國立臺灣大學生物資源暨農學院農業經濟系

碩士論文

Department of Agricultural Economics

College of Bio-Resources and Agriculture

National Taiwan University

Master's Thesis

# 美國社群太陽能立法對太陽能採用之影響

# Shining a Light on Shared Savings: An Examination of the Effect of Community Solar Legislation on Solar Adoption in the United States

陳禹嫺

Yu-Hsien Chen

指導教授: 石曜合 博士

Advisor: Yau-Huo Shr Ph.D.

中華民國 113 年 7 月

July, 2024

doi:10.6342/NTU202404232

# 國立臺灣大學碩士學位論文

# 口試委員會審定書

美國社群太陽能立法對太陽能採用之影響

Shining a Light on Shared Savings: An Examination of the Effect of Community Solar Legislation on Solar Adoption in the United States

本論文係 陳禹嫺 君（學號 R10627009）在國立臺灣大學生農學院農業經濟研究所完成之碩士學位論文，於民國 113 年 7 月 24 日承下列考試委員審查通過及口試及格，特此證明

指導教授：石曜合（簽名）

口試委員：楊豐安（簽名）

謝依芸



doi:10.6342/NTU202404232

# Acknowledgements

*"Our share of night to bear—*
*Our share of morning—*
*Our blank in bliss to fill*
*Our blank in scorning—*
*Here a star, and there a star,*
*Some lose their way!*
*Here a mist, and there a mist,*
*Afterwards —Day!"*
*—Emily Dickinson*

經過黑夜、繁星、迷霧，作為碩士生的一千多個日夜迎來盡頭，回想起來十分充實，因為我所經歷的宇宙——

感謝指導教授石曜合老師。老師總給我充分的空間自行探索研究題目和方法、也以彈性的時間安排包容我時而停滯時而暴衝的產出進度，同時協助我在給定的時空限制下，選擇更有效率的做法。透過和老師的討論，總能發現自己思考的遺漏之處，進而從不同角度去質疑和試圖印證每條論述的可靠性，最後建構更有說服力的故事。每一次的討論都帶回更多的問題，雖然並不總能回答或得到結果，但反覆推敲、縝密求證，是我和老師學到、並會持續精進的研究態度。

感謝研究室好夥伴行慈、嘉辰、俊欽、林華、嘉恆。一直以來受到你們非常多的照顧和陪伴，各種疑難雜症總在你們的協助下迎刃而解；從長居研究室的日常到一起解鎖的新體驗，每每想起來都還是覺得非常有趣。謝謝你們包容我的諧音梗、偶爾消失、和無事不登三寶殿，無論何時總讓我感受到歸屬感和慷慨的支持。謝謝大學以來的朋友賀琳，除了送我的研究生貼圖實用了好幾年、陪我口試預演和給予建議，對生活和研究的自律，也一直是我的榜樣。

感謝爸爸媽媽和姊姊，每次回家或見面豐富的物資補給，讓我在北漂的日子裡持續有力的航行；更重要的是提醒我不要心急、好好完成每件事就行，無條件的信任，使我沒有後顧之憂的以自己的步調往目標前進。

謝謝你們使三年的日子熠熠生輝。



doi:10.6342/NTU202404232

# 摘要

社群太陽能是一種共享光電模式，參與者可以購買或租賃部分比例的大型太陽光電系統，而不必在自家屋頂或土地裝設，並可獲得與持有比例相應的電費收益或抵減。如此一來，過去無法或不願安裝光電板者，也能藉此參與再生能源發展並共享其成果。為推動社群太陽能，自 2008 年起，美國陸續有多個州通過了相關法規。然而，這些州級政策的實際效果尚未獲得充分研究。本研究填補了此一研究缺口，探討州級社群太陽能立法對太陽光電裝置容量的影響。研究採用合成雙重差分法，透過對未實施政策的州和政策實施前的時期進行加權，以建構控制組。此方法確保了政策實施前，實驗組和對照組的裝置容量趨勢保持平行，以利比較政策前後、實驗組與對照組之間的差異。本研究兼論社群太陽能是否對屋頂太陽能的採用產生外溢效果。結果顯示，在 2017 年之前頒布政策的州，社群太陽能的裝置容量顯著增加，且未對屋頂太陽能的採用造成替代效應。這份研究貢獻了社群太陽能政策有效性的實證證據，並闡釋了不同太陽能市場間獨立或互相影響的關係。

**關鍵字：**社群太陽能、太陽光電政策分析、合成雙重差分、交錯採用、再生能源



doi:10.6342/NTU202404232

# Abstract

Bearing the mission of accelerating renewable energy development and engaging a broader population, community solar allows its participants to own or lease a portion of large solar energy systems and get rebates on utility bills. To encourage the adoption of community solar, several U.S. states have passed legislation since 2008 and in the following years. However, the effectiveness of these state-level community solar policies remains unexplored. This study addresses this gap by examining the impact of state-level community solar PV legislation on solar installation capacity in the U.S. To estimate the effects of the inception of community solar legislation on solar PV adoption at the state level, I leverage the synthetic difference-in-differences approach, by which I construct a control group by weighting a combination of untreated states and pre-treatment time periods, ensuring that pre-intervention trends in solar capacity are parallel between treated and untreated states. I also investigate if community solar has any spillover effect on the adoption of rooftop solar. The results show that the state policies significantly increased



doi:10.6342/NTU202404232

community solar capacity in states with policies enacted before 2017 and did not substitute rooftop solar adoption. The paper not only provides some of the first evidence on the effectiveness of community solar in promoting solar adoption but also sheds light on the dynamics between different solar markets.

**Keywords:** community solar, solar policy analysis, synthetic difference-in-differences, staggered adoption, renewable energy



doi:10.6342/NTU202404232

# Table of Contents





doi:10.6342/NTU202404232

doi:10.6342/NTU202404232

# List of Figures




doi:10.6342/NTU202404232

# List of Tables




doi:10.6342/NTU202404232

# Chapter 1 Introduction

The international effort to combat climate change has underscored the importance of deploying renewable energy sources. Solar photovoltaic (PV) technology has emerged as a frontrunner in this transition, experiencing rapid growth and cost reductions in recent years. According to the International Energy Agency (IEA), solar PV accounted for around 75% of additional renewable capacity in 2023, that is, nearly 380 GW. The capacity is expected to keep growing due to supportive policies and market incentives, such as the Inflation Reduction Act in the United States (IEA, 2024).

Despite these advancements, the developments of solar PV in different segments of the market are unequal. According to the Solar Energy Industries Association (SEIA), the first quarter of 2024 saw varying trends in solar deployment. The residential solar sector added a modest 1300 MW-DC of new capacity, marking its lowest growth since 2022, largely due to persistent high interest rates. As for the commercial sector, installation capacity showed growth in new states but declined in states with mature markets, resulting in a net increase of 434 MW-DC. Last but not least, community solar expanded by 279MW-DC; however, its progress remains contingent on supportive state-level policies. Although legislation in several states has made progress, implementation of new policies has been slow (SEIA, 2024).


doi:10.6342/NTU202404232

As a relatively new concept in the market, the development and growth of community solar is intriguing. Community solar is defined by the U.S. National Renewable Energy Laboratory (NREL) as follows: "…also known as shared solar or solar garden, is a distributed solar energy deployment model that allows customers to buy or lease part of a larger, offsite shared solar PV system and receive benefits of their participation" (NREL, 2023). This innovative model allows individuals who face barriers to installing solar panels on their own properties, such as renters or those with limited space, to engage in solar energy generation through purchasing or leasing shares of offsite solar PV systems. Participants then receive credits on their electricity bills, contributing to both financial savings and sustainable energy practices. By facilitating broader access to solar power, community solar plays a pivotal role in democratizing renewable energy and fostering community participation in the transition to cleaner energy sources (Nguyen, 2020).

The developing community solar market not only carries the goals of accelerating the deployment of renewable energy and reducing greenhouse gases, but also bears the intention of increasing the number of groups benefiting from solar energy and reducing inequality in the adoption of renewable energy. In the context of saving carbon emissions and addressing inequality, the number of community solar projects worldwide is growing, with the United States actively leading this development. An increasing number of states have enacted legislation to support community solar initiatives, which is widely considered as a key factor contributing to the rise in installation capacity (Cook & Shah, 2019; Michaud, 2020, Klein et al., 2021, U.S. EPA, 2024). However, there is no quantitative evidence indicating that the increase in installation capacity can be attributed to state legislation. While research suggested that early adopters of climate technologies can achieve better welfare compared to those who delay action (Marcucci & Turton, 2015;


doi:10.6342/NTU202404232

Pollitt et al., 2015; Karkatsoulis et al., 2016), it is worth investigating whether this applies to community solar as well.

On top of that, if community solar policies provide benefits that are more attractive, they may draw some families or businesses that originally planned to install rooftop PV systems to choose community solar projects instead. Although previous studies (Funkhouser et al., 2015; Schunder et al., 2020) have discussed the two solar PV models and noted a potential relationship, the impact of one on the other remains underexplored. Specifically, it is unclear whether the policy for community solar influences the adoption of residential rooftop solar and whether it has a crowding out or substitution effect on the latter. If that is the case, then the goal of increasing overall renewable energy adoption should be reexamined.

This research aims to fill the gaps by evaluating the effect of community solar state policy in the United States on solar adoption, including both community solar and residential rooftop solar capacity. Understanding the effectiveness of community solar policies enables us to verify whether these policies have a measurable impact on solar capacity. I further tested whether community solar has a spillover effect on the adoption of rooftop solar, and therefore deduced if community solar may compete with rooftop solar, or provide an alternative for individuals who would not otherwise adopt solar PV. The research questions are:

a. How do state-level community solar policies impact the adoption of solar PV?

b. Does the timing of policy implementation influence the solar capacity?

c. Is there a spillover effect of these policies on residential rooftop solar capacity?


doi:10.6342/NTU202404232

To achieve this, I employed the synthetic difference-in-differences method proposed by Arkhangelsky et al. (2021). This method created a control group whose pre-treatment trends are parallel to those of the treated group, thereby facilitating a comparison of solar capacity both before and after, as well as states with and without the implementation of community solar legislation.

The remainder of the article is organized as follows: Section 2 provides a comprehensive background on the concept of community solar, including its various types, current trends, and the state legislation and policies that shape its development. Section 3 offers a literature review that identifies the existing research gaps and outlines the potential contributions of this paper. Section 4 details the methodology, including the process for obtaining necessary data, the structure of the analytical framework, and the application of causal inference methods. Section 5 presents the model comparison with robustness check and the main empirical results, the analyses for heterogeneity in policy adopting time, as well as an examination of the potential spillover effect. Finally, Section 6 concludes the paper, summarizing the key findings and their implications for policy and future research.


doi:10.6342/NTU202404232

# Chapter 2 Background

Community solar represents a self-sufficient energy production model and civil engagement program that builds upon the concept of energy cooperatives. Energy cooperatives are jointly-owned, community-based organizations that provide energy services to their members (Soeiro & Dias, 2019). Similar to crowdfunding, community solar allows citizens to invest their money into solar panels located off-site, that is, not located on the property of the individual participants. As the local utilities pay community solar providers for the electricity produced, the revenues generated are enjoyed by the people who invested the money: in the form of reductions or exemptions on their electricity bills (Singh & Wu, 2021).

In the past, barriers to installing solar PV systems included significant upfront costs, issues with site shading, roof orientation constraints, and specific property ownership prerequisites (Funkhouser et al., 2015). These challenges historically limited widespread adoption among households. However, community solar addresses these obstacles, facilitating access to solar energy for individuals who cannot install solar systems on their own properties, such as renters or economically disadvantaged individuals. This approach promotes inclusivity, expanding the potential for more people to benefit from solar energy.

Besides, community solar also offers some other benefits. In areas where solar en-


doi:10.6342/NTU202404232

ergy is cheaper than conventional energy, customers can enjoy savings on their monthly bills. In addition, community solar enhances energy security by decentralizing energy production and reducing dependence on external energy supplies. During emergencies, such as natural disasters or grid failures that can disrupt centralized energy systems, these decentralized systems can continue to provide power, ensuring essential community needs are met and improving overall energy system resilience (Weinrub, 2011).

Operationally, community solar projects involve installing solar systems in a centralized location where electricity is generated and fed into the grid. Participants typically subscribe to a portion of the project's electricity output through a monthly subscription fee. Local utilities compensate solar providers for the energy supplied, and participants receive credits on their electricity bills, potentially lowering their costs. With this functioning, a consumer is able to save about 5% to 20% of annual electricity costs (Mooney, 2023).

In the United States, there are three prevalent models for community solar programs: a) Utility-Led Model: This model involves partnering with the local power company, which typically possesses robust legal, financial, and project management infrastructure necessary for organizing and executing community solar projects effectively. b) Special Purpose Entity Model: Organizers aiming to leverage tax incentives for commercial solar projects may opt for this model by structuring the project as a business enterprise. By doing so, various business entity structures can be utilized to maximize tax incentives while attracting investors outside of the community. c) Non-profit Model: Although not strictly classified as community solar energy, the non-profit model operates on similar principles. Through donations, non-profit institutions, along with their members or donors, can benefit from solar PV systems (Coughlin et al., 2011).


doi:10.6342/NTU202404232

The operating methods of the three categories—utility-led plans, special purpose entities, and nonprofit models—differ significantly, but all are integral to the scope of analysis in my study. Asmus (2008) conducted a review of the early development of community solar projects, asserting that utility-led plans offer a more robust framework. Conversely, other scholars advocated for special purpose entities and nonprofit models as primary options for expanding deployment, because these models, driven by consumers, were seen as more effective in fostering a peer effect, where community members were more inclined to adopt solar technologies upon witnessing their neighbors' involvement (Bollinger & Gillingham, 2012; Noll et al.,2014).

By 2023, community solar installations in the U.S. have reached a capacity of 7,268.24 MW-AC across 43 states and Washington, D.C., with over 2,900 projects listed. The rapid growth since 2016, particularly with the largest annual installation volume to date exceeding 2000 MW-AC in 2021, underlines the increasing momentum of these initiatives. However, distribution remains uneven, with more than 90% of capacity concentrated in ten states: Florida, New York, Minnesota, Massachusetts, Texas, Illinois, Arkansas, Colorado, Georgia, and Maryland (NREL, 2023). Development conditions vary widely from state to state, but a major driving force behind the adoption has been the enactment of state legislation aim at promoting and facilitating community solar initiatives.

As of the current writing, a total of 22 states along with Washington, D.C. have implemented policies to support community solar development, they are: California, Colorado, Connecticut, Delaware, Hawaii, Illinois, Massachusetts, Maryland, Maine, Minnesota, North Carolina, New Hampshire, New Jersey, New Mexico, Nevada, New York, Oregon, Rhode Island, South Carolina, Virginia, Vermont, and Washington. Figure 2.1 below is a map indicating whether each state has relevant legislation and, if so, the year it was


doi:10.6342/NTU202404232

passed. By 2022, states that had passed relevant legislation account for about 59% of the total installation capacity, and the remaining 41% in states without relevant policies, such as Florida, Texas, and Georgia (NREL, 2023). Take Florida as an example. The state, located in the Sun Belt, enjoys excellent sunshine conditions. However, in the past, the installation rate of solar PV was lower than that of states with less sunshine. Although Florida has not passed relevant state legislation, the ”Solar Together” program initiated by Florida Power and Light, which serves nearly half of Florida residents, appears to become the largest community solar program in the country (NREL, 2023). This suggests that state legislation may not be the only or most effective way to promote solar development, which will be examined and elaborated on in the following analysis.

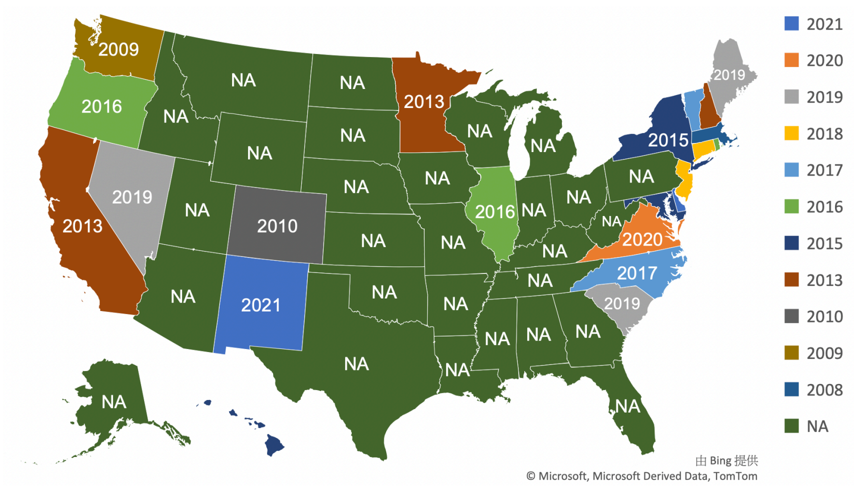



Figure 2.1: States with Community Solar Legislation and the Adoption Years

Note: In this map, the colors represent the years in which community solar legislation was passed in that state. NA means there is no relevant legislation in the state.

I review the policies of those states with related legislation on the Database of State Incentives for Renewables and Efficiency (DSIRE). DSIRE provides a comprehensive source of information on incentives and policies supporting renewable energy and energy efficiency in the United States and is operated by the North Carolina Clean Energy Technology Center at North Carolina State University.


doi:10.6342/NTU202404232

I then find that those community solar policies are embedded in different kinds of legislation. One common type of legislation involves integrating community solar within net metering frameworks. States such as Massachusetts which enacted the legislation in 2008, New Hampshire in 2013, New York in 2015, Rhode Island in 2016, Maine in 2019, and Nevada in 2019 have adopted this approach. Net metering allows participants in community solar programs to receive credits on their electricity bills for excess energy generated by their share of the solar array, which is fed back into the grid.

Other states have incorporated community solar within broader comprehensive renewable energy policies. Examples include Minnesota which passed the policy in 2013, Illinois in 2016, Vermont in 2017, South Carolina in 2019, and Delaware in 2021. These states have developed comprehensive frameworks that not only promote community solar but also encompass various other renewable energy initiatives, fostering a more holistic approach to sustainable energy development.

Some states have enacted dedicated legislation specifically targeting community solar initiatives. They are Washington with legislation passed in 2009, Colorado in 2010, Washington, D.C. in 2013, California in 2013, Hawaii in 2015, Maryland in 2015, North Carolina in 2017, Connecticut in 2018, New Jersey in 2018, and New Mexico in 2021. These dedicated enactments demonstrate a clear commitment to advancing community solar as a viable and accessible renewable energy option for residents.

Last but not least, certain states have included community solar provisions within other administrative regulations or legislative acts. Oregon in 2016 and Virginia in 2020 have integrated community solar into their regulatory frameworks through administrative channels or supplementary legislative measures, further contributing to the expansion of


doi:10.6342/NTU202404232

community solar programs nationwide.

The varied regulatory approaches adopted by states to govern community solar initiatives reflect an increasing acknowledgment of their capacity to broaden access to renewable energy, diminish greenhouse gas emissions, and fortify energy resilience within communities nationwide. Nevertheless, with many states scrutinizing related laws and others debating the pros and cons, limited quantitative research has analyzed the effects of community solar policy on its capacity—this is the gap that my research contributes to.


doi:10.6342/NTU202404232

# Chapter 3 Literature Review

Community solar, although a relatively new model in solar power generation, has attracted increasing attention in the U.S. While economic analysis remains limited, there is a growing body of research exploring its adoption motivations and barriers from various perspectives. Globally, the uptake of community solar aligns strongly with efforts to reduce greenhouse gas emissions and mitigate climate change. The affordability of community solar owes much to declining installation costs, which stoke consumer interest in long-term savings from inexpensive solar technology, bolstered by technological advancements (Shittu et al., 2019). Incentives such as investment tax credits and supportive state and federal policies have further spurred investment by both utilities and private investors in community solar initiatives. Moreover, the design of community solar circumvents the space constraints typical of traditional solar PV systems, like the need for rooftops or land, and lowers initial capital outlays and credit score prerequisites, thus broadening access to solar energy investments. This flexibility has democratized solar energy, making it accessible to a wider range of investors. In recent years, there are also targeted community solar programs aim at including low- and moderate-income groups in the energy transition, ensuring broader societal participation in renewable energy transition efforts.

In the discourse on community solar, the role of policy and regulation emerges as a recurring theme. Noll et al. (2014) indicated that states with lower solar resource poten-


doi:10.6342/NTU202404232

tial can match or even surpass those with higher potential in cumulative installations, for instance, New Jersey surpassed Oklahoma, ranking second place in accumulative capacity in 2014. They thus highlighted the pivotal influence of state policies in disseminating information and providing incentives to spur adoption. This perspective was reinforced by subsequent research. Gai et al. (2021) conducted comprehensive interviews and surveys with decision-makers, developers, and stakeholders from utilities and independent power suppliers involved in community solar projects across the United States. They categorized respondents into early adopters and yet-to-adopt groups based on whether their organizations participated in community solar initiatives. Approximately 80% of early adopters attributed their decision to engage in community solar and integrate low- and moderate-income groups to the impact of state and federal policies. In contrast, however, just over a third of the yet-to-adopt group cited policy influence on their decisions. Key barriers identified across both groups included financing challenges, insufficient industry and community education, and regulatory complexities.

Further insights from Thakur and Wilson (2024) identified twelve barriers to community solar adoption, classified into autonomous, dependent, linkage, and independent categories according to their level of dependence and driving power. Notably, the lack of clear policies and regulations emerged as a prominent independent barrier with a significant driving force but low dependency. This regulatory gap not only hampered adoption directly but also exacerbated issues such as insufficient consumer awareness and stakeholder engagement.

While the policy is frequently mentioned as having a crucial role in influencing solar adoption, its effectiveness varies widely across different contexts. This applies not only to community solar but also to the development of rooftop solar. Therefore, later


doi:10.6342/NTU202404232

in my discussion, I will explore the state policies' impacts on both community solar and rooftop solar. In terms of promoting residential solar PV, Crago and Chernyakhovskiy (2017) underscored the significant influence of state policies on capacity growth. Rebates, aimed at reducing upfront installation costs and enhancing financial benefits, are particularly strong predictors of the adoption. However, the cost-effectiveness of such rebates remained a concern, with other financial incentives like sales tax exemptions and tax credits potentially yielding less impact. In the meantime, non-policy factors such as demographic variables (age, income), technology familiarity, and peer influence also wielded substantial influence over solar PV adoption.

Spatial diffusion analysis conducted by Graziano and Gillingham (2015) revealed that localized solar promotion programs positively correlated with increased solar adoption, yet the influence of neighborhood effects tended to diminish over time. Similarly, Schelly's (2014a) examination of Wisconsin and Colorado as case studies highlighted the potential of feed-in tariffs to accelerate renewable energy adoption and stimulate future energy conservation. Nevertheless, challenges such as scalability limitations, fluctuating wholesale prices within net metering agreements, and divergent policy approaches among utilities within states posed significant obstacles and may inadvertently hinder progress.

Regarding community solar, insights from Michaud (2020) based on interview data indicated diverse perspectives on the most effective approaches to adopting community solar: While formal legislation was generally seen as essential, a notable segment advocated for greater efficacy through local projects or initiatives driven by utility companies. In addition, community solar legislation necessitated holistic collaboration among environmental organizations, governmental agencies, and utility companies. External events such as elections and fluctuations in energy prices alike could significantly shape pub-


doi:10.6342/NTU202404232

lic perception and understanding of solar energy, influencing the likelihood of legislative success and public support for community solar initiatives.

To this point, the literature suggests that policy is important for solar PV adoption, but its effectiveness is context-specific. When examining adoption in terms of timing—dividing adopters into early adopters and late adopters—the drivers behind adoption for these two categories differ. Schelly (2014b) explored the motivations behind early adopters of residential solar. Through interviews with homeowners in Wisconsin, the study found that, while personal environmental values were a factor, economic considerations played a more significant role. Tax credits and rising energy prices led some individuals to view solar technology as a long-term investment that could save their monthly electricity costs. What was more, economic events such as retirement could be more influential than precisely calculated returns, as solar PV was perceived as a stable source of income. Besides, interest in new technologies and information from family and friends, and social networks also contributed to the decision to install solar PV. These findings were echoed as well by research conducted outside the U.S. Palm (2020) conducted a literature review and empirical analysis based in Sweden, revealing that non-financial adoption motivations, such as environmental awareness and a fascination with technology, were more significant for the earliest adopters of residential solar PV, compared to later adopters. Nonetheless, as the market matured, the influence of these non-financial motivations diminished rapidly. Financial considerations became the predominant driver for later adopters, who were motivated mainly by the economic benefits of solar technology. The study by Simpson and Clifton (2017) in Western Australia also obtained the same results: 82% of their respondents installed residential solar for economic reasons; unlike early adopters due to environmental concerns and new technology preferences. The study suggested that financial


doi:10.6342/NTU202404232

incentives, along with peer communication about the benefits of solar PV, could act as a " cue-to-action" for individuals who have not yet adopted solar technology. These subsidies could also help lower-income households benefit from solar adoption. However, the researchers cautioned that intensive subsidies might diminish the economic benefits offered by solar PV per se, and potentially lead to stagnation in adoption rates if subsidies were later withdrawn. To enhance the fairness of subsidy policies, they recommended targeting subsidies towards low-income groups and developing funding mechanisms that avoid regressive impacts. In the subsequent analysis, I also divide the states with community solar legislation into early adopters and late adopters – to test whether the state-level, shared solar model also provides similar results from the above-mentioned individual-level, self-owned residential solar research.

Previous literature has investigated from various perspectives the development of solar PV in the United States, striving to figure out key drivers and obstacles. However, much of the research relies on qualitative methods such as interviews, surveys, and case studies to gather and analyze data. Discussions on the impact of community solar policies often intertwined with other factors or focused primarily on financial viability—effectiveness analyses do exist, but mostly on residential solar PV in general rather than community solar. Quantitative analyses that directly assess the causal effects of state policies on community solar adoption remain a missing piece of the puzzle, presenting a significant research gap.

This article seeks to fill this gap by investigating whether state policies exert a direct influence on community solar installation capacity and, if so, the magnitude of this impact. Besides, there is limited literature addressing the interaction between community solar and rooftop photovoltaics, though some studies did compare the two (Funkhouser et al., 2015;


doi:10.6342/NTU202404232

Schunder et al., 2020). The original intention of community solar was to offer more people an alternative to rooftop solar. This prompted me to explore whether community solar could potentially compete with rooftop PV. In other words, the community solar policy may have a spillover effect, leading some people to choose one type of solar system over the other.

By employing quantitative causal inference methods, this study provides empirical evidence on how state-level policies contribute to or hinder the adoption of community solar across different regions in the United States.


doi:10.6342/NTU202404232

# Chapter 4 Data and Methods

## 4.1 Data

### 4.1.1 Solar Capacity

In order to analyze the impact of state community solar policies on solar installation capacity, I collected data on community solar in each state, supplemented by data on rooftop solar for comparison to investigate if community solar has any spillover effect on the adoption of rooftop solar.

Data on community solar energy were obtained from NREL (2023)'s "Sharing the Sun" dataset. This dataset contains every community solar project since 2006, including project names, their located city and state, developers, utilities and their corresponding types, system sizes, and year of interconnection. This dataset is updated approximately every six months. According to my analysis period from 2006 to 2021, I used the version released in February 2022, which contained data as of December 2021.

In this dataset, my primary focus was on the system size, year of interconnection, and the locating state of each project. When examining system size, I opted to use kilowatts (kW) rather than rounded megawatts (MW), as early capacities were smaller, necessitating


doi:10.6342/NTU202404232

more meticulous numbers without rounding (both kW and MW values are included in the dataset). Furthermore, the February 2022 update specified whether the system size was calculated in AC or DC. I chose to standardize to DC for the following reasons. Firstly, solar panels generate electricity in DC, and their rated capacity (in kWp) is defined in DC. Secondly, using kW-DC ensures accuracy in assessing actual power generation capability before accounting for losses during conversion to AC. Lastly, this unit aligns with rooftop solar data to be discussed later. Therefore, I converted the AC data to DC using a conversion factor of 1,300, as outlined in NREL's "Sharing the Sun" dataset.

Data on rooftop solar are sourced from Lawrence Berkeley National Laboratory (2023)'s "Tracking the Sun" database. This dataset is operated by Lawrence Berkeley National Laboratory, a national laboratory affiliated with the U.S. Department of Energy. It collects data on residential and non-residential solar PV projects from state agencies and utilities. In addition to the project name and code that can be aligned with community solar, including the city and state, developer, utility service territory, system size (recorded in kW-DC), installation date, it also includes detailed items such as total installed price, module model, inverter model, battery model, etc. However, I only used the resident project's state, system size, and installation year here to integrate with the community solar panel data. This dataset provides publicly available information and is updated annually. I used the data released in 2022, but again, only the data up to 2021 was obtained.

### 4.1.2 Legislation and Policy

As mentioned in Chapter 2, according to the U.S. Department of Energy (2024), there are currently 22 states plus Washington, D.C. that have community solar legislation. However, state regulations are somewhat inconsistent in different versions of the website.


doi:10.6342/NTU202404232

For legislation and policies related to community solar, there are two main sources: one is the Database of State Incentives for Renewables and Efficiency (DSIRE), and another is the State Policies and Programs for Community Solar published by NREL. DSIRE is a continuously updated website, which is well-established and widely used in the field of renewable energy policy research. Past research on community solar energy in the U.S. (Crago & Chernyakhovskiy, 2017; Klein et al., 2021) and the Environmental Protection Agency website also refer to this database. NREL (2024) releases the data as a spreadsheet file that records all state legislation or program rules related to community solar in each state. This document was first released in March 2024, and the version I used was released in June 2024. I cross-referenced records of state solar legislation from two sources to ensure that the timing of policy intervention was accurately documented. Overall, DSIRE's records are more directly related to community solar, while NREL's records include the basis for the construction of community solar, such as regulations that allow the construction of distributed energy sources and net metering. I excluded laws and regulations that did not directly mention community solar. If there was still inconsistency between the two sources, the source that appeared earlier and could be verified directly mentioned community solar energy was used.

After this, I created a binary variable "treated" to indicate whether a state has legislation related to community solar programs in the corresponding year.

### 4.1.3 Demographic Data

To enhance the accuracy of assessing policy effects, I incorporated demographic data as control variables from The American Community Survey (ACS) 1-Year Estimates Public Use Microdata Sample. These variables include yearly cost for fuels other than gas and


doi:10.6342/NTU202404232

electricity (denoted as "fuel spending" in the summary statistics and the following content), estimate of the average monthly electricity cost for the household (electricity spending), average age of the state's population (average age), employment status (employed, unemployed, armed forces, not in labor force), average household income in the state (average income), income-to-poverty ratio (income/poverty ratio below 50%, income/poverty ratio 50%-99%, income/poverty ratio 100%-149%, income/poverty ratio 150%-199%, income/poverty ratio over 200%), state population (population), educational attainments (edu less than 9th grade, edu 9th to 12th grade, edu high school, edu college, edu bachelors, edu graduates), and tenure type (owner, renter). Detailed variable selection will be explained in Section 4.2.3. The ACS 1-Year Estimates provide a detailed snapshot of demographic, social, economic, and housing characteristics across the United States based on a robust sample size collected annually. This dataset is particularly advantageous for regions with sizable populations, offering precise insights into current conditions nationwide. Released each September, the ACS 1-Year Estimates are crucial for understanding immediate circumstances, while the ACS 5-Year Estimates, released annually in December after a five-year period, are better suited for tracking long-term trends. Notably, due to the COVID-19 pandemic's impact, the Census Bureau released experimental estimates for the 2020 one-year data, which I utilized for the year 2020. However, the 2020 data exhibits coarser granularity in some variables compared to other one-year estimates. Therefore, I standardized the classification of each year's data based on the 2020 criteria, particularly for employment status and housing tenure. Originally, employment categories distinguished between "at work" and "with a job but not at work"; I consolidated these into "employed", "unemployed", "armed forces", and "not in the labor force", according to the 2020 standards. Similarly, housing tenure, which previously featured four categories,


doi:10.6342/NTU202404232

was streamlined into two categories: “owner” and “renter”. As for missing data points in 2020, such as electricity consumption expenditure and average age, I imputed values using the previous year’s and later year’s averages to maintain consistency and completeness in the dataset. A potential issue with this imputation is that the COVID-19 pandemic may have led to changes in consumer behavior, such as increased remote work, lockdowns, and a surge in online shopping. These factors likely caused unusual variations in electricity use that may not be captured by simply averaging the previous and subsequent year’s data, leading to underestimation of the variability of the data. Table 4.1 below presents the summary statistics of the aforementioned variables and their respective roles in this research.

Table 4.1: Summary Statistics

| Variable Category | Variable | Obs | Unit | $Mean$ | $Std.dev.$ | $Min$ | $Max$ |
|---|---|---|---|---|---|---|---|
| Dependent Variables | community solar capacity | 816 | kW-DC | 16878.09 | 94450.58 | 0 | 1635990.00 |
| | rooftop solar capacity | 816 | kW-DC | 191421.00 | 915641.40 | 0 | 12800000.00 |
| Independent Variable | treated | 816 | | 0.18 | 0.38 | 0 | 1 |
| Covariates | fuel spending | 816 | dollar | 226.30 | 329.65 | 5.00 | 1716.00 |
| | electricity spending | 816 | dollar | 107.80 | 20.75 | 62.00 | 159.00 |
| | average age | 816 | year | 38.07 | 1.73 | 31.00 | 43.00 |
| | employed | 816 | person | 2864144.00 | 3172677.00 | 271240.00 | 18900000.00 |
| | unemployed | 816 | person | 237677.60 | 305451.20 | 9620.00 | 2377891.00 |
| | armed forces | 816 | person | 20898.40 | 29715.29 | 54.00 | 157774.00 |
| | not in labor force | 816 | person | 1760859.00 | 2001412.00 | 117277.00 | 11700000.00 |
| | average income | 816 | dollar | 56013.19 | 14810.99 | 29426.00 | 114938.00 |
| | income/poverty ratio below 50% | 816 | person | 380656.90 | 449396.60 | 18401.00 | 2848309.00 |
| | income/poverty ratio 50-99% | 816 | person | 468063.00 | 569847.60 | 27073.00 | 3494402.00 |
| | income/poverty ratio 100-149% | 816 | person | 542027.70 | 659320.80 | 35017.00 | 4005425.00 |
| | income/poverty ratio 150-199% | 816 | person | 542459.80 | 633350.10 | 29119.00 | 3643090.00 |
| | income/poverty ratio over 200% | 816 | person | 4087469.00 | 4549511.00 | 363575.00 | 28100000.00 |
| | population | 816 | person | 6150135.00 | 6926491.00 | 515004.00 | 39600000.00 |
| | edu less than 9th grade | 816 | person | 234850.40 | 405478.20 | 5064.00 | 2574120.00 |
| | edu 9th to12th grade | 816 | person | 319693.80 | 385452.30 | 14034.00 | 2151703.00 |
| | edu high school | 816 | person | 1153483.00 | 1154758.00 | 75946.00 | 5565798.00 |
| | edu college | 816 | person | 852239.90 | 949445.30 | 53032.00 | 5676581.00 |
| | edu associates | 816 | person | 331257.40 | 365926.00 | 11152.00 | 2150085.00 |
| | edu bachelors | 816 | person | 770806.20 | 904680.50 | 49050.00 | 6117707.00 |
| | edu graduates | 816 | person | 467423.50 | 554432.30 | 24216.00 | 3847887.00 |
| | owner | 816 | person | 1491053.00 | 1461130.00 | 106853.00 | 7513138.00 |
| | renter | 816 | person | 803003.90 | 992202.80 | 60322.00 | 5982791.00 |


doi:10.6342/NTU202404232

## 4.2 Methods

### 4.2.1 Synthetic Difference-in-Differences

To evaluate the effect of community solar policy and legislation on community solar adoption, I implement the synthetic difference-in-differences (SDID) method proposed by Arkhangelsky et al. (2021). This method leverages the strengths of difference-in-differences (DID) as well as synthetic control (SC) methods, offering a robust approach to causal inference in policy evaluation. The key idea behind SDID is to weigh the control units so that the weighted control group's time trend remains parallel to the treated unit's time trend before the policy intervention. Two sets of weights are the most pivotal in accomplishing this: one for each unit and another for each time point.

When analyzing policy effects, the DID method is one of the most commonly used methods. The DID method is a quasi-experimental design that can be utilized to estimate the causal effect of a treatment or intervention. The core concept of DID is to compare the differences in outcomes between a treated group and a control group, both before and after the intervention (Ashenfelter, 1978; Ashenfelter & Card, 1985; Card & Krueger, 2000; Bertrand et al., 2004). By doing so, DID attempts to isolate the effect of the intervention from other factors that might influence the outcome. In the DID setting, there is a balanced panel dataset comprising $N$ units observed over $T$ time periods. Each unit $i$ at time $t$ has an outcome denoted by $Y_{it}$, and a binary treatment status $W_{it} \in \{0, 1\}$ marking the exposure. In this research, the units are 50 states plus Washington D.C.; the time periods are from 2006 to 2021; outcomes are the installation capacity of community solar in the analysis of policy effectiveness, and rooftop solar in the subsequent spillover analysis; the treatment


doi:10.6342/NTU202404232

variable indicates if a state $i$ has any community solar policies enacted. In a two-way fix effect form, the average causal effect $\tau$ can be obtained through DID as follows:

$$\hat{\tau}^{DID} = arg \min_{\mu,\alpha,\beta,\tau} \left\{ \sum_{i=1}^{N} \sum_{t=1}^{T} (Y_{it} - (\mu + \alpha_i + \beta_t + \tau W_{it})^2) \right\} \tag{4.1}$$

Where $\alpha_i$ represents the unit effects, capturing the differences in intercepts for each individual unit, while the time effects $\beta_t$ indicate the overarching trend seen in both treated and control units.

The DID method assumes that if the treatment is absent, the treated and control groups would have followed parallel trends over time. This means that any differences in trends in post-treatment trends between the groups can be attributed to the intervention. Its simplicity and interpretability make it a popular choice for policy evaluation. However, the parallel trends assumption often poses a challenge. If the treated and control groups do not exhibit parallel trends before the intervention, the DID estimates may be biased. In terms of community solar, even if the community solar policies are alike, every state in the U.S. varies in its own way. It becomes a challenge when the unobservable traits of one state are so different from the other states, and moreover, are not fixed over time, the parallel trends assumption does not apply.

This is when the SC method comes to the forefront. To address the limitations of DID, SC method, developed by Abadie and Gardeazabal (2003) and Abadie et al. (2010; 2015), constructs a weighted combination of untreated units (the synthetic control) that closely mirrors the pre-intervention trajectory of the treated unit. The SC method is particularly useful when there are concerns about non-parallel trends and when the treated group consists of a single or a few units.


doi:10.6342/NTU202404232

The SC estimator can also be recast into a two-way fixed effect form, which can be easily compared with the DID estimator:

$$\hat{\tau}^{SC} = arg \min_{\mu,\beta,\tau} \left\{ \sum_{i=1}^{N} \sum_{t=1}^{T} (Y_{it} - (\mu + \beta_t + \tau W_{it})^2) \hat{\omega}_i^{SC} \right\} \tag{4.2}$$

Here, $\hat{\omega}_i^{SC}$ means the estimated optimal weights of control units to resemble the treated units, so that their pre-treatment outcomes and covariates look the most similar, which is the main reform from the DID. But also, noted that it omits the unit fixed effect $\alpha_i$ and the intercept $\mu$. Unlike DID, SC allows for unobservable factors to change over time, providing a more accurate counterfactual estimate. Moreover, SC is well-suited for cases where the treated group has a small number of units, making it a powerful tool for evaluating policies affecting specific regions or entities. Nevertheless, one concern that challenges the reliability of SC is that SC relies on a longer term of pre-treatment periods. If there's only few periods of pre-treatment, then it becomes difficult to distinguish whether the synthetic control group is truly similar to the treated group, or if it is due to random, unpredictable idiosyncratic shocks that affect the outcome variable. This means that there might be differences in factors that do not change over time and are unobserved between the treated unit and the synthetic control, impacting the validity of the causal inference (O' Neill et al., 2016).

The SDID method integrates the best features of both DID and SC, addressing their respective limitations and enhancing their applicability (Arkhangelsky et al.,2021). The primary objective of SDID is to consistently estimate the causal effect of receiving the policy $W_{it}$ specifically for treated units (ATT), even without assuming parallel trends between all treatment and control units on average, nor the level of outcomes of control and treated groups be exactly the same. Estimation of the ATT proceeds as follows, again,


doi:10.6342/NTU202404232

using a two-way fixed effect regression framework, but with optimally chosen unit and time weights $\omega_i$ and $\lambda_t$.

$$\hat{\tau}^{SDID} = arg \min_{\mu,\alpha,\beta,\tau} \left\{ \sum_{i=1}^{N} \sum_{t=1}^{T} (Y_{it} - (\mu + \alpha_i + \beta_t + \tau W_{it})^2) \hat{\omega}_i^{SDID} \hat{\lambda}_t^{SDID} \right\} \tag{4.3}$$

Relative to SC, the novel element incorporated in SDID is the time weights $\lambda_t$. This weight is used to minimize pre- and post-treated periods for the controls. Although this time weight still cannot remove the impact of unexpected shocks, it can eliminate the predictable impacts on outcomes when there is not too little heterogeneity (Arkhangelsky et al., 2021). By incorporating weights for both units and time points, SDID ensures that the control group closely follows the treated group's trajectory before the intervention, thereby more reliably satisfying the parallel trends assumption.

Also, notice that the model accommodates time-fixed effects $\beta_t$ estimation and time-invariant unit fixed effects $\alpha_i$—the latter also appears in DID but not SC. The presence of unit-fixed effects in SDID indicates that the method focuses on matching treated and control units based on similar pre-treatment trends, allowing for a constant difference between treated and control units. In other words, unlike SC, the units in the control group do not need to have identical absolute values with the treated group; they just need to exhibit a parallel trend. This approach is tailored to capture the different impacts of the treatment over time, leveraging within-unit and within-time variation for causal inference.

In the context of community solar policy evaluation, SDID is particularly advantageous because states in the U.S. vary in their community solar policies and corresponding capacity, let alone state characteristics such as economic conditions and demographic factors.


doi:10.6342/NTU202404232

SDID can account for these differences by creating a synthetic control that better matches the treated state's pre-intervention characteristics. Additionally, SDID allows for unobservable factors to vary over time, making it more robust to the changing nature of state-level characteristics and policies. By combining the strengths of DID and SC, SDID provides a more credible estimate of the policy effect, even when the parallel trends assumption of DID is not strictly met.

### 4.2.2 The Staggered Adoption Design

Although the above methods provide powerful techniques for treatment evaluation, in real-world situations, especially local policies, there is often more than a single intervention time—that is, the same policy is introduced in multiple regions at different times. Community solar state policy is exactly the case. Fortunately, SDID can also be augmented in the case of staggered adoption, which means treated units started to be treated in different periods of time (Ben-Michael et al., 2022; Athey & Imbens, 2022).

It is worth noting that whether it is a "block design", as named by Athey et al. (2021), with only a single treatment time or a staggered adoption with multiple treatment starting times, both designs assume that once treated, they will be exposed to it forever. Moreover, in the setting of SDID, units that are treated from the beginning to the end cannot be included, and at least two pre-processing periods are required to compose the control unit.

For the case of community solar state policy, the adoption matrix is composed by 50 states plus Washington D.C. from 2006 to 2021, and the earliest legislation was enacted in 2008, which meet the need of a minimum two pre-treatment periods. Conceptually, it


doi:10.6342/NTU202404232

looks like follows:

$$D_1 = \begin{bmatrix} 0_{AL,2006} & 0_{AL,2007} & 0_{AL,2008} & \cdots & 0_{AL,2021} \\ 0_{AK,2006} & 0_{AK,2007} & 0_{AK,2008} & \cdots & 0_{AK,2021} \\ 0_{AR,2006} & 0_{AR,2007} & 0_{AR,2008} & \cdots & 0_{AR,2021} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0_{MA,2006} & 0_{MA,2007} & 1_{MA,2008} & \cdots & 1_{MA,2021} \end{bmatrix}$$

$$D_2 = \begin{bmatrix} 0_{AL,2006} & \cdots & 0_{AL,2009} & \cdots & 0_{AL,2021} \\ 0_{AK,2006} & \cdots & 0_{AK,2009} & \cdots & 0_{AK,2021} \\ 0_{AR,2006} & \cdots & 0_{AR,2009} & \cdots & 0_{AR,2021} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ 0_{WA,2006} & \cdots & 1_{WA,2009} & \cdots & 1_{WA,2021} \end{bmatrix}$$

$$D_3 = \begin{bmatrix} 0_{AL,2006} & \cdots & 0_{AL,2010} & \cdots & 0_{AL,2021} \\ 0_{AK,2006} & \cdots & 0_{AK,2010} & \cdots & 0_{AK,2021} \\ 0_{AR,2006} & \cdots & 0_{AR,2010} & \cdots & 0_{AR,2021} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ 0_{CO,2006} & \cdots & 1_{CO,2010} & \cdots & 1_{CO,2021} \end{bmatrix}$$


doi:10.6342/NTU202404232

$$D_4 = \begin{bmatrix} 0_{AL,2006} & \cdots & 0_{AL,2013} & \cdots & 0_{AL,2021} \\ 0_{AK,2006} & \cdots & 0_{AK,2013} & \cdots & 0_{AK,2021} \\ 0_{AR,2006} & \cdots & 0_{AR,2013} & \cdots & 0_{AR,2021} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ 0_{CA,2006} & \cdots & 1_{CA,2013} & \cdots & 1_{CA,2021} \\ 0_{DC,2006} & \cdots & 1_{DC,2013} & \cdots & 1_{DC,2021} \\ 0_{MN,2006} & \cdots & 1_{MN,2013} & \cdots & 1_{MN,2021} \\ 0_{NH,2006} & \cdots & 1_{NH,2013} & \cdots & 1_{NH,2021} \end{bmatrix}$$

$$D_5 = \begin{bmatrix} 0_{AL,2006} & \cdots & 0_{AL,2015} & \cdots & 0_{AL,2021} \\ 0_{AK,2006} & \cdots & 0_{AK,2015} & \cdots & 0_{AK,2021} \\ 0_{AR,2006} & \cdots & 0_{AR,2015} & \cdots & 0_{AR,2021} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ 0_{HI,2006} & \cdots & 1_{HI,2015} & \cdots & 1_{HI,2021} \\ 0_{MD,2006} & \cdots & 1_{MD,2015} & \cdots & 1_{MD,2021} \\ 0_{NY,2006} & \cdots & 1_{NY,2015} & \cdots & 1_{NY,2021} \end{bmatrix}$$

$$D_6 = \begin{bmatrix} 0_{AL,2006} & \cdots & 0_{AL,2016} & \cdots & 0_{AL,2021} \\ 0_{AK,2006} & \cdots & 0_{AK,2016} & \cdots & 0_{AK,2021} \\ 0_{AR,2006} & \cdots & 0_{AR,2016} & \cdots & 0_{AR,2021} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ 0_{IL,2006} & \cdots & 1_{IL,2016} & \cdots & 1_{IL,2021} \\ 0_{OR,2006} & \cdots & 1_{OR,2016} & \cdots & 1_{OR,2021} \\ 0_{RI,2006} & \cdots & 1_{RI,2016} & \cdots & 1_{RI,2021} \end{bmatrix}$$



doi:10.6342/NTU202404232

$$D_7 = \begin{bmatrix} 0_{AL,2006} & \cdots & 0_{AL,2017} & \cdots & 0_{AL,2021} \\ 0_{AK,2006} & \cdots & 0_{AK,2017} & \cdots & 0_{AK,2021} \\ 0_{AR,2006} & \cdots & 0_{AR,2017} & \cdots & 0_{AR,2021} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ 0_{NC,2006} & \cdots & 1_{NC,2017} & \cdots & 1_{NC,2021} \\ 0_{VT,2006} & \cdots & 1_{VT,2017} & \cdots & 1_{VT,2021} \end{bmatrix}$$

$$D_8 = \begin{bmatrix} 0_{AL,2006} & \cdots & 0_{AL,2018} & \cdots & 0_{AL,2021} \\ 0_{AK,2006} & \cdots & 0_{AK,2018} & \cdots & 0_{AK,2021} \\ 0_{AR,2006} & \cdots & 0_{AR,2018} & \cdots & 0_{AR,2021} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ 0_{CT,2006} & \cdots & 1_{CT,2018} & \cdots & 1_{CT,2021} \\ 0_{NJ,2006} & \cdots & 1_{NJ,2018} & \cdots & 1_{NJ,2021} \end{bmatrix}$$

$$D_9 = \begin{bmatrix} 0_{AL,2006} & \cdots & 0_{AL,2019} & \cdots & 0_{AL,2021} \\ 0_{AK,2006} & \cdots & 0_{AK,2019} & \cdots & 0_{AK,2021} \\ 0_{AR,2006} & \cdots & 0_{AR,2019} & \cdots & 0_{AR,2021} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ 0_{ME,2006} & \cdots & 1_{ME,2019} & \cdots & 1_{ME,2021} \\ 0_{NV,2006} & \cdots & 1_{NV,2019} & \cdots & 1_{NV,2021} \\ 0_{SC,2006} & \cdots & 1_{SC,2019} & \cdots & 1_{SC,2021} \end{bmatrix}$$


doi:10.6342/NTU202404232

$$D_{10} = \begin{bmatrix} 0_{AL,2006} & \cdots & 0_{AL,2020} & \cdots & 0_{AL,2021} \\ 0_{AK,2006} & \cdots & 0_{AK,2020} & \cdots & 0_{AK,2021} \\ 0_{AR,2006} & \cdots & 0_{AR,2020} & \cdots & 0_{AR,2021} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ 0_{VA,2006} & \cdots & 1_{VA,2020} & \cdots & 1_{VA,2021} \end{bmatrix}$$

$$D_{11} = \begin{bmatrix} 0_{AL,2006} & \cdots & 0_{AL,2021} \\ 0_{AK,2006} & \cdots & 0_{AK,2021} \\ 0_{AR,2006} & \cdots & 0_{AR,2021} \\ \vdots & \ddots & \vdots \\ 0_{DE,2006} & \cdots & 1_{DE,2021} \\ 0_{NM,2006} & \cdots & 1_{NM,2021} \end{bmatrix}$$

By doing so, the original matrix that records staggered adoption is broken down into 11 matrices, each of which presents as a block design. To calculate the ATT, it is necessary to perform SDID on these matrices respectively and perform a weighted average of the obtained ATT. These weights are determined according to the number of treated units and the duration of each adoption period relative to the total number of treated units and periods across all groups. To enhance visual clarity in the adoption matrix, Figure 4.1 illustrates the treatment status of each state across various time periods, distinguishing whether a state is already treated, not yet treated, or never treated.


doi:10.6342/NTU202404232

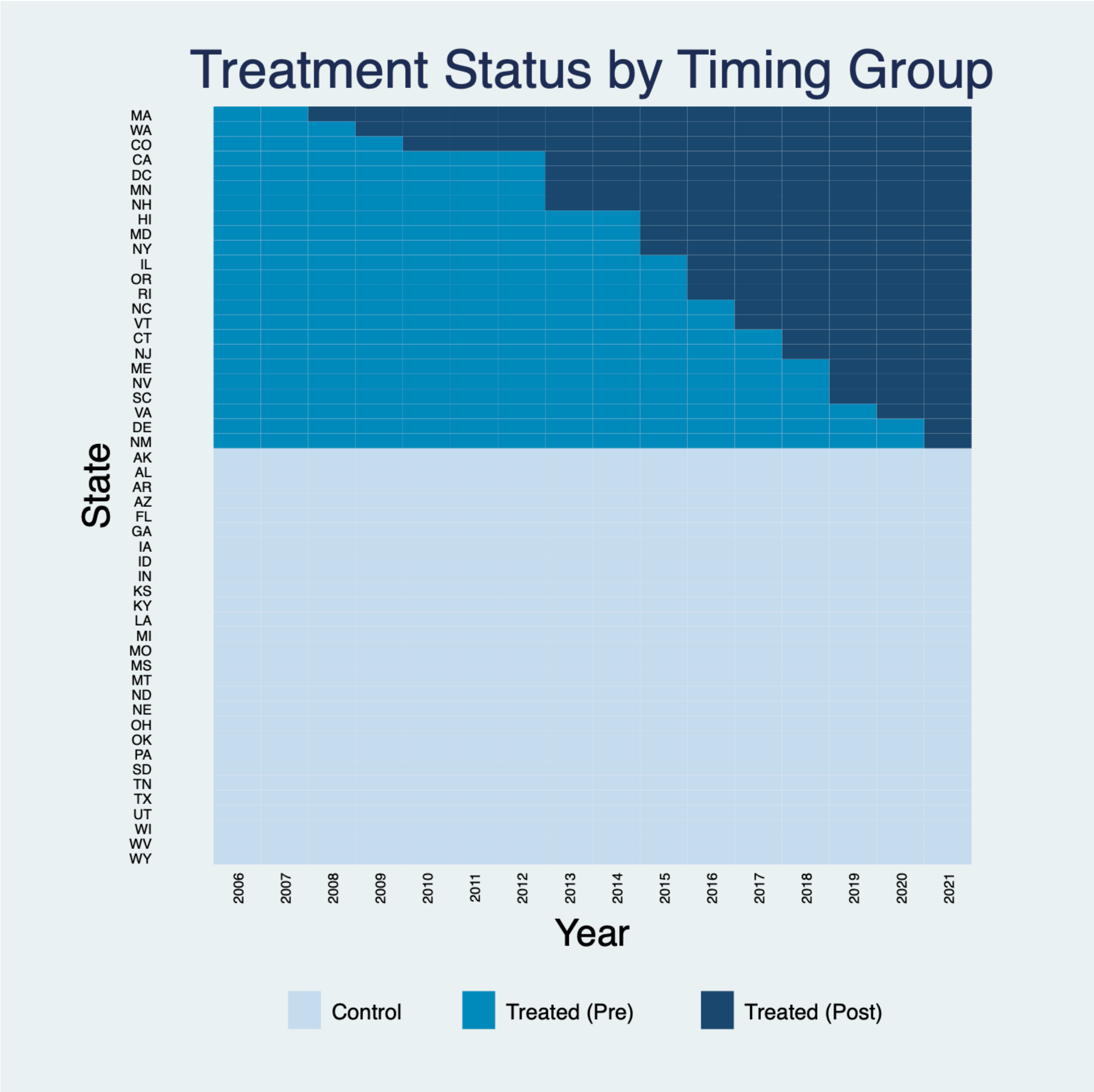



Figure 4.1: Treatment Status of Each State

Note: This figure shows the policy adoption status for each state: light blue indicates the never-adopters, serving as the control group; sky blue indicates treated unit's not-yet-adopt status; and dark blue indicates the treated units' periods of adoption. This figure was generated using Stata code from Mou et al. (2023).


doi:10.6342/NTU202404232

### 4.2.3 Covariates

In the SDID model, results can be enhanced by incorporating covariates by controlling for additional factors that could influence the outcome (Clarke et al., 2023). Covariates in this context refer to additional variables that are accounted for to control their potential impact on the outcomes. It's noteworthy to recognize that although the use of covariates in SDID is akin to the concept in DID, it differs from the SC method. In the SC model, covariates are used to create a synthetic control group that matches the treatment group as closely as possible. In SDID, however, covariates are used as a preprocessing step to control for their influence on the outcomes, ensuring that the effects of the treatment variables of interest are not confounded by these additional factors.

Incorporating covariates helps to isolate the true effect of the community solar policies by accounting for other variables that might influence solar adoption rates. This ensures a more accurate estimation of the policies' impact. Previous research indicates that the adoption of solar energy is influenced not only by policy interventions but also by various non-policy factors. Among these factors are consumer characteristics, including education level, age, income, occupation, and personal motivations such as environmental awareness and economic interests. Additionally, contextual factors such as the sociopolitical environment, community characteristics, and market conditions play significant roles (Crago & Chernyakhovskiy, 2017).

Regarding demographic characteristics, Crago and Chernyakhovskiy (2017) discovered that lower median age and higher income correlate positively with the growth of solar PV power generation capacity. Age and education are also highlighted by Kwan (2012) and Zahran et al. (2008), who argued that higher education levels and younger age groups


doi:10.6342/NTU202404232

tended to adopt new technologies more readily.

Moreover, residential environment characteristics such as housing density and urbanization levels influence the adoption rate of solar PV (Kwan, 2012). Here, I use the variables of renter and owner as key factors in residential status, because community solar is designed to be inclusive, implying providing benefits to renters who might otherwise be unable to access renewable energy options.

Considering these factors, the study includes several state-level covariates to control for their potential impact on solar adoption rates. These covariates include a state's average age, average income, population, population with different levels of educational attainment, population under different employment statuses, average yearly fuel costs excluding gas and electricity, estimated average monthly household electricity costs, and the number of households renting and owning houses. These variables are derived from publicly available one-year estimate data from the U.S. ACS.

These variables can influence both the adoption of solar energy and identified demographic groups that might encounter obstacles to installing solar (Schunder et al., 2020). I experimented with several methods to incorporate covariates, including adding a subset of them, including all of them, and converting absolute values into percentages before adding some or all of them. I then compared these results with those obtained without covariates. These findings will be detailed in Section 5.1. By incorporating these covariates, the study aims to provide a more robust analysis of the impact of community solar policies on solar installation capacity, ensuring that the observed effects are attributable to the policies themselves rather than other confounding factors.


doi:10.6342/NTU202404232

### 4.2.4 Inference

Arkhangelsky et al. (2021) considered three main inference methods for calculating standard errors, each with unique applications and limitations when dealing with different types of data and research questions. First, the Clustered Bootstrap method (Efron, 1979) is a common statistical technique particularly suitable for processing large panel data, such as tracking the same group of individuals over an extended period. One of the primary advantages of this approach is its simplicity and its ability to naturally handle correlations that may exist over time in panel data. However, a caveat of this method is its computational cost. Also, in the context of using the bootstrap procedure for statistical inference, there is a requirement for the number of treated units to increase proportionally with the total number of observations within each period when the treatment is adopted. If there are very few treated units during certain adoption periods, the bootstrap method may not be reliable or valid.

The Placebo Variance Estimation method is often used when there are only a few treated units or when dealing with large panel data. The central idea of the placebo method is to assess noise levels by converting effect estimates for treated units into effect estimates for untreated units. This approach relies on the empirical distribution of placebo estimator residuals over control units, and its validity depends on the homogeneity across units. However, the reliability of this approach is affected by the degree of homogeneity, and if there are significant differences between control and treatment groups, the accuracy of the estimates may be questioned.

Finally, there is the Jackknife method (Miller, 1974). This method also works with asymptotic arguments when there are numerous treated units, and it is less computation-


doi:10.6342/NTU202404232

ally intensive. The Jackknife method can ensure the accuracy and reliability of results, especially when the characteristics of the treatment and control populations are similar enough. It provides a more conservative estimate, though it may be biased in some cases, such as when using the SC estimator. Furthermore, the Jackknife estimator requires multiple observations to iteratively estimate the treatment effect. If there is only one treated unit in a given adoption period, removing this single unit leads to an undefined situation for calculating the treatment effect, as there are no other treated units left to compare with. This makes it impossible to estimate the treatment effect meaningfully using the Jackknife method, rendering the estimator ineffective when any adoption period includes only one treated unit.

In the case of community solar, there are multiple treated units across different time periods, making the bootstrap method preferable compared to placebo variance estimation. Additionally, in some years, there is only one treated unit, rendering the Jackknife method inapplicable. The bootstrap method is most appropriate in this context because it effectively handles the correlation over time in the panel data and accommodates the varying number of treated units across different periods. Therefore, I use bootstrap inference as the primary method to retrieve standard errors while keeping placebo standard errors for comparison.


doi:10.6342/NTU202404232

# Chapter 5 Results

## 5.1 Model Testing and Robustness Checks

### 5.1.1 SC, DID, and SDID with Two Inference Options

In this research, I utilized Stata's "sdid" command released by Pailanir and Clarke (2022) to conduct the analysis. The command allows for canonical SDID estimation, SDID with staggered adoption, and the three main inference methods mentioned above, and last but not least, it also supports the execution of SC and DID methods as comparisons to the SDID approach.

To start with, I compared the impact of state policies on community solar installation capacity across three different methods. This comparison was to assess whether the SDID method was as applicable to community solar policy analysis as anticipated. At this stage, I did not include any covariates in the analysis. Meanwhile, I utilized two inference methods, bootstrap and placebo, to generate standard errors. The results of this analysis are presented in Table 5.1 below.

The results show that under the three models, the effects are not significant. However, from the perspective of standard errors, using the bootstrap method overall produces


doi:10.6342/NTU202404232

Table 5.1: Comparison of SC, DID, and SDID

| | (1)<br>**SC** | (2)<br>**DID** | (3)<br>**SDID** |
|---|---|---|---|
| Treated | 28982.2<br>(31187.0)<br>[37487.2] | 31020.4<br>(28843.3)<br>[35481.7] | 35099.6<br>(26809.8)<br>[39219.1] |
| N | 816 | 816 | 816 |

Note: This table compares the ATTs of SC, DID, and SDID methods, and two types of standard errors are presented. Bootstrap SE in parentheses ( ) and placebo SE in brackets [ ].

smaller standard errors than using the placebo method. I chose to use the bootstrap method to obtain the standard errors because I have growing treated units, which is suitable for its application. Besides, the dataset is not so large that it incurs excessive computational costs, and all results are generated with 500 replications.

Unlike DID, which may suffer from biases due to differences in pre-treatment trends between treated and control units, SDID mitigates these biases by creating a synthetic control group that closely resembles the treatment group in terms of pre-treatment characteristics. This local fit improvement is achieved through weighting, ensuring that the synthetic control group is a better match for the treated units than what is possible with standard DID. It can also be seen that the standard error obtained for SDID is smaller than that for DID. This is the result of improving the SDID local fit through weighting (Arkhangelsky et al., 2021).

In addition, SDID is more flexible in handling staggered adoption designs, which is particularly relevant in this study where different states adopted community solar policies at different times. This flexibility allows for a more nuanced analysis that can account for varying treatment timings and intensities, providing a more comprehensive understanding of the policy impacts.


doi:10.6342/NTU202404232

### 5.1.2 Results with Covariates

As Clarke et al. (2023) suggested, covariates help in reducing omitted variable bias, ensuring that the observed effect is more likely due to the treatment rather than other confounding factors. To probe the robustness with respect to the set of covariates included, I experimented with various configurations of covariates: no covariates (as in the last section), a subset of covariates, all covariates, and variables transformed into population proportions. Each configuration provides insights into how these additional variables affect the robustness of the results.

For variables selected in the subset, I followed the method conducted by Kwan (2012), who selected variables that were most pertinent to high solar adoption rates based on existing literature. Hence, in the subset part, I selected average electricity expenditure, average fuel expenditure, the number of the unemployed, income, the number of people below the poverty line, the state population, the number of people with college degrees or above, and the number of renting households as covariates. By doing so, I neglected people with education below university level and retained the renters and economically disadvantaged people that community solar is designed to help. I also converted the number of people from absolute numbers to population proportions and included them in full, or in part. In the subset models with ratio variables, covariates include electricity costs, fuel costs, unemployment rate, income, the proportion below the poverty line, the proportion of college or above, and the number of renting households.

The results across these configurations (Table 5.2) show that in most of the cases, although the overall ATT is positive, it is not statistically significant. Only by adding all covariates does the effect become marginally significant. This suggests that while the


doi:10.6342/NTU202404232

policies may have a beneficial impact, the effect is not strong enough to be detected with high confidence given the variability in the data. I proceed the analysis with Model (3), for it accounts for as many relevant factors as possible, reducing potential omitted variable bias. Also, compared with Model (5), Model (3) preserves the original scale of variables, offering crucial insights into real-world magnitudes and implicitly accounting for state size. This can be particularly relevant for policy-making and understanding state-level dynamics. For instance, absolute figures like the number of renting households or those below the poverty line may provide more actionable information than percentages when assessing solar capacity adoption. By using raw values, Model (3) captures these scale effects, and reveals important relationships between state size, socioeconomic factors, and solar energy implementation that might be obscured in ratio-based analyses.

Table 5.2: ATT with Different Covariate Sets

| | (1)<br>**no cov** | (2)<br>**subset cov** | (3)<br>**all cov** | (4)<br>**subset(ratio) cov** | (5)<br>**all(ratio) cov** |
|---|---|---|---|---|---|
| Treated | 35099.6<br>(26809.8) | 24183.2<br>(35792.2) | 64499.6*<br>(37074.2) | 17333.3<br>(41794.9) | 25412.9<br>(33243.1) |
| N | 816 | 816 | 816 | 816 | 816 |

Note: This table presents the ATTs of state-level community solar policies on the total capacity of community solar (in kW) based on SDID models controlling for different sets of covariates. Model (1) includes no covariates. Model (2) includes only a selected subset of covariates. Model (3) further includes all covariates. In Model (4) and Model (5), variables with person as the unit are transformed into the share of population. Model (4) retains the same selected variables as Model (2), whereas Model (5) includes all ratio-transformed covariates. Bootstrap standard errors with 500 replications are presented in parentheses. Bootstrap standard errors with 500 replications are in parentheses. * $p<0.1$.

## 5.2 Primary Results from the Selected Model

After using the SDID model with bootstrap to obtain standard errors and adding all covariates, the ATT shows that community solar capacity increased by 64,499.6 kW-DC,


doi:10.6342/NTU202404232

which is marginally significant at the 10% level.

To examine the dynamic treatment effects over time, the following Figures 5.1, 5.2 and 5.3 are respectively the event study outcomes, including synthetic weights, outcome trends, and point estimates with confidence intervals. This analysis helps assess whether the treatment and control groups followed parallel trends before the treatment and investigate how the treatment effect evolves over time after the adoption, which can reveal whether the effect is immediate, delayed, or changes in magnitude over time. The following is based on the 2013 event study. In 2013, four states passed legislation related to community solar energy, the most in a single year. This increase in legislative activity provides a valuable opportunity to analyze the immediate impacts and trends associated with the adoption of community solar policies (see Figure 5.2 and Figure 5.3).

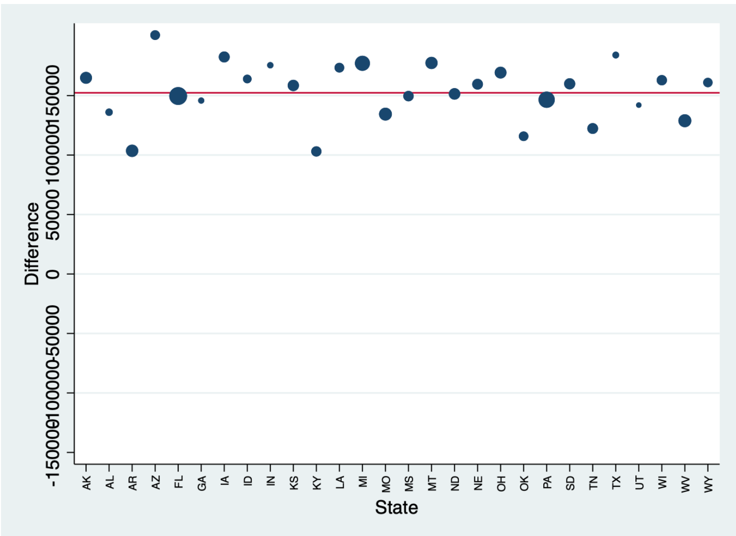



Figure 5.1: Synthetic Weights for each State in 2013

Note: The figure shows the weight of each state in the control group when generating the synthetic control group. The size of the dot corresponds to the size of its weight.


doi:10.6342/NTU202404232

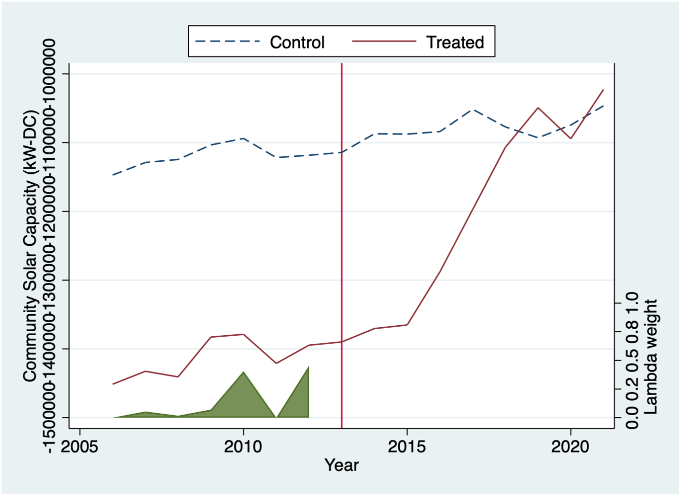



Figure 5.2: Outcome Trends in 2013

Note: This figure shows the effects and time trends for the states in the 2013 year cohort. The solid line represents the capacity trends of the states that passed community solar legislation, while the dotted line represents control states resulting from synthetic control. The green shaded area indicates the time weight.

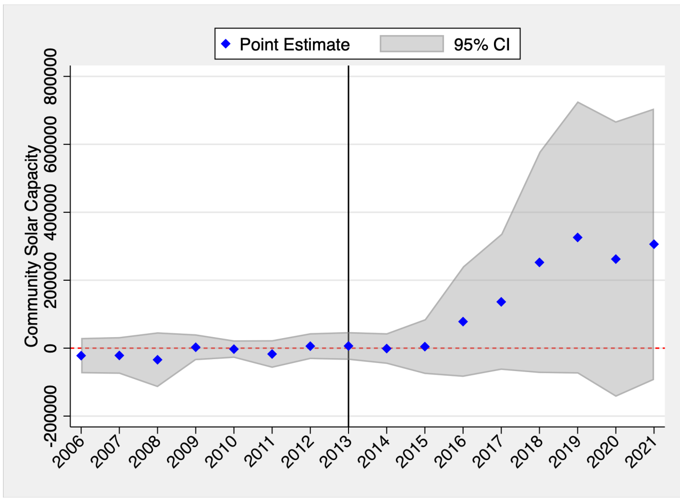



Figure 5.3: Point Estimates and Confidence Interval in 2013

Note: This figure presents point estimates of the state effect of passing community solar legislation for the cohort 2013, indicated by the blue points. The confidence intervals are represented by the gray-shaded areas.



doi:10.6342/NTU202404232

As can be seen from the figures, after 2013, the installation capacity of the treated group with state policies increased sharply. However, despite the seeming effectiveness of the policy among these four states, the overall ATT is only marginally significant as disclosed earlier. To understand this discrepancy, I examined the 2019 outcomes (Figures 5.4, 5.5, and 5.6). In 2019, three states passed community solar legislation, but their trend chart indicates that the policy effect declined.

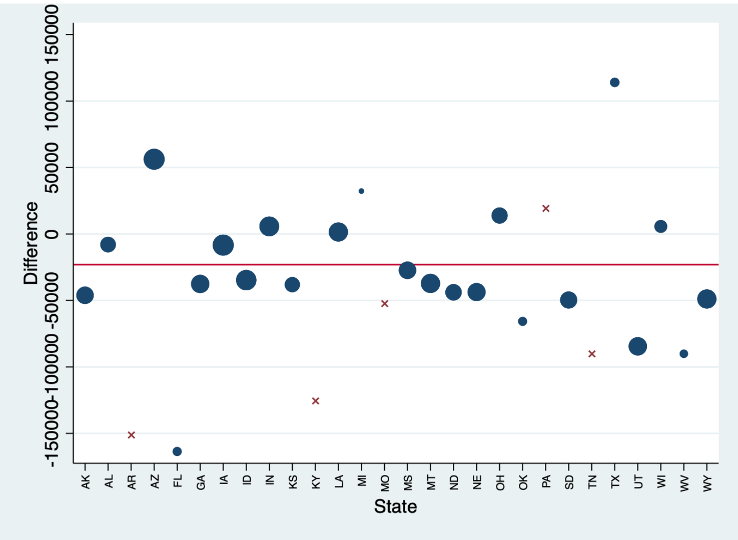



Figure 5.4: Synthetic Weights for each State in 2019

Note: The size of the dot corresponds to the size of each control unit' s weight, and when the weight is 0, it is represented by an ×.

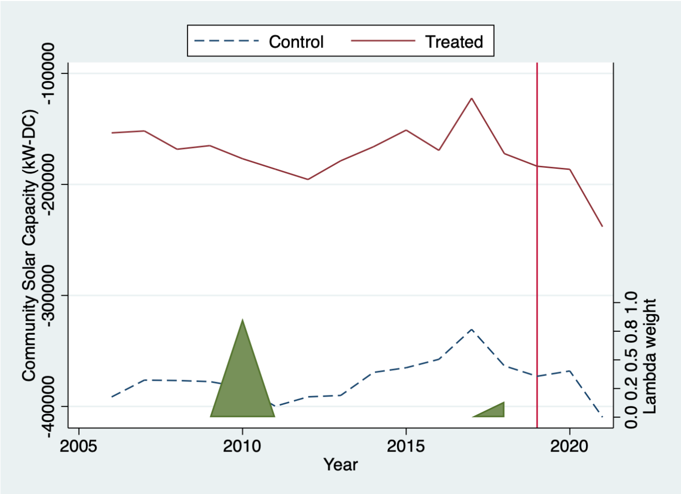



Figure 5.5: Outcome Trends in 2019



doi:10.6342/NTU202404232

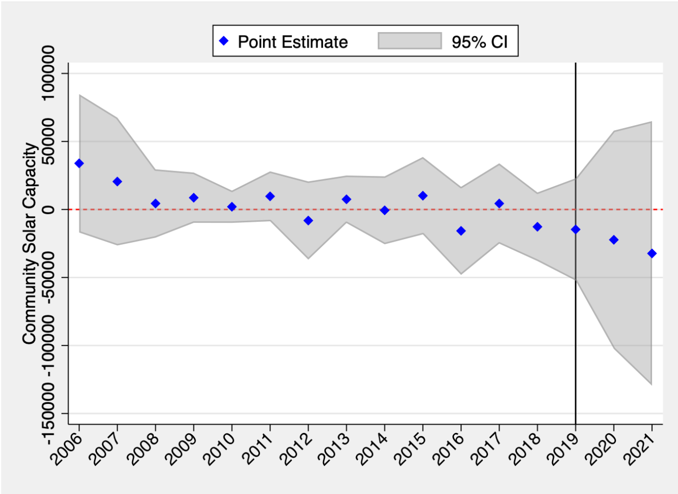



Figure 5.6: Point Estimates and Confidence Interval in 2019

These results indicate that policy effects change over time, prompting further analysis of how the ATT differs among states that passed community solar legislation at different points in time. A detailed discussion of these analyses and findings is presented in the next section. Additionally, the event study outputs for each event year are provided in the appendix, with figures of their corresponding synthetic weights, outcome trends, point estimates, and confidence intervals (Appendix A.1, A.2, and A.3).

## 5.3 Heterogeneity: Early and Late Adopters

To explore the abovementioned heterogeneity, I examine the variations in ATT for states that enacted the legislation early in the period versus those that did so later. When discussing the characteristics of technology pioneers, Roger's (2003) "Diffusion of Innovations" theory is often referenced. He used an S-shaped curve to categorize adopters into five groups based on the time of adoption: innovators (2.5% of adopters), early adopters (13.5%), early majority (34%), late majority (34%), and laggards (16%). However, Palm (2020) argued that the development of solar technology is still in its early stages, and terms like early adopters and late adopters should only be used relatively. This is especially true


doi:10.6342/NTU202404232

for community solar. Since I use states rather than individuals as units, I classify the first 50% of adopting states as early adopters and the last 50% as late adopters. This is intended as a relative term and does not exactly correspond to Roger's discrete classification. Therefore, the year 2017 is chosen as the cutoff, for it roughly divides the adoption periods in half: before 2017, 6 out of 11 cohorts and 13 out of 23 regions had passed community solar legislation. To be more specific, a total of 12 states and Washington D.C. enacted community solar legislation between 2006 and 2016. Massachusetts was the pioneer in 2008, followed by Washington in 2009, Colorado in 2010, and then California, D.C., Minnesota, and New Hampshire in 2013. Hawaii, Maryland, and New York followed in 2015, and Illinois, Oregon, and Rhode Island in 2016. These states constitute the first 6 of the 11 cohorts. From 2017 to 2021, another 10 states joined the ranks of those promoting community solar: North Carolina and Vermont in 2017, Connecticut and New Jersey in 2018, Maine, Nevada, and South Carolina in 2019, Virginia in 2020, and Delaware and New Mexico in 2021.

Moreover, since 2017, a federal-level community solar campaign, National Community Solar Partnership (NCSP), has been underway, and the change of president that year may also have influenced the direction of energy policy. The results are shown in Table 5.3 below.

The results indicate a stark contrast between early and late adopters. Policies in early adopter states have a positive and statistically significant impact on community solar capacity. After the implementation of the relevant laws, community solar capacity increased by 88171.2 kW-DC. Such installation capacity is equivalent to 33.5% of the cumulative installation capacity across all states from 2006 to 2016. This suggests that early adopters successfully leveraged their legislative frameworks to boost community solar capacity.


doi:10.6342/NTU202404232

Table 5.3: ATT Comparison Across Overall, Early Adopters, and Late Adopters

| | (1) **Overall** | (2) **Early Adopters** | (3) **Late Adopters** |
|---|---|---|---|
| Treated | 64499.6* | 88171.2** | -22550.8 |
| | (37074.2) | (43006.2) | (25065.2) |
| N | 816 | 656 | 608 |

Note: This table shows the ATTs of state-level community solar policies on the total capacity of community solar (in kW) based on SDID models controlling all covariates. Model (1) shows the overall policy effect. Model (2) shows the policy on early adopters, and Model (3) presents the effect on late adopters. Bootstrap standard errors with 500 replications are in parentheses. * p<0.1, ** p<0.05.

In contrast, for late adopters, there was a decline in capacity, dropping by 22550.8 kW-DC, although this reduction was not statistically significant. This shows that the growth of community solar energy is mainly led by early adopters, and that states implementing the policy later did not achieve substantial increases in installation capacity and may have even seen decreases.

These findings underscore the complexity of policy impacts on solar energy adoption. The significant positive impact of early adopter policies on community solar capacity can be attributed to several factors. One crucial factor is the importance of timely legislative action and the advantages of early market entry. As research suggests, early adopters of climate technologies or first-movers in climate policies can potentially gain environmental, economic, and employment benefits compared to delayed action (Pollittet al., 2015; Karkatsoulis et al.,2016; Bednar-Friedl, 2016). The results of this study seem to echo the previous literature. Early-adopting states may have benefited from first-mover advantages, enabling them to establish more robust community solar markets. They gained early market entry advantages, allowing them to build infrastructure, establish partnerships, and refine operational models ahead of others. This early momentum often translates into a leadership position, as these states can leverage their experience and established networks


doi:10.6342/NTU202404232

to attract investments and further expand their community solar capacity.

Additionally, the favorable development conditions of these early-adopting states likely played a significant role in their willingness to adopt relevant policies to accelerate solar energy development. Factors such as geographical location, spatial distribution, population density, degree of urbanization, and political conditions may have contributed to their readiness to embrace community solar initiatives, only that these factors were not included in the current analysis.

Another contributing factor is that early-adopting states already had some laws and regulations in place that provided a foundation for community solar energy. For example, rules for net metering or the use of distributed energy sources, as documented by the National Renewable Energy Laboratory (NREL), facilitated the smoother adoption of community solar policies. These pre-existing regulations helped streamline the implementation process, allowing these states to more effectively promote and expand their community solar programs.

On the other hand, the lack of significant impact for late adopters points to potential challenges such as market saturation, policy fatigue, or the need for more innovative or aggressive policies to spur growth. These states may have encountered difficulties in stimulating solar installation capacity due to various complex factors that emerged after 2017.

Several late-market factors may have influenced these outcomes. One key factor is the NCSP, initiated in 2017. Originally a competition designed to develop innovative models to support underserved markets, the NCSP aimed to enhance community solar deployment through innovative ways. It later evolved into an initiative led by the U.S.


doi:10.6342/NTU202404232

Department of Energy in collaboration with the NREL and Lawrence Berkeley National Laboratory. This alliance promotes and shares resources through stakeholder networks, technical assistance, and collaboration with partners and advocacy groups to address common barriers to solar adoption. While the NCSP's broad support was beneficial, it may have impacted the effectiveness of later state policy promotions by diluting or replacing the resources and support provided by individual state policies.

In addition, the political landscape in 2017 underwent significant changes that likely influenced the solar energy market. The election of President Donald Trump brought about a reduction in investment in renewable energy, as his administration prioritized fossil fuel industries over renewable energy development. This shift may have slowed states' willingness to promote community solar initiatives, as federal support and incentives waned. The reduced emphasis on renewable energy at the national level created an uncertain environment for investments, causing a plateau in state-level solar policies. Nonetheless, in fact, the annual installation capacity continues to rise, which may mean that the increase in capacity at a later stage was driven by other factors instead of policies.

Compounding these challenges was the passage of the Tax Cuts and Jobs Act in November 2017. This legislation reformed and lowered personal and corporate tax rates, altering the financial landscape for businesses and individuals. Through this tax reform bill, companies no longer needed to invest as heavily in the solar industry to receive the Investment Tax Credit (ITC), which had previously been a significant driver of solar investments. The reduction in the ITC's attractiveness may have led to a decrease in the financial incentives for companies to invest in solar projects, further dampening the growth of community solar installations in states that adopted policies later.


doi:10.6342/NTU202404232

In a nutshell, the lack of significant impact for late adopters of community solar policies highlights the multifaceted challenges they may encounter, including the influence of the NCSP, changes in the political landscape, tax reforms, market saturation, and policy fatigue. These factors collectively underline the importance of timely and proactive policy implementation to maximize the potential benefits of community solar initiatives.

## 5.4 Spillover Effect on Rooftop Adoptions

Furthermore, I explored whether state policies promoting community solar had any spillover effects on residential rooftop PVs, so as to identify their potential substitutive relationships. To do so, I changed the dependent variable from community solar capacity to residential rooftop solar capacity. As the results showed in Table 5.4, overall, community solar policies did not have a significant impact on the growth of rooftop PVs. This suggests that the expansion of community solar projects did not detract from or significantly boost the adoption of rooftop solar systems. When comparing early and late adopter

Table 5.4: Spillover Effect on Rooftop Capacity

| | (1)<br>**RT Overall** | (2)<br>**RT of Early Adopters** | (3)<br>**RT of Late Adopters** |
|---|---|---|---|
| Treated | 246824.2<br>(393418.5) | 312432.5<br>(518446.7) | 5555.3<br>(92499.6) |
| N | 816 | 656 | 608 |

Note: This table shows the ATTs of state-level community solar policies on the total capacity of community solar (in kW) based on SDID models controlling all covariates. Model (1) shows the overall policy spillover effect on rooftop solar. Model (2) presents the policy spillover effect on early adopters, whereas Model (3) on late adopters. Bootstrap standard errors with 500 replications are in parentheses.

states again, with 2017 as the demarcation, the same holds. Both early and late adopter states have positive but not significant ATTs. Meanwhile, the scale of the effect is larger


doi:10.6342/NTU202404232

in the early adopters' group, implying that the overall effect may be dominant by the early adopters, just the same as the case of community solar capacity. It should also be noted that the outcomes are not statistically significant, meaning that there is no evidence that community solar policies have a spillover effect on residential rooftop solar. In other words, while rooftop solar installations are growing, this growth is not directly influenced by the policies targeting community solar. The growth in rooftop PVs is likely driven by other factors such as decreasing costs, technological advancements, and increasing consumer awareness and demand for renewable energy.

The decline in community solar adoption among later adopters, although not significant, combined with the non-significant growth in rooftop solar, suggests a potential, if any, substitutive relationship between the two. Late adopters may be less responsive to community solar projects due to various barriers or perceived benefits that differ from early adopters. The continued growth, albeit non-significant, in rooftop solar for later adopters suggests a steady but less aggressive adoption growth. This can imply that rooftop solar remains an option for those states within which people or utilities prefer individual control over their solar investments in the states.

Nonetheless, the absence of significant spillover effects on residential rooftop PVs implies that community solar and rooftop solar markets may operate somewhat independently. While both types of solar installations can potentially lower electricity costs for participants or homeowners, they are not necessarily substitutes. This highlights how community solar projects can, as its embedded intention, provide solar access to underserved communities that might otherwise be excluded from the benefits of solar energy.

In conclusion, the implementation of community solar policies has had varied im-


doi:10.6342/NTU202404232

pacts at different stages and in different states. The above findings show that policies aimed at promoting community solar energy have positive impacts among early adopting states, but the overall effectiveness remains ambiguous. This can be attributed to the diverse positioning of these policies across states, where some are integrated into broader renewable energy frameworks or decentralized energy laws, while others require additional pilot legislation as the foundation for effective implementation.

Moreover, during later periods, federal-level factors began to appear in the market, potentially exerting influence, including initiatives like the NCSP, broader national tax reform policies, and even political atmosphere shifts. These federal interventions may dilute the effectiveness of state-level policies by introducing additional complexities and regulatory dynamics. Furthermore, it is plausible that the state policies primarily functioned as enablers for the adoption of community solar models. These policies facilitated the initial setup and operation of such initiatives, but they did not guarantee a consistent increase in capacity or widespread adoption. This distinction highlights the role of state policies in the initiation rather than sustained expansion of community solar.

Despite these challenges, community solar state policies have little impact on residential rooftop solar adoption. This implies that community solar to some extent broadens the solar market beyond traditional residential rooftop installations, thereby catering to a wider spectrum of stakeholders and enhancing solar adoption options.


doi:10.6342/NTU202404232

# Chapter 6 Conclusion

This article explores whether state-level community solar legislation in the United States positively impacts the capacity of community solar installations in each state and whether these policies have spillover effects on residential rooftop solar capacity. I use the SDID method to measure the policy effect by distinguishing states that passed legislation at different points in time and those that had no policy, and by measuring the difference in installation capacity before and after the legislation passed.

The results indicate that, overall, community solar state policies have a marginally significant, positive effect on community solar installation capacity. For early adopters before 2017, significant positive benefits are observed. As for late adopters, the installation capacity decreases, but the effect is not significant. This suggests that policies passed earlier have a more substantial impact on those states, while the effects of later policies might be moderated by external factors at the federal level, such as changes in political regimes and community solar initiatives.

I also find that community solar policies show no significant spillover effect on rooftop solar capacity. In spite of the state policies, rooftop solar installation capacity increased overall, both before and after 2017. This indicates that community solar and rooftop solar cater to different markets. Community solar may indeed reach the groups


doi:10.6342/NTU202404232

that might not have had access to rooftop installations due to factors such as high upfront costs, unsuitable roof conditions, or rental housing status.

These findings contribute to the understanding of how state-level community solar policies affect solar installation capacity and the dynamics between community solar and rooftop solar markets. In summary, an increasing number of states are passing community solar legislation to promote its installation and development; however, these policies have a limited effect on increasing installation capacity, suggesting that other factors may be driving the growth in capacity. State policies, while important, seem to serve primarily as enablers, laying the groundwork for further development rather than being the sole drivers of capacity increases. Despite the overall evaluation, it is still worth noticing that early adopting states enjoy significant growth due to the legislation, which implies that the timing of adopting policies does matter. The sooner, rather than later adoption can create a favorable environment that allows a head start in establishing infrastructure, attracting investment, and thus, fostering market development.

The study has several limitations. First, it focuses on state-level policies without considering local or municipal initiatives, which means that the study might not capture the full range of factors influencing solar adoption, potentially leading to an incomplete understanding of the dynamics at play. Second, the analysis does not include household-level data, preventing an in-depth examination of the characteristics and behaviors of participants within these states. Understanding the demographic, socio-economic, and behavioral factors at the household level could provide valuable insights into the adoption patterns and effectiveness of community solar policies. Third, this study does not take into account detailed aspects of the legislation, such as the number of members in each project, the category of participant credit rate, and other specific provisions. These legislative de-


doi:10.6342/NTU202404232

tails can vary significantly across states and can affect how policies are implemented and their subsequent effectiveness.

Future research can explore in more detail the reasons that drive the increase in installation capacity. For example, further analysis could investigate how different incentives, such as tax credits, rebates, and subsidies, affect households' decisions to adopt community solar energy. Understanding these incentives' influence could help design more targeted and efficient policy measures. Since more and more projects are targeting low- and moderate-income groups, their effectiveness also merits exploration. By digging into this topic, researchers can further assess its potential in alleviating energy poverty. Examining how community solar projects designed for these income groups perform in terms of participation rates, cost savings, and energy access can provide valuable insights into their impact. This could include studying how these projects are structured, the types of incentives offered, and the specific barriers these communities face in accessing solar energy. Meanwhile, extending the research to incorporate household-level data would provide a more granular understanding of these deciding factors and could aid in refining and improving community solar policies to maximize their effectiveness and accessibility. These analyses would help policymakers and stakeholders better understand the barriers and facilitators to community solar adoption and design interventions that address the specific needs and contexts of different communities.


doi:10.6342/NTU202404232

# References

[1] Abadie, A. (2005). Semiparametric difference-in-differences estimators. *Review of Economic Studies, 72*(1), 1-19. https://doi.org/10.1111/0034-6527.00321

[2] Abadie, A., & Gardeazabal, J. (2003). The economic costs of conflict: A case study of the Basque Country. *American Economic Review, 93*(1), 113-132. https://doi.org/10.1257/000282803321455188

[3] Abadie, A., Diamond, A., & Hainmueller, J. (2010). Synthetic control methods for comparative case studies: Estimating the effect of California's Tobacco Control Program. *Journal of the American Statistical Association, 105*(490), 493-505. https://doi.org/10.1198/jasa.2009.ap08746

[4] Abadie, A., Diamond, A., & Hainmueller, J. (2015). Comparative politics and the synthetic control method. *American Journal of Political Science, 59*(2), 495-510. https://doi.org/10.1111/ajps.12116

[5] Arkhangelsky, D., Athey, S., Hirshberg, D. A., Imbens, G. W., & Wager, S. (2021). Synthetic difference-in-differences. *American Economic Review, 111*(12), 4088–4118. https://doi.org/10.1257/aer.20190159

[6] Ashenfelter, O. (1978). Estimating the effect of training programs on earnings. *Review of Economics and Statistics, 60*(1), 47–57. https://doi.org/10.2307/1924332


doi:10.6342/NTU202404232

[7] Ashenfelter, O., & Card, D. (1985). Using the longitudinal structure of earnings to estimate the effect of training programs. *Review of Economics and Statistics, 67*(4), 648–660. https://doi.org/10.2307/1924810

[8] Asmus, P. (2008). Exploring new models of solar energy development. *The Electricity Journal, 21*(3), 61-70. https://doi.org/10.1016/j.tej.2008.03.005

[9] Athey, S., & Imbens, G. W. (2022). Design-based analysis in difference-in-differences settings with staggered adoption. *Journal of Econometrics, 226*(1), 62-79. https://doi.org/10.3386/w24963

[10] Athey, S., Bayati, M., Doudchenko, N., Imbens, G., & Khosravi, K. (2021). Matrix completion methods for causal panel data models. *Journal of the American Statistical Association, 116*(536), 1716-1730. https://doi.org/10.1080/01621459.2021.1891924

[11] Bednar-Friedl, B. (2016). Is there a first-mover advantage in international climate policy?. *The Implementation of the Paris Agreement on Climate Change (pp. 155-170)*. Springer. https://doi.org/10.1007/978-3-319-23324-6

[12] Ben-Michael, E., Feller, A., & Rothstein, J. (2022). Synthetic controls with staggered adoption.*Journal of the Royal Statistical Society: Series B (Statistical Methodology), 84*(2), 351-381. https://doi.org/10.1111/rssb.12448

[13] Bertrand, M., Duflo, E., & Mullainathan, S. (2004). How much should we trust differences-in-differences estimates? *Quarterly Journal of Economics, 119*(1), 249–275. https://doi.org/10.1162/003355304772839588

[14] Bollinger, B., & Gillingham, K. (2012). Peer effects in the diffusion of solar photovoltaic panels. *Marketing Science, 31*(6), 900-912. https://doi.org/10.1287/mksc.1120.0727


doi:10.6342/NTU202404232

[15] Card, D., & Krueger, A. B. (2000). Minimum wages and employment: A case study of the fast-food industry in New Jersey and Pennsylvania: Reply. *American Economic Review, 90*(5), 1397-1420. https://doi.org/10.1257/aer.90.5.1397

[16] Clarke, D., Pailañir, D., Athey, S., & Imbens, G. (2023). Synthetic difference in differences estimation. arXiv preprint arXiv:2301.11859. https://doi.org/10.2139/ssrn.4015931

[17] Cook, J., & Shah, M. (2018). Focusing the Sun: State Considerations for Designing Community Solar Policy. https://doi.org/10.2172/1419711

[18] Coughlin, J., Grove, J., Irvine, L., Jacobs, J. F., Phillips, S. J., Moynihan, L., & Wiedman, J. (2011). Guide to community solar: Utility, private, and non-profit project development.*National Renewable Energy Laboratory.* https://doi.org/10.1080/15575330.2011.553566

[19] Crago, C. L., & Chernyakhovskiy, I. (2017). Are policy incentives for solar power effective? Evidence from residential installations in the Northeast. *Journal of Environmental Economics and Management, 81*, 132-151. https://doi.org/10.1016/j.jeem.2016.09.008

[20] Efron, B. (1979). Bootstrap methods: Another look at the jackknife. *Annals of Statistics, 7*(1), 1–26. https://doi.org/10.1214/aos/1176344552

[21] Funkhouser, E., Blackburn, G., Magee, C., & Rai, V. (2015). Business model innovations for deploying distributed generation: The emerging landscape of community solar in the US. *Energy Research & Social Science, 10*, 90-101. https://doi.org/10.1016/j.erss.2015.07.004


doi:10.6342/NTU202404232

[22] Gai, D. H. B., Shittu, E., Attanasio, D., Weigelt, C., LeBlanc, S., Dehghanian, P., & Sklar, S. (2021). Examining community solar programs to understand accessibility and investment: Evidence from the US. *Energy Policy, 159*, 112600. https://doi.org/10.1016/j.enpol.2021.112600

[23] Graziano, M., & Gillingham, K. (2015). Spatial patterns of solar photovoltaic system adoption: The influence of neighbors and the built environment. *Journal of Economic Geography, 15*(4), 815-839. https://doi.org/10.1093/jeg/lbu036

[24] Heeter, J. S., Xu, K., & Fekete, E. (2020). Community solar 101 [Slides]. United States. https://doi.org/10.2172/1602184

[25] International Energy Agency. (2024). Renewables 2023. IEA. https://www.iea.org/reports/renewables-2023

[26] Karkatsoulis, P., Capros, P., Fragkos, P., Paroussos, L., & Tsani, S. (2016). First-mover advantages of the European Union's climate change mitigation strategy. *International Journal of Energy Research, 40*, 814-830. https://doi.org/10.1002/er.3487

[27] Klein, S. J., Hargreaves, A., & Coffey, S. (2021). A financial benefit-cost analysis of different community solar approaches in the Northeastern US. *Solar Energy, 213*, 225-245. https://doi.org/10.1016/j.solener.2020.11.031

[28] Kwan, C. L. (2012). Influence of local environmental, social, economic and political variables on the spatial distribution of residential solar PV arrays across the United States. *Energy Policy, 47*, 332-344. https://doi.org/10.1016/j.enpol.2012.04.074

[29] Lawrence Berkeley National Laboratory. (2023). Tracking the Sun Data Viewer. https://trackingthesun.lbl.gov


doi:10.6342/NTU202404232

[30] Marcucci, A., & Turton, H. (2015). Induced technological change in moderate and fragmented climate change mitigation regimes. *Technological Forecasting and Social Change, 90*, 230-242. https://doi.org/10.1016/J.TECHFORE.2013.10.027.

[31] Michaud, G. (2020). Perspectives on community solar policy adoption across the United States. *Renewable Energy Focus, 33*, 1-15. https://doi.org/10.1016/j.ref.2020.01.001

[32] Miller, R. G. (1974). The jackknife - A review. *Biometrika, 61*(1), 1–15.

[33] Mooney, M. (2023). How much can you save with community solar? EnergySage. https://www.energysage.com/community-solar/community-solar-savings/

[34] Mou, H., Liu, L., & Xu, Y. (2023). Panel data visualization in R (panelView) and Stata (panelview). *Journal of Statistical Software, 107*(7), 1–20. https://doi.org/10.18637/jss.v107.i07

[35] Nguyen, T. C. (2020). Power to the people? Community solar and energy democracy in New York and Minnesota (Doctoral dissertation, Franklin & Marshall College). https://doi.org/10.15823/p.2016.28

[36] Noll, D., Dawes, C., & Rai, V. (2014). Solar community organizations and active peer effects in the adoption of residential PV. *Energy Policy, 67*, 330-343. https://doi.org/10.1016/j.enpol.2013.12.050

[37] O’Neill, S., Kreif, N., Grieve, R., Sutton, M., & Sekhon, J. S. (2016). Estimating causal effects: Considering three alternatives to difference-in-differences estimation. *Health Services and Outcomes Research Methodology, 16*, 1-21. https://doi.org/10.1007/s10742-016-0146-8


doi:10.6342/NTU202404232

[38] Palm, A. (2020). Early adopters and their motives: Differences between earlier and later adopters of residential solar photovoltaics. *Renewable and Sustainable Energy Reviews, 133*, 110142. https://doi.org/10.1016/j.rser.2020.110142

[39] Pailañir, D., & Clarke, D. (2022). SDID: Stata module to perform synthetic difference-in-differences estimation, inference, and visualization. *Statistical Software Components, Boston College Department of Economics.* https://ideas.repec.org/c/boc/bocode/s459058.html

[40] Pollitt, H., Summerton, P., & Klaassen, G. (2015). A model-based assessment of first-mover advantage and climate policy. *Environmental Economics and Policy Studies, 17*, 299-312. https://doi.org/10.1007/s10018-014-0098-6

[41] Rogers, E. M. (2003). *Diffusion of innovations (5th ed.)*. New York: Free Press.

[42] Schelly, C. (2014a). Implementing renewable energy portfolio standards: The good, the bad, and the ugly in a two state comparison. *Energy Policy, 67*, 543-551. https://doi.org/10.1016/j.enpol.2013.11.075

[43] Schelly, C. (2014b). Residential solar electricity adoption: What motivates, and what matters? A case study of early adopters. *Energy Research & Social Science, 2*, 183-191. https://doi.org/10.1016/j.erss.2014.01.001

[44] Schunder, T., Yin, D., Bagchi-Sen, S., & Rajan, K. (2020). A spatial analysis of the development potential of rooftop and community solar energy. *TIDEE: TERI Information Digest on Energy and Environment, 20*(2), 197-197. https://doi.org/10.1016/j.rsase.2020.100355

[45] Shittu, E., Kamdem, B. G., & Weigelt, C. (2019). Heterogeneities in energy tech-

nological learning: Evidence from the US electricity industry. *Energy Policy, 132*, 1034-1049. https://doi.org/10.1016/j.enpol.2019.06.052

[46] Singh, S., & Wu, O. (2021). Community solar value generation and distribution. *SSRN Electronic Journal.* https://doi.org/10.2139/ssrn.3795453

[47] Simpson, G., & Clifton, J. (2017). Testing diffusion of innovations theory with data: financial incentives, early adopters, and distributed solar energy in Australia. *Energy Research & Social Science, 29*, 12-22. https://doi.org/10.1016/j.erss.2017.04.005

[48] Soeiro, S., & Dias, M. (2019). Renewable energy cooperatives: A systematic review. *2019 16th International Conference on the European Energy Market (EEM) (pp. 1-6)*. IEEE. https://doi.org/10.1109/EEM.2019.8916546

[49] Solar Energy Industries Association. (2024). US solar market insight executive summary Q2 2024. https://www.seia.org/us-solar-market-insight

[50] Thakur, P., & Wilson, V. H. (2024). Analysis of barriers affecting the adoption of community solar from consumer's perspective: A hybrid ISM-DEMATEL approach. *Energy & Environment, 35*(1), 113-141. https:// doi.org/ 10.1177/0958305x221122930

[51] US Department of Energy. (n.d.). Community solar market trends. US Department of Energy. https://www.energy.gov/communitysolar/community-solar-market-trends

[52] US Environmental Protection Agency. (2024). Shared Renewables. US Environmental Protection Agency. https:// www.epa.gov/ green-power-markets/ shared-renewablestwo



doi:10.6342/NTU202404232

[53] Weinrub, A. (2011). Community power: Decentralized renewable energy in California. US Department of Energy.*Clean Coalition.* https:// doi.org/ 10.1109/ ICCEP.2011.6036306

[54] Xu, K., Chan, G., & Sumner, J. (2023). Sharing the sun: Community solar deployment and subscriptions (as of June 2023). *National Renewable Energy Laboratory.* https://doi.org/10.2172/2217117

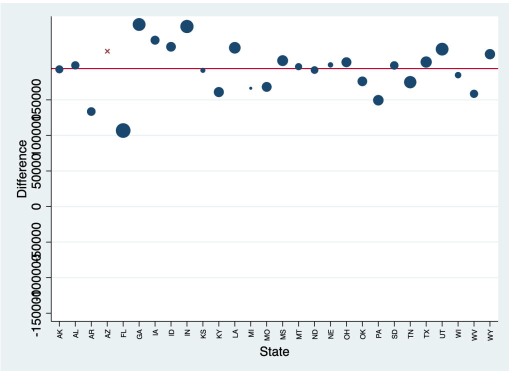
[55] Xu, K., Nabirye, S., Sandler, S., & Harmon, J. (2024). State policies and programs for community solar (2024 Q3 Update). *NREL Data Catalog*. Golden, CO: National Renewable Energy Laboratory. Last updated: June 27, 2024. https://doi.org/10.7799/2377753

[56] Zahran, S., Brody, S. D., Peacock, W. G., Vedlitz, A., & Grover, H. (2008). Social vulnerability and the natural and built environment: A model of flood casualties in Texas. *Disasters, 32*(4), 537-560. https://doi.org/10.1111/j.1467-7717.2008.01054.x

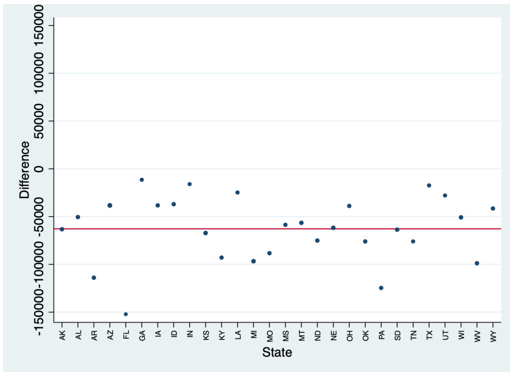

doi:10.6342/NTU202404232

# Appendix A — Weights, Trends, and Point Estimates of Each Event Year

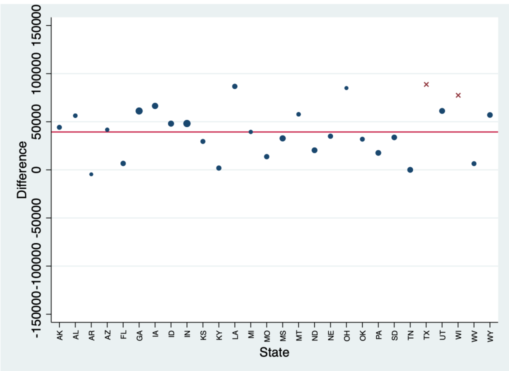
## A.1 Event Studies: Synthetic Weights in Each Event Year



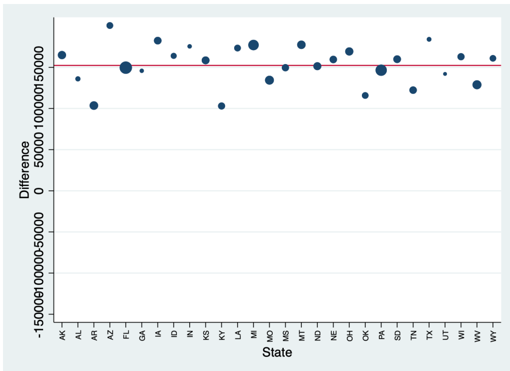

(a) 2008




(b) 2009

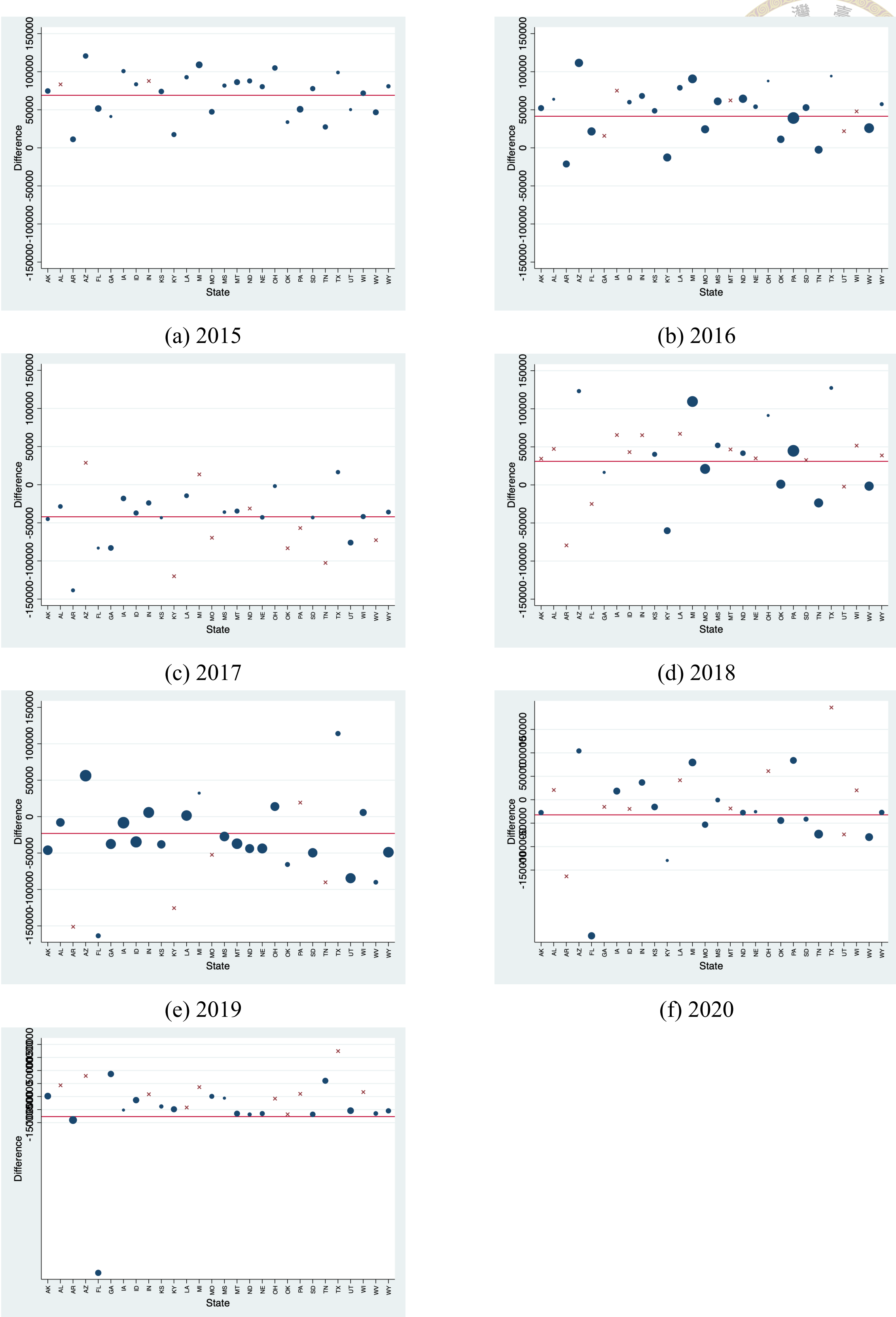



(c) 2010




(d) 2013


doi:10.6342/NTU202404232




(a) 2015

(b) 2016

(c) 2017

(d) 2018

(e) 2019

(f) 2020

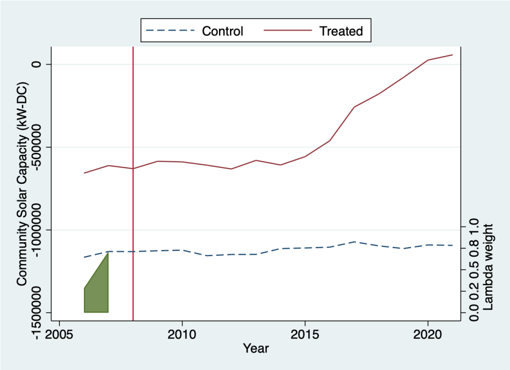
(g) 2021

Note: These figures show the weight of each state in the control group when generating the synthetic control group. The size of the dot corresponds to the size of its weight, and when the weight is 0, it is represented by an ×.

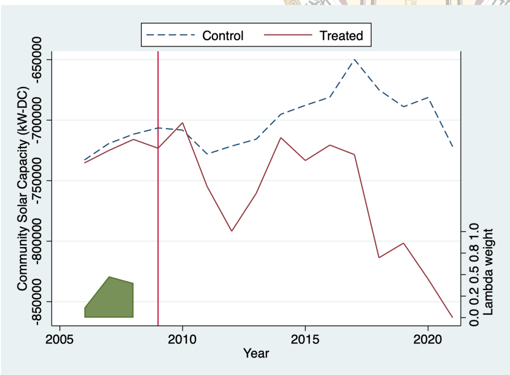


doi:10.6342/NTU202404232

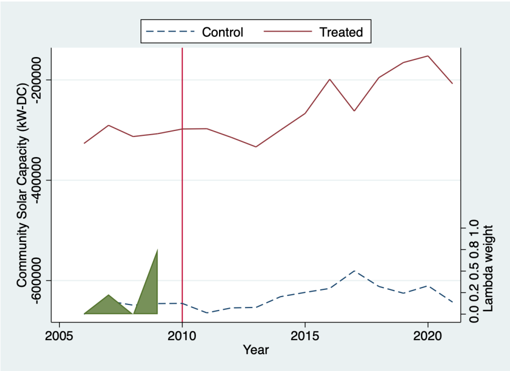
## A.2 Outcome Trends in Each Event Year



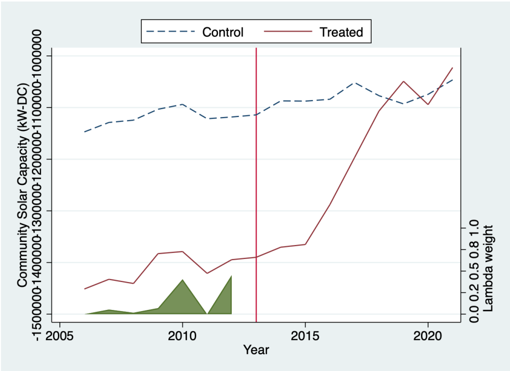

(a) 2008



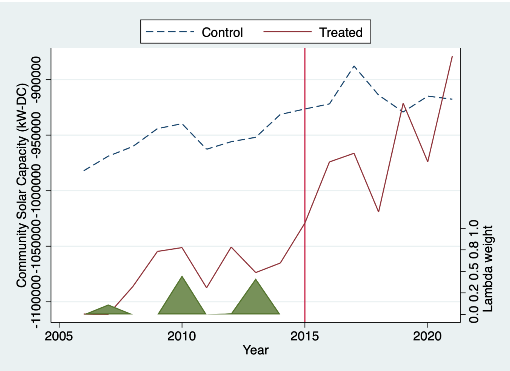

(b) 2009



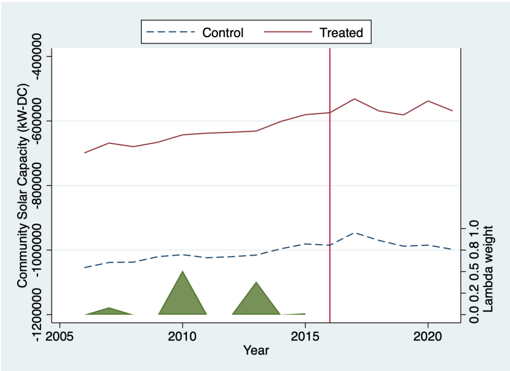

(c) 2010




(d) 2013



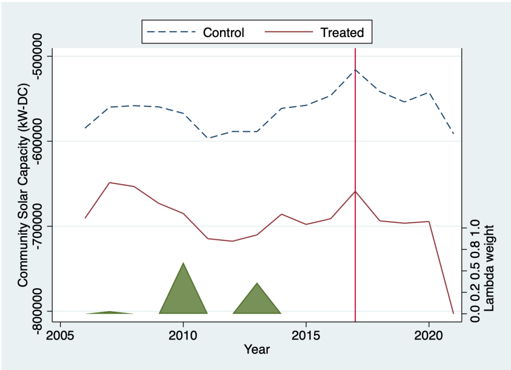

(e) 2015



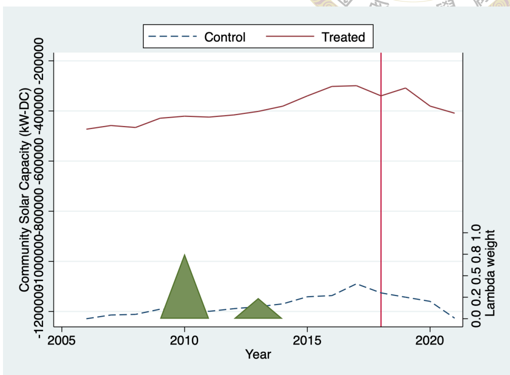

(f) 2016



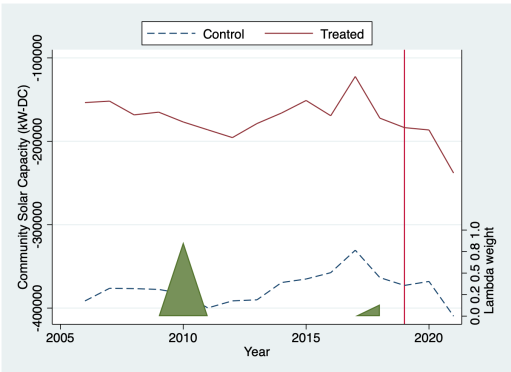
doi:10.6342/NTU202404232



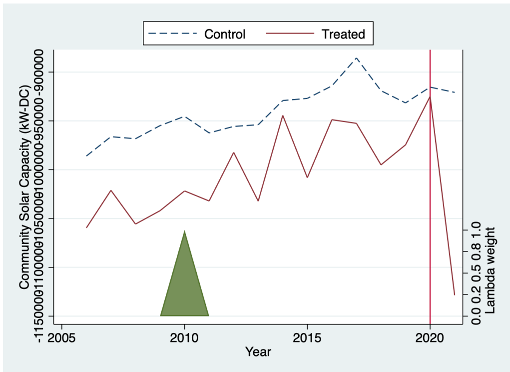

(a) 2017



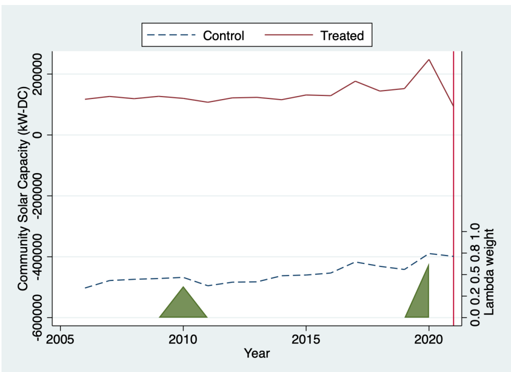

(b) 2018




(c) 2019




(d) 2020



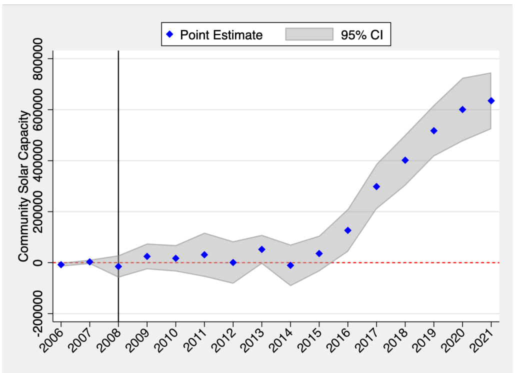

(e) 2021

Note: These figures illustrate the effects and time trends for the states in the event year cohort. The solid line represents the capacity trends of the states that passed community solar legislation, while the dotted line represents control states resulting from synthetic control. The green shaded area indicates the time weight. I use the vce(noinference) option to simply plot outcome trends without the added computational time associated with inference procedures.

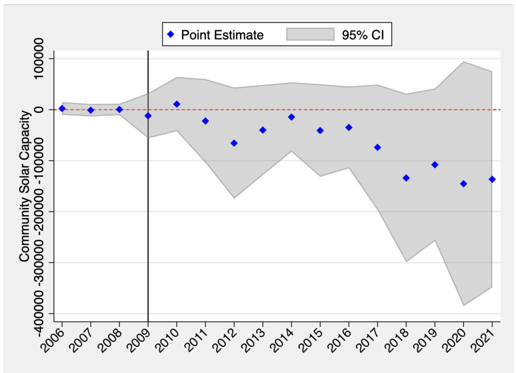


doi:10.6342/NTU202404232

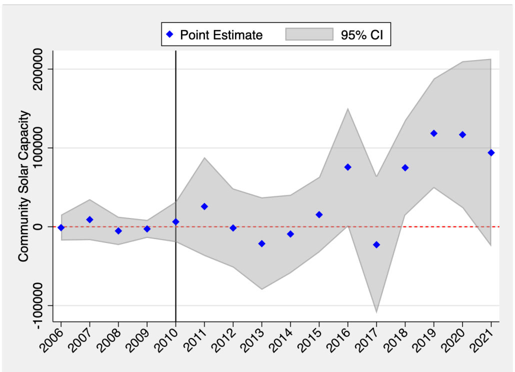
## A.3 Point Estimates and Confidence Intervals in Each Event Year



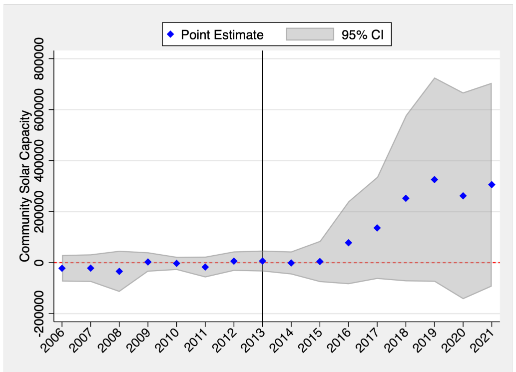

(a) 2008



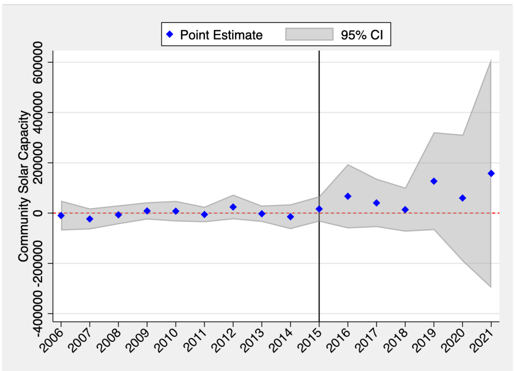

(b) 2009



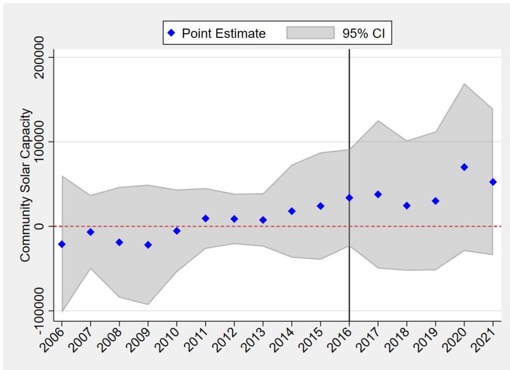

(c) 2010




(d) 2013



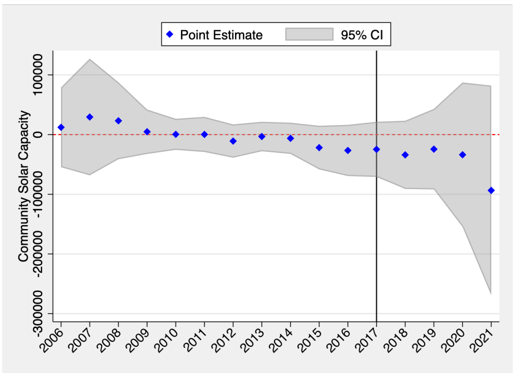

(e) 2015



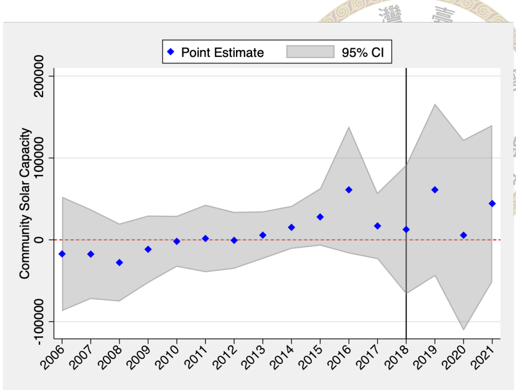

(f) 2016



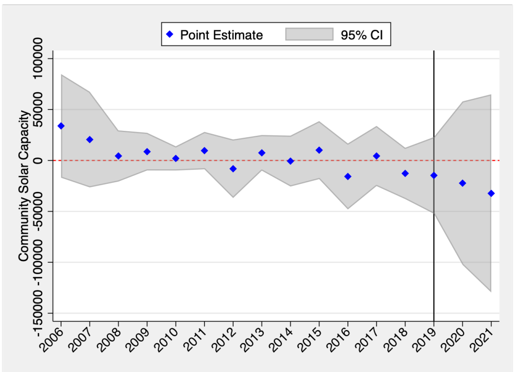
doi:10.6342/NTU202404232



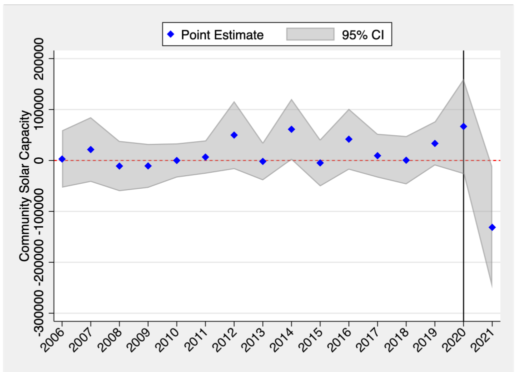

(a) 2017



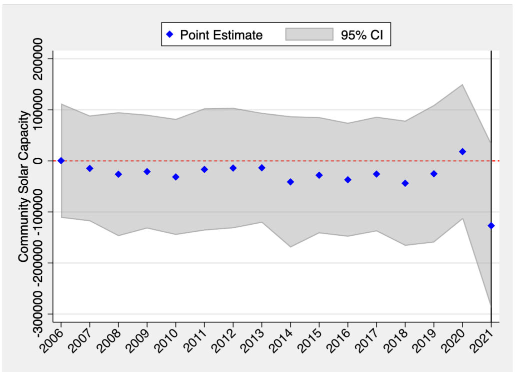

(b) 2018




(c) 2019




(d) 2020




(e) 2021

Note: These figures show point estimates of the state effect of passing community solar legislation for each event year, indicated by the blue points. The confidence intervals are represented by the gray-shaded areas.



doi:10.6342/NTU202404232