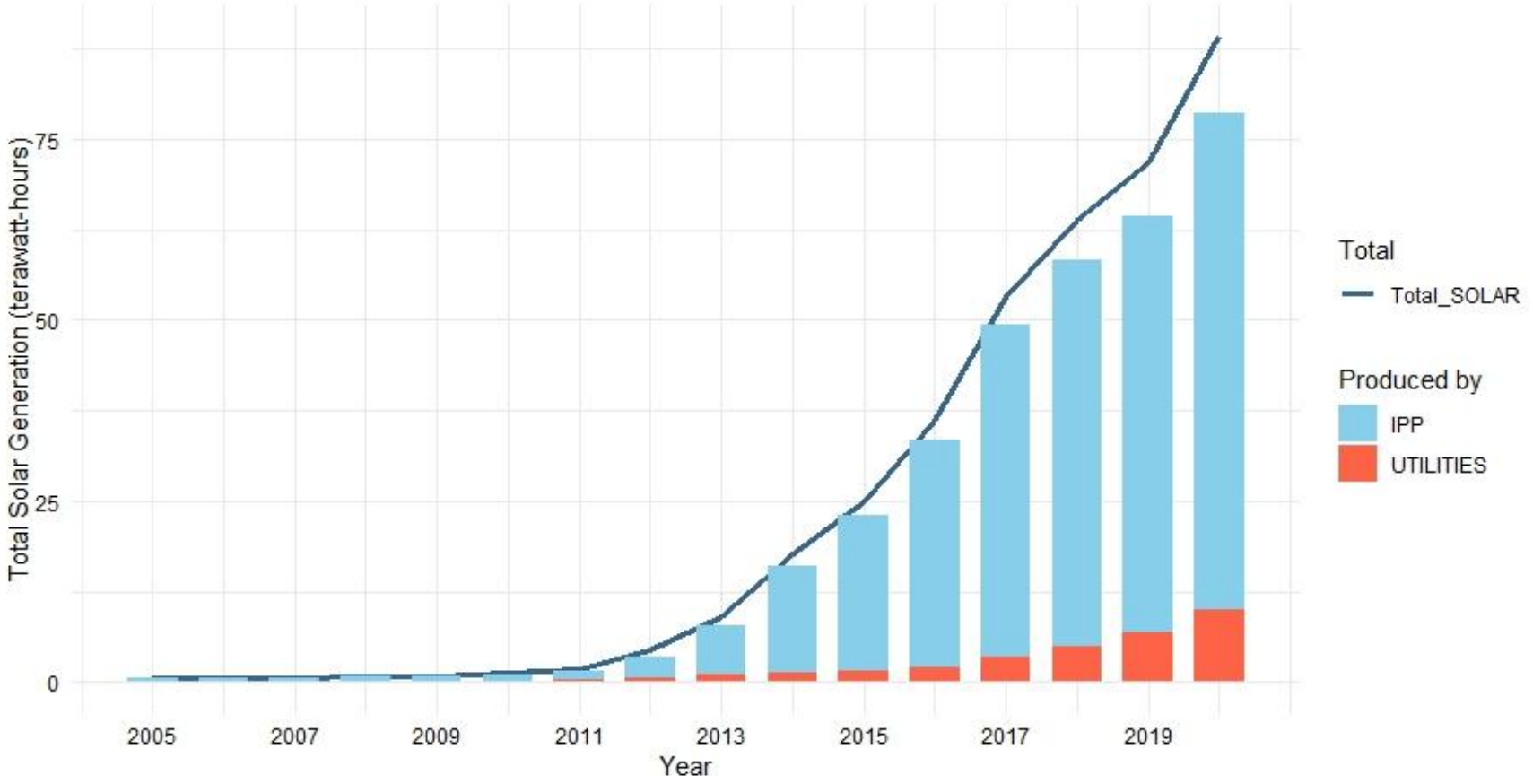


**Fig. A1. Cumulative total of annual solar electricity generation in the United States from 2005 to 2020.**

Notes: (1) The blue line graph presents the cumulative total of the annual electricity produced by the all the states in the US over the years from 2005 to 2020. (2) Unit of this solar electricity generation is terawatt-hours (1 terawatt-hours = 1,000,000 megawatt-hours of solar electricity). (3) The bar graphs present the cumulative total of solar electricity by the independent power producers or IPPs (blue-color bars) and the electric utilities (orange-color bars). IPPs are private entities that generate electricity for sale, focusing solely on production, while electric utilities are responsible for the entire process of generating, transmitting, distributing, and selling electricity to consumers.

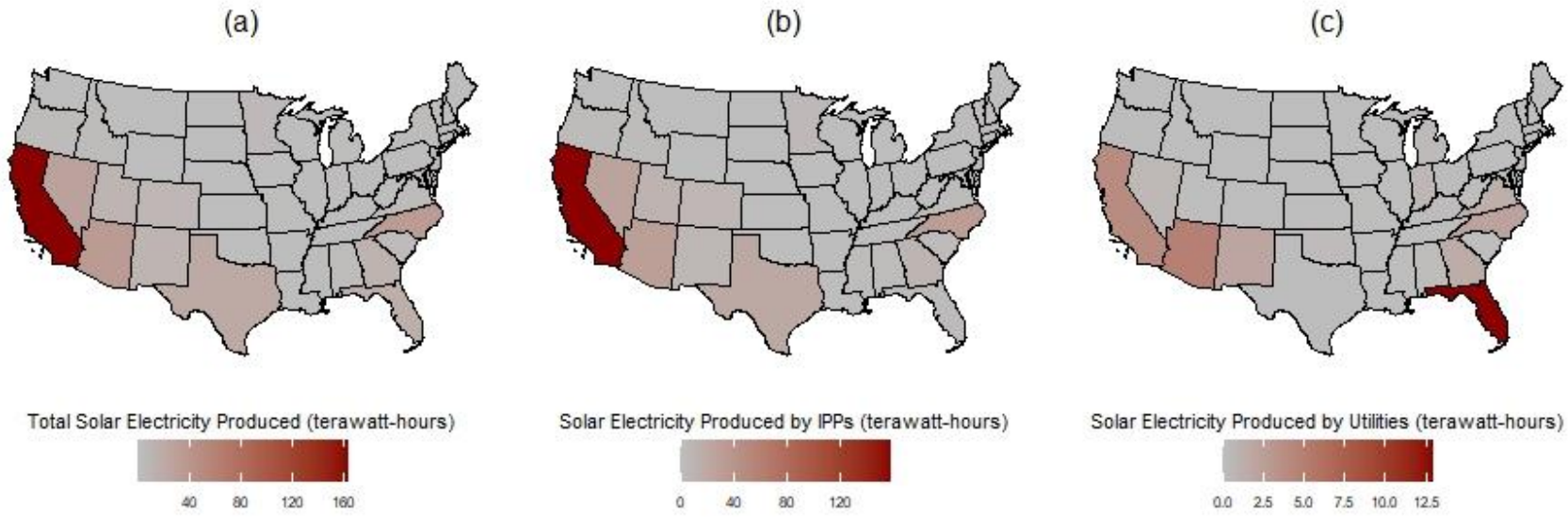


**Fig. A2. Total solar electricity generation by IPPs and electric utilities from 2005 to 2020 by U.S. states.**

Notes: (1) Gray color represents less solar electricity generation by a state. On the other hand, the dark-red color represents high solar electricity generation during our sample period: 2005-2020. (2) Graph (a) illustrates the total utility-scale solar electricity generation from 2005 to 2020 by each U.S. state. (3) Graph (b) and (c) illustrate the total utility-scale solar electricity generation from 2005 to 2020 by the independent power producer (IPPs) and electric utilities, respectively. Independent power producer (IPPs) are private entities that generate electricity for sale, focusing solely on production, while electric utilities are responsible for the entire process of generating, transmitting, distributing, and selling electricity to consumers.

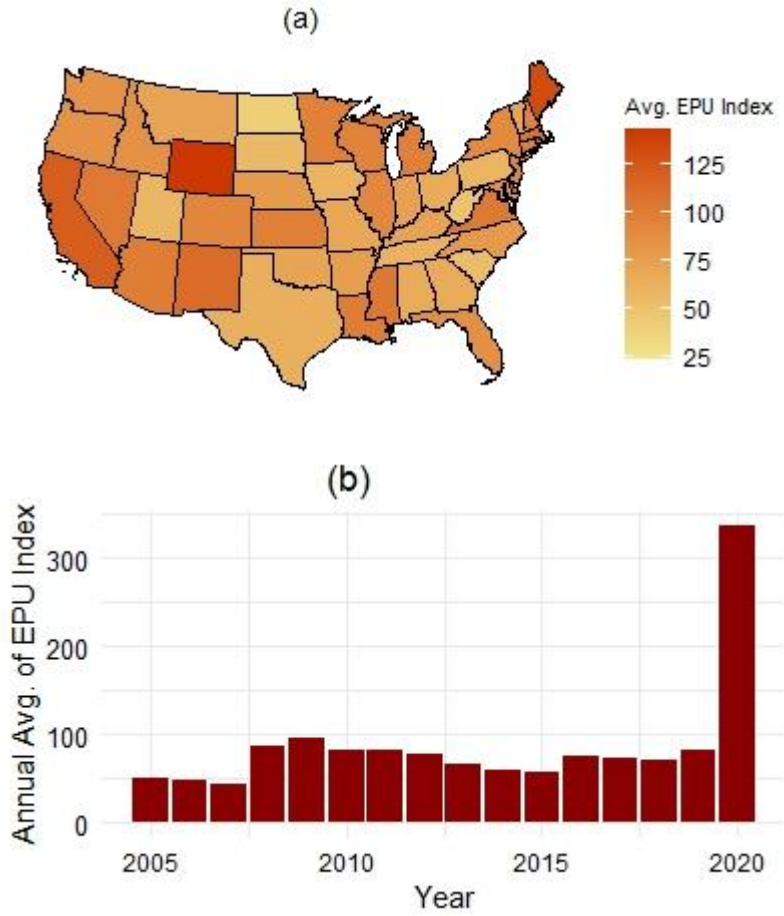


**Fig. A3. Spatial and temporal distribution of the average Economic Policy Uncertainty (EPU) Index.**

Notes: (1) Graph (a) illustrates the distribution of the average EPU index from 2005 to 2021 across the U.S. states. (2) Graph (b) illustrates the temporal distribution of the average EPU index from 2005 to 2021 annually. EPU is a monthly index by the independent power producer (IPPs) and electric utilities, respectively. Independent power producer (IPPs) are private entities that generate electricity for sale, focusing solely on production, while electric utilities are responsible for the entire process of generating, transmitting, distributing, and selling electricity to consumers.

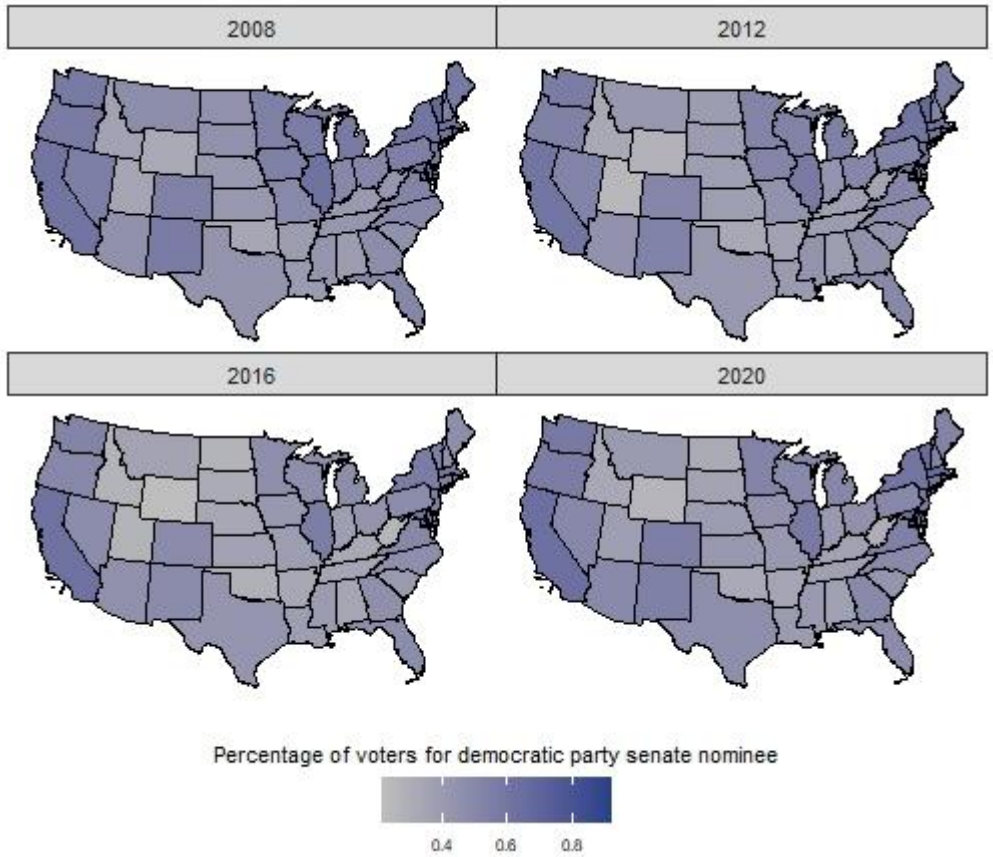


**Fig. A4. Percentage of voters for the democratic senate nominee in last four US general elections.**

Notes: The graph is developed based on the "U.S. Senate statewide 1976–2020" dataset from the MIT Election Data and Science Lab. This dataset represents the number of voters for both democratic and republican nominee for the U.S. senate in the general elections. We calculate the percentage of voters for the democratic party for each state by simply dividing democratic votes by the total number of voter turnout. The dataset can be downloaded using the following link: https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/PEJ5QU.

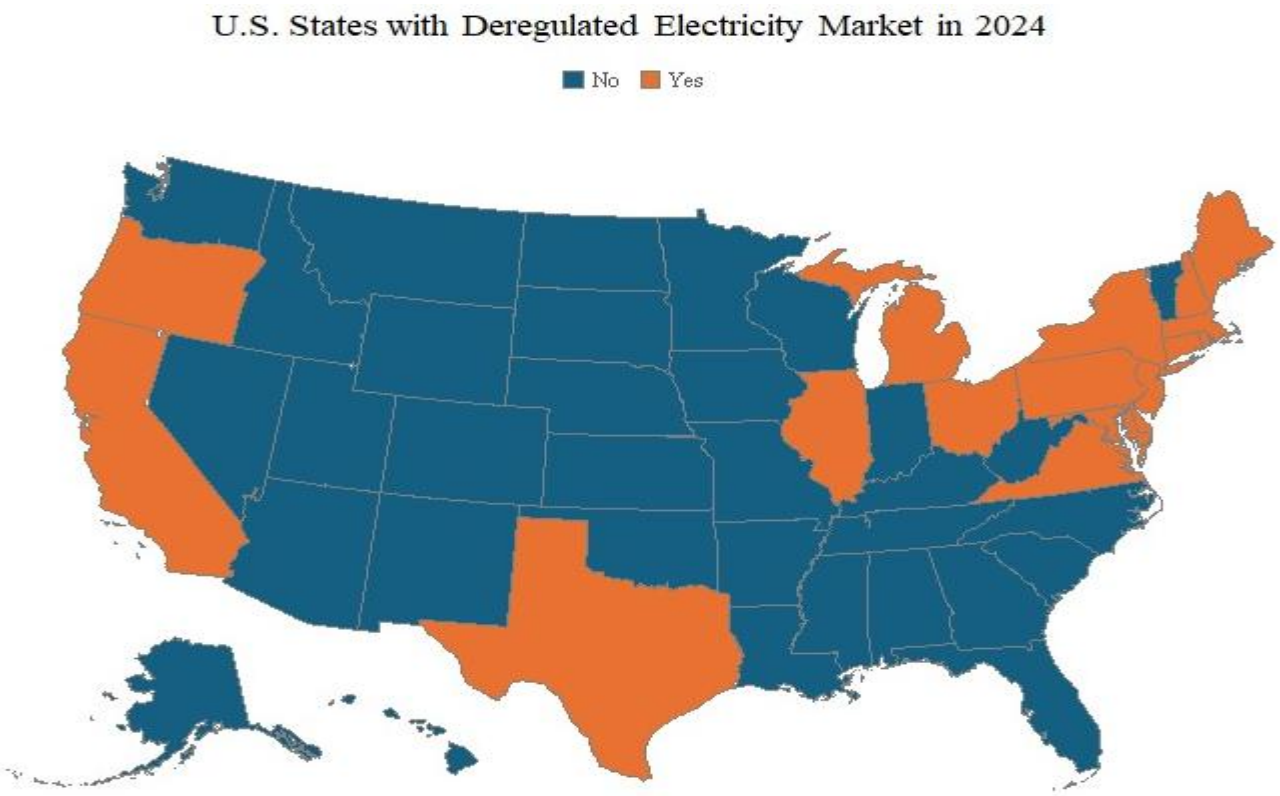


**Fig. A5. U.S. states with deregulated electricity market in 2024.**
Note: (1) The source of information for this figure is the Electric Choice[5]. (2) Although our study period spans from 2005 to 2020, current deregulated markets largely resemble those of 2020.

[5] https://www.electricchoice.com/map-deregulated-energy-markets/

**Table 1**
Descrptive Statistics of Variables

| | Unit | Obs. | Mean | SD | Min | Max |
|---|---|---|---|---|---|---|
| **Response variables** | | | | | | |
| State-level annual solar electricity generation | megawatt-hours (MWh) | 736 | 511,790.50 | 2,411,388.00 | 0.00 | 30,300,000.00 |
| State-level annual solar electricity generation by independent power producers (IPPs) | megawatt-hours (MWh) | 736 | 462,658.10 | 2,318,957.00 | 0.00 | 29,600,000.00 |
| State-level annual solar electricity generation by utilities | megawatt-hours (MWh) | 736 | 43,052.03 | 273,193.00 | 0.00 | 5,734,012.00 |
| **Key explanatory variables** | | | | | | |
| State-level annual economic policy uncertainty | Index value | 733 | 88.02 | 78.15 | 14.39 | 612.35 |
| Percentage of voters for democratic party senate nominee | in percentage | 736 | 0.48 | 0.10 | 0.22 | 0.71 |
| Deregulated electricity market | Dummy variable | 736 | 0.35 | 0.48 | 0.00 | 1.00 |
| **Control variables** | | | | | | |
| Renewable portfolio standard (RPS) | Terawatt hours (TWh) | 736 | 3.33 | 7.84 | 1.00e-06 | 62.12 |
| Residential retail electricity price | Cents per kilowatt hours (KWh) | 736 | 10.89 | 3.78 | 6.21 | 34.68 |
| Annual total precipitation | in inches | 720 | 1,005.91 | 393.77 | 179.89 | 1,940.66 |
| Annual average temperature | in Fahrenheit (°F) | 720 | 11.79 | 4.33 | 3.41 | 22.92 |
| Per capita gross domestic product | Billions of chained 2012 dollars | 720 | 50.46 | 9.11 | 33.07 | 78.51 |

**Table 2**

Dependent variable: annual solar electricity generation by state (negative binomial fixed effect model)

| | Model (1) | Model (2) | Model (3) | Model (4) | Model (5) | Model (6) | Model (7) |
|---|---|---|---|---|---|---|---|
| | | | | | | | |
| Economic policy uncertainty (EPU) | -0.075* | -0.137*** | -0.136*** | -0.144*** | -0.136*** | -0.149*** | -0.144*** |
| | (0.036) | (0.031) | (0.031) | (0.031) | (0.031) | (0.033) | (0.031) |
| | | | | | | | |
| Percentage of voters for democratic party senate nominee | | 6.851*** | 6.702*** | 6.469*** | 5.337*** | 5.381*** | 5.860*** |
| | | (0.581) | (0.684) | (0.698) | (0.817) | (0.836) | (0.842) |
| | | | | | | | |
| Deregulated electricity market | | | 6.376 | -0.281 | 2.348 | 5.034 | 41.380* |
| | | | (15.270) | (15.741) | (15.679) | (17.349) | (18.548) |
| | | | | | | | |
| Renewable portfolio standard (RPS) | | | | 1.446* | 1.107 | 1.121 | -0.631 |
| | | | | (0.642) | (0.640) | (0.700) | (0.700) |
| | | | | | | | |
| Residential retail electricity price | | | | | 4.704** | 3.152 | 5.551 |
| | | | | | (1.742) | (2.820) | (3.017) |
| | | | | | | | |
| Per capita gross domestic product (Two-periods-lagged) | | | | | | 0.608 | 0.551 |
| | | | | | | (0.745) | (0.782) |
| | | | | | | | |
| Annual total precipitation | | | | | | | -0.107*** |
| | | | | | | | (0.016) |
| | | | | | | | |
| Annual average temperature | | | | | | | 9.391*** |
| | | | | | | | (1.617) |
| | | | | | | | |
| Number of observations (N) | 733 | 733 | 733 | 733 | 733 | 630 | 630 |

Notes: (1) A time trend has been included in all the models (Model 1-7), (2) All the coefficients are multiplied by 100 except time trend and the percentage of voter for democratic party senate nominee, (3) Asterisks indicate the following p-values: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses.

**Table 3**
Robustness 1 (Including additional control variables)
Dependent variable: Total solar electricity generation by state; Method: Negative binomial fixed effect)

| | Model (1) | Model (2) | Model (3) |
|---|---|---|---|
| Economic policy uncertainty (EPU) | -0.157*** | -0.143*** | -0.154*** |
| | (0.032) | (0.031) | (0.032) |
| Percentage of voters for democratic party senate nominee | 4.853*** | 5.631*** | 4.867*** |
| | (0.991) | (0.853) | (0.989) |
| Deregulated electricity market | 0.411* | 0.284 | 0.309 |
| | (0.184) | (0.203) | (0.202) |
| Renewable portfolio standard (RPS) | -0.045 | 0.035 | 0.363 |
| | (0.777) | (0.796) | (0.832) |
| Residential retail electricity price | 4.445 | 2.979 | 2.673 |
| | (3.048) | (3.348) | (3.326) |
| Per capita gross domestic product (Two-periods-lagged) | -0.397 | 0.099 | -0.581 |
| | (0.934) | (0.828) | (0.948) |
| Annual total precipitation | -0.107*** | -0.111*** | -0.109*** |
| | (0.016) | (0.016) | (0.016) |
| Annual average temperature | 9.559*** | 8.532*** | 8.840*** |
| | (1.636) | (1.701) | (1.725) |
| Education | 0.076* | | 0.062 |
| | (0.038) | | (0.040) |
| Population density | | 65.990 | 51.478 |
| | | (35.331) | (36.796) |
| Number of observations (N) | 630 | 630 | 630 |

Notes: (1) A time trend has been included in all the models (Model 1-7), (2) All the coefficients are multiplied by 100 except time trend and the percentage of voter for democratic party senate nominee, (3) In Model (1), education has been included as an additional control variable to our preferred model in the main estimation. In Model (2), state-level population density has been included as an additional control variable. Finally, in Model (3), both education and state-level population density have been included as an additional control variable to our preferred estimation model, (4) Asterisks indicate the following p-values: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses.

**Table 4**

Robustness 2 (alternative response variables)

Dependent variable: total solar electricity generation by IPPs by state; method: negative binomial fixed effect model

| | Model (1) | Model (2) | Model (3) | Model (4) | Model (5) | Model (6) | Model (7) |
|---|---|---|---|---|---|---|---|
| Economic policy uncertainty (EPU) | -0.037 | -0.122*** | -0.128*** | -0.141*** | -0.126*** | -0.149*** | -0.133*** |
| | (0.042) | (0.035) | (0.035) | (0.034) | (0.033) | (0.037) | (0.033) |
| | | | | | | | |
| Percentage of voters for democratic party senate nominee | | 7.458*** | 8.067*** | 7.620*** | 5.495*** | 5.439*** | 6.133*** |
| | | (0.640) | (0.728) | (0.750) | (0.892) | (0.919) | (0.904) |
| | | | | | | | |
| Deregulated electricity market | | | -0.247 | -0.365* | -0.249 | -0.319 | 0.109 |
| | | | (0.153) | (0.159) | (0.161) | (0.174) | (0.186) |
| | | | | | | | |
| Renewable portfolio standard (RPS) | | | | 2.348*** | 1.686** | 1.661* | -0.829 |
| | | | | (0.649) | (0.653) | (0.700) | (0.722) |
| | | | | | | | |
| Residential retail electricity price | | | | | 7.497*** | 10.249*** | 13.324*** |
| | | | | | (1.670) | (2.824) | (2.981) |
| | | | | | | | |
| Per capita gross domestic product (Two-periods-lagged) | | | | | | -0.197 | -0.337 |
| | | | | | | (0.798) | (0.821) |
| | | | | | | | |
| Annual total precipitation | | | | | | | -0.138*** |
| | | | | | | | (0.017) |
| | | | | | | | |
| Annual average temperature | | | | | | | 9.697*** |
| | | | | | | | (1.653) |
| Number of observations (N) | 717 | 717 | 717 | 717 | 717 | 616 | 616 |

Notes: (1) A time trend has been included in all the models (Model 1-7), (2) All the coefficients are multiplied by 100 except time trend and the percentage of voter for democratic party senate nominee, (3) Asterisks indicate the following p-values: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses.

**Table 5**

Robustness 3 (alternative response variables)

Dependent variable: total solar electricity generation by utilities by state; method: negative binomial fixed effect)

| | Model (1) | Model (2) | Model (3) | Model (4) | Model (5) | Model (6) | Model (7) |
|---|---|---|---|---|---|---|---|
| Economic policy uncertainty (EPU) | -0.024 | -0.105* | -0.124* | -0.126* | -0.126* | -0.126* | -0.148** |
| | (0.053) | (0.051) | (0.051) | (0.051) | (0.051) | (0.051) | (0.050) |
| | | | | | | | |
| Percentage of voters for democratic party senate nominee | | 5.400*** | 3.680*** | 3.517*** | 3.514** | 4.657*** | 6.914*** |
| | | (0.804) | (0.919) | (0.940) | (1.130) | (1.191) | (1.254) |
| | | | | | | | |
| Deregulated electricity market | | | 0.876*** | 0.832*** | 0.832*** | 1.062*** | 0.793*** |
| | | | (0.181) | (0.188) | (0.193) | (0.206) | (0.232) |
| | | | | | | | |
| Renewable portfolio standard (RPS) | | | | 0.733 | 0.733 | 0.883 | -1.287 |
| | | | | (0.774) | (0.786) | (0.872) | (0.926) |
| | | | | | | | |
| Residential retail electricity price | | | | | 0.009 | 1.882 | 6.856 |
| | | | | | (2.305) | (3.843) | (4.050) |
| | | | | | | | |
| Per capita gross domestic product (Two-periods-lagged) | | | | | | -4.106** | -3.117* |
| | | | | | | (1.326) | (1.405) |
| | | | | | | | |
| Annual total precipitation | | | | | | | -0.069** |
| | | | | | | | (0.022) |
| | | | | | | | |
| Annual average temperature | | | | | | | 13.237*** |
| | | | | | | | (2.352) |
| | | | | | | | |
| Number of observations (N) | 575 | 575 | 575 | 575 | 575 | 490 | 490 |

Notes: (1) A time trend has been included in all the models (Model 1-7), (2) All the coefficients are multiplied by 100 except time trend and the percentage of voter for democratic party senate nominee, (3) Asterisks indicate the following p-values: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses.

**Table 6**
Robustness 4 (bootstrapping 500 times)
Dependent variable: total solar electricity generation by state; method: negative binomial fixed effect

| | Bootstrap coefficient | Std. error | 95% Confidence interval | | |
|---|---|---|---|---|---|
| Economic policy uncertainty (EPU) | -0.139 | 0.046 | -0.230 | -0.048 | (N) |
| | | | -0.252 | -0.078 | (P) |
| | | | -0.221 | -0.046 | (BC) |
| Percentage of voters for democratic party senate nominee | 5.824 | 1.159 | 3.553 | 8.095 | (N) |
| | | | 3.708 | 8.124 | (P) |
| | | | 3.237 | 7.908 | (BC) |
| Deregulated electricity market | 0.438 | 0.239 | -0.032 | 0.907 | (N) |
| | | | 0.009 | 0.940 | (P) |
| | | | -0.044 | 0.881 | (BC) |
| Renewable portfolio standard (RPS) | -0.602 | 1.290 | -3.130 | 1.927 | (N) |
| | | | -2.826 | 2.013 | (P) |
| | | | -2.541 | 2.202 | (BC) |
| Residential retail electricity price | 5.834 | 3.792 | -1.598 | 13.267 | (N) |
| | | | -0.976 | 13.517 | (P) |
| | | | -1.595 | 13.207 | (BC) |
| Per capita gross domestic product | 0.272 | 1.098 | -1.879 | 2.423 | (N) |
| | | | -1.634 | 2.418 | (P) |
| | | | -1.951 | 2.127 | (BC) |
| Annual total precipitation | -0.112 | 0.021 | -0.154 | -0.070 | (N) |
| | | | -0.166 | -0.079 | (P) |
| | | | -0.148 | -0.060 | (BC) |
| Annual average temperature | 9.712 | 2.162 | 5.475 | 13.950 | (N) |
| | | | 6.098 | 14.475 | (P) |
| | | | 4.512 | 12.865 | (BC) |

Notes: (1) A time trend has been included in all the models (Model 1-7), (2) All the coefficients are multiplied by 100 except time trend and the percentage of voter for democratic party senate nominee, (3) In the 95% confidence interval, **(**N) stands for normal confidence interval, (P) stands for percentile confidence interval, and (BC) stands for Bias-corrected confidence interval. (4) We run a repetition of subsampling 500 times for our dataset and produce these results. (5) We could not use the lagged variable of per capita gross domestic product since subsampling does not allow lagged variables.