THE EFFECTS OF DISTRIBUTED SOLAR ON UTILITIES AND THEIR CUSTOMERS

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THE EFFECTS OF DISTRIBUTED SOLAR ON UTILITIES AND THEIR CUSTOMERS

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LIST OF SYMBOLS AND ABBREVIATIONS

CDD	Cooling Degree Days
DER	Distributed Energy Resources
DOE	Department of Energy
DPV	Distributed Photovoltaics
DID	Difference in Differences
FERC	Federal Energy Regulatory Commission
GW	Gigawatt
HDD	Heating Degree Days
IRP	Integrated Resource Plan
LCOE	Levelized Cost of Energy
NARUC	National Association of Regulatory Utility Commissioners
NEM	Net Energy Metering
NERC	North American Electric Reliability Corporation
PJM	Pennsylvania-New Jersey-Maryland Interconnection
RFP	Request for Proposal
PSC	Public Service Commission
PUC	Public Utility Commission
PV	Photovoltaics
RPS	Renewable Portfolio Standard
RTO	Regional Transmission Organization

SUMMARY

The goal of this dissertation is to evaluate the impact of distributed solar on utilities and their customers. It reconciles an analysis of the effect of increasing DPV penetration at the system scale, with an understanding of how installing DPV alters behavior at the household level. To provide such a comprehensive view on the role of DPV in the evolving utility, I construct a utility financial model and populate that with customer load and solar data. I compliment that analysis with utility customer data to gain insights on the interaction between solar installation, rate design, and electricity consumption. By incorporating insights from the macro and micro levels, I demonstrate that proper policy incentives and rate design can generate incentives for DPV installers which promote system level efficiencies. This dissertation bridges utility modeling literature with empirical work to better understand prosumer behavior and shed light on the future of utility operations.

The introduction describes the changing technical and policy landscape in response to growth of DERs, highlighting the operational and financial challenges created for utilities. For context, initial sections describe the techno-political nexus of grid operation. I explain the historical utility business model and demonstrate why DERs are perceived as a threat. This provides background on the unique attributes of distributed solar including siting, operational, and ownership characteristics that distinguish it from traditional generation. From there, the first chapter introduces the costs DPV imposes on the system and the benefits it creates to frame the debate on DPV and set the stage for the analysis.

In chapter 2, I investigate the utility revenue, rate, and bill impacts of solar penetration resulting from an exogenous policy mandate. The utility is constrained to operate under the same cost-recovery mechanism and rates allowed to fluctuate to recover

costs as solar growth changes electricity market prices and utility sales. Chapter 2 uses PJM market data, demand profiles from a PJM utility, and solar data from New Jersey PV. The results indicate that significant solar can be incorporated with only a 2% increase in non-participant bills. This should assuage fears of a "utility death spiral" among regulators. However, at higher levels of penetration, DPV alters system peak hour, which directly affects the allocation of costs between rate-classes. These distributional impacts warrant careful consideration from policymakers. Expanding the model to include consumers with heterogeneous load shapes illustrates that benefits for adopters, and penalties for non-adopters, are dependent on aggregate use, time-of-use, and kurtosis of the load curve. The design of rates and the implementation of demand charges can result in very different sets of winners and losers. This has important equity implications, particularly if DPV adoption and load shape are correlated with demographic characteristics or business sector.

An increase in the system-wide penetration of distributed solar has important consequences for utility cost-recovery and consumer equity, but analysis at the system level can mask some of the challenges introduced by distributed resources. In chapter 3 I investigate the spatial distribution of solar installations and construct a model which predicts solar adoption at a more granular level. To do so, I leverage solar installation data and customer billing data from more than 300,000 premises in a PJM utility. The results of the modelling show that substantial spatial clustering exists and is likely to be exacerbated as penetrations grow. The value of projects is thus dependent on their location in the system, a fact that is not reflected in RFP processes or policy incentives. This likely contributes to the wide range of "value of solar" estimates in the literature. In the discussion, I underscore the importance of including DER forecasting in the IRP process and explore the potential of community solar and virtual net metering to overcome the challenges of spatial clustering of rooftop PV with appropriate policy design.

In chapter 4, I study a yet undeveloped aspect of the literature: what happens to household electricity consumption once a consumer has installed residential PV in a net-metering scheme. On one hand, the installation of residential PV reduces the average bill for consumers. Although the marginal costs don't change, consumers may respond to lower bills by increasing consumption, an effect similar to, but distinct from, the rebound effect studied in the energy efficiency literature. On the other hand, the installation of microgeneration allows consumers to become more informed about their energy use and its impacts. As the salience of energy use and environmental impacts increases, theory suggests consumption should decline. Using the same customer billing data from Chapter 3, I conduct a set of analyses that investigate post-adoption consumption changes. I show that although solar installers in a net-metering scheme use less electricity from the grid, their aggregate consumption increases following adoption.

Finally, Chapter 5 discusses some of the policies and rates that have been proposed to address the concerns generated by increasing penetrations of distributed energy. In particular, I examine the desire for "cost-causal" rates and the feasibility of implementing dynamic pricing. I identify barriers and using evidence from my analysis discuss whether such a policy is likely to be successful in addressing the vicissitudes presented by DPV. To conclude, I lay out a research agenda describing the need for additional study of the political and institutional factors at play in utility regulation.

CHAPTER 1. INTRODUCTION

Solar energy represents a small but growing share of the national electricity generation profile. Distributed Photovoltaics (DPV), defined here as smaller installations incorporated on the distribution as opposed to transmission network, represent a fraction of the overall solar market. Considering this nascent status and as of yet diminutive contributions, it has received a disproportionate share of attention in Public Service Commissions, regulatory and legislative hearings, utility board rooms, and the media. This reflects two factors. First, is the potential of the solar resource. With the looming reality of climate change and increasing scrutiny of emissions from the electric sector, solar energy represents a carbon-free generation source. Costs have fallen quickly with the levelized cost of electricity from solar already reaching grid parity in some regions (Ondraczek et al., 2015). Distributed photovoltaics can generate electricity near load centers in dense urban and suburban environments where traditional power plants cannot be cited (Freitas et al., 2015). It has enabled capacity to be added and electricity generated outside the traditional bounds of utility control. Distributed solar has also been used, and will continue to be deployed, to electrify portions of the world that have not received grid access to date (Aklin et al., 2018). DPV in conjunction with emerging information technologies, can simultaneously address the needs of the 1.3 billion people without electricity and drive action towards a sustainable, decarbonized energy system (Alstone et al., 2015).

Second, the rise of solar energy has been in conjunction with other disruptions in the energy industry. Solar, and the policies which supported the developing industry, have often been the scapegoat for those looking to protect the traditional order and power structure. The reality is much more complicated. For example, lower natural gas prices from shale gas unlocked through fracking have driven coal shutdowns far more than renewables (Fell and Kaffine, 2018). Advances in computing, information technology, and telecommunications have facilitated two-way power flows, and alternative tariff designs that may have been "caused" by solar in the eyes of disgruntled actors. Stagnant load growth, driven by more efficient end uses, has contributed significantly to utility cost recovery concerns (Morgan and Crandall, 2017). Parsing out the impacts of distributed solar in this era of unprecedented change within the industry is challenging. That said, understanding said impacts from the system level to the effect on individual consumers will be critical as the solar industry continues to grow. Distributed solar changes the cost causality of electricity generation, transmission, and distribution service and in doing so engenders legitimate concerns about equity. As distributed solar emerges as a legitimate contributor to meet electricity demand and other distributed technologies such as battery storage begin to enter the marketplace, ensuring equity will fall to policymakers. They must structure future planning processes, regulations, markets and tariffs, to reduce the misalignments among technical, social, and economic dimensions that are developing from legacy rulemaking.

Understanding the impacts of distributed solar and properly allocating costs will allow higher penetrations of distributed resources, contributing to the overall goal of addressing climate change. The focus of this dissertation is on U.S. institutions, and in particular on the PJM RTO. The justification is two-fold. First, the data required to conduct this research is not readily shared by utilities. Access to utility financial data, solar output data, and customer use data represent a unique combination of datasets. While there has been some academic research done on the impacts of solar PV and the value of the resource in the U.S. nearly all of it has been based on California. This makes sense given California is the leading adopter of solar capacity and DPV specifically. However, California's electricity markets, pricing structures, politics, and solar resource do not necessarily translate to the rest of the country. Results from the Northeast contribute new insights and are more representative of the solar markets which are growing most quickly (Association, 2018). As shown in Figure 1, the PJM territory also has a much larger share of distributed to grid scale solar installations, making it an optimal location to study the effects of distributed PV (Donahue, 2018).

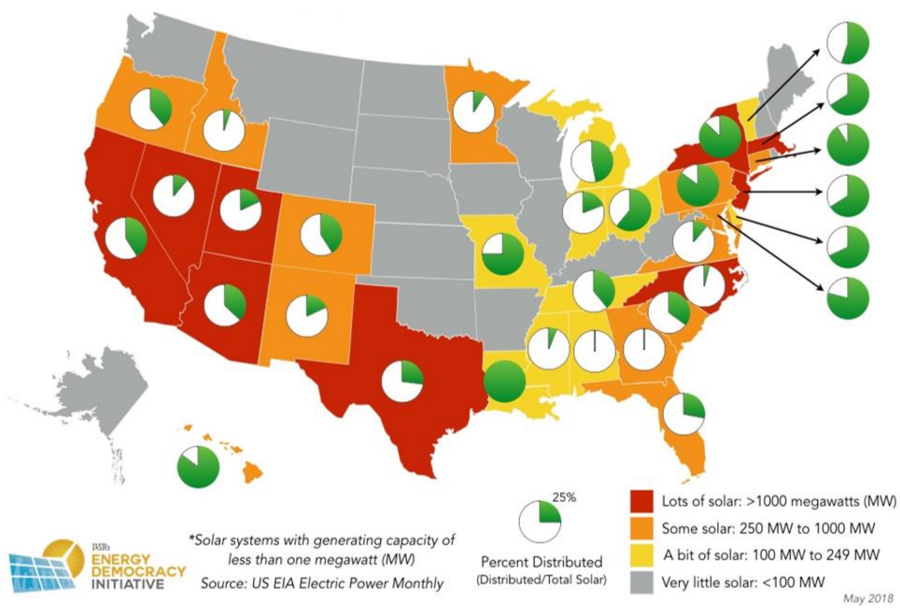

Figure 1: Map of U.S. solar installations[1]

Second, although the U.S. is not the largest global installer of solar capacity it does have the largest number of distributed solar installations. The relative wealth of American consumers has allowed them to purchase and install rooftop PV. Creating a robust market

[1] Reprinted from The State(s) of Distributed Solar – 2018 Update, by Institute for Local Self-Reliance, November 15, 2018 retrieved from https://ilsr.org/the-states-of-distributed-solar/

for smaller systems helps provide efficiency of scale in manufacturing, refine process, and improve technology efficiencies, all of which reduce costs globally. As this process continues distributed solar becomes more accessible to consumers in emerging economies. However, as the U.S. distributed solar market has grown it has faced resistance, and currently finds itself at a crossroads where policy support is being challenged and new tariffs developed (Carley and Davies, 2016). This dissertation can shed light on the impact of distributed photovoltaics and help inform the next generation of policy frameworks.

In Section 1.1 I present a brief snapshot of the U.S. electricity sector couching the growth of solar in global and historical context. I then offer a brief overview of the unique technical aspects of grid operation that bound policy. The following section, 1.2, describes the policy landscape, including an illustration of the different techno-political zones and the institutions that regulate them. It describes the multitude of actors involved in the rate case, and an example of the IRP process which governs rate designs in most states. Finally, it introduces net-metering and renewable portfolio standards, two primary policy mechanisms which have buoyed distributed solar. Section 1.3 describes the unique characteristics of distributed solar and explains the disruptions that this technology present to the status quo. Section 1.4 frames the analysis to follow and describes how the remaining chapters of the dissertation seek to contribute to the ongoing debate about the value of distributed solar and its impacts on utilities and their customers.

1.1 Energy Landscape and Technical Dimension

Globally, in 2017, cumulative solar PV capacity reached 398 GW and generated over 460 TWh, representing around 2% of global power output. Utility-scale projects account for just over 60% of total PV installed capacity, with the rest in distributed applications (residential, commercial and off-grid). Over the next five years, solar PV is expected to lead renewable electricity capacity growth, expanding by almost 580 GW (Birol, 2018). Domestically, solar capacity has reached 60 GW with an average annual growth rate of 59% over the last 10 years. Solar now generates more than 1.5% of the nation's electricity annually, enough to power more than 11.3 million homes. This generation offsets more than 75 million metric tons of CO2 emissions annually, the equivalent to removing 16.2 million vehicles from the road (Association, 2018). These numbers provide a sense of scale for the resource, but to give context for the challenges of incorporating additional solar, a brief overview of the U.S. electric grid is required.

The U.S. electric grid is considered the largest machine in the world. It is a network of power plants and wires which deliver electricity to end users. Traditionally, it has been comprised of four major components: generators, transformers, transmission, and distribution. Generators historically constitute large power plants such as coal, natural gas, hydroelectric, or nuclear which spin turbines to generate electricity. While their output can be directly controlled, adjusting output takes long periods of time and reduces efficiency.[2] Generators are measured in terms of capacity (GW) (the amount of electricity that they can produce at any one time) in units of power, and energy (GWh) (the amount of power delivered over a period of time). Transformers are used to step up the voltage of the electricity so that it may be sent over long distances via transmission lines. High voltages reduce the loss of electricity through resistance to heat. Transformers then step the voltage

[2] Natural gas plants are now the leading source of electricity generation and are typically more flexible in following load than coal or nuclear.

back down to the distribution network where it is delivered to end users. This entire chain is summarized in Figure 2.

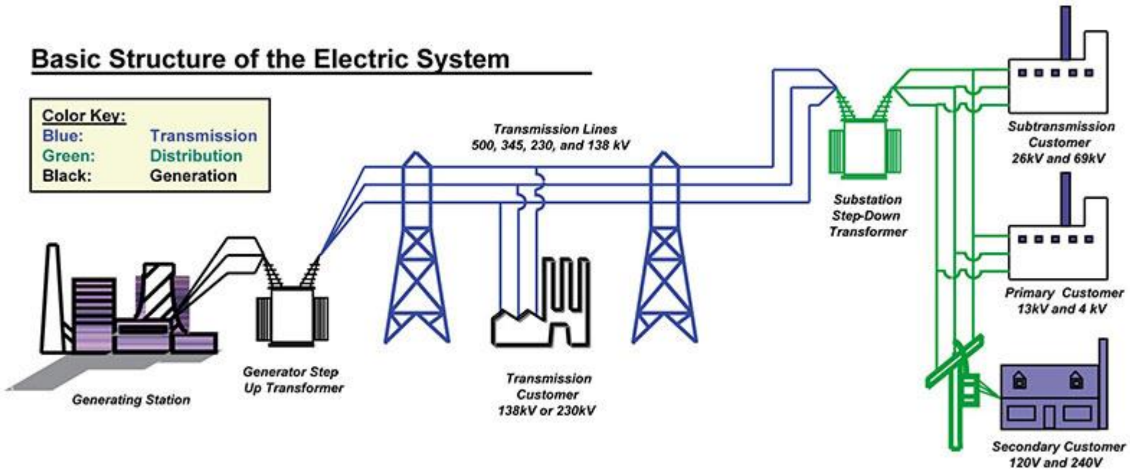

Figure 2: Structure of the electric grid[3]

Electricity follows the path of least resistance, meaning it cannot be directly sent down a desired path without altering electrical components though capacitors, inductors, and load manipulation. Before the introduction of distributed resources electricity always flowed from left to right in Figure 2. This was referred to as the hub and spoke model as the generator formed the hub and the network carried electricity away in all directions to end users. As will be discussed in Section 1.3, distributed resources generate electricity on the distribution network and can induce electricity flows in both directions.

Because the entire system is interconnected, an issue in one part of the grid can ripple through and affect large territories. On the other hand, since the grid is an enormous network, electricity can be deployed to the right places across large regions of the country

[3] Image credit United States Department of Energy, retrieved January 2019 from: https://www.webpages.uidaho.edu/sustainability/chapters/ch06/ch06-p3a.asp

with resource constraints in one location being compensated for in another. Electricity cannot currently be cost-effectively stored on a large scale, so a large transmission network allows grid operators to deal with anticipated and unanticipated losses, while still meeting local electricity demand. Another implication of no energy storage is that electricity supply must match electricity demand at every instance to ensure reliability. The U.S. grid is subdivided into 3 interconnections, shown in Figure 3, which each have their own frequency and voltage monitoring. The North American Reliability Corporation (NERC) further subdivides into regions to monitor grid reliability and security.

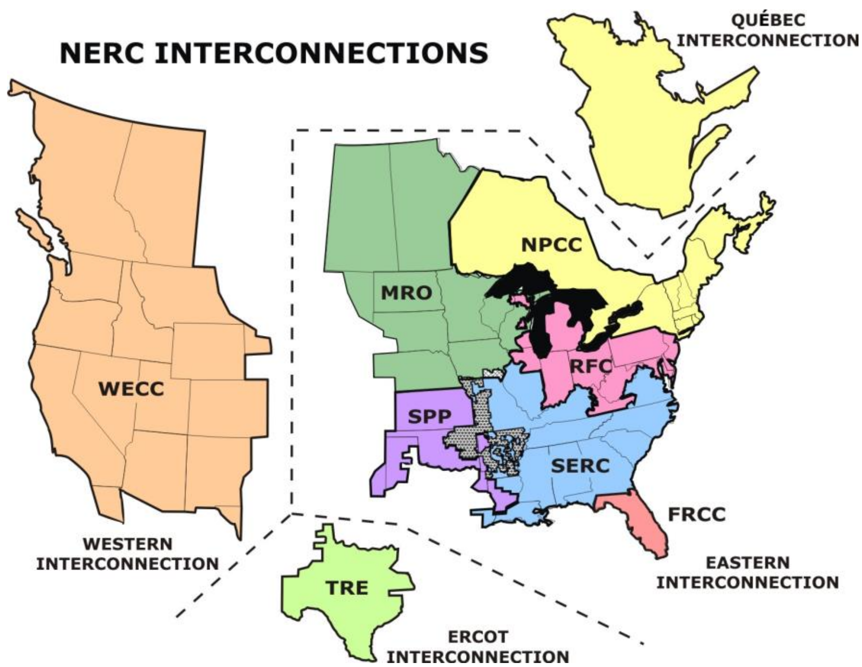

Figure 3: NERC regions[4]

The actual operation of the electric system is managed by entities called balancing authorities. Most, but not all, balancing authorities are electric utilities that have taken on

[4] Image credit North American Electric Reliability Corporation, retrieved Jan 2019 from: https://www.nerc.com/AboutNERC/keyplayers/pages/default.aspx

the balancing responsibilities for a specific portion of the power system. In some cases, regional transmission organizations (RTOs), in including PJM, also function as balancing authorities. RTOs are independent, membership-based, non-profit organizations that optimize supply and demand bids for deregulated wholesale electric power and will be discussed in the context of asset ownership in Section 1.2. Figure 4 shows the balancing areas with circle size indicating the relative amount of electricity handled.

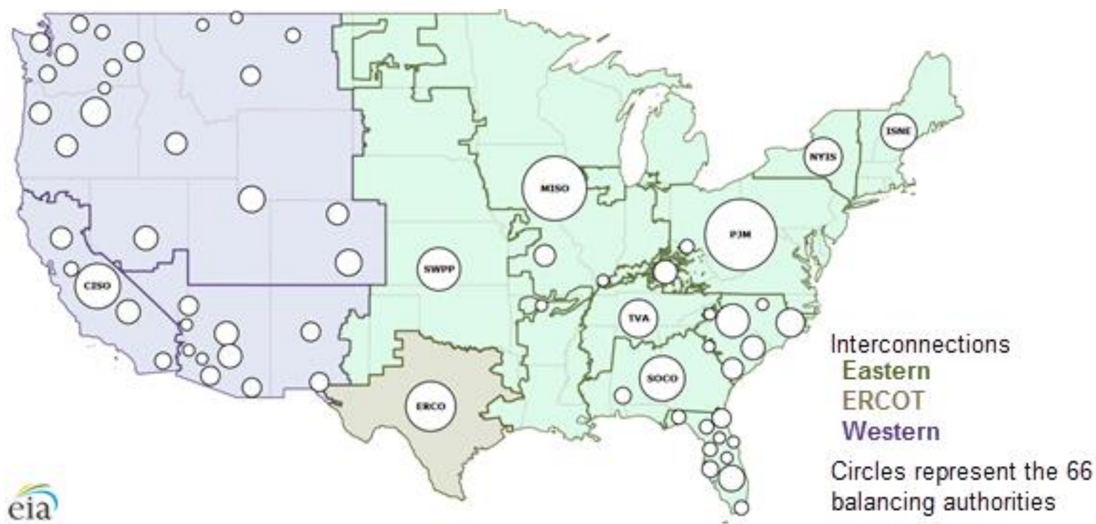

Figure 4: U.S. balancing areas[5]

This extensive system and complex network of actors must all be operating correctly and in sync to ensure a customer receives power when they flip the switch. Similarly, such a complex and infrastructure intensive system must be paid for by the users of electricity. Distributing these costs to users is challenging and distributed resources are upsetting the conventional order.

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[5] Image credit U.S. Energy Information Administration, retrieved Jan 2019 from: https://www.eia.gov/todayinenergy/detail.php?id=27152

1.2 Electricity Policy and Economics

Paying for electricity involves more than just the electrons that are consumed, it must cover all other aspects of the system. Traditionally all pieces of the electric sector were owned by a utility who was regulated and received a rate of return on their capital investments. However, starting in the 1990s the electric power industry went through a period of deregulation and restructuring in which generation, transmission, and distribution were divided into separate components in some states. If the generation segment of the electricity supply chain has been deregulated, utilities were forced to divest their electricity producing assets. Power plants then compete with one another to provide service. Electric transmission has been restructured throughout the U.S. with transmission regulation shifting from a local to regional scale, and from state to federal authorities. The PJM territory is both deregulated and restructured as shown in Figure 5.

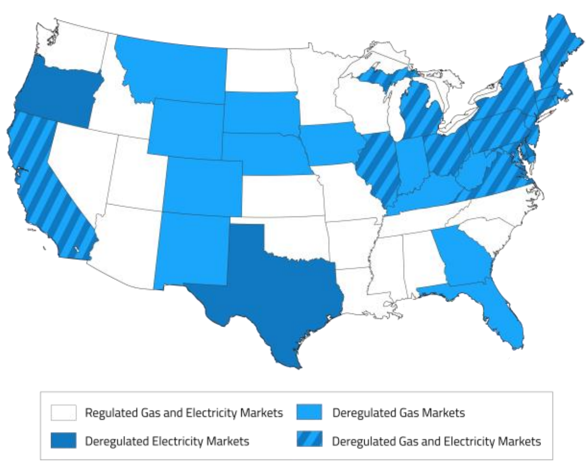

Figure 5: Map of utility deregulation by state

Electric distribution has, with few exceptions, retained the same regulated structure and remains a textbook example of a natural monopoly, where one firm can provide a good or service at lower cost due to economies of scale. Economies of scale enable lower long run average costs with increasing quantity (Weimer and Vining, 2015). In order to prevent distribution utilities from exercising market power, these utilities have been regulated by state public service commissions or locally-owned cooperatives. In firms with substantial fixed costs, such as utilities, setting price equal to marginal cost fails to cover total costs, and firms would fail to make necessary investments. To enable such investments, regulators set prices equal to average variable costs and allow utilities to earn a fixed rate of return on their assets.

Another economic challenge in electricity pricing is that the generation and distribution of electricity produce negative externalities. To price electricity at the social marginal cost, these externalities should be internalized. Without a price for carbon in most of the United States, and an amalgamation of other pollution regulations that are not directly tied to social damages, prices fail to provide a price signal equal to the social marginal cost. Borenstein (2016) has noted that utilities seldom have to pay for the negative externalities they create. Solar advocates argue that this makes it harder for solar to compete and should in part give license for them to receive higher costs than traditional wholesale generation markets.

Another set of market failures unique to electricity follow from the need to meet specific physical criteria to maintain proper network frequency. Grid voltage and stability have public good attributes, as do grid security and reliability. Joskow and Tirole (2007) note that the possibility of network collapse makes operating reserves a public good and, without regulatory mandates on operating reserves, there would be underinvestment in such reserves resulting in lower overall levels of reliability.

Thus, while some aspects of electricity are readily translated into marginal costs, many others are not. In the nearly sixty years since Bonbright laid out the principles for public utility rates, policy makers are still struggling to construct rates that reflect these ideals. The latest ratemaking guidance from the National Association of Regulated Utility Commissioners (2016) underscores the persistent challenges of functionalization and allocation of costs. As a result of these challenges, questions of who pays for the fixed costs of the grid, and how much they contribute, are unsettled. The prospect of distributed generation and prosumers[6] only complicates the equation. As a result, electricity tariffs are truly a policy outcome, dictated as much by political and equity consideration as by economics.

The main policy process for most distribution utilities is the Integrated Resource Plan (IRP), an outline for meeting the company's objective of providing reliable and least-cost electric service to all customers. These typically occur on 3-5 year time horizons, with minor adjustments in between. Any substantive changes in the interim are subject to rate cases or other hearings. The IRP is developed with considerable public involvement from state utility commission staff, state agencies, customer and industry advocacy groups, project developers, and other stakeholders. The key elements of the IRP include: a finding of resource need, determining the preferred portfolio of supply-side and demand-side resources to meet this need, determining how these resources will be paid for, and an action plan. A traditional flow chart illustrating the components is shown in Figure 6.

[6] An electricity user who both purchases electricity from the grid and has the capacity to supply energy to the grid.

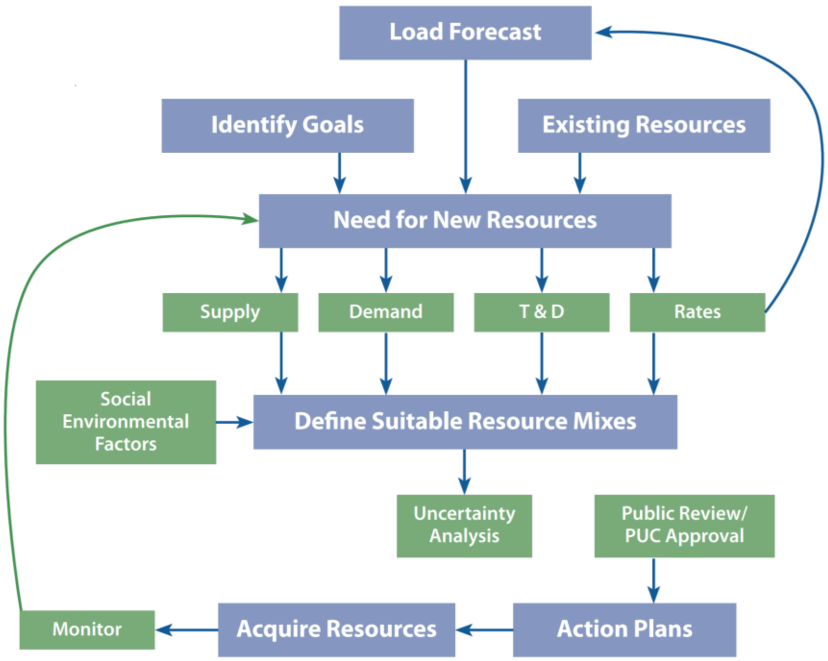

Figure 6: Flow chart for Integrated Resource Planning

The goal is to build the system to meet national regulations on security, reliability, and grid access at the least cost to customers. These national requirements come primarily from two agencies: FERC and NERC. The Federal Energy Regulatory Commission oversees the interstate transmission and sale of electricity. It is involved in ensuring fair sales practices when electricity moves across state boundaries and manages the development of infrastructure that extends across state lines. The North American Electric Reliability Corporation develops and enforces reliability standards and monitors grid security. State governments, through their public utility commissions or equivalent bodies, regulate retail electric service and oversee facility planning and siting.

State utility commissions are responsible for assuring utility service is fair, reasonable, and nondiscriminatory. These organizations are represented in federal issues and share best practices through the National Association of Regulatory Utility

Commissioners, but otherwise operate largely independently. As such, rates and policies differ across state lines. Most state commissioners are appointed to their positions by their governor or legislature, while commissioners in 14 states are elected.

As discussed further in the conclusion, a better understanding of utility service commission politics and policy processes is warranted, given the rapid technological changes taking place and pressure on current rate structures. The existing work on the politics and policy of PUCs suggests that utilities, interest groups, and the public influence decision making by affecting personnel and providing information. That said, there remain several competing theories that attempt to explain the operation of public utility commissioners. An economic theory of regulation suggests that public service commissioners are captured by organized interests (Peltzman, 1976; Stigler, 1971). In contrast, Berry's study of commissions found that commissioners operate with two objectives: a "nonpecuniary" principle of rates and a goal of survival (Berry, 1984). Gormley's study on public utility commissions focuses on the role of grass roots advocates and finds that they can be effective in PUC decision-making processes when issues are low in technical complexity (Gormley Jr, 1983). More recently, Ka and Teske (2002) found that legislative ideology is a central driver of redistributive decisions such as rate making. Understanding the policy process in this domain is critical to promoting progress but remains unclear. Further, the primary work on these issues pre-date the disruption of distributed energy technologies and the opportunities of the smart grid. Additional study of the politics of regulatory rate-making is warranted in light of the significant impacts these decisions have.

State PUCs manage grid access requirements for solar energy, dictate how installers will be compensated, set electricity tariff levels that implicitly dictate investment payback periods, and oversee the construction process for larger installations. However, they are not responsible for directly setting policy incentives which promote solar energy. This is the responsibility of state legislators who can write legislation providing subsidies or mandating requirements for the PUCs to enforce. Because efforts to address climate change have largely stalled at the federal level, the onus has shifted to the state and local levels (Rutland and Aylett, 2008).[7] To date there are two primary incentives which promote distributed solar at the state level: net-metering and renewable portfolio standards.[8] Renewable portfolio standards require utilities to ensure a stated percentage of electricity sales come from renewable sources. This policy diffused through the states based on citizen's demands (Matisoff, 2008) and now 29 states have some form of RPS as shown in Figure 7. More recently, some states have added solar carveouts which require a certain percentage of electricity come from solar or give bonus credit to distributed solar sources.

[7] The federal government does directly subsidize the purchase of renewable energy capital. The federal solar tax credit, also known as the investment tax credit (ITC), allows the deduction of 30 percent of the cost of installing a solar energy system from federal taxes. This is a significant driver of solar growth, but given that its value is fixed, and for the installation as opposed to operation I chose not to discuss it in depth. This policy does not affect the "value of solar" i.e. the compensation for the electricity produced or the avoided costs of electricity which has a much larger effect on the payback period.

[8] That is not say that these are the only state policy incentives. RPS and net metering are simply the most widespread. For a discussion of the over 400 state and utility incentives that promote the installation of residential PV see: Matisoff, D.C., Johnson, E.P., 2017. The comparative effectiveness of residential solar incentives. Energy Policy 108, 44-54.

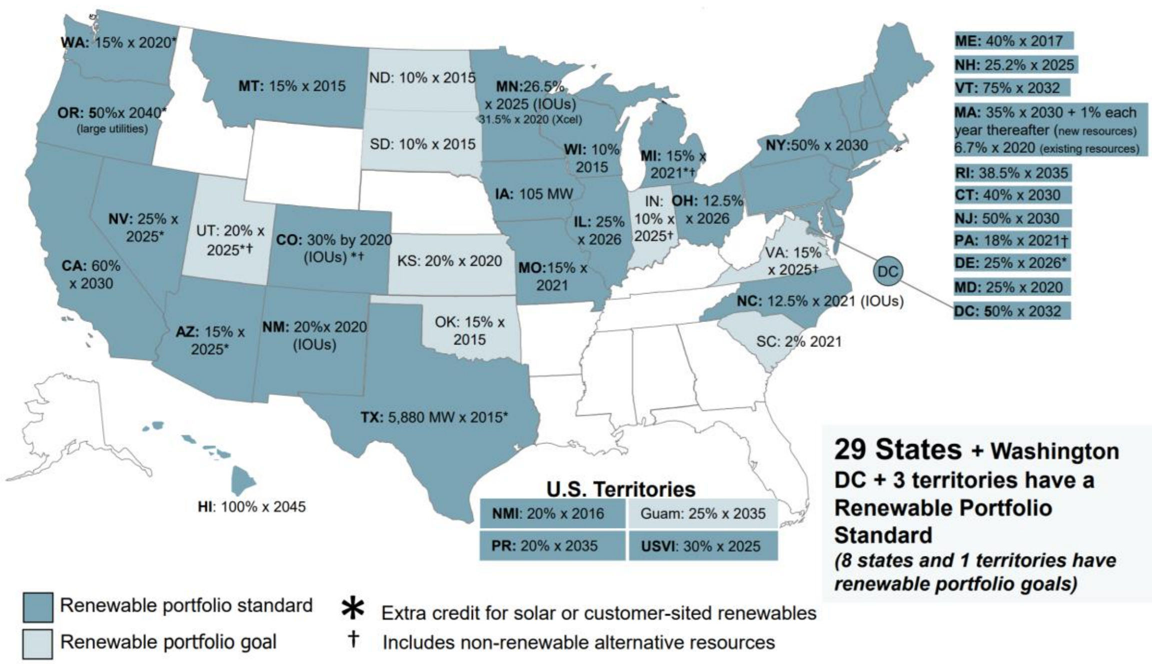

Figure 7: Renewable portfolio standards by state[9]

RPSs are an external mandate which require utilities to procure renewable resources or install them themselves. This encourages utilities to provide customer incentives, but does not directly change the compensation for solar installers. Net metering on the other hand provides an implicit subsidy to customers. Net metering is a billing mechanism that credits solar energy customers for the electricity that they send back to the grid at the same rate as retail electricity prices. The meter runs forward when the home or business is drawing energy from the grid and backward when exporting electricity. Figure 8 illustrates this process. The fact that customers receive a retail price (the same rate they pay) for their excess generation is an important distinction because this price includes much more than

[9] Reprinted from Detailed Summary Maps, by Database of State Incentives for Renewables and Efficiency, January 2019 retrieved from http://www.dsireusa.org/resources/detailed-summary-maps/

the wholesale electricity price. In most service territories the wholesale price of electricity is around a third of the final retail price.

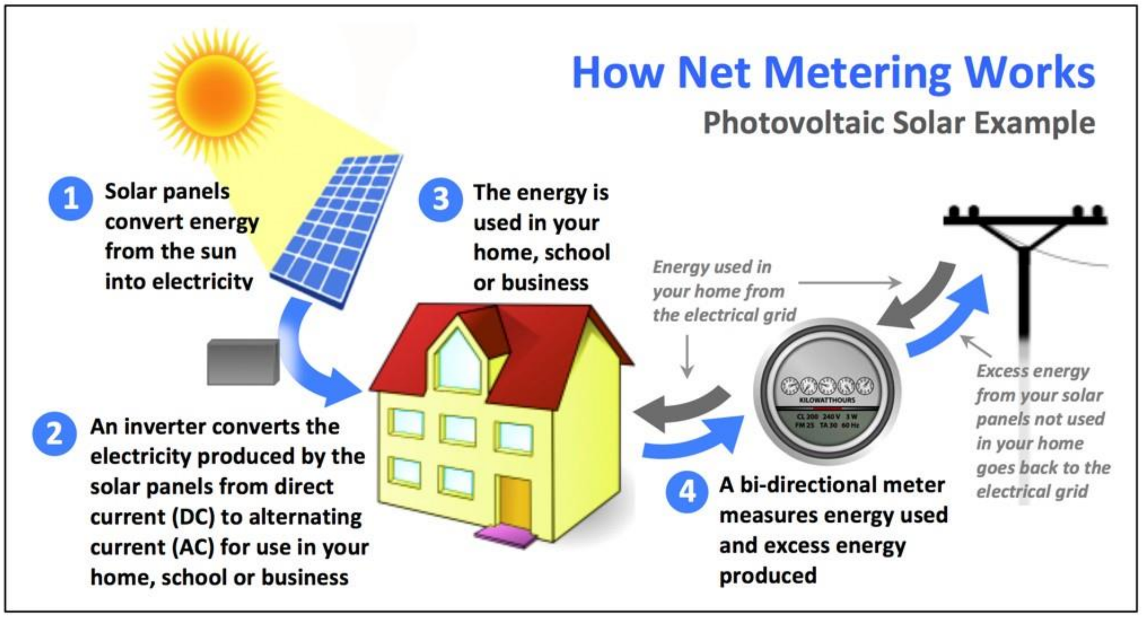

Figure 8: Net metering example[10]

The retail vs. wholesale price discrepancy sets up a debate about which price more accurately reflects the true value of solar. This is currently a point of contention in PUCs across the country, including in the PJM territory, and has significant consequences for the continued spread of DPV. In the following section I further discuss how distributed solar, and in particular DPV with net-metering, are impacting electricity policy.

1.3 Impact of Distributed Solar

It is in the complicated technical and policy network described above that distributed solar is attempting to gain a foothold. Spurred on by cost reductions, policy

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[10] Image credit Florida Solar One, retrieved Jan 2019 from: http://floridasolarone.com/solar-home-net-metering/

incentives, new financing options and changing consumer preferences, distributed solar energy has seen exponential growth in the U.S. over the last decade. This expansion of distributed solar has changed the traditional utility/customer relationship and invigorated policy discussion about how to efficiently and equitably encourage continued growth of DPV while maintaining grid reliability. Electricity sector stakeholders across the country are recognizing the need to properly evaluate DPV, and acknowledging the current ambiguity surrounding the costs and benefits that drive DPV's value. Under today's regulatory and pricing structures, misalignments along economic, social, and technical dimensions have emerged, leading to inefficient policy incentives and price signals. Current pricing mechanisms based on kilowatt-hour (kWh) energy sales do not have the capacity to appropriately charge PV customers for the services they both use and provide.

As solar penetrations grow utilities have pushed back on DPV and forced regulators to re-evaluate incentives. From a financial perspective, utilities are concerned about revenue erosion as customers self-generate, and argue that they pay too high a premium for energy they are required to purchase from customers under net-metering schemes. Because retail rates are in excess of wholesale rates, they also pay costs associated with operation and maintenance of the grid and electricity delivery, services not provided by DPV installers. Previous studies have noted that the magnitude of utility lost revenues due to net metering is non-trivial and to compensate for lost sales, utilities may be forced to raise rates (Cardwell, 2013; Kind, 2013). These financial vicissitudes are challenging a utility business model that has remained largely unchanged since the 1930s, with the passage of the Public Utility Holding Company Act. Previously, decades of predictable electric load growth brought reliable returns for utilities and load was met primarily through fossil fuel capacity expansions. Guaranteed rates of return were collected through kilowatt-hour charges on ever increasing demand. More recently, however, stagnant load growth, DPV, energy efficiency and other disruptive technologies have begun to threaten standard business practices.

In addition to the financial concerns, DPV systems have several unique attributes including siting, operational, and ownership characteristics which differ from more conventional resources such as coal or natural gas power plants. Since these PV systems are smaller, more modular, and have lower capital costs than traditional generation they can be added to the grid by actors outside the bounds of a utilities' central planning. The electrical output of DPV resources is variable and uncertain, which means installers typically retain access to the grid. However, central resource planners do not have an ability to dispatch or shutoff the resource. This can make the real-time balance of supply and demand for electricity more challenging. The intermittency of solar has real social costs and requires system planners to re-optimize grid operations and retool capacity investments. Unforecastable intermittency accounts for a portion of the social costs (Gowrisankaran et al., 2016) as load peaks occur in the evening, just as solar output is in decline. The steep ramp rate needed from conventional generators have been captured in the infamous "duck curve" (Denholm et al., 2015). Add in the need to accommodate must-run plants, institutional constraints such as long-term contracts, transmissions congestion, and the result is a need for increased system flexibility to maintain reliability and accommodate solar. At the local level, increasing concentrations on individual feeders have led to concerns with harmonic distortion, voltage spikes, and reverse flows (Agnew and Dargusch, 2015). Allocated optimally, solar can delay or offset the need for infrastructure investment, but it can also necessitate additional spending on protections and control equipment to handle two-way flows.

On the other hand, advocates note that DPVs provide some distinctive advantages in that they require no fuel, produce no emissions in generating electricity, and reduce line losses by generating at or near the point of consumption. In some jurisdictions solar costs are competitive with avoided cost estimates, and consumers have proven willing to pay a premium for "green electricity" (Roe et al., 2001). Additionally, distributed solar has been suggested as a means of improving grid resiliency. At least in theory, PV can contribute to reducing outages by increasing the diversity of the system generation portfolio, dispersing generation assets to avoid dependence on electricity corridors, and providing backup power and black start capabilities when paired with control technologies, inverters, and storage. These factors interact in complex and often non-intuitive ways to produce a variety of costs and benefits for DPV owners, utilities, and society. Further complicating matters is the fact that the value of DPV is temporally, operationally, and geographically specific down to the individual feeder. This makes it very difficult to generalize from cost-benefit studies conducted on DPV or to compare any values across regions and will be discussed in more detail in Chapter 3.

The growth of DPV has interacted with increased scrutiny of the contributions of fossil generation to climate change, a digital economy increasingly dependent on electric reliability, and aging transmission and distribution infrastructure, to propel the electric industry into a period of unprecedented change. Utilities, policymakers, and grid operators are now adapting to a market in which agents operate in a more decentralized grid, and in capacities that blur the lines between producer and consumer. These rapidly evolving changes require, more than ever, that policymakers structure markets and tariffs in a manner that maximizes social benefits and minimizes welfare loss (Parag and Sovacool, 2016). In order to do so, policy makers must be informed about the impacts distributed solar has on system operation, cost-recovery, the value of solar, and how solar installation changes patterns of customer use. The following section describes how this dissertation attempts to address that need.

1.4 Framing the Analysis

Having presented an overview of the technical and policy landscape, and the challenges introduced by distributed solar, the remaining task is to outline the importance of this analysis for the public and the policy audience. Electricity is involved in everything we do. Its reliability is central to national security, nearly every economic sector in today's digital economy, and our general health and comfort. Nearly all citizens are consumers of electricity and as such are impacted by electricity rates. Distributed solar may affect both reliability and costs. While customers are very attuned to electricity outages they are notoriously insalient when it comes to energy costs (Sexton, 2015) and regulatory processes (Berry, 1979). That said, increasing penetration of distributed solar will require substantial changes to rates and rate structures and consumers will want to know why these changes are occurring and how it will affect them.

Even in territories where low penetrations of DPV will mask the underlying issues for consumers, their tax dollars are being used for subsidies for renewable energy and their utility rates have built in costs associated with meeting the climate and energy policy goals that have been established by state legislatures. The continued development and deployment of solar is in the best interests of all, as it helps decarbonize the sector with the largest emissions footprint. In order to achieve international climate goals distributed solar will have to play a larger role, particularly in electrifying the developing world (Rogelj et al., 2018).

From a policy perspective this analysis is at the core of discussions on equity and efficiency. To date the high cost of panels even with policy incentives has restricted their adoption primarily to high income consumers (Barbose et al., 2018). This is not unusual of new technology adoption, but what is concerning is that low-income users may be the ones subsidizing their spread. This occurs both directly as they contribute to the incentives, and more substantially, indirectly as their electricity rates rise to cover the fixed costs of the grid. According to the EIA's 2015 Residential Energy Consumption Survey Energy, one in three American households face a challenge meeting their energy needs (EIA, 2015). As such, even a small change in their rates and bills can have a substantial impact. This is particularly concerning in light of evidence suggesting that African American & Latino households have energy burdens three times higher than average (Drehobl and Ross, 2016).

This is a domain in which policies truly affect outcomes and interact often in unintended ways. For example, in California a steeply tiered tariff structure was intended to discourage consumption above a threshold and recover more costs from large users. In practice it drove the heaviest electricity-consuming households to adopt solar because the tariff structure increased the private value of solar to such customers while reducing the incentive for consumers below median consumption. The implicit financial incentive for those who adopted solar due to California's tiered tariff structure was nearly as large as the 30% federal tax credit. The California experience suggests that rate design can greatly influence the economic incentives for residential solar adoption and which customers receive those benefits (Borenstein, 2017).

Finally, electricity rates are developed through a policy process that is understudied and poorly explained. This analysis sets the stage for further study on how policy change occurs in the electric sector. In chapter 2, I investigate the utility revenue, rate, and bill impacts of large-scale solar penetration resulting from an exogenous policy mandate. In chapter 3 I investigate the spatial distribution of solar installations, construct a model which predicts solar adoption at a more granular level, and demonstrate the importance of including distributed resource plans in IRP processes. In chapter 4, I study consider what happens to household electricity consumption once a consumer has installed residential PV. This yields important insight for load forecasting and equity discussions. To conclude, I discuss some of the policies and rates that have been proposed to address the concerns generated by increasing penetrations of distributed energy. In particular, I examine the desire for “cost-causal” rates and the feasibility of implementing dynamic pricing.

CHAPTER 2. THE IMPACTS OF SOLAR PV ON ELECTRICITY COSTS

2.1 Introduction

Chapter 1 established that solar energy has been a rapidly growing source of electricity in the United States over the last decade, with 40 GW installed through 2018.[11] In recent years, the proliferation of solar rooftop systems has taken off at the residential and commercial level, and utility-scale solar installations have grown as well. Recent evidence suggests residential photovoltaic (PV) systems were the fastest growing sector in the U.S. solar market in 2015 (Solar Energy Industries Association, 2016). This trend in residential PV installations has been accelerated by the combination of declining manufacturing costs for PV modules and attractive local, state, and federal financial incentives. As a consequence, several states in the U.S., particularly California, New Jersey, Colorado, and Texas, have seen substantial deployment of solar resources in recent years (Rai and McAndrews, 2012b). However, even current levels of deployment represent only about 1% of electricity generation in 2015 (EIA, 2016) and is a small portion of the market potential in the U.S. (Paidipati et al., 2008), indicating the possibility of future market expansion. This expansion of distributed solar changes the traditional utility-customer relationship and demands additional research into how solar growth will affect both sets of stakeholders.

Previous studies have noted that the magnitude of utility lost revenues due to eroding sales is non-trivial, especially if there are no mechanisms in place to adjust for lost

[11] Solar Energy Industry Association: http://www.seia.org/news/us-solar-market-set-grow-119-2016-installations-reach-16-gw

sales. To compensate for lost sales, utilities may be forced to raise rates, which further incentivizes customers to invest in energy efficiency and distributed generation, leading to an additional decline in revenues for the utility. This cycle has been coined the "death spiral" (Cardwell, 2013; Kind, 2013); as a result, utilities may be forced to explore different business models and rate options (Brown et al., 2015; Costello and Hemphill, 2014). When utilities raise retail prices for all customers, this rate adjustment process leads to an implicit subsidization because net metered customers are, in effect, permitted to sell excess generation back to the utility at the retail rate (Borlick and Wood, 2014; Brown and Lund, 2013; Rose et al., 2008). Prior literature establishes that bills will be reduced for distributed solar adopters but will increase for nonparticipants (Eid et al., 2014). The implicit subsidization between non-adopters and adopters of solar technology may have important distributional effects within a given rate-class because residential solar adopters are typically households with higher incomes (California Public Utilities Commission, 2013).[12] While other studies have focused on the subsidy between net energy metering (NEM) participants and non-participants (henceforth simply participants and non-participants), I examine how solar penetration can also impact the distribution of costs across rate classes, causing one or more rate classes to subsidize others.

The purpose of this paper is to investigate and highlight the channels through which subsidization across and within rate classes can arise in practice. This effect has not been widely studied in the literature because most research focuses only on impacts to residential consumers. Importantly, there are substantial differences between residential and non-

[12] Not all NEM participants are residential consumers as both small and large commercial customers are also eligible to participate in NEM.

residential rates and rate structures. By simulating the effects of combining a solar renewable portfolio standard (RPS) carve-out with a utility-level NEM program, I am able to investigate and detail the consequences of different solar installation patterns on the rates and bills of customers of electric utilities operating in wholesale markets. The simulation combines data from the PJM wholesale market, solar production data from installations in New Jersey, and publicly available demand profiles from a New Jersey electric utility. My methodology explicitly focuses on two metrics that are likely impacted by solar penetration and quantifies the extent of cross-subsidization between rate-classes: (1) retail electricity rates (cost per unit) and (2) electricity bills (total monthly cost). On one hand, rate impacts provide an indication of the extent to which overall electricity rates might increase. On the other hand, bill changes reflect the *ceteris paribus* effect of solar installations between NEM participants and non-participants.

This analysis contributes to the existing literature in three important dimensions. First, nearly all of the research on net metering focuses only on the impacts on residential or commercial customers.[13] By only modeling the impact on a single class of customers, these studies do not permit analysis of cross-subsidization between rate classes. This analysis considers multiple rate classes and thus permits explicit analysis of cross-subsidization patterns. Second, past studies primarily focus on the adoption decision and rate design. In comparison, this study (1) employs a constant rate design, (2) treats solar adoption as exogenously driven through predetermined RPS requirements, and (3) incorporates effects of solar penetration on the timing of system-wide peak demand. This

[13] The limited exceptions to this include an analysis by the California Public Utilities Commission (2013) and Brown et al. (2016).

allows me to clearly isolate the effects of solar generation from these other factors. Third, most related studies in the U.S. focus only on changes in one state, California. Given California's unique rate structures and high electricity prices, the results of these studies may not be representative of how solar carve-outs and NEM programs may impact electricity rates or customer's bills in other regions across the U.S. In contrast, I model these impacts using rate structures and electricity prices derived from representative wholesale electricity markets and electricity distribution companies in the northeastern U.S.

The results of this study indicate that the fear of a utility "death spiral" may be exaggerated. I find that solar can provide significant electricity generation in 2030 with only a modest increase in bills for non-participants. Even in an extremely aggressive scenario, bill increases for non-participants would not be cost prohibitive. The findings acknowledge the subsidy of participants by non-participants but also highlight the cross-subsidization between rate-classes. In particular, I find impacts on customer rates and bills depend on the installation pattern. High levels of distributed solar can alter the system peak hour, which affects the allocation of costs.

The article is organized as follows. Section 2 provides a brief summary of the current literature on NEM impacts for customer rates and bills and describes how this study contributes to this literature. In Section 3, I describe the model used to analyze the impacts of NEM at various levels of PV penetration. This includes discussion of the underlying data and methodology used to simulate these effects. Section 4 presents the results, demonstrates the multiple facets of cross-subsidization issues, and illustrates how the distribution of savings varies across the counterfactual installation scenarios. Finally, Section 5 concludes with a summary, addresses the policy implications of the results from the analysis, and sets the stage for future contributions.

2.2 Background and Literature Review

Along with other complementary financial incentives, two common programs for incentivizing solar adoption in the U.S. are renewable portfolio standards and net energy metering. RPS statutes require a certain percentage of electricity generation or retail sales to come from renewable sources. Associated solar carve-outs, where a fraction of the RPS requirement must be accounted for by generation from solar resources, are now commonplace and create additional incentives for adoption of distributed PV systems. As of 2015, 29 states have implemented RPS statutes, and 22 of these states have specific provisions for solar or distributed generation (DSIRE, 2016). In nearly all these states, RPS requirements interact with the NEM programs offered by some or all utilities.[14]

A large portion of the literature on NEM is focused on California. A combination of excellent solar resource, high electricity rates, and aggressive policy support has made the state a leader in solar installations. This, in turn, has made the consequences more pressing and relevant for California, but other locales are reaching significant penetration levels. Borenstein (2007) provided the early work on calculating bill savings for residential NEM customers of two utilities by analyzing the impact of 2 kW systems. The same data set was later used for an analysis of how rate design affects bill savings (Darghouth et al., 2011). Related studies include Borenstein (2005b, 2008) and Darghouth (2016), which

[14] As of 2015, 44 states required some or all utilities to offer some form of NEM programs Database of State Incentives for Renewable Energy (DSIRE), 2015. Map of Net Metering Policies North Carolina State University, Raleigh, NC.

investigate the impact of time-of-use or real-time pricing structures on PV adoption. Cai et al. (2013) have also studied the impact of PV on retail electricity rates using a modelling approach and including a model of the rate case proceeding. The grey literature is rich in this subject area, including a thorough ratepayer impact analysis conducted by the California Public Utility Commission (2013).

Additional studies for other U.S. states are sparse. The literature on the east coast impacts of solar is quite dated (Cook and Cross, 1999). The most similar study to my own analysis is that of net-metering impacts among low-voltage network users in Spain (Eid et al., 2014). Eid et al. (2014) examine cross subsidies, revenue requirements, and cost causality; however, scenarios are focused on variations in program definitions, examining how different net metering timeframes can impact utility cost recovery. Furthermore, Eid et. al. (2014) make use of hypothetical solar production; in contrast, this study employs observed solar production data from NEM program participants.

Central to the results are questions concerning cross-subsidies both within and between rate classes. Cross-subsidies have taken on multiple meanings in the literature. In some cases, they refer to subsidization of grid services to solar adopters by other grid users (see Eid et al. (2014) and Picciariello (2015b)). In other cases, cross-subsidies may refer to subsidization across rate classes and voltage levels (see Rodriguez Ortega (2008), Picciariello (2015a)). In this study, I examine both cross-subsidization patterns, namely within-rate class and across-rate class subsidization.

2.3 Model, data, and methodology

In this section, I describe the construction of the model, the assumptions it incorporates, and the sources of the data used for simulating electricity rates and customers' bills. Given my assumptions and calibrations, I model the impact that varying penetrations of solar electricity has on system costs, as well as impacts on household, commercial, and industrial consumer electricity bills. The model uses data from wholesale electricity markets, distribution costs, customer hourly demand curves, and solar generation profiles in order to compile the total revenue that customers need to pay. After revenue requirements are calibrated, the model allocates the utility's revenue requirements across different rate classes to simulate a typical set of customer rate structures.[15] The flexible construction of the model allows me to demonstrate impacts of solar electricity generation requirements under a wide range of counterfactual scenarios.

This simulation model is relevant for a representative utility that divides its business into an electricity supply system (that buys and sells power and manages high-voltage transmission lines along with associated transformers) and an electricity delivery system (that manages distribution substations, transformers, poles, and service lines that deliver electricity to customers) that is located in a region with a competitive wholesale electricity market. The model assumes the utility's customer base is divided into three separate classes: residential, small commercial, and large commercial and industrial (C&I) to align

[15] Though I model a distribution utility in an area with a restructured electricity market, I assume that the distribution customers are also electricity customers. Though this may not strictly be true since in many areas customers can choose their electricity provider, all providers would be responsible for the same electricity and renewable requirements. Therefore, for simplicity, and without loss of generality, I model the distribution utility as also providing electricity to all customers.

with many existing rate structures.[16] All customers are billed based on a rate structure that is composed of charges based on electricity usage while non-residential customers are also billed based on their level of peak demand.

I first begin by detailing the data and methodology I use to generate customer and electricity market profiles underlying the simulation. I then discuss how solar generation is incorporated into electricity prices and rate structures, including a Net Energy Metering program and how this affects electricity rates and bills in the model. I then present the details of the four different counterfactual scenarios I simulate before presenting the results in of these simulations in the following section.

2.3.1 Customer load shape profiles

I calibrate the model using aggregate customer load profiles from 2011 to 2014 obtained from a utility operating in the PJM wholesale electricity market. A separate load profile was calculated for each of the three rate classes in the model: residential, small commercial, and large commercial and industrial. Using monthly averages across the four years, a load profile is constructed to simulate representative hourly load for a typical weekday, weekend, and a system peak day for each rate class. Based on these calculations, a total of nine load profiles were constructed from these underlying data. Additionally, these load profiles are unique for each month of the year.

[16] I use data from a northeastern U.S. utility to serve as a representation of how an average utility's business is divided between these two groups.

2.3.2 Hourly solar generation of participants

In addition to the customer load shapes, I build solar generation profiles based on data from solar customers in New Jersey from 2010 to 2013. The customer-level dataset includes both the system size (kW) and hourly solar generation (kWh) for customers with installed PV systems. I divide the hourly generation by the total system size to calculate a capacity factor for every hour of the year. Independent solar profiles are then created for each of the rate classes to account for different optimizations (i.e., to maximize peak simultaneity or maximize total output). In addition to the average solar profile, a peak solar profile was created to represent the solar production on a peak demand day in each month for each of the four years.[17]

2.3.3 Supply cost data

In order to simulate how a representative utility customer's bills will change in response to increased solar penetration, I model the effect of solar on the region's wholesale market prices. Since data in the model are obtained from a utility in the northeastern U.S., I model the PJM wholesale electricity market to simulate wholesale electricity price changes. I focus primarily on changes to the electricity markets through both reduced demand (from NEM customers) and increased supply from grid-scale solar installations. I statistically estimate a market supply curve using historical market data as well as hourly demand using historical data from the PJM electricity market averaged over 4 years. Specifically, I model the hourly, PJM supply curve as a quadratic function of hourly load

[17] I compared the monthly average precipitation and temperature over a 4-year solar production sample period to the National Oceanic Atmospheric Administration's "climate normals" and find no statistical difference between those normals and the average temperature and precipitation.

and a linear function of daily natural gas prices. However, the simulation holds natural gas prices constant over the time horizon of the study. This assumption allows me to isolate changes in electricity rates to only reflect changes caused by increased solar penetration. Nevertheless, due to the size of the wholesale market relative to the utility's electricity demand and the exogenously determined solar requirements, there are limited price changes[18] in the PJM wholesale market price in response to increased solar penetration.

In addition to wholesale electricity prices, supply costs typically include the costs of electricity transmission, ancillary services that ensure grid reliability, and, in this case, the cost of complying with the solar mandate from the RPS. Firms usually comply with solar mandates by purchasing Solar Renewable Energy Credits (SRECs) from owners of solar installations. One SREC certifies that 1 MWh of electricity was produced from a solar installation. Retail electricity providers must purchase enough SRECs each year to show that they have met the percentage of solar generation required by the relevant legislative statute. If firms do not purchase enough SRECs to comply with the statute, then they must pay an alternative compliance payment (as set forth in the statute) to the regulator for each MWh of generation they are short. This mechanism implicitly puts a price ceiling on the price of SRECs.

Since the market for SRECs tends to be illiquid and volatile,[19] I am forced to make some assumptions about the future price of SRECs in this simulation. New Jersey has one

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[18] These price changes depend on the amount of solar penetration in the model, however, since the PJM market is large (hourly load of 80-100 GW) even extremely aggressive assumptions about solar penetration does not change load or PJM electricity prices by more than 1%.

[19] For example, during energy year 2014 in New Jersey, SRECs were traded at between 40 and 670 dollars per MWh. The number of SRECS traded by month varied from 40,538 to 2,923,695. http://www.njcleanenergy.com/srecpricing

of the most aggressive solar mandates in the country in combination with a transparent SREC market, I have chosen to model SREC compliance costs as a function of the alternative compliance payment in New Jersey.[20] Other industry analysts have used 50% of the alternative compliance payment, and historically this has been a reasonable estimate.[21] This analysis follows suit. It is important to note that while the non-compliance price drives the maximum value of an SREC, actual SREC prices are dependent on the market supply. After computation of these costs, SREC compliance costs are added to electricity, transmission, and ancillary service costs to construct a total supply cost for the utility.

2.3.4 Rate design

I model a rate design that is relatively common across many electric distribution utilities in restructured electricity markets in the U.S. This rate design combines volumetric energy charges (cents per kilowatt-hour, ¢/kWh) with peak demand charges (dollars per kilowatt, $/kW) to recover the costs of providing electricity to the customer. The bulk of the volumetric energy charge is for the cost of electricity generation: the supply rate. The supply rate is used to recover costs from electricity generation purchased on the PJM wholesale markets and SRECs as discussed above.

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[20] While solar costs do vary somewhat throughout the United States, these differences tend to be somewhat small and have begun to converge across locations.

[21] In New Jersey energy year 2014 (referenced above) the weighted average trade price over the year was 179.23 which is 53% of the alternative compliance price of 339 dollars.

2.3.4.1 Supply Rate

For all customers, supply rates are distinct for summer and winter. Residential and small commercial customers have day and night rates while for C&I customers the day/night distinction is replaced by on-peak/off-peak rates. These rates are calculated for each rate class by dividing the total cost of energy over a period (summer and winter, days and nights, and on-peak or off-peak) by the amount of energy used during that period. The total cost over a period is simply the hourly price multiplied by the quantity that each customer class uses. The supply rate is then the average cost of energy over a period for each rate class.

2.3.4.2 Distribution Rate

The utility recovers the costs of delivery through a distribution rate that varies by customer class. Residential customers are billed for distribution services using a volumetric energy charge to recover costs associated with delivering electricity to the customer's premises. The model also incorporates a simple seasonal variation in the residential customer's rate structure, where summer distribution rates (June through September) are higher than winter rates.

Small commercial customers have a more complicated distribution rate structure. They are charged both volumetric energy and demand rates, each accounting for approximately 50% of the total small commercial distribution costs. The volumetric energy charge ($/kWh) is broken down into summer and winter as well as day and night rates. The demand charge has only a summer/winter distinction.

Finally, large commercial customers have a distribution rate composed entirely of demand charges which again are higher in summer than winter months. The demand charge is based on each customer's maximum hourly demand (kW) in each month. Typically, maximum demand is based on usage in any 30 minute or smaller periods, but the granularity of this model imposes an hourly restriction.

2.3.4.3 Rate for miscellaneous expenses

In addition to supply and distribution rates, the final energy charges include volumetric (per kWh), social benefit charges and other miscellaneous fees commonly imposed by public utility commissions to finance market transition costs, securitization of stranded costs, system control charges, energy-efficiency programs and electricity assistance for low-income households. The total value of these fees in the simulation is about 2.5 ¢/kWh. These additional charges for each customer class are assumed to be constant over the analysis period, although the amount of energy over which they are recovered over does vary. This means there are only re-distributional effects within customer classes. Because utilities incorporate them into rates in various forms, I chose to categorize them separately. Thus, in the results they are not included in supply or distribution rates, but they are included in customer bills.

2.3.5 The NEM program

Net energy metering can be applied very differently across jurisdictions with diverging impacts. In this analysis, NEM enables retail customers who generate electricity through their own renewable systems to receive the full retail price for each kWh of electricity their system produces up to, but not exceeding, 100% of their electricity usage over the course of the year. Based on this program stipulation, the simulation constrains customer electricity bills to be non-negative.

In practice, to be eligible for net metering, customers must have an interconnection agreement in place with their utility, which confirms that the generating capacity of their system does not exceed the customer's annual electric needs. The most common NEM program design allows for customers to be credited at 100% of the retail rate for all electricity produced less than their consumption in each month.[22] Additionally, when production exceeds usage the meter spins backwards and customers are provided with credits. These credits are "netted" and then paid back on an annual basis. Previous literature has shown that yearly rolling credits can exacerbate problems of network cost recovery (Eid et al., 2014). In the simulation, no customers receive annual payments for generated electricity, and for all customers, annual consumption of electricity always exceeds annual generation of solar electricity.

2.3.6 Simulation Methodology

I use the above inputs and assumptions to simulate both rates and bills under various solar penetration scenarios. To understand the impact of solar penetration on electricity rates and bills, it is essential to understand the underlying accounting methods used to calculate rates in the model. The model construction assumes that rates are calculated so that the utility exactly meets its revenue requirement and rate of return. Further, I make additional assumptions to isolate the impact of solar penetration on revenue requirements

[22] The "value of solar" has been a hotly contested issue between utilities and the solar industry. While some jurisdictions have rolled back net metering policies or capped participants, the norm remains a retail rate. https://www.technologyreview.com/s/545146/battles-over-net-metering-cloud-the-future-of-rooftop-solar/

and market outcomes. First, I assume that demand in the PJM wholesale market remains fixed over the time period of study, except for the new solar installed. Additionally, I assume the representative utility demand is constant across all rate-classes during the period of study. Second, I hold the number of customers in each rate class fixed throughout the simulation period. Holding the ratio of demand and number of customers fixed allows me to comment on the shifting costs between rate classes, isolating these effects from population dynamics or changing energy use patterns which would also influence cost allocation.[23] Third, the distribution costs of the utility remain constant in real dollars each year. Thus, the utility is not forced to make extraordinary equipment upgrades nor able to defer routine maintenance, a reasonable assumption at these relatively low penetrations.

These assumptions imply that all the changes in supply rates are due to changes in demand due to NEM customers, the addition of more grid-connected solar, and changes in the costs and quantities of SRECs, rather than other changes in the electricity market. Moreover, since distribution costs are held constant in the simulation, changes in these rates are a function of the addition of NEM customers and a reallocation of costs across customer classes.

This simulation takes the inputs and assumptions described above and calculates counterfactual electricity and distribution rates. Electricity rates are calculated by using the estimated PJM market supply curve and adding zero marginal cost production from the solar generation in the scenario to the base of the supply curve. This effectively shifts the

[23] In concert, these assumptions are likely to slightly over-state the effects of high levels of solar penetration since growth in electricity demand will mute the effect that solar has on wholesale electricity prices and additional customers would allow the distribution utility to have a larger customer base over which to spread any decrease in sales due to more net metering customers.

supply curve outwards and reduces wholesale electricity prices in hours with solar generation. The electricity rate is then determined by this new wholesale electricity price, transmission costs (assumed constant within the simulation), and the cost of SRECs associated with meeting the RPS requirement and dividing by the total quantity of electricity consumed.

The distribution rates are calculated by apportioning distribution costs to each rate-class based on their respective percentage of demand during the peak demand hour of the electricity system, termed "coincident peak demand" and converting this into a rate. The apportionment of total distribution costs to each rate class is affected by solar in two ways: (1) by changing the hour of coincident peak demand, and (2) by reducing demand from a particular rate class. Once the share of total costs attributable to a rate class is determined, they are further divided into energy/demand, summer/winter or day/night rates based on average total and peak monthly usage.

To calculate bills, the rates for each rate class are multiplied the by the respective energy usage and fraction of coincident peak demand of the rate class. Average bills are determined by multiplying demand (net of solar) by the supply and distribution rates. This method introduces an implicit constraint on bills, as average bills should also equal the utility's total costs divided by the number of customers. Participant and non-participant demands are also broken out separately and multiplied by rates to determine the diverging effects on these groups. Using the average system size, the solar generation profile, and the required MWh to meet the RPS mandate, I construct an estimate for the number of solar participants in each rate-class. Thus, while all customers face the same rates, NEM customers buy less energy from the utility and thus have smaller bills. Unlike previous studies, I hold the rate structure constant throughout the simulations.

2.3.7 Solar Penetration Scenarios

Since New Jersey is widely recognized to have one of the most aggressive solar generation goals in the country and because New Jersey publicly reports disaggregated data on solar installations, I use currently proposed solar mandates in New Jersey as a template for the solar penetration scenarios. New Jersey's current law requires 4.1% of electricity sold in 2028 to come from solar sources with yearly interim goals. I choose my counterfactual simulation scenarios to closely match these requirements, with a base case requirement of 5% by 2030. Further, the allocation of solar installations that are distributed systems (residential, small commercial, and large commercial and industrial participants in a NEM program) versus utility-scale systems are also chosen to match the New Jersey data.

Across the different counterfactual scenarios, I vary three parameters and explore how variations in these parameters affect both electricity rates and customer bills across the three rate classes. These parameters are: (1) the amount of solar generation required in each year of the analysis (determined by the solar mandate), (2) the proportion of solar that is grid-connected versus distributed and therefore participating in a NEM program, and (3) the allocation of distributed solar across three rate classes (residential, small commercial, and large C&I). In each of the scenarios, the current stock and distribution of solar capacity is based on 2015 EIA data on solar generation in the mid-Atlantic region. 30% of installed solar is grid-connected. Of distributed systems, 33% has been installed by residential consumers, 13% by small commercial, and 54% by large commercial and industrial clients.

I first model a "base-case" scenario where I approximate existing New Jersey solar requirements and recent growth rates in solar installation across customer classes.[24] The base-case specifies that 5% of electricity sold in New Jersey must be from solar by 2030. In the base-case, grid-connected solar accounts for 35% of new, annual installed capacity, residential solar accounts for 35% of new additions of NEM solar, small commercial solar accounts for 13% of new additions of NEM solar, and C&I accounts for 52% of new distributed capacity.

There have been recent proposals in many states to dramatically increase the solar carve-out (and renewable requirements in general) up to twenty or twenty-five percent of sales. Therefore, I compare the base case to three other scenarios where 15% of electricity sold is generated by solar by 2030.[25] This increased solar requirement also accentuates the impacts of solar additions and clarifies the impacts of higher levels of solar penetration. Lower levels of solar additions have more muted effects. I vary the distribution of solar across customer classes and the fraction of grid-connected solar to examine how solar installation patterns affect both rates and bills for customers. These scenarios are summarized in Table 1.

[24] Growth rates of solar installation only affect the flow of new installations. These are added to the existing stock of installations across rate classes.

[25] Since all of the solar adoption in the model is driven by the Renewable Portfolio Standard, changing financial incentives for the adoption of solar either on the federal or state level will not affect the results I display, though of course they will have important distributional effects outside of the electricity rates and bill I discuss here.

Table 1: Solar scenario definitions

	Base Case	High Case	High – High Residential	High – High Grid
Solar Requirement in 2030	5%	15%	15%	15%
Proportion of grid-connected (utility scale) solar additions	30%	30%	30%	70%
Proportion of NEM solar additions in residential	33%	33%	67%	33%
Proportion of non-residential NEM additions in small-commercial	20%	20%	20%	20%

2.4 Results and discussion

I examine the impacts of these solar penetration scenarios, over time, across customer classes, and between NEM participants and non-participants. The metrics of interest include electricity rates (supply and distribution), electricity bills, shifting peak hours, and differences in bills for solar participants and non-participants. All results are reported in constant 2010 dollars.

It is useful to note that despite making a number of modeling assumptions in the analysis, such as constant demand and natural gas prices across time, all these assumptions are held constant across scenarios detailed in Table 1. Therefore, comparing across scenarios allows an accurate assessment despite imprecision caused by making necessary assumptions about the rate-making process and economics of the wholesale electricity market.

2.4.1 Rate impacts by customer class

I begin by investigating how electricity rates change as solar penetration increases. As noted above, the electricity rate is composed of both a supply and distribution component (as well as miscellaneous expenses). When measuring the impacts as a percentage change in rates in 2030 relative to 2015, it is important to note that on average, supply rates (largely electricity, transmission, and SREC costs) are higher than distribution rates leading to smaller percentage changes in supply rates than in distribution rates. Also, both supply and distribution rates are higher in the summer than the winter. Comparing the Base Case and the High Solar scenarios leads to the conclusion that the penetration of solar PV systems has disparate effects on supply and distribution rates.

Figure 9 presents the changes in supply rates across scenarios relative to 2015. Across all customer classes, supply rates are forecast to remain relatively constant between 2015 and 2030 in the Base Case. The *de minimis* change is due to slight decreases in wholesale electricity prices and the cost of SRECs. In contrast, there is a significant difference between the base case in 2015 and the high cases in 2030. Supply rates increase in the High Cases due to an underlying cost increase of about 5-10% driven by increases in SREC and ancillary service costs, which are paid for by all customers, and a larger reduction in sales, which spreads the SREC costs over a smaller base. The SREC increase accounts for about 1¢/kWh of the increase over the Base Case in 2030; however, this estimate is an outcome of input price assumptions for SRECs. No increase in ancillary services is assumed in the Base Case but an increase of 1% of the value of sales is assumed in the High Case, reflecting a doubling of these costs above the Base Case. The amount of solar installed in the High Case is not enough to significantly alter the PJM supply curve to drive down energy costs. This is mainly a consequence of the assumption that changes in market supply are limited to the effects of an RPS in one state of the PJM market. In reality, the broader addition of solar across the region would have a more substantial effect on the PJM supply curve and potentially drive down energy prices throughout the region.

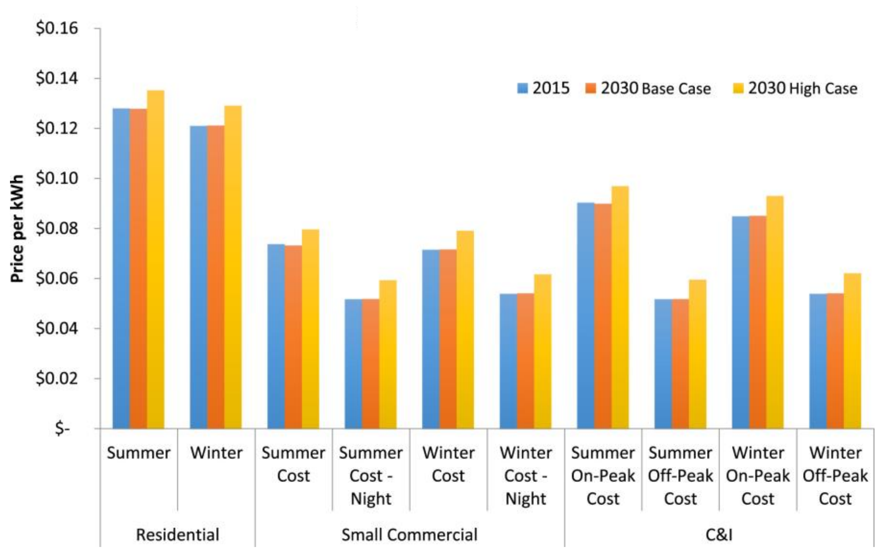

Figure 9: Supply rates

Since differences in supply rates among the high cases are minimal, I only present one of the high solar cases here. The supply rates are primarily impacted by the level of solar installation and not by installation patterns across rate-classes, which have a more pronounced effect on distribution rates.

Comparatively, the impacts on distribution rates are more variable across the scenarios and customer classes as shown in Figure 10. Results are presented as percentage changes relative to 2015. In the Base Case, distribution rates for residential and small commercial customers are forecast to increase between 2015 and 2030, while they are forecast to stay relatively constant for commercial and industrial customers. For all three rate classes, Base Case changes in distribution rates over the 15-year period increase less than 8% relative to rates in 2015. Similarly, rates for the miscellaneous expenses, described in Section 3.4.3, increase by less than 5% in the Base Case.

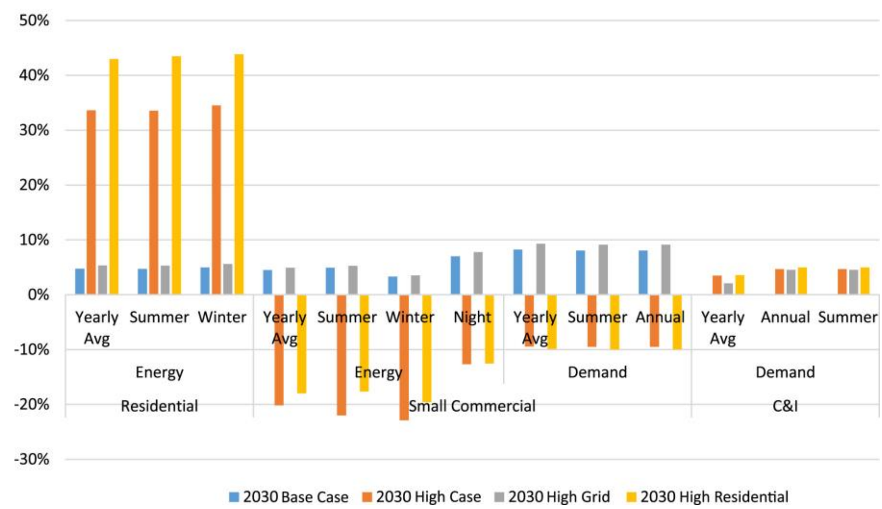

Figure 10: Changes in distribution rates

Distribution rates change much more significantly in the high solar penetration scenarios. With high solar penetration, distribution rates are higher in the High Case and the High Residential (Res) Case than in the High Grid Case for residential customers. In contrast, distribution energy rates decline in these cases for small commercial customers. The increase for residential customers (as much as 27%) is due to changes in the hour of peak system demand, which is caused by changes in solar generation which impacts the allocation of distribution costs. When customers are generating their own electricity from behind-the-meter solar, this generation translates to a reduction in demand for the utility and not as additional supply of energy. Since solar is generating energy during the afternoon when the utility system peak has traditionally occurred, it reduces this system peak during those hours. As a result, peak utility system demand shifts and the new peak occurs when solar production drops off in the evening. As the hour of peak demand moves later in the day, the proportion of the peak that is attributed to residential customers grows. Because of this shift, residential customers move from being responsible for 45% to 53% of total system distribution costs, driving up their costs substantially. In the High Grid case, this transition is not as drastic since the majority of the RPS mandate is met by supply-side installations and, hence, does not differentially affect hourly demand across rate classes. In the 2030 High Grid case, residential customers are only responsible for 46.7% of system peak. In this case, the increase in the distribution rate is driven by reduced sales to NEM customers.

In the High Case, the majority of NEM solar capacity is in the C&I sector, with only 35% of the installation capacity in the residential rate-class. This explains why distribution rates for residential customers increase slightly more between 2015 and 2030 in the High Case compared with the High Res Case. The beneficiary of increasing residential rates in the High and High Res cases are small commercial customers. As the peak shifts later in the day, from 4:00 p.m. in 2015 to 8:00 p.m. in 2030, small commercial customers reduce their percentage of system peak demand. Intuitively, this makes sense because they primarily use electricity during daylight business hours, and their usage begins to decline after 4:00 p.m.

In contrast, demand charges for small commercial and C&I customers generally increase across all scenarios. This is mainly due to reductions in peak demand for NEM customers, which causes rates to increase for all customers in order to recover the same level of costs. In general, the alternative high penetration scenarios adjust the allocation of new solar installations across rate-classes, and the simulations reveal these variations lead to non-trivial changes in the distribution costs attributable to each customer class. Overall, the rate class that installs solar at the highest rate avoids more distribution costs and pushes these charges on other rate classes. Because these scenarios are fit to only approximate current (and alternative) policy, I do not make any conclusions about the total value of the impacts. Rather, I emphasize that the results of the simulation illustrate that the impact on rates for a particular class of customers is highly dependent on the level of solar installations in other rate-classes.

2.4.2 Bill impacts by customer class

When discussing the impacts of solar, it is important to distinguish between electricity rates and bills. Even when rates go up, solar installers buy less electricity and, as a result, pay lower bills. This is a primary source of cross subsidies between participants and non-participants within the same rate-class that has been documented previously (Picciariello et al., 2015b), and I discuss further below. However, unlike existing studies, this analysis also allows for the possibility that cross-subsidies can occur between the rate classes, a phenomenon not yet documented in the literature. In the presentation of bill results, all comparisons are made relative to 2015 non-participant bills.

As with distribution rates, customer bills are dependent on the distribution of new solar installations. In the Base Case, average residential electricity bills are projected to decrease by about 1%, small commercial customers experience a 0.1% increase in average bills, and C&I bills show the most significant average savings at 4.4%.[26] These savings are, as expected, primarily determined by the assumptions regarding how the distribution of solar generation is allocated across rate classes. Another reason for significant savings for C&I customers is that their bills are driven primarily by demand charges, which are influenced more significantly by solar since solar peak and demand peak are typically correlated for these customers.

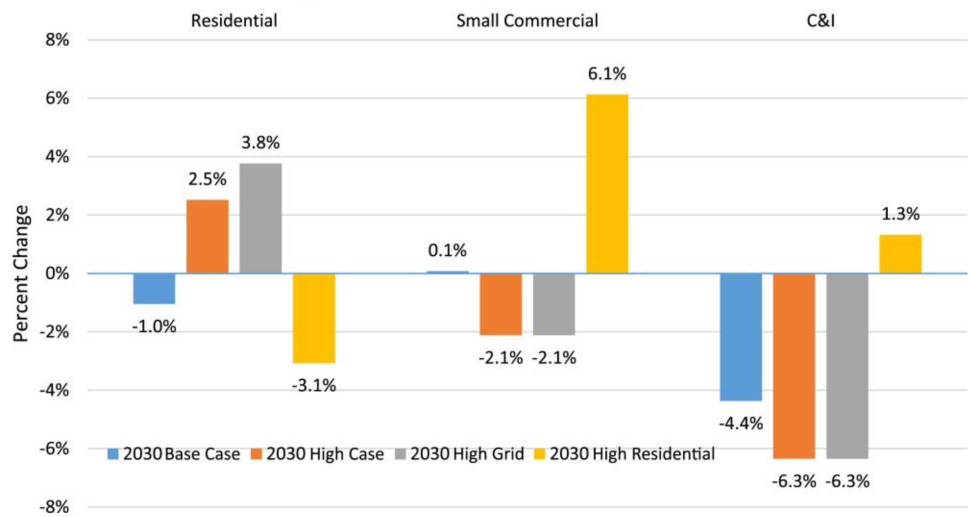

Figure 11: Average percent changes in electricity bills: 2015 – 2030

Average percent changes in electricity bills can be misleading as they represent a weighted average of participant and non-participant bills. The weighting changes as more customers install solar so more information can be gleaned from looking at the disaggregated effects, shown in Figure 12 and Figure 13.

[26] All percentage changes are reported in real terms.

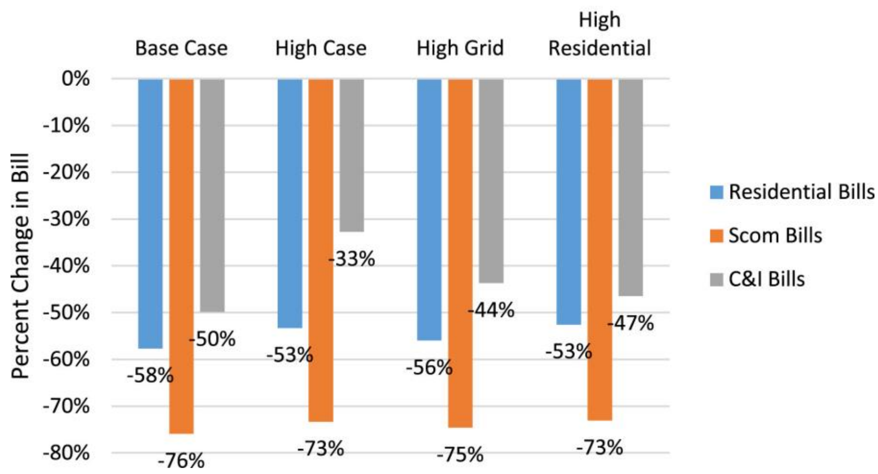

Figure 12: Percent changes in participant bills: 2015-2030

The magnitude of participant bill savings is driven primarily by the assumption of average system size, as expected. The assumptions for solar system sizes were derived from the Solar Energy Industries Association statistics on system installations.

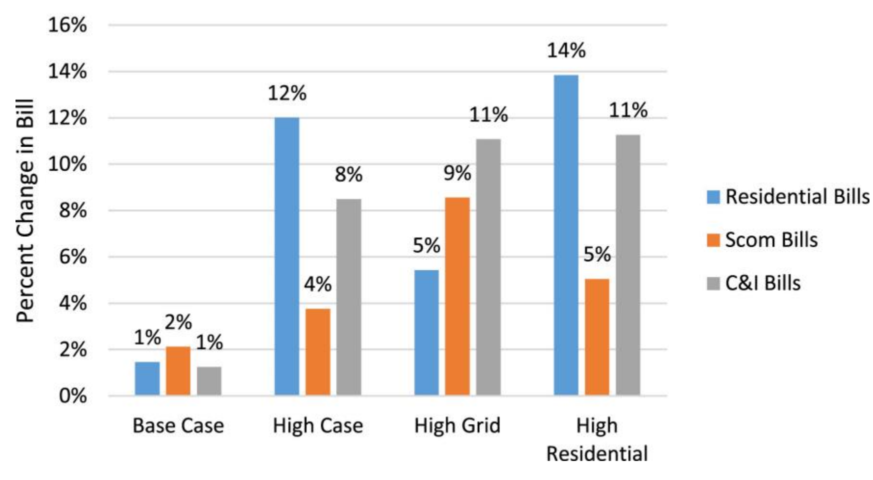

Figure 13: Percent changes in non-participant bills: 2015 – 2030

Non-participant bills are influenced by assumptions about SREC costs. If SREC costs are high, then non-participants will be forced to cover those higher costs. The Base

Case simulations suggest that a significant amount (5%) of solar capacity can be added with only modest (1-2%) increases to non-participant bills. Bill increases in the high penetration scenarios (15%) reflect the cross-subsidization between non-participants and participants. Depending on the rate-class and scenario, average non-participant bills increase between 4% and 14%. When comparing across the high penetration scenarios, I find that the High Grid scenario has a different distribution of bills. This results from a fundamental difference in distributed vs. grid-scale solar generation. On one hand, grid-scale solar generation shifts the market supply-curve outward and reduces energy prices. Consequently, when demand is sufficiently inelastic, installation patterns at the grid-scale do not affect the utility's demand. On the other hand, distributed (and particularly NEM) solar generation influences energy prices by reducing the utility's demand. As demand is reduced, at high levels of penetration, the hour of peak demand shifts. This changes the allocation of costs and results in the "kinks" in Figure 14. As solar generation declines at the end of the day, the peak hour shifts to the evening while the demand for electricity remains high. This phenomenon has been documented elsewhere in the literature and termed the "duck curve" (Lazar, 2014b). It plays a major role in the emergence of subsidization across rate-classes.

Based on the representative rate-structure, the proportion of costs attributed to each rate class is based on their percentage of peak demand. However, the proportion of demand attributed to each rate-class varies on an hourly basis and, thereby, is not consistent across a typical day. For example, residential customers typically use more electricity in the evenings while small commercial customers tend to use considerably less electricity in the evening. This explains why, in the higher distributed generation scenarios, small commercial bills do not increase as much. However, residential customers are penalized in these cases because their demand accounts for a larger percentage of peak demand.

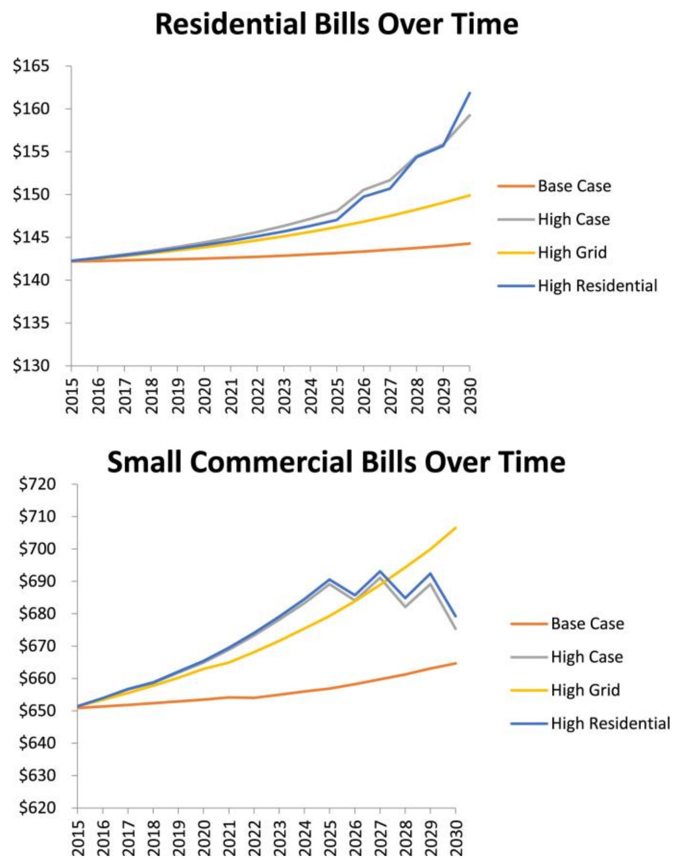

Figure 14: Non-participant bills over time

In the High Case and High Grid scenarios, rates increase for residential customers and the vast majority of residential customers still do not have solar, causing an increase in average bills. However, when a higher percentage of residential customers install solar, the average bills of the rate-class decreases as shown by the High Residential case, although they are still higher than in the Base Case. The forecast in Figure 11 shows residential customers experience the largest bill increases in the High Case and High Grid scenarios, when supply costs also rise. In addition, residential customers account for an increasing proportion of the utility's coincident system peak, which shifts by four hours to 8pm, which increases the residential rate-class' share of distribution costs. This can be seen by the discontinuities in Figure 14.

Small commercial customers also experience higher bills in the High Residential case (but not in the Base Case). Unlike residential customers, the shift in the utility's coincident system peak leads to a reduction in the small commercial rate-class' share of distribution costs. However, this class has the fewest participants installing solar across the scenarios. Furthermore, while their energy rates decrease in only two of the scenarios, their demand rates increase across all penetration scenarios.

C&I customers experience a decrease in bills in three of the four scenarios. Because C&I customers account for the largest share of NEM solar generation in the Base Case, High Case, and High Grid scenarios, their bills decrease by the largest percentage across the rate classes. In the High Residential case, the case in which C&I customers do no account for the largest share of distributed solar generation, average bills increase by slightly more than 1%. Additionally, the peak demand for the C&I customer class shifts away from the coincident system peak. The magnitude of these changes is more significant for C&I customers because their bills are orders of magnitude larger.

2.5 Conclusions and policy implications

While much of the results section was spent discussing the variations among impacts in the high penetration scenarios, the most important result from this analysis is that a significant amount of solar can be incorporated with little impact on customer bills. In the Base Case, which most closely represents current policy, non-participant bills increase by 2% or less, even when solar accounts for 5% of generation. While the theory that increasing solar penetration will cause rates to go up is correct, the impacts do not appear to be as large as some utility stakeholders' expectations. This analysis suggests that a utility "death spiral," where rising rates push more and more customers to distributed generation, is not likely to occur with a continued expansion of solar generation. Future research should examine the possible existence of an inflection point past which increasing solar has a more significant impact.

Like many others, this work finds that non-participants subsidize solar adopters. Customers who install solar are able to reduce bills substantially and transfer costs to non-program participants. Solar renewable energy credit costs, ancillary services, transmission costs, and social benefits charges are allocated across total electricity sales. Solar-participants avoid these charges and non-participants experience increases in rates and bills as a result. This may have important distributional consequences: if solar non-adopters are systematically poorer and therefore spend a higher proportion of discretionary income on electricity costs, then expanded solar installation under current rate design is regressive. In appendix A I investigate the extent to which this subsidization occurs within rate classes by using a sample of hourly customer data. The results support the modeling outputs on average impacts and provide further insights into the distribution of outcomes. Examining the impacts of changing the rate structure to a more cost-causal model clearly indicates the cross-subsidies inherent in the current tariff design. Any move to a more cost causal structure will result in a set of winners and losers who have definitive load shape characteristics.

The modeling provides a unique contribution by highlighting another form of subsidization. It suggests that customer classes that install solar systems fare better than customer classes that do not. I call this “rate class cross-subsidization”. This phenomenon results from a shift in the hour of system peak demand. Net-metered solar causes a reduction in system demand to the utility. Thus, during the current peak hour, 4pm, demand is eroded by higher penetrations of distributed solar. This has a direct effect on rates and bills because costs are allocated based on the amount each rate class contributes toward demand during the peak hour. As the peak shifts to the evening, when solar generation diminishes, the residential rate class becomes responsible for a greater percentage of costs. There are often different incentives for customers in each of the rate classes to install solar and efficiencies to scale in doing so, which means the potential for unequal capacity additions is a real possibility.

Together, these findings suggest the need for increased attention and analysis to better understand the potential impacts of alternative rate structures and apportionment of fixed and volumetric costs. Current pricing policies are imperfect reflections of economic pricing principles, such as aligning charges with cost causation. Current energy (kWh) based pricing schemes do not adequately differentiate the components of the electricity price. The cost of energy, or alternatively of generation, is only about half of retail electricity cost. Other costs include grid infrastructure and maintenance, reserves, administrative costs, and public purpose charges. However, these costs are also recovered primarily through energy charges. Breaking down rates to attribute costs to individual components has become increasingly important with the further implementation of distributed generation, because solar adopters are dramatically reducing their energy purchases from the utility but continue to rely on many of the other services. Nevertheless, it is unclear how these individual components of the grid should be charged. The analysis suggests that rate design and cost causality may be as much of a political endeavor, deciding who ought to pay for energy services, as much of an economic endeavor, attempting to determine cost causality. Alternative rate designs have the potential to shift the burden of electricity supply, transmission, distribution, and associated services across customers and rate classes.

Utilities across the country are considering a variety of alternative pricing schemes to enable them to adequately recover fixed costs under increasing amounts of self-generation (Lively and Cifuentes, 2014). Alternatives include the use of minimum bills, straight fixed variable rates with dynamic pricing, time of use pricing, demand charges for residential customers, various net metering rate structures, and differential charges for distributed generation participants and non-participants. Pricing options are hampered in the short run by the limited penetration of smart metering that is required to measure maximum demand and to move to time-of-use pricing to better reflect long-run marginal costs (U.S. Energy Information Administration, 2014).[27] As distributed resources become more prevalent, the tradeoffs and consequences of alternative pricing strategies require further analysis. In the likely future of universal smart meters, a new generation of pricing options may emerge. These issues will be explored further in the conclusion chapter which discusses the barriers to implementing a more cost-causal rate and the need for further research to understand the rate-making process. In the following chapter, I move from an

[27] In 2014, there were 52 million smart meters installed in the residential sector (U.S. Energy Information Administration, 2014). Smart meters range from basic hourly interval meters to real-time meters with built-in two-way communication.

analysis at the system level to one at the substation level to show that assuming an even distribution of solar across the service territory as done in this chapter may mask impacts that arise from the substantial clustering of solar installations. Like the system wide analysis this has impacts on utility costs which will ultimately affect customer rates and bills.

CHAPTER 3. THE IMPORTANCE OF GRANULAR ESTIMATION

As shown in Chapter 1, an increase in the system wide penetration of distributed solar has important consequences for utility cost-recovery and consumer equity. Further, analysis at the system level can mask some of the challenges introduced by distributed resources. A system level analysis ignores the spatial distribution of solar installation. In this chapter I explain why that is a problem and construct a model which predicts solar adoption at a more granular level. To do so I leverage solar installation data from a PJM utility along with billing data that allows for the identification of solar adoption at the substation level. I use this data to visualize existing clustering and project future penetrations. Unlike previous models of granular solar adoption, this model uses only data which utilities already collect, making it feasible for utilities to incorporate into the planning process. The purpose is to demonstrate why such a model is critical for maintaining reliability under higher solar penetrations. The results of the modelling show the substantial spatial clustering and its consequences. In the discussion, I underscore the importance of including DER forecasting in the IRP process, explore how this might explain the range of value of solar estimates, and consider the potential of community solar and virtual net metering to overcome the challenges of spatial clustering of rooftop PV.

3.1 Introduction

Much of the work exploring the consequences of PV makes the implicit assumption that the distributed resources are added evenly across the service territory (Eid et al., 2014; Johnson et al., 2017; Satchwell et al., 2018). In practice, the adoption of distributed solar tends to be highly clustered (Graziano and Gillingham, 2015). As a result, there are likely to be individual feeders where solar capacity is a large share of peak load, even when system wide penetration remains relatively low. This can introduce grid operational challenges but is also important from a policy perspective because the value of distributed energy resources is contextual. They depend on the local penetration level, load profiles, demand growth, type of equipment, system capacity, distance from substation, and a host of other issues (Brown and Bunyan, 2014). Two of the most important factors are system configuration and resource location within the network (Smith et al., 2017).

High concentrations of distributed solar resources can result in power flows that oppose the traditional flow direction from feeder head to load, and as a result offset upstream power needs directly. This can create value or impose costs. Increasing concentrations on individual feeders have led to concerns with harmonic distortion, voltage spikes, and reverse flows (Agnew and Dargusch, 2015). To accommodate these conditions utilities may be forced to make equipment and protections and controls upgrades which impose costs. Furthermore, any overloads downstream of the distributed resource are unlikely to benefit from the installation of PV (Smith et al., 2017). Finally, without smart inverters, solar can change the balance between active and reactive power which can require utilities to implement capacitors or spinning loads to maintain proper power factors.

On the other hand, properly placed resources can provide value to the utility by relieving overloading of upstream lines and reducing line losses. This is particularly valuable in areas undergoing load growth where equipment may need to be retrofitted or upgraded to handle additional power demands. Delaying capacity expansion represents value. For example, in the rapidly growing boroughs of New York City, the utility Con Edison has estimated the cost to expand the grid there to meet growing electricity demand would be nearly $1 billion using traditional methods. However, in response to the public service commission's reforming the Energy Vision initiative, Con Edison developed a strategy including PV and other distributed resources which could meet the same objectives at a cost of only $200 million (Coddington et al., 2017). Additionally, solar can help manage voltage sagging and load growth on fringe lines. Feeders far from major lines or substations are more costly for a utility to build out or upgrade as they require longer lines and benefit fewer customers (Levin and Thomas, 2014).

Depending on contextual circumstances, DPV can be either beneficial or damaging from the utility perspective. Either way evaluating and planning for said impacts is critical. The coordination of projects is key to the overall success of DPV at higher penetrations (Sherick and Yinger, 2017). Recent analysis from the Electric Power Research Institute underscored the need for "advanced forecasting methods capable of characterizing customer inclination to adopt various DER technologies" (Smith et al., 2017). By developing a model to quantitatively forecast DPV adoptions, electricity stakeholders can maximize value from installations, encouraging further growth in the DPV market.

3.2 Background and Literature Review

3.2.1 Utility Distribution Planning

Traditional utility planning processes are not well equipped to handle forecasting the growth of DERs at a granular level. While utilities have historically been adept at evaluating risks and operating prudently, the expansion of non-controlled generation significantly stress their ability to respond effectively (Brown, 2016). DERs have added complexity to the distribution system planning process, and increased the stakes of inaccurate forecasting (Gagnon et al., 2018). The adoption of solar by customers outside the planning process, introduces significant uncertainty and creates a challenge for long term planning. Current resource planning practices vary widely and the state of the art in DPV adoption forecasting is undergoing continuous refinement. Most of the forecasting effort to this point has exclusively considered the bulk power system (Gagnon and Sigrin, 2016). With improved location precision DPV forecasting could also benefit distribution system planning (Gagnon et al., 2018). Figure 15 diagrams the elements of a distribution planning process to incorporate DPV forecasts in resource planning (Mill et al., 2016)

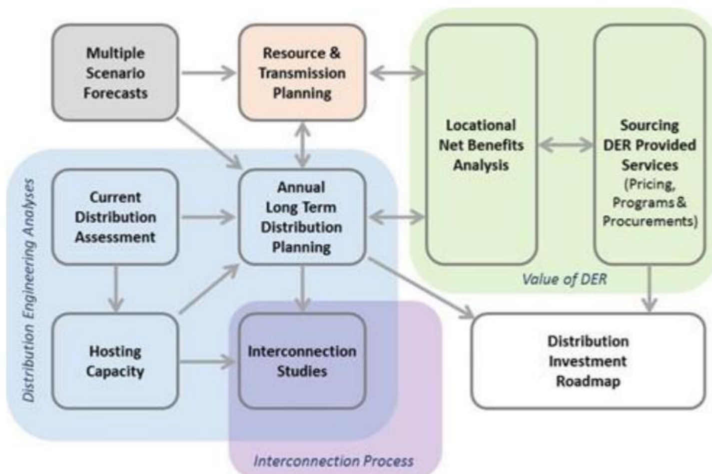

Figure 15: Distribution planning diagram[28]

A growing number of states are beginning to consider regulatory stipulations for comprehensive distribution system planning processes. A recent National Lab report reviewed state engagement in this process (Homer et al., 2017). Table 2 summarizes the findings on states with activities on electric distribution system planning.

[28] Image Credit Planning for a Distributed Disruption: Innovative Practices for Incorporating Distributed Solar into Utility Planning retrieved from: https://emp.lbl.gov/publications/planning-distributed-disruption.

Table 2: State activities on distribution system planning

	California	Hawaii	Massachusetts	Minnesota	New York	D.C.	Florida	Illinois	Indiana	Maryland	Michigan	Ohio	Oregon	Pennsylvania	Rhode Island	Washington
Statutory requirement for long-term distribution planning	✓			✓					✓							
Commission requires long-term distribution planning		✓	✓		✓					✓	✓					
No requirement but proceeding underway						✓							✓		✓	✓
Voluntary filing of grid-mod plans								✓				✓		✓		
Non-wires alternatives analysis requirement	✓				✓										✓	
Hosting capacity analysis requirement	✓	✓		✓	✓											
Locational net benefits analysis requirement	✓				✓											
Smart grid planning requirement													✓			
Reporting on poor performing circuits							✓	✓				✓		✓	✓	
Storm hardening requirements							✓			✓						
Investigation into DER markets		✓														

The states in Table 2 represent those on the leading edge of distribution system planning processes, but interest is growing and methods evolving. Some jurisdictions have also begun to utilize Geographical Information Systems (GIS) to assess where existing distributed solar has been deployed. Unfortunately, low-voltage distribution circuits have never been modeled in detail and this information cannot yet be incorporated in forecasts (Quiros-Tortos et al., 2017). Part of the concern in mandating DPV adoption forecasting is that the methodologies which provide actionable information incur significant costs. They often require investing in new software tools, collecting different types of data, training staff or hiring outside consultants (Warwick et al., 2016). While initial evidence suggests that the costs of misforecasting DPV adoption outweigh the costs of such planning in territories with significant growth expected (Gagnon et al., 2018), cost reductions are necessary to bring the practice to the mainstream.

3.2.2 Distributed Resource Forecasting

Non-utility actors from academia and government have attempted to fill the void in forecasting the adoption of distributed solar resources. Some rely on statistically modeling adoption trends and future penetration rates based on solar cost projections and national growth forecasts (Denholm et al., 2009; Drury et al., 2012; Paidipati et al., 2008). The granularity of these estimates is not fine enough to provide substation level estimates and are intended for use in the bulk power markets. Reviewing recent utility distribution resource plans, the main forecasting approaches include stipulated forecasts, historical trend matching, and program-based approaches. These methods rely on few to no quantifiable predictive factors and make up about 70% of the current practice (Mill et al., 2016). In contrast, customer-adoption modeling explicitly uses historical DPV deployment, location specific DPV potential, economic considerations, and/or end-user behavior as predictive factors. Because it explicitly captures several predictive factors, customer-adoption modeling is the most comprehensive forecasting approach. Figure 16 describes the basic process of customer-adoption models.

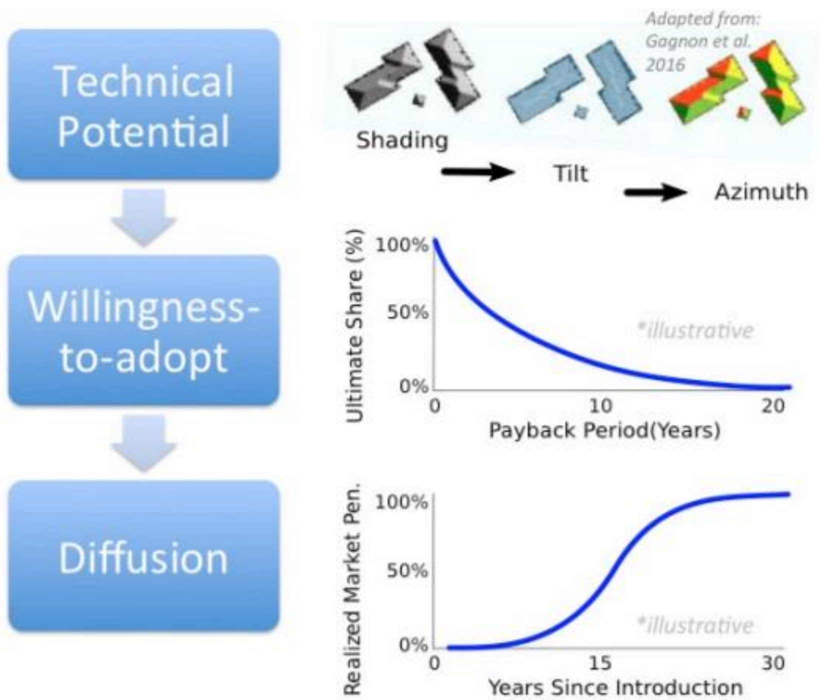

Figure 16: Customer adoption modeling process[29]

In this analysis I focus on the diffusion modeling and willingness to adopt aspects of the customer adoption models. Diffusion processes in general follow an S curve documented in the growth of many natural phenomena (Grübler, 1996). Since the 1960s with the introduction of the seminal Bass model (Bass, 1969), diffusion trends have taken many mathematical forms and iterations (Meade and Islam, 2006). Their primary

[29] Image Credit Planning for a Distributed Disruption: Innovative Practices for Incorporating Distributed Solar into Utility Planning retrieved from: https://emp.lbl.gov/publications/planning-distributed-disruption.

application has been to the diffusion of innovations such as cars and consumer electronics, but they have also been used in the study of health outcomes, disaster modeling, and economic cycles. Mahajan and Peterson provide a classification of diffusion models and describe the refinements and extensions made to the original specification (Mahajan and Peterson, 1985). Diffusion models have also been used more recently to predict the spread of renewable energy technologies. Rao and Kishore (2010) and Huh and Lee (2014) provide reviews of the applications in this domain. They highlight the role of policy in influencing the relative growth rate of these technologies. In the methodology section, I dive further into the specifics of the diffusion model utilized herein.

The primary contribution of this analysis is in pairing a propensity to adopt model on top of the diffusion forecast to predict solar adoption at a more granular level. Previous studies have investigated solar adoption at finer spatial resolutions while looking at peer effects, but these were post installation results explaining why a clustering had occurred (Bollinger and Gillingham, 2012; Graziano and Gillingham, 2015; Kwan, 2012). There is also a robust body of literature exploring the relationships between values, lifestyles, expected financial return, information provision, and customer attitudes on the adoption of solar (Faiers and Neame, 2006; Islam and Meade, 2013; Rai et al., 2016; Schelly, 2014). These studies attempt to predict adoption at the household level, but the results have been inconsistent (Rundle-Thiele et al., 2008). In addition, almost all work in this area has relied on retrospective surveys of DPV adopters or in rare cases non-adopters (Wolske et al., 2017). All the granular models suffer from the same flaw from a utility planning perspective: they rely on data not regularly collected by the utility.

To overcome this barrier to granular DER forecasting I build a model which uses only data readily available to utilities to estimate customer propensity to adopt solar. Even if the individual household predictions don't capture all the variation in the data, when binned at the substation level, forecasts show a high degree of accuracy. Using such a tool, utilities can plan for equipment and protections upgrades to handle reverse flows and bus voltages that may exceed reliability regulations on peak solar days. With the inclusion of meteorological data, it is possible to predict how that future solar would operate. The results of this forecasting would enable a prediction of future system flows and could be executed as part of the year-ahead load forecasting that utilities already do (Enslin et al., 2016). This addresses a direct need identified in a comparative analysis of roughly 30 recent utility planning studies. The report identified nine areas where even the best current practices might be enhanced (Mill et al., 2016), and this study addresses three of those areas. First, in forecasting DPV deployment it combines forecasting methods to generate location specific estimates of adoption. Second, it acknowledges DPV's location-specific value. The propensity-to-adopt method employs several variables to predict future DPV locations which would allow utilities to locate or promote DPV strategically to enhance its benefits. Finally, it considers changes in DPV's value at higher local solar penetrations and suggests methods for addressing the clustering to maximize benefits of further PV penetration.

3.3 Data and Methodology

3.3.1 Diffusion Model

Purohit and Kandpal (2005) analyzed diffusion trends of four renewable energy technologies including solar PV, and estimated their future dissemination levels using the Bass, Gompertz, Logistic, and Pearl models. They showed that technical potential is achieved fastest in the case of the Logistic model, whereas the diffusion following the Gompertz model is the slowest; the Bass model represents an intermediate diffusion trend and was selected as the method of choice for this analysis.

The Bass model suggests that individual adoption of an innovation in a population is driven by three factors. The first is a desire to innovate (the coefficient of innovation is p). The second is an imitation of others in the population (the coefficient of imitation is q). Finally, the growth is bounded by the market potential (m). The probability that a potential installer adopts at time t is driven by ($p+qF(t)$) where $F(t)$ is the proportion of adopters at time t. Comparing innovation diffusion to the spread of an epidemic, imitation is often called a contagion or word-of-mouth effect and in a pure imitation scenario ($p = 0, q > 0$) diffusion follows a logistic curve. In the opposite scenario of pure innovation ($p>0, q=0$), diffusion follows a modified exponential. In a bass diffusion model ($p+q$) controls the scale and (q/p) controls the shape. For the curve to produce its traditional S shape (q/p) must be greater than one.

In this paper I use the continuous time formulation of the Bass model as derived by Schmittlein and Mahajan (1982) and employed more recently in the study of solar diffusion by Islam (2014). The formulation is presented in equation 1 where A is the cumulative adoption and t is the time interval.

$$A = m\,[\frac{1 - e^{-(p+q)t_i}}{1 + \frac{q}{p}e^{-(p+q)t_i}}] \tag{1}$$

Using a nonlinear least squares estimation on historical data it is possible to estimate the coefficients of innovation, imitation, and market size.[30] Most diffusion models include in their parameterization variables which underly the coefficients of innovation and diffusion. These models include factors such as consumer preferences, technology costs, socio-economic factors, macro-economic environment, and competing products (or in this case energy sources). See Lee and Huh (2017) for a review of the attributes that have been investigated to this point. While many of these attributes are useful for explaining product adoption their utility for creating ex-ante predictions is limited. For example, forecasting adoption using a model dependent on technology costs requires estimates of future technology costs. Furthermore, policy has shown to be among the most important drivers of renewable energy adoption (Polzin et al., 2015), but predicting policy change is nearly impossible. For the purposes of this analysis the modeling is intended to be done in the context of distribution system planning. Within planning cycles there are shorter time horizons and a relatively consistent policy landscape owing to the fact that policy changes are coincident with planning cycles. Given these conditions I forecast adoption in the

[30] If there are too many parameters relative to the time series data, it will be difficult to estimate the model efficiently due to the small number of degrees of freedom. In the PJM territory under consideration the residential and small commercial markets are already fairly robust with ample data for estimation of coefficients, however the virtual net-metering installations are a nascent enterprise and their growth was modeled differently as discussed in the section on community solar.

absence of any policy shocks, allowing the model to generate the coefficients of innovation, imitation, and market size[31] directly and treat those as constant during the forecasting window. Prior evidence suggests that given sufficient historical data the bass model fits well even in the absence of additional decision variables (Bass et al., 1994). I estimate the coefficients separately for the residential and non-residential markets under the assumption that they have different drivers of adoption.

Danneels (2004) was among the first to use extant methods of technology diffusion to predict the spread of disruptive innovation ex ante. Since, the literature have established a number of precedents for applying these insights to the micro level (Liu and Gupta, 2012). These methods are employed by Islam in the study of household level diffusion of PV using stated preference data, and that study serves as the inspiration for this methodology (Islam and Meade, 2013). In that model, the hypothesis was that technology awareness, environmental attitudes, socio demographics, and preferences drive adoption, and data were captured through choice experiments. The primary innovation of this methodology is to predict household level adoption without needing to conduct surveys or choice experiments to explain household behavior. In their stead, I use data already collected by the utilities or derived from load data.

3.3.2 Propensity to adopt

Solar adoption has been shown to be correlated with income and demographics of adopters (Barbose et al., 2018). These same attributes are also correlated with electricity

[31] A more sophisticated approach could provide a market potential estimate using information on number of customer premises with adequate solar resource. Utilities have the capability to collect this data using Lidar measurements, but that technology is expensive and not part of the data that was available during this study.

use. For example, the aggregate annual use of electricity is strongly related to household income, home square footage, and other unobserved covariates (Yohanis et al., 2008). As such, I use characteristics of electricity load, paired with limited categorical variables from customer bills, to predict household level propensity to adopt in the place of demographic data. While this propensity model will certainly capture less of the variation in the data than a model with robust household characteristics, it could be implemented by a utility with no additional data collection costs.

As a proxy for household vintage and type, I use the weather sensitivity of electricity load. Older structures have less thermal inertia as do standalone properties. I investigated weather sensitivity separately for both hot and cold temperatures using heating and cooling degree days. This data was then merged with the kWh usage during the bill period to generate a set of correlation coefficients for each customer. Another predictor of solar adoption is a customer's seasonal load pattern. Seasonal load patterns capture variance due to lifestyle factors, appliance stock, and electrification of end loads. For example, those customers without electric water or space heating may be less likely to adopt solar. To create clusters of usage patterns the data was normalized such that each month represented a percentage of annual consumption. A k-means cluster algorithm was employed to group accounts into clusters of load shapes. Categorical variables including rate class and zip code supplement the propensity model. The highest percentage of solar adopters are from customers in non-default rate classes, perhaps because opting into a non-default tariff indicates higher awareness of electricity costs. Customers in different geographic locations may install at different rates and the inclusion of a zipcode dummy captures any variation in demographics that exists at that level.

To determine the set of available covariates which best predict solar adoption in the population I included all potential variables in a least angle regression model selection algorithm (Efron et al., 2004). This modification of the Lasso technique improves the prediction accuracy and interpretability of the model by selecting only a subset of the provided covariates for use in the final model. Those selected were weather sensitivity, annual usage, load profile, and rate code. Because the dependent variable (solar adoption) is binary I employ a model which accounts for the restricted range and implied nonlinearities. I use a simple probit model employed previously in this domain (Woersdorfer and Kaus, 2011). The probability of adoption is captured in equation 2 where Φ is he cumulative distribution function of a normal distribution and X_i is the set of covariates.

$$\Pr(y = 1|x) = \Phi(\beta' X_i) \tag{2}$$

The final step in the process is to combine the results of the system level forecast with the individual adoption probabilities. Across customers I summed probabilities and scaled to 100%. The next forecasted adoption in the system was then assigned to the customer with the highest adoption probability. The assumed capacity was based on a ratio of capacity to usage at each substation. Finally, I aggregate all the customers with service provided by a given substation to reach a substation level forecast.

3.3.3 Community Solar

Community Solar is defined as a solar-electric system that provides power and/or financial benefit to, or is owned by, multiple members. It can be implemented through several different sponsorship models and is an increasingly popular means of affording access to solar for customers who may not have been eligible otherwise. In the utility territory at the time of this analysis, there were not yet any community solar projects online, but the utility had received applications for over 500 MW worth of projects since the first applications were received in 2015. It is evident that community solar will comprise a significant portion of distributed solar resources in the future, but with a lack of historical installation data the forecasting process was slightly different. This process is detailed below.

In a similar fashion to the residential and non-residential models, a Bass diffusion curve was used to estimate future solar projects. However, rather than being based on installed projects the curve was modeled on applications. I begin the estimation of the curve following an application process change implemented in 2016 that provided a standard format for applications and introduced a series of screening tests. The Bass diffusion curve produces estimates of future capacity applied for, but to predict installed capacity I must estimate the likelihood that an application makes it through the entire process. To accomplish this task, I implemented a Markov chain, or transition matrix, Monte Carlo simulation (Gilks et al., 1995) which estimates the probability of reaching a different state given the presence in the starting state. For my purposes, this was interpreted as: given that an application reaches a certain stage in the process, what is the likelihood that it reaches the next stage vs. the likelihood that it withdraws from the process. The mean survival rate was estimated from historical applications, but to generate confidence bands around these estimates a bootstrapping technique was used. At each stage, the number of observations was set at the number of applications in that stage and an observation was said to move on if the draw from a uniform distribution from 0 to 1 was less than the transition matrix survival rate. In each simulation the survival rate was the percentage of applications that "move on." 1,000 simulations were run and the results from these simulations provided a distribution of the survival rate for projects. The mean approximated the value from the transition matrix, and the 5th and 95th percentile were used as the lower and upper bound respectively.

For each stage of the application, there is data on the date that stage was reached. Using this information, I could ascertain how long an average application takes to make it through each stage. Because no applications have reached the completion stage, I employed a beta distribution with long tails to estimate the days from full payment to construction. For the beta distribution, the minimum number of days was set at 450 since there have been projects in the final stage of the queue without coming online for that long already. For applications already in the queue, the information on which substation they will be installed at is included with the application. Thus, for existing applications it is straightforward to create a more granular forecast at the substation level. For predicted applications, the distribution of forecasted applications to the substation level was made on the basis of the percentage of total application capacity. I calculated the percentage of applied for capacity at each substation and assumed the same distribution of applications going forward.[32]

[32] This was a simplifying assumption used for lack of a better option. This will exacerbate existing clustering over the long term, but given the relatively slow growth in applications and the 3.5 year lead time from application to installation it will not have a significant impact on the planning horizon relevant for this analysis. In the results section I also discuss implications of targeting community solar to locations of value for the system which replaces this assumption with an alternative.

3.3.4 Data Sources

The primary data source used in this analysis was a record of historical solar interconnections provided by a PJM utility. Customer billing data with corresponding account numbers was used to match distributed solar and develop predictors for the propensity score model. Weather data was obtained from NOAA's National Climactic Data Center and used to develop additional adoption predictors.

The PJM utility provided a record of all solar interconnections in their service territory. The interconnection data spans from December 2001 through June 2018. I bin installations by month to generate a time series of adoption records that can be merged with monthly billing data. Because I am interested in forecasting solar adoption under the current policy context, I normalize the residential installation data to the start of 2013. The year prior, the service territory began allowing customers to participate in net-metering through a lease or power purchase model. This removed a significant capital barrier and triggered a much different trajectory for residential solar. Using the account id, the interconnection records could be matched with customer billing data. Billing data includes information on customer usage and the substation which customers are served by. Summary statistics on variables of interest are shown in Table 3.

Table 3: Summary statistics

Variable	Observations	Mean	Std. Dev.	Min	Max
Account id	17,095,449	55,800,000	23,200,000	11,000,000	89,800,000
Installed kW	376,757	9	21	0	1,584
Install date	376,757	3/16/2015	905	12/6/2001	7/16/2018
Service class	376,757	3	1	1	10
Use (kWh)	17,095,449	1,730	73,121	-72,114	44,000,000
Rate code	17,095,449	6	9	1	82
Read date	17,095,449	19,651	1,482	10,959	21,270
Bill id	17,095,449	11	6	1	47
Bill period	17,095,449	48	16	1	101
Zipcode	17,095,449	4	4	1	13
Substation	17,095,449	43	24	1	82
Avg temp	17,081,250	51	18	-5	88
Hdd55	17,095,449	10	10	0	51
Cdd60	17,095,449	4	5	0	27

3.4 Results and Discussion

Through May 2018 there were roughly 8,000 distributed solar installations in the utility territory which provided over 75 MW of installed capacity. There is already significant variation in penetration by location as evidenced by Figure 17, which shows the installed capacity by substation in 2018. This underscores the importance of producing granular forecasts.

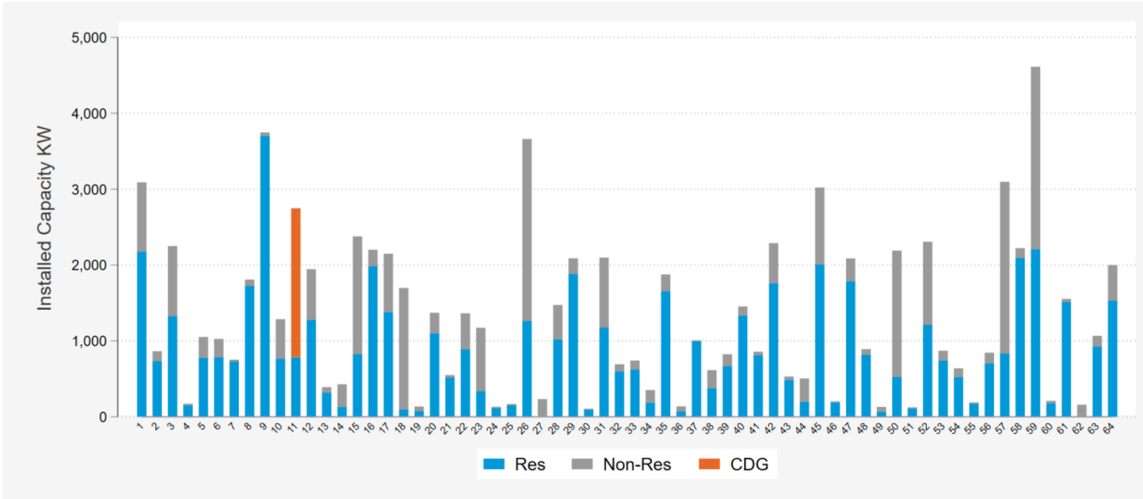

Figure 17: Substation level installed solar capacity 2018

Given the historical data, the bass diffusion model was used to estimate the parameters of market size, innovation, and imitation for the residential and non-residential markets. Table 4 presents the results from the residential model, and the non-residential results are in Table 5.

Table 4: Residential solar market diffusion results

Coefficient	Coef.	Std. Err.	t	P>t	[95% Conf. Interval]	
/M	7226.795***	56.16507	128.67	0.000	7115.338	7338.253
/p	9.65E-05***	7.23E-06	13.35	0.000	8.21E-05	0.000111
/q	0.095802***	0.001472	65.08	0.000	0.09288	0.098723

The results of the model match expectations given the assumptions. The coefficient of innovation is near zero, which is logical given that the model is assuming a constant policy context and does not incorporate any reductions in technology cost or changes in market conditions. The estimated market potential of 7,227 is for installations post 2012 since the data was normalized to begin with the current policy environment. Adding installations from before 2012 yields an estimate of the total number of residential installations of 8,693. This represents 3.4% of residential accounts in the service territory and seems reasonable considering the policy goals referenced in Chapter 2. The estimate of 0.096 for the coefficient of imitation is nearly identical to the result found by Islam (2014). The residential forecast may seem conservative, as it yields relatively low numbers of new installations. I believe this is a reasonable prediction given the innovations in the distributed solar market have made community solar a much more appealing option for many residences. Participating in community solar does not require the capital liquidity, and participation is not constrained by availability of roof space or appropriate solar resource. Given that the utility service territory allows remote net-metering, customers can receive the same financial incentives even without the panels directly on-site. This will serve to limit the adoption of residential solar going forward.

Table 5: Non-residential solar market diffusion results

Coefficient	Coef.	Std. Err.	t	P>t	[95% Conf. Interval]	
/M	573.4198***	14.27596	40.17	0.000	545.2056	601.634
/p	0.001571***	3.23E-05	48.6	0.000	0.001507	0.001635
/q	0.025348***	0.000828	30.62	0.000	0.023712	0.026985

The non-residential market model results are shown in Table 5. The estimated market potential for non-residential customers is 573 installations which represents 1.4% of non-residential customers in the sample. While the number of installations and percent of the population are smaller in the non-residential market, the average size of a non-residential system is significantly larger yielding installed capacity from the non-residential market roughly two-thirds that of the residential market. The coefficient of innovation is again small, though larger than the residential market. The coefficient of imitation is smaller, but is in line with the mean values of a diffusion of innovations meta-analysis which found a mean of 0.038 (Sultan et al., 1990). The different relationship between these two-values in the two different markets explains the difference in curve shape evident from the visual depiction of the historical installations by month and the forecasted values shown in Figure 18.

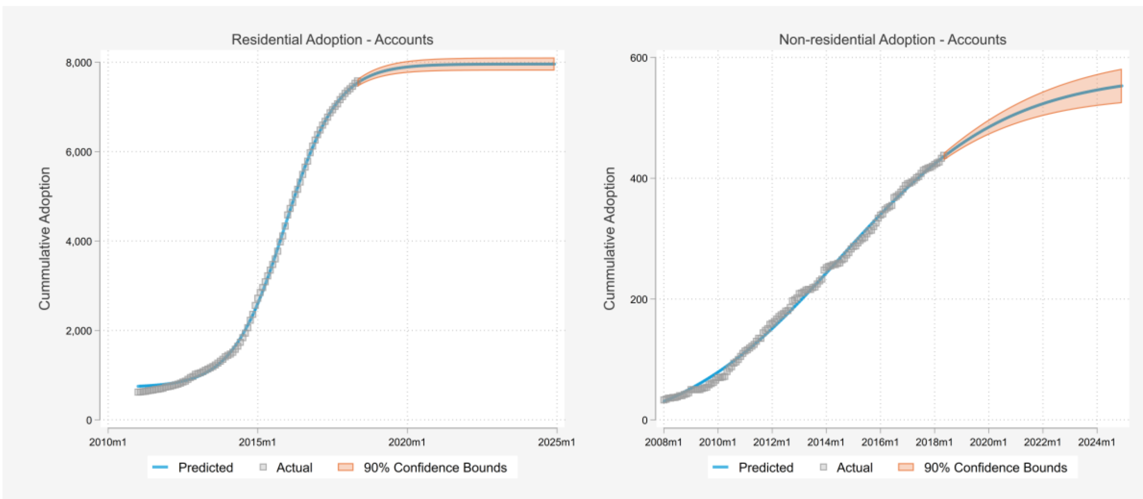

Figure 18: Distributed solar account forecasts based on bass diffusion models

The sector that is likely to see the largest growth in the planning horizon, based on the number of applications received by the utility, is community solar. Even without any forecasted applications, at the time of data collection there was 150 MW of community solar projects in the applications queue. This is double the size of the residential and non-residential markets combined. As discussed in the methodology section, because no community solar has been installed to date, the challenge is determining how many projects are likely to make it through the application process and how long it will take them to come online. Figure 19 shows a survival curve for projects in the application process. Less than 20% of received applications make it to the final stage where full payment is due to the utility. Thus far all projects that have survived in the application process for 600 days have gone on to full payment. Applications can be dropped at one of six stages in the process for failing to complete partial payments, or for technical reasons due to inadequate plans or unsuitable proposed system interconnection.

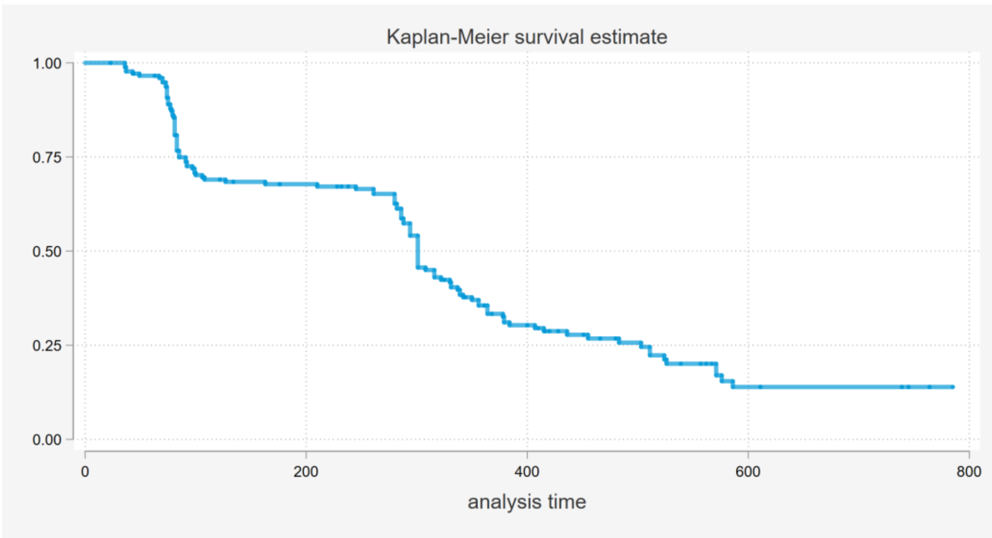

Figure 19: Kaplan-Meier survival curve

The survival rate at each stage in the application process is shown in the transition matrix in Table 6. For each row in the matrix the columns represent the mean survival rate, what percent of applications move to the next stage. The process is sequential so it’s a question of whether an application proceeds or is withdrawn.

Table 6: Markov chain transition matrix

Stage:	Stage 2	Stage 3	Stage 4	Stage 5	Stage 6	Stage 7	Withdrawn
Stage 1	100	0	0	0	0	0	0
Stage 2	0	98.8	0	0	0	0	1.2
Stage 3	0	0	44.93	0	0	0	55.07
Stage 4	0	0	0	100	0	0	0
Stage 5	0	0	0	0	88.46	0	11.54
Stage 6	0	0	0	0	0	97.22	2.78
Average Duration (Days)	19	82	89	52	172	Beta Distribution	

The stages with the largest withdraw rates are stage 3, a preliminary technical analysis, and stage 5, a full interconnection review. Table 6 also displays the average duration a project remained in a given stage. Because no applications have reached the online stage, I used a beta distribution with long tails to estimate the days from the final approval of the application to operation. For the beta distribution, the minimum number of days was set at 450 since there have been several projects in the final stage of the queue without coming online for that long already. The mean anticipated online time was 2 years. In sum, I estimate it takes an application an average of 3.5 years from the date of application submission until the project is operational. This will put the first community solar projects online at the end of 2018. Applying the results of the transition matrix and the completion time analysis to projects currently in the queue and forecasted future applications yields the forecast for installed community solar presented in Figure 20.

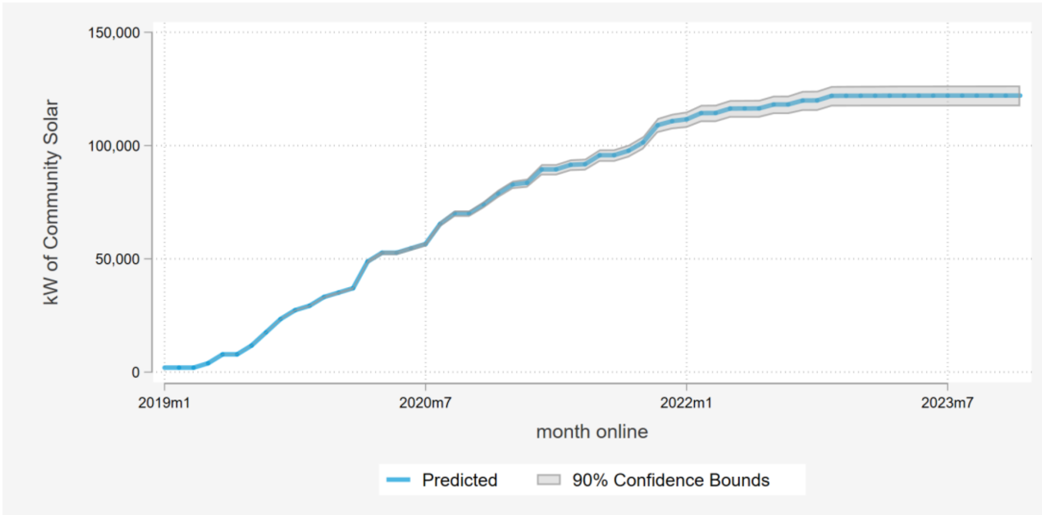

Figure 20: Community solar forecast

Having generated forecasts for system wide installations I now turn my attention to the results of models for estimating adoption at the individual level. In other words, given the number of new installations predicted, which customers are those installations most likely to come from. This was done through a probit model which estimated for each customer their propensity to adopt solar. The final model was selected through a lasso technique that determined which potential predictors generated a model with the best prediction accuracy. The results of the probit model are shown in Table 7.

Table 7: Propensity to adopt solar

Dep Var = Solar Adoption	Coef.	Std. Err.	t	P>t	[95% Conf. Interval]	
Weather Sensitivity	1.456054	0.043552	33.43	0.000	1.370693	1.541415
Load Percentile	0.025684	0.000606	42.41	0.000	0.024497	0.026871
Load Shape						
2	1.609543	0.052993	30.37	0.000	1.50568	1.713407
3	0.663006	0.037675	17.6	0.000	0.589164	0.736847
4	1.199989	0.042929	27.95	0.000	1.11585	1.284128
Rate code FE	Y					

The variables selected for the final model are all statistically significant and their direction matches intuition. Customers who have a load that is more sensitive to weather conditions are more likely to adopt. Greater weather sensitivity is likely a result of electric heating and cooling. Similarly, customers who have larger aggregate loads are more likely to install solar. Aggregate load is correlated with income and building ownership. Customers who use more electricity during the summer are more likely to install solar which makes sense given this is the period when more load will be offset post-installation. Customers on non-default rates also have higher propensity to adopt. While the model only captures approximately 12% of the variation in the data, it does capture well which bins of customers are likely to adopt as shown in Figure 21. If anything, the model slightly underpredicts probabilities for the most likely adopters.

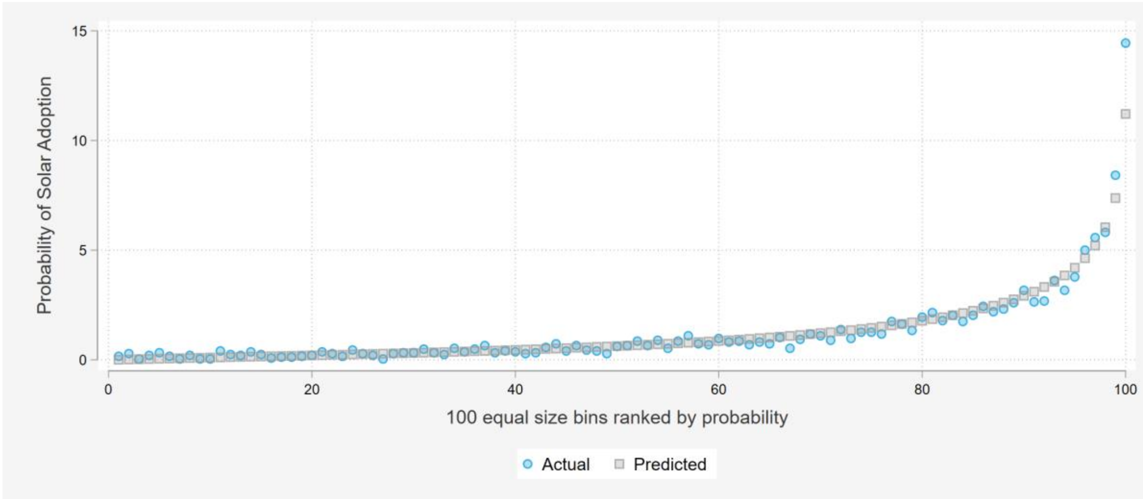

Figure 21: Binned adoption probabilities

With predicted probabilities at the customer level and a system wide forecast, I combine the results and distribute the predicted solar additions to customers based on their adoption probability. The size of the system a customer adopts is based on the ratio of capacity to usage for previous installers on the same substation. Finally, I combine the predictions from each service class: residential, non-residential, and community solar and aggregate the estimates from the customer level to the substation level to generate the forecast installed capacity by substation shown in Figure 22.

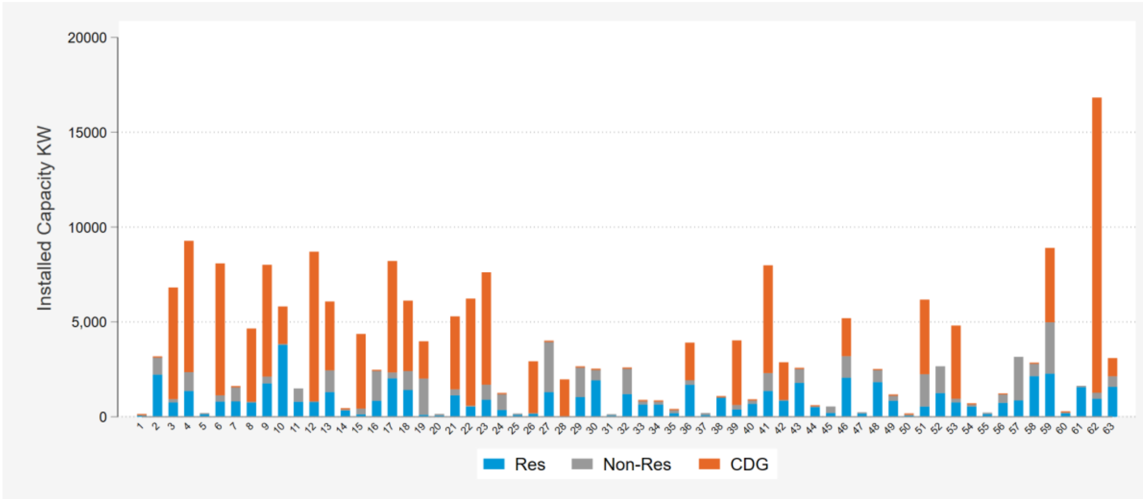

Figure 22: Substation level installed solar capacity 2023

As can be seen by comparing Figure 22 with Figure 17, further penetration of solar does not more evenly distribute installations across substations, but rather exacerbates existing clustering. This is particularly troubling when considering that community solar projects, which represent the bulk of projected growth, are not tied to a specific location on the grid by home or business location. This demonstrates clear information asymmetries between project developers and the utility itself which could also explain the high attrition rate for project applications. There are two potential consequences to this clustering. The results of the interconnection analysis may indicate that the substation or feeder cannot accommodate additional distributed solar resources without equipment upgrades. The project developers are responsible for a portion of these costs and may withdraw their application. This may limit, or at least slow the growth of solar and results in needless work by both the developer and the utility. Alternatively, the utility may make the upgrades to enable equipment to handle further DPV penetration. In this case, those capital costs are added to the rate base and paid for by all customers, not just those with solar. Here the value of that resource is diminished because it was put in a suboptimal system location.

Figure 23 illustrates how substation level installed capacity would look under a scenario in which each successive community solar project was installed on the substation with the lowest penetration of solar.

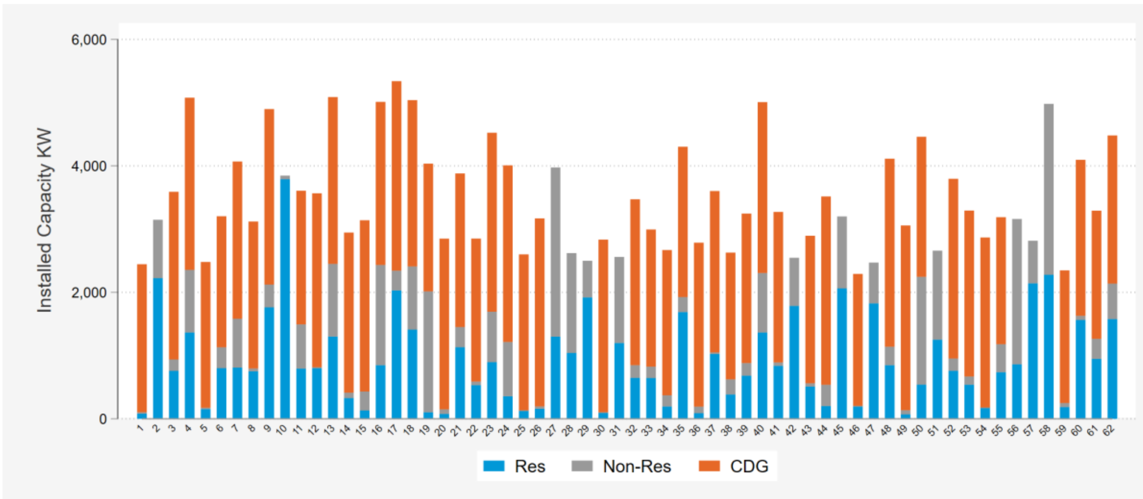

Figure 23: Potential installed PV capacity by substation under alternative conditions

Maximizing the benefits from PV depends on identifying locations where it can deliver value by deferring or avoiding infrastructure costs or improve reliability. Figure 23 was generated using a simple rule of thumb assumption in absence of any data from the utility on growth rates or reliability by substation. In practice, utilities have forecasts of infrastructure investments associated with load growth which are highly location-specific. These growth-related investments may affect only a small portion of a utility's service territory over the course of a 5-year period. Without identifying and targeting those locations, the avoided cost potential of distributed resource is unrealized or diluted. The implication is that the maximum value of solar is only attained if resources are placed in the right locations. For example, if the system-wide avoided investment value is an average of $10/kW-year but is concentrated in 5% of the utility service territory, it means that, on average, the value is $200/kW-year at those locations. This example may demonstrate why the industry has struggled to determine an appropriate estimate of the value of solar (Hansen et al., 2013), the value is extremely contextually dependent.

I propose an adaptation of the community solar development process to smooth the variation and target locations where distributed resources confer the most value. In this model a utility determines locations of high grid value for voltage support, congestion reduction, or load growth during the distributed resource evaluation planning period. They then provide stakeholders with a means of accessing this information and restrict applications from developers to high value locations. In this case, the installers can take advantage of efficiency of scale from larger installations, and don’t waste resources on projects that will eventually be withdrawn. The key is reducing the information asymmetry between utilities and developers through stakeholder engagement in the planning process. This information asymmetry is a source of value erosion that could be mitigated through improved utility policy.

An additional opportunity with community solar is the ability to attract customers who have previously been unable to adopt. Community solar has the potential to allow low income residents to participate which may serve to address some of the equity concerns associated with the spread of distributed resources (Coughlin et al., 2012; Nieto, 2016). In fact a number of states have identified community solar programs as a means for reducing the energy burden of their low income households (Cook and Shah, 2018). These programs are consistent with reports that utilities are motivated to develop community solar to satisfy consumer demand, meet regulatory requirements, and alleviate revenue losses related to distributed PV adoption (Funkhouser et al., 2015).

3.5 Conclusion

In this paper I developed a model of granular solar adoption, which makes use of only data which utilities already collect. The ability of such a simple model to forecast substation level solar growth is important for improving the ability of resource-constrained utilities to accurately forecast future loads and infrastructure needs. An NREL report concluded that for the vast majority of the 3,000 U.S. utilities, it would not be cost-effective to implement detailed probabilistic models of customer adoption because mis-forecasting costs would not be high enough, but all utilities should include some DPV projections in their integrated resource plans (Gagnon et al., 2018). Using the methods employed here would substantially reduce costs and enable utilities to incorporate distributed resource forecasts into their integrated resource plans.

The results of the modelling show substantial spatial clustering exists already and is likely to get worse given the status quo. Such clustering will only intensify the problems associated with cross subsidies highlighted in chapter 2 because it increases costs and reduces the value of solar. That said, the majority of new solar growth in the utility territory under investigation is projected to come from large community solar installations. This enables a number of new opportunities. First, community solar systems can take advantage of more optimal siting conditions to maximize solar resource and take advantage of efficiencies of scale. Combined with a remote net-metering policy they can open the solar market to populations who have been largely excluded to this point. Finally, community solar projects can be specifically targeted at locations in the system where they confer the most value. In order to take advantage of these opportunities it is imperative that we remove the information asymmetries between system operators and project developers. Because these large capacity projects have long lead times new policies are needed now. Given the evidence provided I suggest all public utility commission require include DPV forecasting in resource planning.

This chapter built on Chapter 2 by investigating how the imposed solar additions were likely to be distributed across the system. This information is vital for infrastructure planning but does not necessarily translate directly to system operation. To understand how solar additions will affect loads an understanding of the customer response to solar adoption is required. Chapter 4 will investigate one aspect of customer behavior, whether adoption leads to a change in overall consumption.

CHAPTER 4. THE SOLAR REBOUND

Chapter 2 demonstrated the subsidization of non-adopters by solar installers. Chapter 3 showed that adoption of solar to date has been clustered and that such trends are likely to continue, hurting the value of solar and reducing system efficiency. In spite of these factors, subsidization of distributed solar has become more pervasive as policy makers around the country seek ways to reduce consumers' reliance on conventional, carbon-intensive energy technologies.

The growth of distributed solar has changed the traditional utility/customer relationship. The policy support has invigorated discussion about how to efficiently and equitably encourage continued growth of solar while maintaining cost reflective electricity prices and grid reliability. A key policy question is whether the reduction in grid electricity demand resulting from installation of rooftop PV systems justifies the cost of providing policy support for this technology. The behavioral response of households in relation to electricity consumption needs to be understood to evaluate whether the adoption of distributed solar is contibuting to reducing electricity demand and emissions. The results have implications for policy design to achieve environmental goals, and for electric system operation in procuring resources to meet peak demand.

The goal of this paper is to study a yet undeveloped aspect of the literature: what happens to household electricity consumption once a consumer has installed rooftop solar. In other words, does a "solar rebound" exist? The rebound effect is well documented regarding energy efficiency but has yet to receive much empirical study regarding the adoption of solar. Furthermore, the adoption of a generation source under a net metering policy differs in important theoretical ways from more traditional energy efficiency improvements.

To answer this question, I define a solar rebound and then use an extensive set of solar adoption records and customer electricity bills to empirically test for this phenomenon. Section 1 provides background on the rebound effect and reviews the literature. Section 2 presents competing theories which generate opposing hypotheses to form a critical test. Section 3 describes the data and matching and section 4 the methodology. In section 5 I present and discuss the results. Section 6 concludes.

4.1 Background and Literature Review

The rebound effect traces its roots to the 19th century when William Stanley Jevons noted that efficiency improvements in coal combustion were yielding increased levels of coal consumption. The idea that economically justified energy-efficiency improvements might increase, rather than reduce, energy consumption became known as Jevon's paradox.

A formalization of this concept was dubbed the Khazzoom-Brookes postulate after two contemporary economists (Daniel Khazzoom and Len Brookes) instantiated the modern study of the rebound effect (Sorrell, 2009). The rebound effect is generally understood as a response to improved energy efficiency in which potential energy savings from efficiency improvements are partially offset by increased consumption of energy services. As the marginal cost of consuming a service declines, a consumer will use more of it, the direct rebound effect. In the classic example, as fuel efficiency improves, consumers drive heavier cars and more miles.

The direct effect is the most familiar and widely studied component. Beginning with Khazzoom (1980), there have been a series of estimates of its magnitude in contexts from transportation to lighting, with varying rigor and results. More challenging to estimate is the indirect effect, in which energy efficiency improvements in one good or service lead to increased consumption of other energy goods and services through increased purchasing power (Ghosh and Blackhurst, 2014).

The least well understood aspect of the rebound effect is a macroeconomic effect which may occur if efficiency improvements reduce demand to the point that market conditions change. For example, if fuel efficiency leads to lower overall demand for gasoline, gas prices may drop. Because solar generation affects whole home electricity demand, the unit of measurement in this study, the direct rebound effect will be most relevant.[33]

There are several studies which have attempted to measure the direct rebound effect in the context of household energy services including heating (Milne and Boardman, 2000; Davis, 2007), lighting (Nadel, 1993), water heating (Guertin et al., 2003), and cooling (Hausman, 1979). Greening et al. (2000) and Sorrel et al. (2009) provide thorough reviews and conclude that the direct rebound effect should generally not exceed 30% with most reliable estimates between 10% and 30%. More recent studies by Azevedo et al (2013), Borenstein (2015), and Chan & Gillingham (2015) fall within these bounds. These direct rebound studies measure the increased use of a new product with improved efficiency to

[33] That is not to say that the indirect or macro effects are not present, as reduced electricity costs could increase natural gas consumption and large volumes of solar generation could reduce wholesale electricity prices. However the necessary data to investigate these more complicated relationships is not available.

that of an earlier vintage: i.e. a household installs led lights and then leaves them on for longer periods of time. The question at hand is does changing the source and cost of electricity as a whole produce the same effect?

There have been limited attempts to this point to study the rebound effect associated with distributed solar. Most to date have been done on the basis of survey data and outside the United States. Havas et al. (2015) used survey data from Australian households and found that the adoption of PV can confound consumer behavior because the installation does not necessitate conservation-oriented behavior and electricity savings from adoption encourage further use. They estimated a rebound effect of 15%. Other survey-based estimates include Caird et al. (2008) and Keirstead (2007), but they suffer from small sample sizes and self-reported estimates of electricity savings. An estimate using data aggregated at the census block level found that higher solar subsidies encouraged higher electricity consumption, thereby failing to alleviate grid demand (Motlagh et al. 2015). A similar aggregated approach was undertaken by Oliver et al. (2017) who find that solar rebound effects tend to be higher for lower-income adopters. High frequency hourly consumption and generation data was used by Spiller et al. (2017) to estimate a rebound effect of 11% but the study lacks pre-post adoption data. While they term their effect a solar rebound, the research question was whether solar adopters use more energy when the sun is shining, not whether they use more than the counterfactual post adoption.

The most relevant study to date was conducted by Deng and Newton (2017). It finds a 20% rebound among 1,951 solar adopters in Australia. However, there are a number of important differences that distinguish their study from this analysis. First, results from Australia may not generalize to the U.S. context. The primary reason for this assertion is that Australian solar adopters operate under a gross metering scheme in which households sell all solar generation to the grid at a subsidized fixed rate and purchase everything they use from the utility under a standard tariff. Feed in tariffs of this form are much less common in the U.S. This analysis studies households under a net-metering scheme and the difference has important consequences for the salience of energy use and prices. Further, Deng and Newton rely on a representative sample of households from the utility as opposed to the full residential customer population. Finally, their data are quarterly as opposed to monthly for the billing data in this study.

4.2 Model and Theory

This section presents a model illustrating the demand for electricity across multiple solar adoption scenarios and generates a set of hypotheses from evidence in the literature about why a rebound may or may not occur.

4.2.1 Economic Model

The economic model borrows from Chan & Gillingham's (2015) general model of constrained utility maximization to study the rebound effect, and is adapted from Oliver's (2017) application to the solar rebound. I assume a household's utility function is of the Cobb Douglas form shown in equation 3 where e_t is total electricity consumption and x is a numeraire good. I assume $\beta = 1 - \alpha$.

$$U(e, x) = e_t^{\alpha} x^{\beta} \tag{3}$$

Total electricity consumption is shown in equation 5, simply the sum of the electricity consumed from the panels and the electricity from the grid. The source of the electricity is indistinguishable to the household at the time of use and thus grid and solar electricity are perfect substitutes at the point of consumption.[34] I distinguish between the amount of solar generated by the panel $e_{pv,g}$ and the amount consumed $e_{pv,c}$ in equation 4 where θ represents the share of electricity generated by the panels that is consumed by the household onsite. The electricity generated by the panels is exogenous, the amount consumed is chosen by the household.

$$e_{pv,c} = \theta e_{pv,g} \ , \qquad 0 \leq \theta \leq 1 \tag{4}$$

$$e_t = e_{pv,c} + e_g \tag{5}$$

4.2.1.1 No Solar Case

If the household has not installed solar then e_{pv} is zero and total consumption is equal to grid consumption. Assuming the price per unit of electricity is p_e, then the household budget constraint M is shown in equation 6.

$$M = pe_g + x \tag{6}$$

[34] Note that while electricity from the grid and generated by panels are perfect substitutes at any instance where both are available, over a billing period they are not perfectly substitutable due to the time restrictions imposed on PV production. In order for the two to be perfect substitutes over a longer period, either load must be perfectly responsive (unlikely) or there must be a way to store electricity at the household (the penetration of distributed storage in the service territory during the period of analysis was near zero).

In this no PV case, maximizing utility subject to the budget constraint requires a household choose just the optimal level of grid electricity and the numeraire good. Solving for the Marshallian demand of grid electricity produces the result in 7.

$$e_g^* = \frac{\alpha M}{p_e} \tag{7}$$

4.2.1.2 Solar Without Net Metering

After the adoption of solar, $e_{pv,g} > 0$. Without a net-metering policy in place, the marginal cost of electricity consumed from the panels is zero. If we assume that electricity from the panels perfectly offsets the grid electricity (an assumption unlikely to be true and discussed in more depth below) then $e_{pv,g} = e_{pv,c}$ and demand for grid electricity is shown in equation 8. Total electricity consumption is shown in equation 9.

$$e_g^* = \frac{\alpha M}{p_e} - \beta e_{pv} \tag{8}$$

$$e_t^* = \frac{\alpha M}{p_e} + \alpha e_{pv} \tag{9}$$

These results show that after installing solar grid electricity consumption will not decrease by an amount equivalent to the production of the panels. The grid consumption will be less than the no solar case, but not by the amount e_{pv} because $0<\beta<1$. This can also be seen in the increase in total electricity consumption over the no solar case. There is an increase of αe_{pv}. in total electricity consumption post solar adoption with the magnitude of the rebound dependent on the elasticity (α) of electricity consumption. This matches intuition that as marginal cost for a good decreases consumption should increase.

However, the results in equation 8 and equation 9 are dependent on the assumption that electricity from the panels perfectly offsets the grid electricity (θ=1). In reality this is not the case as generation may exceed consumption during daytime periods and electricity from PV production is not available when required at night. This simple model cannot capture the intertemporal aspect of electricity production. As such, the results in equation 8 and 9 both serve as lower bounds. The results in practice are likely to be significantly higher since a household's ability to shift load is limited. This is reflected in equations 10 and 11.

$$e_g^* \geq \frac{\alpha M}{p_e} - \beta e_{pv} \tag{10}$$

$$e_t^* \geq \frac{\alpha M}{p_e} + \alpha e_{pv} \tag{11}$$

4.2.1.3 Solar With Net Metering

Under a net metering policy, solar generation can be sold back to the grid at the retail rate. From a household's perspective, consumption of electricity from the panels now has an opportunity cost of p_e. Put differently, under net metering, installing solar does not change the marginal cost of electricity consumption. Rather, the household can be thought of as receiving a fixed subsidy s, where s is equal to the price of electricity times the generation from the panels ($s = p_e * e_{pv,g}$). In this context the consumer chooses the amount of total electricity consumption which is composed of both grid and solar electricity. The budget constraint can be rewritten as in equation 12.

$$M + s = p_e(e_g + \theta e_{pv,g}) + x \tag{12}$$

Net-metering is allowing installers to use the grid as a giant battery, in this case making grid electricity and solar electricity perfect substitutes regardless of the time of production.[35] In other words $\theta = 1$and $e_{pv,g} = e_{pv,c}$. Because the marginal cost of the electricity is the same in either case the household again chooses only their total level of electricity consumption, but this time with a larger income. Under a net metering policy, the demand for total electricity becomes:

$$e_t^* = \frac{\alpha M}{p} + \alpha e_{pv} \tag{13}$$

Note that this is equal to equation 9, the lower bound of the no net-metering case. This makes sense because if solar electricity perfectly offsets grid consumption, as was the assumption to produce that result, then net-metering is irrelevant.

Under net-metering, the marginal cost of electricity consumption does not change, thus we would not expect a rational actor to change their consumption ceteris paribus. However, net-metering is a subsidy and affects the household income which leads the model to predict an increase in total electricity consumption. That said, the size of the

[35] Nearly all net-metering policies are designed to prevent customers from generating more electricity than they consume. However, during low load months production may exceed consumption. Typically, and in the case of the service territory used for this study, that bill credit can be rolled forward for up to a calendar year. This preserves the perfect substitutability.

income adjustment from net-metered electricity is likely small relative to total income. Further, adopters of solar must pay for the panels. Given the sharp increase in adoption following the introduction of third party ownership legalization, it is likely that household are paying a fee each month for their solar[36] which would further mitigate the income adjustment. The results suggest that the solar rebound will be smaller under a net-metering policy than without.

4.2.2 Relaxing Assumptions on Rational Behaviour

The models above were derived on the assumption of perfectly rational consumer behavior. Based on Simon's (1955) ideas on bounded rationality, people do not process all the information needed to make rational choices. These ideas have been applied to electricity usage in previous studies demonstrating that electricity consumption or prices are not salient to the average consumer (Gilbert and Graff Zivin, 2014; Jessoe and Rapson, 2012). Rather consumers may be more responsive to non-price signals and framing (Asensio and Delmas, 2016; Delmas et al., 2013). There are a number of behavioral economic drivers which generate alternative hypothesis about the magnitude and direction of the rebound effect.

While standard economic theory predicts that consumers respond to marginal price, evidence has shown that the demand for electricity is much more sensitive to average price. Customers tend to react to the total amount on the bill (Ito, 2012). In fact, lagged average prices have been shown to be a stronger predictor of consumption than current prices (Ito, 2014). While the income adjustment from net-metered solar is likely to be small compared

[36] This would also be the case if households took out a loan to purchase the PV system themselves.

to total income, it represents a significant percentage of the electricity bills. Based on the sample averages, customers are likely to see bill reductions in the range of 50% to 75%. Consumers may react to these dramatically lower bills by increasing electricity consumption in excess of rational economic predictions based on two drivers.

First, evidence suggests that individuals regularly violate the economic principle of fungibility and instead engage in “mental accounting” which assigns costs to specific categories (i.e. utilities) to determine budgets (Thaler, 1999). If households practice mental accounting they will be more likely to spend their gains in the category they originated in (Antonides et al., 2011). This would lead to predictions of a larger solar rebound following electricity bill savings. Second, households have demonstrated a tendency to evaluate information about their current bills by revisiting previous bills (Buchanan et al., 2015). Thus, the previous bill amounts may serve as an anchor which primes consumers to previous expenditures and causes an adjustment in consumption levels to align with previous information provision and expectations (Tversky and Kahneman, 1974). That the new bills represent net as opposed to total electricity consumption may drive up total electricity consumption and lead to a solar rebound.

The psychology literature offers additional justification for a rebound effect in conjunction with economic considerations. Moral licensing is an effect in which engaging in a good deed can liberate individuals to engage in behaviors that are immoral, anti-social welfare, or otherwise problematic which they would ordinarily avoid (Khan and Dhar, 2006; Merritt et al., 2010; Nisan, 1990). Evidence of moral licensing has been found across a wide variety of domains, and recently applied to explain the rebound effect in energy consumption (Dütschke et al., 2018). The decision to install solar panels may give people the perception that they can use more electricity since they have completed a good deed and are generating green electricity (Peters and Dütschke, 2016). Importantly, moral licensing can be prospective. The anticipation of engagement in moral behavior has been shown to negatively influence current behavior (Cascio and Plant, 2015). If moral licensing is a driver of the rebound effect we might see evidence of increased consumption between when the consumer makes the decision to install (the application date) and the panels starting to generate electricity (the installation date).

On the basis of the economic model and additional evidence presented above:

> *Hypothesis 1: Consumers who install residential PV will increase their aggregate electricity use compared to non-adopters post-installation.*

4.2.3 Double Dividend

In psychology, the change of an energy product or service constitutes an intervention that interrupts previous routines and thereby leads to behavioral change in how the relevant product or service is used (Frondel, 2018). If the behavioral change leads to a greater use of energy or other resources than expected, it is termed a rebound effect. However, there is also a stream of literature that reports opposite findings i.e., an increase in conservation behavior (Truelove et al., 2014). If this increase in conservation occurs in the same domain, it is termed sufficiency behavior (Seidl et al., 2017). This has led to the development of a "double dividend" argument for distributed generation in which adopters not only generate energy, but also reduce their own consumption as a result of installation.

The installation of solar energy has been shown to increase the salience of environmental impacts of energy use (Keirstead, 2007). The role of this information, and consumers ability to process it, plays a key role in “conservation chains” (Haas et al., 1999), and green cues (Allcott and Rogers, 2014). The visible presence of solar panels may remind or encourage people to make other green choices. In a cue-driven, or persuasive advertising model (Becker and Murphy, 1993), the intervention of panel installation may serve as an exogenous cue which lowers the marginal utility of energy consumption. While the cue remains active consumers form habits and make capital stock changes that cause persistent effects (Allcott and Rogers, 2014).

These results mirror the effects of efficiency correlation (Ghosh and Blackhurst, 2014) which suggests that household investments in efficiency and conservation are positively correlated. Thus, installing solar panels may encourage further energy efficiency investment, particularly in a solar leasing model where capital liquidity is not compromised. In small sample surveys, both Haas (1999) and Keirstead (2007) found evidence to support a similar “conservation chain,” particularly with regard to lighting and insulation stocks. Rai and McAndrew’s (2012b) post-installation survey results also suggest that PV adoption appears to raise the environmental concern of households.

Further, installation of solar is routinely accompanied by an in home display or mobile application for checking PV output. The use of in home displays has been shown to extend conservation behaviors through habit formation and learning (Jessoe and Rapson, 2012). Hondo and Baba (2010) test this hypothesis by measuring household awareness of solar installations and the effects of awareness. Households who more frequently engaged in “PV-checking behavior”, which includes both looking at the panels themselves and checking their output, were more likely to increase pro-environmental behavior post-installation.

There may also be a financial justification for reducing consumption of electricity post-installation. The adoption decision makes electricity use more salient. First, in the installation decision customers consider their electricity price and usage in determining whether distributed generation is a sound financial investment. In a Texas survey, 87% of the responding PV owners used a payback period approach to calculate the financial attractiveness of a PV system. Payback period duration is a significant predictor of adoption (Rai and McAndrews, 2012b). Consumers under at net metering scheme discover that the payback period for their panels shrinks if they use less electricity. Again referencing the Texas survey, "Over 70% of the sample reports that their awareness as regards their electricity use (amount used, bill paid, and purpose of use) is 'higher or much higher' as a result of installing solar" (Rai and McAndrews, 2012b).

The information and cue effects of solar installation yield predictions that directly oppose Hypothesis 1 and form a critical test:

> *Hypothesis 2: Consumers who install residential PV will decrease their aggregate electricity use compared to non-adopters post-installation.*

The goal of this paper is then to test for a causal connection between solar installation and changes in aggregate electricity use. To do so I examine a population of solar adopters with sufficient pre and post installation billing data and compare them to a matched control group using a difference in differences analysis.

4.3 Data

4.3.1 Customer Data

The data for this study was supplied by a PJM utility that provides electricity to over 500,000 residential customers. The utility provided both historical billing data and records of solar interconnections for all the residential and small commercial accounts in their service territory. This is unique from previous studies of the solar rebound which have relied on aggregated data or a representative sample of customers. Weather data was extracted from NOAA's National Climactic Data Center.

Solar interconnection data spans from December 2010 through June 2018. In addition to the date of grid interconnection, it includes an application date at which point the account applied to the utility to install solar. Other variables of interest include the installed capacity of the system, the type (residential, small commercial, community), and the billing structure (net-metered, buy all sell all etc.). Figure 24 shows the adoption of solar in the territory over time. Through June 2018 there were roughly 8,000 distributed solar installations in the utility territory which provided 77.6 MW of installed capacity.

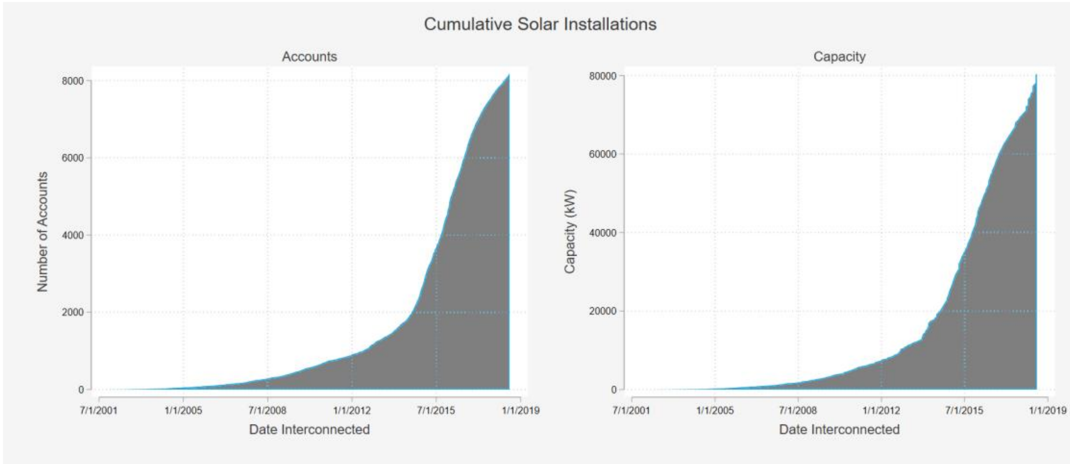

Figure 24: Cumulative solar installations over time

Using an eight-digit account number, the interconnection records could be matched with customer billing data. Billing data includes information for more than 300,000 unique premise locations with over 15,000,000 bills in the sample. Due to data quality concerns bills before 2010 were dropped[37]. Account number was unique to both a premise location and customer number: it records information only for the period in which a customer was at the same location. This removes concerns about changes in consumption following a change in occupancy. Across zip codes in the service territory the ratio of adopters to non-adopters ranges from 0.4% to 10%. Areas with fewer customers tend to have higher penetrations and the system wide average is just under 2%.

One challenge in using this data is that billing data is not standardized across customers: individual customers could have bills that begin and end on different dates and differ in number of bill days. This creates a challenge for directly comparing usage.

[37] Data from prior to 2010 had a much higher rate of missing bills, estimated readings, and missing customer information.

Converting from billing data to a standardized format is a common problem in analyzing utility data (Abdou et al., 2015). For each customer bill, I generate the number of heating and cooling degree days that occur during the billing period. I then allocate usage from bill to month on the basis of percentage of heating degree days in winter months, or percentage of cooling degree days in summer months. In shoulder months, the allocation is done on percentage of bill days that fall in each month.

For example, if a bill spans November 15th through December 15th and over that period there were 100 heating degree days in November and 200 in December two thirds of the bill usage would be allocated to December.[38] This improves on the more basic approach of allocating bill usage across months based on the share of days. Figure 25 illustrates why, as electricity use is strongly correlated with average monthly temperature. Thus, a month with more extreme temperatures should have slightly higher electricity usage than a milder month that precedes or follows it.

[38] This example is deliberately extreme. In practice, the allocation was much more representative of the number of billing days than the example.

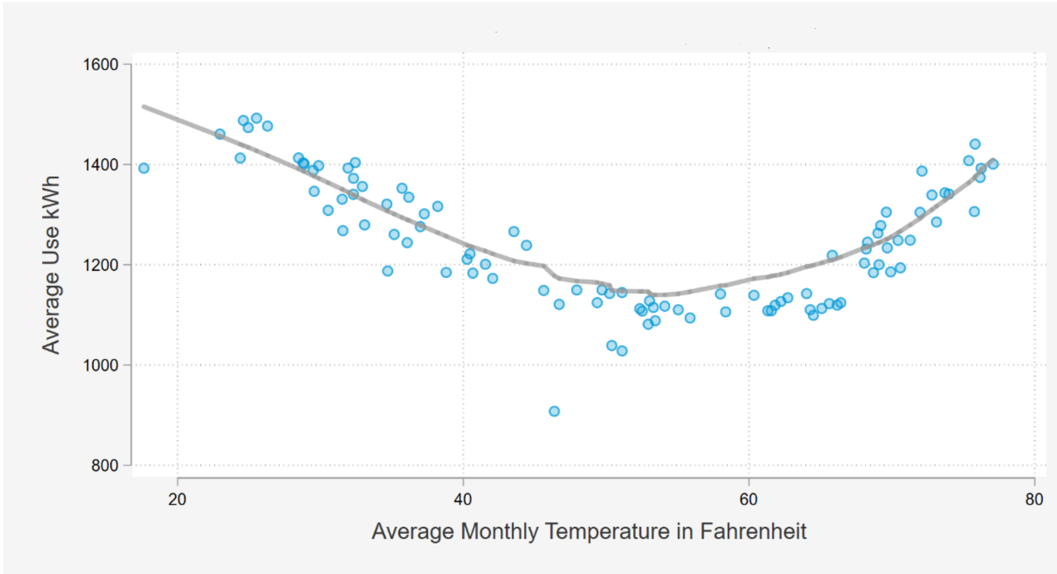

Figure 25: Relationship between electricity use and temperature

With a consistent timescale for measuring each customer's electricity consumption it is possible to directly compare across households. With a full set of electricity consumers, it is not necessary to use only a representative sample. Previous studies have relied on comparing solar adopters to a representative sample of all electricity consumers (Deng and Newton, 2017). However, it is well documented that solar adopters differ from the general population in manners correlated with electricity consumption including home square-footage and income (Barbose et al., 2017). Figure 26 shows the distribution of pre-adoption average annual use in the population of eventual solar adopters (treated) against the population as a whole (untreated).

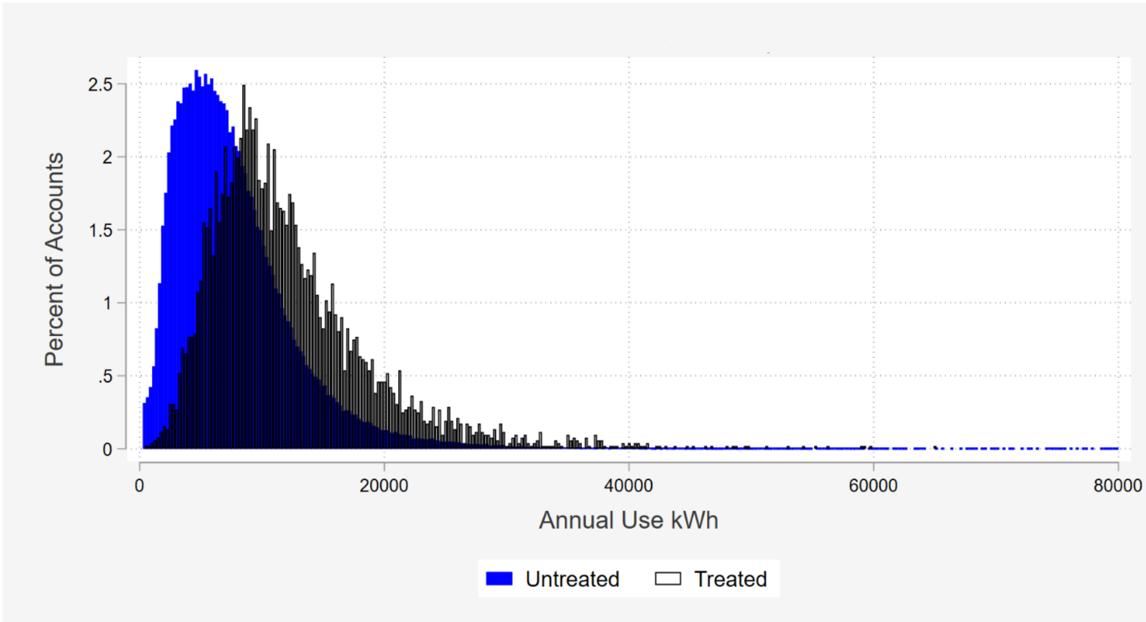

Figure 26: Pre-matching average annual use comparison

Solar adopters on average use considerably more electricity than non-adopters before installation. Thus, using a representative sample drawn from the whole population as a counterfactual may bias estimates of the rebound effect due to a lack of sampling density in the region of common support, a common problem with finite samples (Heckman et al., 1996), and discrete differences in pre-treatment outcomes. To avoid these problems, I employ a matching technique to pair each solar adopter with a non-adopter whose pre-treatment observables are similar.

4.3.2 Matching

In this study, I employ matching procedures to control for the fact that the treatment and control groups differ in ways that matter for the outcome under study. One limitation of the study is that the variables for potential matching are restricted to data fields used in customer billing by the utility and do not contain information related to the household (e.g.

size, income, number of occupants, etc.) or dwelling (e.g. age, type).[39] Instead, I employ a series of measures obtainable from billing data and described below.

4.3.2.1 Weather Sensitivity

One potential predictor of solar adoption is the degree to which a customer's load is correlated with temperature. This can be thought of as a proxy for household vintage and type as older homes have less thermal inertia. I investigated this weather sensitivity separately for both hot and cold temperatures using heating and cooling degree days. This data was then merged with the kWh usage during the bill period to generate a set of correlation coefficients for each customer.

4.3.2.2 Seasonal Load Shape

Another predictor of solar adoption is a customer's seasonal load pattern. Seasonal load patterns capture variance due to lifestyle factors and appliance stock. For example, those customers with natural gas service use less electricity, particularly during the winter and their lower electricity bills may make them less likely to adopt solar. To create clusters of usage patterns, the data was normalized such that each month represented a percentage of annual consumption. A k-means cluster algorithm was employed to group accounts into clusters of load shapes. Figure 27 shows an example of the resulting seasonal load profiles across clusters.

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[39] As a result even after matching there may be some remaining bias. Electricity usage patterns cannot capture environmental attitudes or provide insight into whether a household's current electricity consumption is utility maximizing. For example two residences with the same usage may respond differently to treatment if one is currently setting their thermostat to a sub-optimal level to conserve electricity while the other has their thermostat set at their ideal temperature.

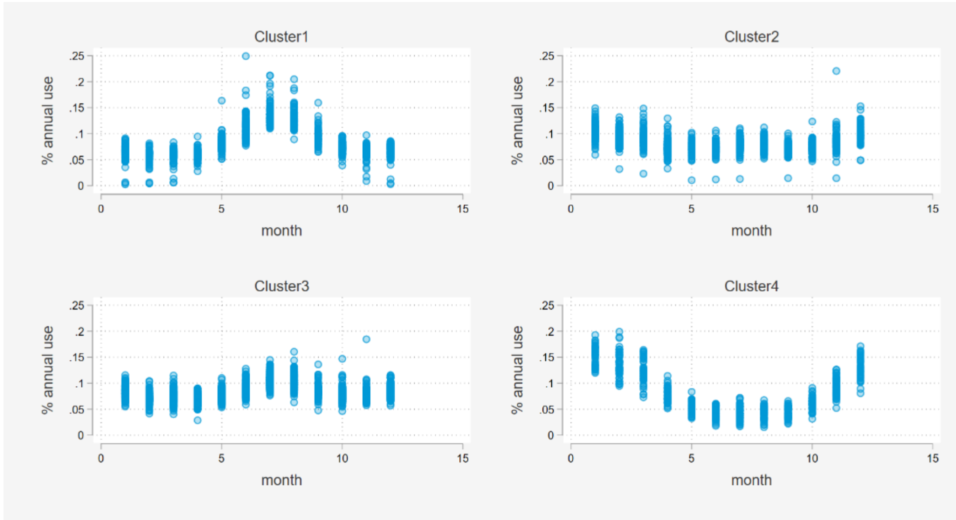

Figure 27: Seasonal load shapes by cluster

4.3.2.3 Annual Usage

In addition to the pattern of use, the aggregate annual use of electricity is strongly correlated with solar adoption. This metric is also correlated with household income, home square footage and other unobserved covariates (Yohanis et al., 2008).

4.3.2.4 Customer Type and Location

Additional categorical variables such as rate class and zip code were included in the matching procedure. The highest percentage of solar adopters are from customers in non-default rate classes, perhaps because opting into a non-default tariff indicates higher salience of electricity costs and use.

Before matching, the population was trimmed to remove outliers which had average annual use more than the 99th percentile or less than the 1st percentile. I also removed any accounts in which there were months with near zero usage which might indicate only part time occupancy. To ensure that there were sufficient pre-treatment observations I dropped solar adopters who applied for installation before 2014 and removed those without at least 6 months of data. Finally, I removed non-residential accounts as commercial accounts may have different use drivers.

Using a propensity score model, the available variables capture little of the total variation, and the model poorly predicts expected adoption. In other words, an individual customer's adoption is not particularly well explained, as can be seen in Figure 28. There were many untreated observations which had a higher adoption probability than the actual solar installers. It is worth noting however that there was common support for the entire range of the treated population among the non-adopters.

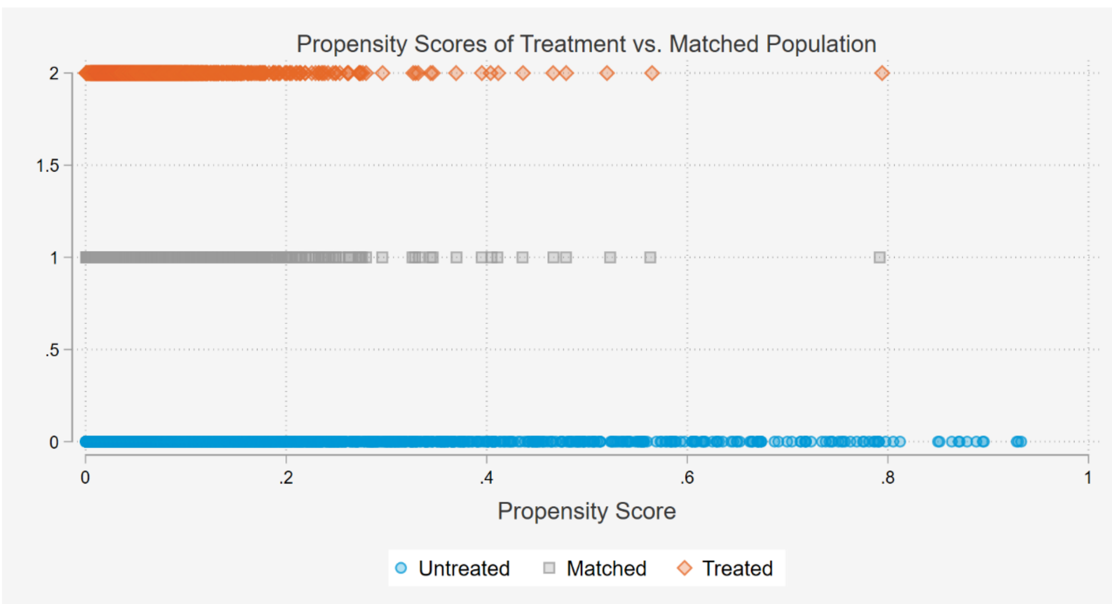

Figure 28: Propensity score comparison

I explored a number of variations of matching (1:1, k-nearest neighbor, kernel, cluster, etc.) but those methods failed to provide a matched set which sufficiently eliminated the pre-treatment difference of means in electricity consumption between the treatment and control group. Due to the relatively low percentage of solar adopters in the overall population (there are roughly 50x more non-adopters in the sample), there are enough untreated observations to employ coarsened exact matching (CEM) as described in Blackwell et al. (2009). This method ensures that matches share the categorical covariates of zipcode, seasonal load cluster, and rate class and are within a binned range on continuous variables such as average annual load and weather sensitivity. Benefits of CEM include bounding the imbalance between the treated and control groups, ensuring the congruence principle, and restricting the data to areas of common support (Iacus et al., 2012). Thus, for each treatment observation I created a pool of matches from the same zip code, seasonal load shape cluster, rate classification, and binned values of annual usage and weather sensitivity. The final selection was for the nearest neighbor based on average annual use.

To capture the most appropriate counterfactual, I construct a control group for each cohort of solar installers as employed by Gill and Lang (2018) in their study on the effects of energy education programs on home electricity consumption. The results are a set of matches which exactly share the available covariates and align much better on pre-treatment use than the population at large as shown in Figure 29. Following the matching procedure, a paired sample t-test (t = -1.09, p = 0.278) fails to reject the null hypothesis that the two groups have the same pre-treatment means.

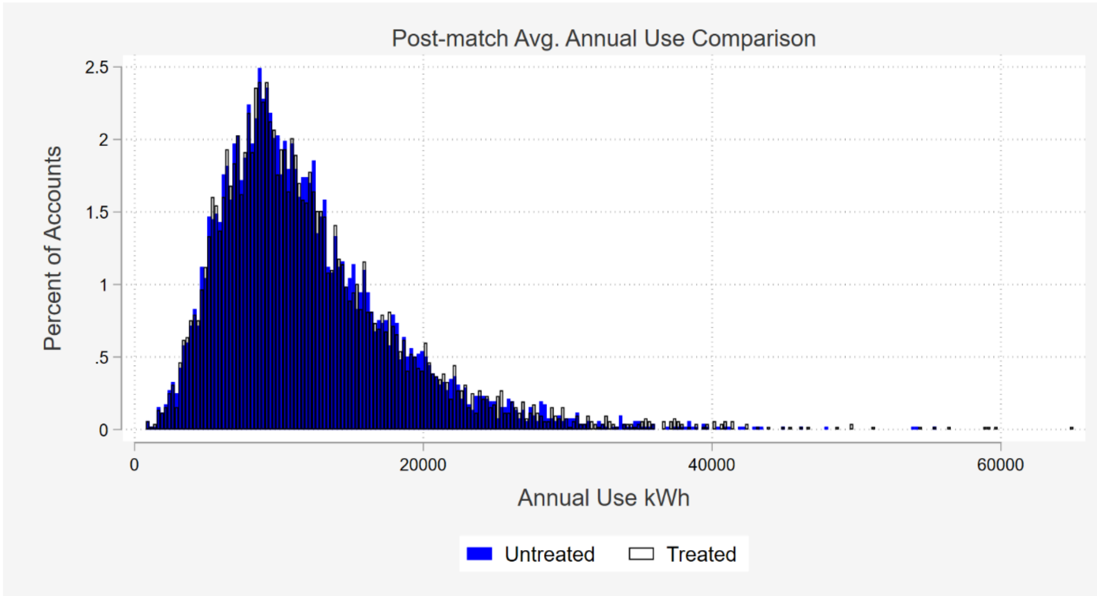

Figure 29: Post-matching average annual use comparison

4.3.3 Solar Data

By definition, customers with net metered solar installations do not get separate readings of solar production and energy consumed. Only the net amount used from the grid is reported in the billing information, so solar output must be estimated. This is a limitation of working with net-metered data.

In this study, I improve on the methodology of previous studies such as Eid et. al. (2014) which make use of hypothetical solar production from tools such as NREL's PVWatts calculator. I employ solar data from a sample of distributed solar installations in the same market territory. The solar dataset includes both the system size (kW) and hourly solar generation (kWh) for the PV systems. I divide the hourly generation by the total system size to calculate a capacity factor for every hour of the year. Averaging across systems and aggregating to the monthly level provides a yearly profile of solar data for a 1 kW system. I can then multiply this output by the installed system size for each customer to estimate their PV production.[40] Figure 30 shows that while the profile generated from my sample follows the curve of the hypothetical data it is a more conservative estimate in every month, particularly in winter months. This likely reflects the fact that my sample from installed panels incorporates the effects of suboptimal tilt angle, shading, and snowfall accumulation beyond just precipitation days.

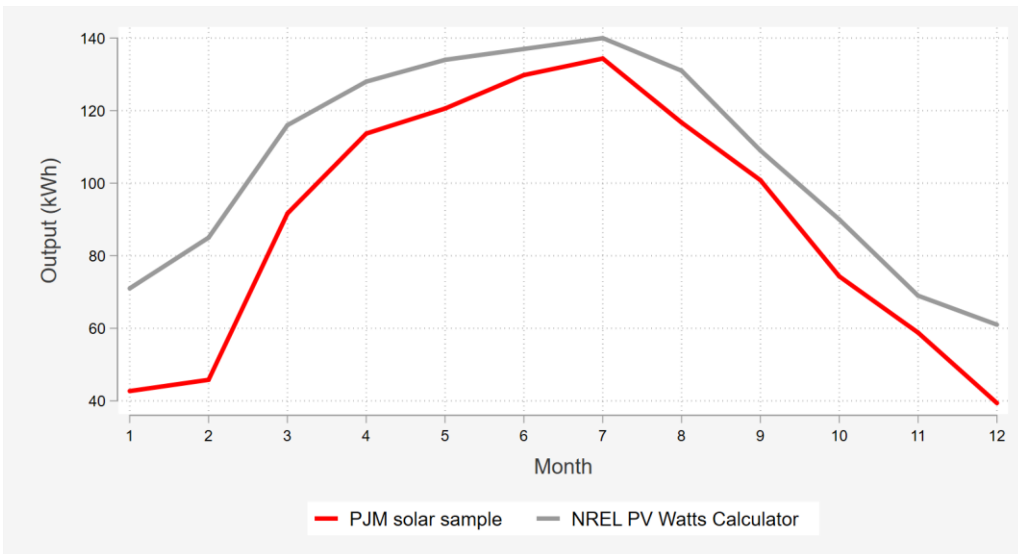

Figure 30: Solar output

4.4 Methodology

4.4.1 Difference in Differences

To perform a critical test of the hypotheses I employ a difference in differences (DND) model to compare the treatment group (households that install solar) to the control group (households who do not obtain solar) to examine whether there is differential energy

[40] I compared the monthly average precipitation and temperature over a 4-year solar production sample period to the National Oceanic Atmospheric Administration's "climate normals" and find no statistical difference between those normals and the average temperature and precipitation in the solar data years.

use after the installation relative to the pre-treatment period. Difference-in-differences is among the most common and perhaps the oldest quasi-experimental research designs.[41] The method is described in all econometrics texts (Angrist and Pischke, 2008; Cameron and Trivedi, 2010; Wooldridge, 2015) and has been used frequently and recently in the study of electricity consumption (Allcott, 2011; Fowlie et al., 2017; Gill and Lang, 2018; Jessoe and Rapson, 2014a). The coefficient of interest is β, the difference between the change in outcomes pre and post treatment for a treatment group as compared to the control group. The basic empirical model is:

$$y_{it} = \gamma + \gamma_i TREAT_i + \gamma_t POST_t + \beta\, TREAT_i \times POST_t + u_{it} \tag{14}$$

where y_{it} is the dependent variable, $TREAT_i$ is a binary indicator which is one for all the treatment group and zero otherwise, $POST_t$ a binary indicator which is one in post treatment periods, $TREAT_i \times POST_t$ is an interaction of the two which is one for the treatment group in post treatment periods, and u_{it} is the error term.

In my application of the DND model I have two periods of interest. The first is the application period during which the household has completed the application to the utility for the ability to install solar, but before the panels are operational. This will allow me to test for anticipation effects and prospective moral licensing. The second is the post-installation period when the panels are generating electricity. My standard model thus becomes:

[41] The method dates to the investigation of the London cholera outbreak: Snow, J., 1855. On the mode of communication of cholera. John Churchill.

$$load_{it} = \gamma_i SOLAR_i + \alpha APP_t + \lambda_t INSTALL_t + \beta_1 SOLAR_i \times APP_t + \beta_2 SOLAR_i \times INSTALL_t + u_{it} \tag{15}$$

where the unit of observation is household-month, the dependent variable $load_{it}$ is electricity consumption in kWh for household i in month t, $SOLAR_i$ is a binary variable equal to one if the household is an eventual solar adopter, APP_t is a binary variable equal to one if the application for solar has been filed but solar not installed at month t and zero otherwise, $INSTALL_t$ is a binary variable equal to one if installation has occurred at month t and zero otherwise, $SOLAR_i \times APP_t$ is the interaction of SOLAR and APP equal to one for adopters during the application period, and $SOLAR_i \times INSTALL_t$ is the interaction of SOLAR and INSTALL equal to one for households who have solar installed in that month. The coefficients of interest are the interaction terms β_1 and β_2 which measure the change in load from pre- to post-treatment for the treated group, relative to the change in load for the control group. The coefficient β_1 measures any anticipation effect association with applying for solar. A positive, significant coefficient indicates an increase in electricity consumption for households who have applied for solar but not yet installed it. For the average household there is a two and a half month gap between the application period and the installation. β_2 measures the change in consumption once the panels have been installed and are operational. The error term u_{it} is clustered at the household level to allow for correlation in electricity use within a residence.

4.4.2 Event Study

In this study, the treatment timing is not homogeneous across cohorts, allowing me to exploit variation across groups of units that receive treatment at different times. This is often referred to as an “event study” and allows for the estimation of a general DND estimator that is comprised of a weighted average of all the possible two-group/two-period DND estimators in the data (Goodman-Bacon, 2018). For each cohort, I define relative time as the time relative to the initial treatment. It is then possible to identify causal treatment effects for a given cohort at many different relative times to form cohort-specific average effects on the treated (CATT) and obtain a weighted average of CATTs from a linear two-way fixed effects regression model with household and time fixed effects (Abraham and Sun, 2018). Equation 16 presents the specification of the fixed effects model for this study.

$$load_{it} = \beta_1 SOLAR_i \times APP_t + \beta_2 SOLAR_i \times INSTALL_t + \alpha_i + \theta_t + u_{it} \qquad (16)$$

The household fixed effect, α_i, allows me to control for unobservable household specific fixed effects. This controls for time-invariant factors which might include demographics, house characteristics, appliance stock, space heating and cooling preferences, etc. The time fixed effect, θ_t, accounts for determinants of electricity use that affect all households and vary over time including weather and general trends in electricity consumption. The benefit of a time fixed effect is being able to control for complex determinants such as temperature and humidity without imposing an assumption about the functional form of those relationships (Gill and Lang, 2018).

Working from the model presented in equation 16, I make a number of modifications to test for robustness and explore variations of the research question. First, I include the summation of coefficients on the three months prior to the application for solar, the first term in equation 17. This specification tests the assumption of parallel trends between treatment and control. Finding an insignificant result for these coefficients would enhance confidence that the solar adopters have an appropriate counterfactual.

$$load_{it} = \sum_{k=1}^{3} \delta_k PreApp_i \times Solar_t + \sum_{k=1}^{6} \eta_k PostInstall_i \times Solar_t + \beta_1 SOLAR_i \times APP_t + \alpha_i + \theta_t + u_{it} \tag{17}$$

Equation 17 introduces summation terms where δ in $\sum_{k=1}^{3} \delta_k PreApp_i \times Solar_t$ provides a separate estimate of the DND coefficient in each of the three months prior to the solar application and η in $\sum_{k=1}^{6} \eta_k PostInstall_i \times Solar_t$ provides separate estimate of the treatment effect in each of the six months following installation. This tests for variation in the treatment effect over the periods following the installation. In other words, does the affect grow or attenuate as residences become accustomed to the new normal of solar panels? The coefficient of interest is η equal to one in each period following installation. Coefficients that are significantly distinguishable from zero would indicate the persistence of treatment effect and comparison between coefficients will shed light on the changes in the treatment effect over time.

I am also interested in the extent to which the treatment may vary across different types of customers. While I have limited customer characteristics interacting the treatment effect with the rate code will allow me to see if the response to solar adoption differs for customers who were on non-default rates. Interacting the treatment effect with zipcode may show geographic diversity in the impact of solar adoption. For example, households from richer zip codes may exhibit a larger treatment effect.

Finally, I include an interaction term with heating degree days and cooling degree days. While the time fixed effects should capture the weather variations, it is possible that residences with solar are especially peak sensitive. In other words, because they have solar, they do not feel guilty about maintaining more comfortable temperature setpoints in the home even when outside temperatures are more extreme. This full model is depicted in equation 18 and represents a robust test of the hypotheses presented above.[42]

$$\begin{aligned} load_{it} = {} & \beta_1 SOLAR_i \times APP_t + \beta_2 SOLAR_i \times INSTALL_t \\ & + (\beta_2 SOLAR_i \times INSTALL_t) \times Characteristic_x + \alpha_i \\ & + \theta_t + u_{it} \end{aligned} \tag{18}$$

4.5 Results and Discussion

Before presenting the results of any formal modeling it is useful to inspect the impact of solar adoption visually. Figure 31 shows a time series comparing average monthly usage.

[42] Some previous work on the solar rebound also makes use of a lagged dependent variable (Deng and Newton, 2017). The difference between the two models is a source of debate in panel data analysis as described by Achen (2000): Adding a lagged dependent variable will typically provide strongly significant coefficients and improved fit even when the lagged dependent variable has no causal interpretation. The authors suggest that the decision to include the lagged dependent variable is a theoretical as opposed to methodological one. Does the lagged variable have explanatory power? On one hand Deng and Newton suggest that household electricity demand typically exhibits significant inertia as household size, appliance stock, and financial situation do not tend to change suddenly. This makes more sense for their seasonal time scale. In this study there is significant fluctuation in usage between months, and there is nothing about the previous month's usage which constrains or encourages usage in the current month. I argue most consumers' relationship with electricity is one of comfort and convenience. A lagged model is presented in the appendix.

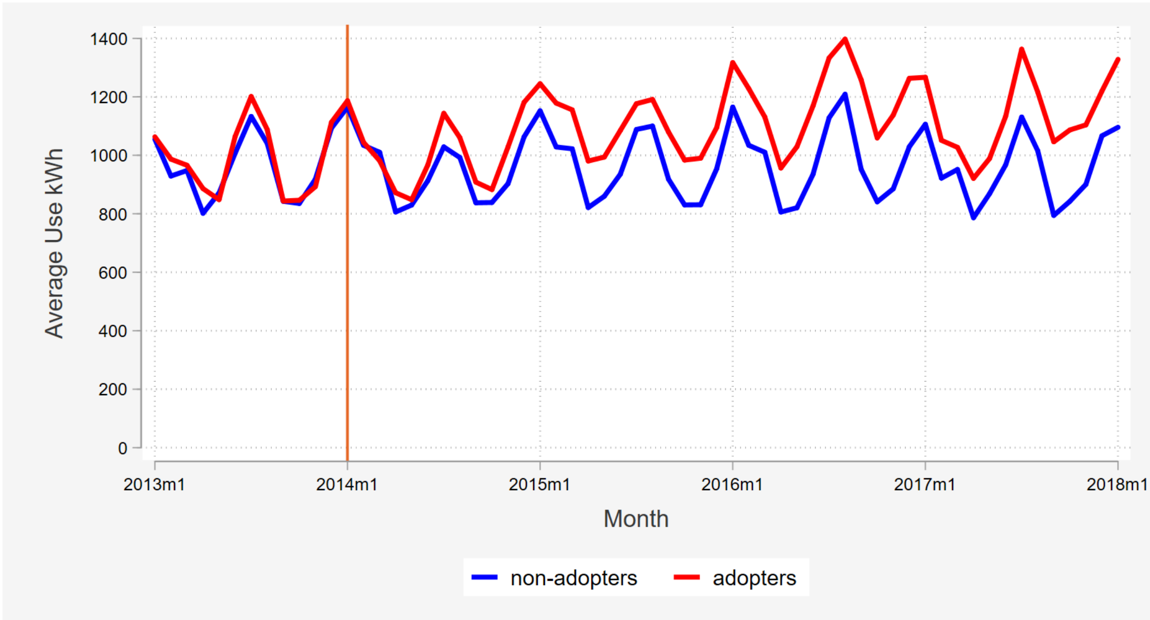

Figure 31: Timeseries comparison of average monthly use

Two points are worth highlighting. First, in the year prior to 2014 nobody in the sample has adopted solar and the profiles are closely overlapping, further evidence that the control group provides a valid counterfactual. Second, the adopters appear to use more electricity post-adoption. The adopter average line includes the average for all eventual solar adopters in the sample regardless of which month they install. As a result, the effect size appears to grow over time as more and more users adopt solar. Figure 31 is useful for examining the periodicity of electricity use but cannot present a visualization of the effect size since the installers adopt solar in cohorts binned by month starting in January 2014.

A more useful figure for examining adoption impacts shows average usage for the two groups in relative time, with respect to a common reference point. Figure 32 show the average use of the adopters and their matched non-adopters one-year pre and post adoption.

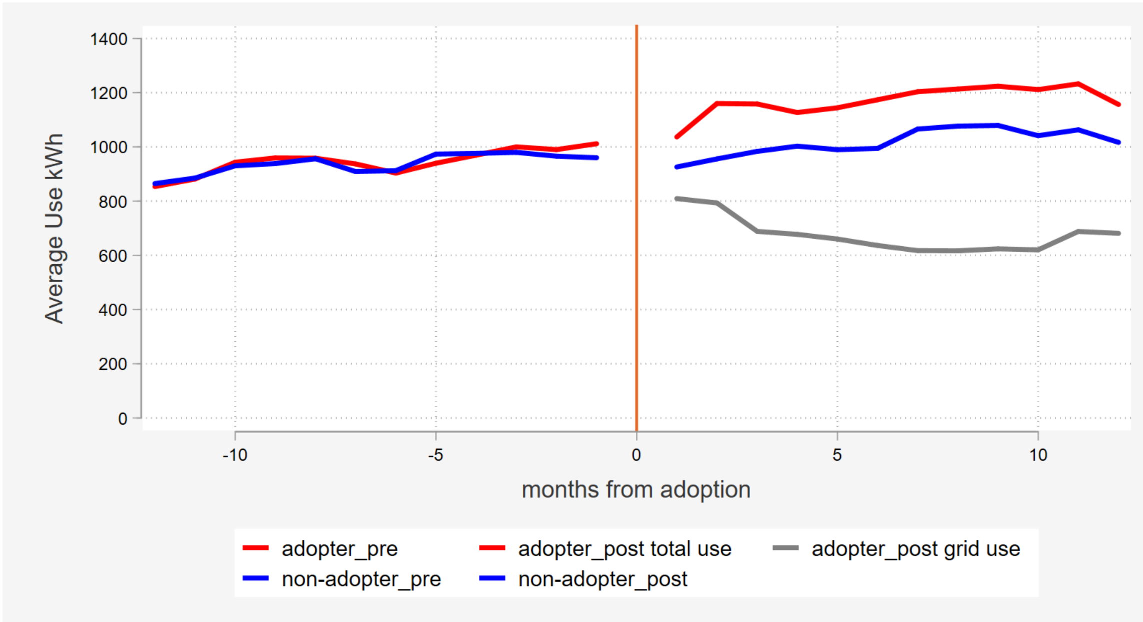

Figure 32: Comparison of average monthly use from adoption reference point

The periodicity of electricity use is no longer evident since different months are being averaged but the trend and level of pre-adoption usage is nearly identical between the two groups. In Figure 32 a discrete change in use by the adopters is clear following adoption. The red line indicates the total electricity consumption, the gray line their use from the grid, and the difference between those line the amount of PV generation. The result is a model difference in differences graph, showing a treatment effect.

I present the first set of regression results in Table 8. The dependent variable is monthly load for each household, with the coefficients of interest on the $SOLAR_i \times APP_t$ and $SOLAR_i \times INSTALL_t$ variables interpreted as a kWh increase in electricity use in the periods after applying for solar and installing it, respectively.

Table 8: Treatment effect of solar adoption

DV= Monthly Load (kWh)	(1) Estimate	(1) P-value	(2) Estimate	(2) P-value
Solar Adopter	27.456	0.356	-	-
Application Period	65.198**	0.011	-	-
Installation Complete	134.752***	0.000	-	-
Solar × App	38.064	0.326	7.313	0.714
Solar × Install	146.592***	0.000	157.832***	0.000
Household Fixed Effects	N		Y	
Time Fixed Effects	N		Y	

Notes: Column 1 uses a difference-in-differences model while Column 2 adds household and time fixed effects. Errors are clustered at the household level. *, **, and *** indicated significance at the 10%, 5% and 1% levels respectively.

Specification 1 interacts binary variables for months prior to and after the installation with a binary variable indicating treatment status. Results indicate that even after matching the eventual solar adopters use slightly more electricity than non-adopters on average, but the results are not significant. Positive significant coefficients on the application period and installation period variables likely reflect that average load in the service territory is increasing over time. This is due to further penetration of households with electric space heating and central air-conditioning, as well as the further electrification of end use loads.

The interaction of the treatment and the application period indicate a small increase in electricity consumption following application for solar, but prior to installation. This could represent an anticipation effect (Frondel and Schmidt, 2005) in which customers anticipate the lower bills with solar and begin to use more. This would lend support to the prospective nature of moral licensing in which the decision to install solar panels gives people the perception that they can use more energy (Peters and Dütschke, 2016). However the results are not significant.

In this model specification, without time fixed effects, it is also possible that the greater usage during the interaction of application period and treatment reflects the fact that most adopters install during the summer when electricity loads are higher. Finally, the interaction of solar and installation period shows a statistically significant increase of 147 kWh per month on average following adoption. This seems to support the hypothesis that there is a positive solar rebound and reject the hypothesis that solar installation results in a double dividend.

Specification 2 includes household and day fixed effects and is the preferred model specification as it allows for the incorporation of all possible DND estimators by taking advantage of the variation in treatment time. The results are consistent with the simple DND model with the installation effect being slightly larger, and the application effect slightly smaller. The significance of those results was unchanged between models. Investigating the coefficients on the time fixed effects provides further evidence that electricity consumption is slowly increasing during the study period, although it is highly cyclical.

For further visual evidence of the treatment effect, I employ the technique of Deng and Newton (2017), to investigate what would happen if the impact of solar adoption were ignored. Specifically, the equation was estimated with the interaction terms removed. Figure 33 shows the regression residuals (obtained by subtracting the fitted values from the actual consumption data) averaged for the treatment and control group and separated into pre- and post-solar periods.

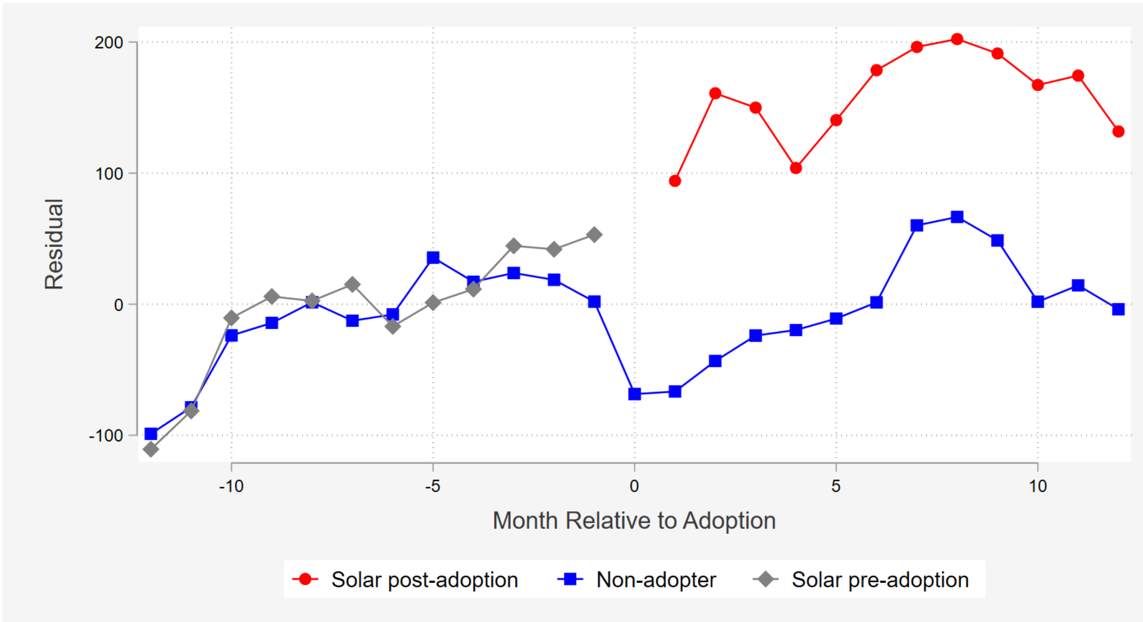

Figure 33: Regression residuals

Before the installation of PV residuals from both groups exhibit very similar behavior fluctuating above and below zero, which matches expectations. There is a small increase in the adopter use in the months leading up to adoption which again may be an anticipation effect. Post adoption of solar, however, while the control group maintains a similar pattern, the treatment group has residuals well above zero in all post installation periods. A positive residual indicates that the total actual electricity consumption exceeded the predicted amount. Thus, the differences in the residuals appear to be correlated with the presence/absence of the solar adoption term.

4.5.1 Treatment Effect Over Time

Having established from the base model that solar installers use more electricity following adoption, I now seek to understand whether the treatment effect changes over time. The regression results in Table 9 examine time differentiated treatment effects and stem from the model specified in equation 12.

Table 9: Time differentiated treatment effect

	(3)	
DV= Monthly Load (kWh)	Estimate	P-value
1 month prior × application	0.444	0.973
2 month prior × application	-1.777	0.91
3 month prior × application	3.946	0.826
1 month post × treatment	57.338***	0.000
2 month post × treatment	104.108***	0.000
3 month post × treatment	104.271***	0.000
4 month post × treatment	72.416***	0.001
5 month post × treatment	86.922***	0.000
6 month post × treatment	85.304***	0.001
Household Fixed Effects	Y	
Time Fixed Effects	Y	

Errors are clustered at the household level. *, **, and *** indicated significance at the 10%, 5% and 1% levels respectively

The results indicate treatment effects by month that are consistent with models 1 and 2. The coefficients of interest post-installation are all positive and significant with the estimate of the rebound in any given period between 57 and 108 kWh. Furthermore, this model specification provides additional evidence that the parallel trends assumption holds.

As described in Angrist and Pischke (2008), if the interaction between the treatment variable and a time variable in leading periods is statistically indistinguishable from zero one can reasonably expect the parallel trends assumption to hold. Figure 34 presents the results displayed in Table 12 in graphical form.

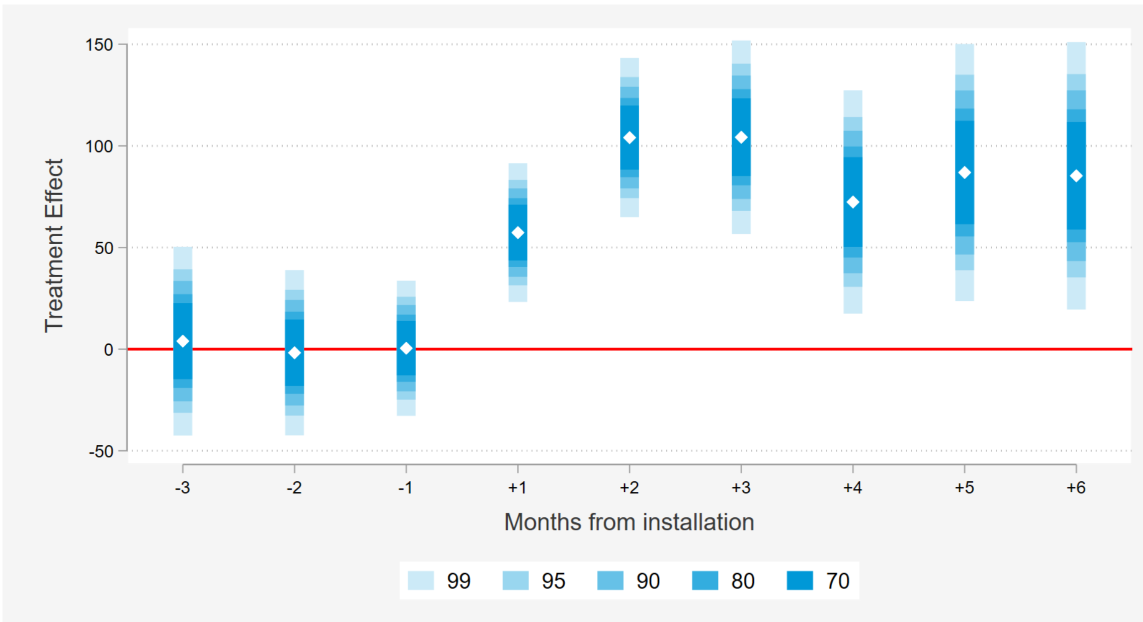

Figure 34: Time differentiated treatment effects

There does not appear to be a clear pattern in the rebound effect over time, results remained reasonably consistent even when additional post-periods were added. The exception is the first month post installation which has a noticeably smaller rebound effect. This may be evidence that customers are responding to lagged average price rather than marginal price. In the second month post-installation customers have received their lower electricity bill from the first month. Seeing that the bill is lower they respond by increasing use in subsequent periods. When their bill increases to a level they were primed by previous bills to expect, the effect stabilizes. Alternatively, the smaller rebound in the first month may be an artifact of the billing period to month conversion. For example, if a solar adopter installed in June, but their bill extended from June to July, the distribution of kWhs between those months would include some period before the installation began and thus bias the estimate downward.

4.5.2 Treatment Effect Across Customer Types

Next, I explore heterogeneity in the treatment effect across several characteristics. Table 11 presents results from alternative model specifications. In model 4, I investigate differences in treatment effect across rate classes. For reference, Table 10 describes the rate class characteristics. Nearly 65% of customers in the sample are on a default full service rate, meaning the distribution utility also supplies them electricity. Retail choice rates indicate that customers have opted for another supplier in the deregulated PJM market. The remaining distinctions are on the basis of electrification of end loads.

Table 10: Breakdown of rate codes

Rate	Description	% of sample
Default	Single phase residential full service	64.85
1	Residential full service with water heater	6.87
2	Retail choice	19.33
3	Retail choice with electric space heating	1.46
4	Apartment full service with electric space heating	0.33
5	Residential full service with electric water and space heating	7.16

Table 11: Alternative model specifications to explore heterogeneity of treatment

DV = load	(4)		(5)		(6)		(7)	
(kwh)	Estimate	P-value	Estimate	P-value	Estimate	P-value	Estimate	P-value
app_dnd	4.834	-0.809	6.133	-0.76	11.525	-0.562	-6.853	-0.745
install_dnd	148.86***	0.000	137.566	-0.227	210.79***	0.000	284.32***	0.000
i × rate1	109.944	-0.105						
i × rate2	-87.444**	-0.013						
i × rate3	164.129	-0.19						
i × rate4	265.397**	-0.005						
i × rate5	236.854**	-0.006						
i × zip1			-141.196	-0.417				
i × zip2			23.793	-0.889				
i × zip3			-210.612	-0.096				
i × zip4			32.444	-0.784				
i × zip5			24.778	-0.83				
i × zip6			36.063	-0.779				
i × zip7			219.953*	-0.055				
hdd60					0.793***	0.000		
cdd60					1.680***	0.000		
i × hdd					-0.146***	0.000		
i × cdd					0.182*	-0.089		
i × a_kwh							-0.139***	-0.002
HH FE	Y		Y		Y		Y	
Time FE	Y		Y		Y		Y	

Errors are clustered at the household level. *,**, and *** indicated significance at the 10%, 5% and 1% levels respectively.

Looking at the coefficients of interest on the interaction of treatment effect and rate code two trends are immediately clear. First, further electrification of loads leads to a larger rebound. This makes intuitive sense as those customers with space and water heating are likely to have a higher upper bound on potential use. The effect is stronger for electric space heating than water heating which makes sense since it represents a larger load. Second, retail choice appears to mitigate the effect of the treatment in producing a solar rebound. I hypothesize that customers who have opted out of the default provider are likely to be more aware of their electricity use and have greater price salience. As a result, they do not react to changes in bills and continue using electricity as before given that the marginal price has not changed. The coefficients on the interaction of installation and rate 3 indicate that the effects of retail choice and electrification of loads appear to offset. These customers have an increase in the rebound effect over the default, but it is not statistically significant.

In model 5, I investigate the extent to which the treatment effect may differ by zip code. The zip codes in the data represent mostly urban and suburban environments. Investigating census data uncovered that there is some heterogeneity in median income by zipcode in the service territory. Neither of these factors appear to be correlated with the size of the solar rebound. None of the coefficients on zip codes are statistically significant.

The base model does not include any temperature variables even though temperature is known to be a strong correlate of electricity use. These effects are captured by the year-month time fixed effects and allow me to avoid specifying a functional form for the weather data (Gill and Lang, 2018). Having said that, it is reasonable to assume that the rebound effect may be stronger in months when temperatures are more extreme, as adopters feel less inclined to be conservative with indoor temperature setpoints. Model 6 investigates heterogeneity in the treatment effect based on the number of heating and cooling degree days in a month. Even with the inclusion of time fixed effects the coefficients on heating and cooling degree days are statistically significant and positive. The effect of hot temperatures (CDD) are twice as large as cold temperatures as expected because only a portion of customers have electric heat. The interaction of treatment effect and degree day variables shows that the rebound is smaller in cold months. The coefficient on cooling degree days is of the opposite sign but is not significant.

Finally, in the last model I investigate whether the size of the rebound is conditional on the pre-treatment average annual usage. I find that as pre-treatment usage increases the size of the rebound effect goes down. While this may seem counter-intuitive, prior work suggests that the rebound effect is stronger for lower income customers (Oliver and Moreno-Cruz, 2017). Those customers with large pre-treatment annual usage may already be maximizing utility with their current level of electricity consumption and thus do not seek to consume more post installation. Another hypothesis generated from the correlation of income and electricity use is that larger customers may have more capital liquidity and co-adopt solar with home improvements or technologies that mask the size of the rebound (Rai and McAndrews, 2012a).

4.5.3 Discussion and Limitations

The results of the analysis presented above indicate a robust rebound effect. Taking the coefficient estimate from the base model, average total electricity consumption increases by roughly 150 kWh a month following solar adoption. Given that the pre-installation average monthly consumption for eventual solar installers was 975 kWh the rebound effect is on the order of 15.4%. This is between the estimates derived from other studies of the solar rebound (Deng and Newton, 2017; Spiller et al., 2017), and generally in line with estimates of the direct rebound effect broadly (Gillingham et al., 2016; Sorrell et al., 2009). The rebound effect did not show signs of decreasing over time.

This evidence rejects the hypothesis that there is a double dividend effect of solar adoption with adopters conserving following installation. Rather this analysis lends support to the presence of a solar rebound. It is tempting based on the presentation of the economic model to attribute this effect to lower bills. I stop short of this conclusion for two reasons. The reduction in bills represents an income effect not a change in the marginal price of electricity when solar is installed with net-metering. Adopters have made a substantial investment to install panels, so the idea that they then respond to lower electricity bills by using more seems unintuitive. Second, the behavioral economics and psychology literature offer other justifications. Moral licensing may give people the perception that they can use more electricity since they have completed a good deed. The coefficient on the application period was positive, though not significant, indicating the potential for a moral licensing effect. Anchoring, priming, and mental accounting may contribute to the rebound effect.

Distinguishing between these drivers is important because a rebound derived from rational economic behavior or psychological drivers have very different policy implications (Dutshke et al., 2018). If the observed rebound is in fact triggered by the moral licensing, then traditional policy mechanisms such as pricing signals or information programs to mitigate the rebound are unlikely to work. This motivates future research in this and other domains to distinguish between economic rebound and moral licensing.

This study has some limitations. A lack of customer demographic data inhibits the ability to predict solar adoption in the matching process and limits the investigation of how the rebound effect may vary based on household characteristics. An alternative model specification using an unmatched control group is presented in the appendix and shows consistent results. With only utility sourced data, it is also impossible to determine if customers were co-adopting solar with other technologies. While most evidence indicates that co-adoption occurs with measures that would reduce electricity loads (new roofing, insulation, energy efficient windows, etc.) (Rai and McAndrews, 2012a), it is possible that solar adoption occurring at the same time as electric vehicle purchases, or other electrification of end loads that could bias estimates of the rebound effect upward. Finally, in dealing with net-metered data only grid consumption is truly known. I made every attempt to be conservative in my estimation of household PV generation, but the results would be sensitive to an overestimation of panel output.

These limitations provide several opportunities for additional research. Pairing utility data with customer demographics could yield important insights about the decision to adopt solar and the response to adoption. Higher frequency electricity data would be useful to investigate whether loads are shifting in response to solar adoption. This may have even more important implications for system operation than the magnitude of the solar rebound, as most costs are peak driven.

I am also curious about how the rebound effect may differ between early adopters and later adopters. Unfortunately, the data quality from the period of initial solar installations was not sufficient for me to investigate. By the time the first adopters in the sample install solar they fall squarely in the period of rapid solar deployment.

While this study focused on residential customers, the implications for larger non-residential customers may have bigger implications for system operation. It is worth investigating the same research question in utility territories that do not offer full net-metering. If utilities instead offer a partial credit or value of solar rebate does the policy structure influence the size of the treatment effect.

Finally, given the anticipated shift toward community solar and remote net metering indicated in Chapter 3 it would be worthwhile to explore whether a rebound exists for customers participating in a remote net-metering program. Given the initial penetrations of solar plus storage and rapid cost decline, the implications of these combined systems on household consumption will be a topic of particular interest in the years to come.

4.6 Conclusion

This chapter proves that a rebound effect related to installation of residential distributed PV under a net-metering scheme exists. Installation of PV, while reducing grid consumption for the average household by around 400 kWh a month, leads to an increase in total electricity consumption of nearly 150 kWh. This equates to a 15% rebound and has important implications for both system planning and policy design.

A rebound erodes the benefit of renewable energy generation in contributing to climate goals. More clearly, it affirms that human behavior will be central in any transition to a low carbon future (Gram-Hanssen, 2013). That said, significant net energy and carbon savings still accrue, and in my opinion a rebound effect of this scale and in the context of net-metering (a significant implicit subsidy) is not sufficient to warrant removing policy support for the growth of distributed solar.

This study does not provide a clear picture of the behavior pathway associated with future rebound effects or what the effect will look like in a policy environment post net-metering. It is worth noting that a rebound effect is not in and of itself a bad thing. If adopters achieve greater utility by using more electricity post adoption that is a net benefit. This will be especially relevant concerning the growth of solar in the developing world.

The presence of a rebound signals the need for an examination of what constitutes an appropriate incentive, and how those incentives can be structured to signal adopters to further conserve. To derive maximum value from distributed solar rates and market structures must signal to households and investors the true value of the resource. This considers the benefits of green electricity and generation close to load, while not shifting the costs of grid maintenance and system operation onto those who could not afford to adopt even if so inclined. It also warrants the investigation of the behavioral response of households in relation to electricity consumption for other technologies on the horizon including electric vehicles and battery storage. In the concluding chapter I look more closely at the role of dynamic pricing as a means of providing signals which incent socially optimal individual behavior.

CHAPTER 5. CONCLUSTION

In Chapter 2 I demonstrated that solar adopters are being-subsidized by non-adopters. Chapter 3 showed that solar deployment is clustered and the value of solar to the grid is dependent on its location within the network. The evidence from Chapter 4 suggests solar adopters increase electricity use post adoption, and clearly continue to rely on grid services. Putting together these insights in the current policy context, with volumetric rates and net-metering, the regulatory structures are not promoting system efficiencies. Adopters do not see price signals to indicate where optimal locations for installation are, and no customer currently faces price signals that indicate when supply is constrained. Solar adopters will receive full net-metered prices even when generating at locations of little value and at times when supply is being curtailed. This harms system efficiency and the resulting transfer of wealth impedes equity. All this evidence has reinvigorated a fundamental question about how to finance the electric grid.

5.1 The Need for New Rates

In the academic literature, these developments have spawned renewed calls for cost-causal rate design (Convery et al., 2017), charging customers for the costs they incur through the services they use. The cost-causal model argues that efficiency, equity, and environmental goals are simultaneously achievable if rate design properly passes through energy and delivery service costs to customers. For example, dynamic price signals for electricity services might provide customers information that results in more responsive consumer demand patterns. Currently, the traditional rates bundle the costs of many energy services in the sale of kilowatt-hours and does not reflect the source of costs or current market conditions.

There are reasons why preexisting rate designs do not reflect dynamic and accurate prices. James Bonbright's (1961) seminal work on public utility rates advocated for rates that are simple, understandable, acceptable to the public, and feasible to apply and interpret. Additional factors to consider are effectiveness in meeting revenue requirements, stability of rates and revenues, equity, and efficiency. Historically, in an environment with relatively homogeneous customer classes, steadily growing demand, natural monopoly retail providers, and no ability to determine individual customer load patterns, flat volumetric rates[43] achieved many of these goals and were easy to calculate: simply divide the revenue requirement by the forecasted kWh sales.

Unfortunately, a flat volumetric rate no longer reflects the principles of cost-causation. Recovering disparate fixed costs through equivalent marginal rates leads to cross-subsidization within and across consumer classes and masks the temporal variation in the cost of electricity as shown in Chapter 2. Such rates can also lead to over-consumption during peak times and under-consumption during off-peak hours. Over-consumption during peak hours is especially costly, since utilities must purchase expensive capital equipment or energy services to serve critical peak loads, even though this capacity is only used about 60 to 100 hours a year (Faruqui et al., 2009).

[43] Volumetric refers to the practice of recovering costs by charging per unit of electricity consumed (kWh). Flat indicates that the per unit price is constant and unresponsive to changes in supply and demand.

Although distributed solar growth is a primary driver, the U.S. electricity industry has experienced additional changes that make flat volumetric rates outdated. For example, climate change concerns have increased scrutiny of the electric sector's contribution of greenhouse gas emissions and lead to new regulations, the proliferation of renewable portfolio standards, and further spending on energy efficiency. A digital economy has become increasingly dependent on electric reliability and has made the economic costs of power outages larger and consumer expectations greater. Aging transmission and distribution infrastructure and new threats, both natural and malicious, have increased the stakes for grid resilience and security. In addition to these market and regulatory changes, technology developments in advanced metering infrastructure (AMI) and the smart grid are removing constraints that previously necessitated flat volumetric rates.

Adoption of distributed solar and other DERs has increased the heterogeneity of customer loads, which makes applying the same rates outdated. Users now rely to various degrees on different components of the grid, but this wide range of energy services bundled into volumetric prices have very different economic characteristics. The distribution system has large fixed costs that create natural monopolies. Grid services such as reliability, security, and resiliency exhibit properties of public goods. Finally, even perfectly efficient prices may not reflect societies' equity goals. These various factors lead to a rate-making process that it as much art as economic science, bounded by political and institutional constraints, and subject to substantial path dependency.

Utilities have begun to experiment with alternative rate designs and pilot programs. Academics too have modeled the consequences of alternative tariff structures (Azarova et al., 2018). In fact, most jurisdictions have incrementally adopted rates that move beyond a flat volumetric structure. These rates incorporate elements such as fixed charges, block rates, demand charges, peak/off-peak variation, or time-of-use charges. These rate options exist across a spectrum from flat volumetric rates to real-time distribution locational marginal pricing illustrated in Figure 35.

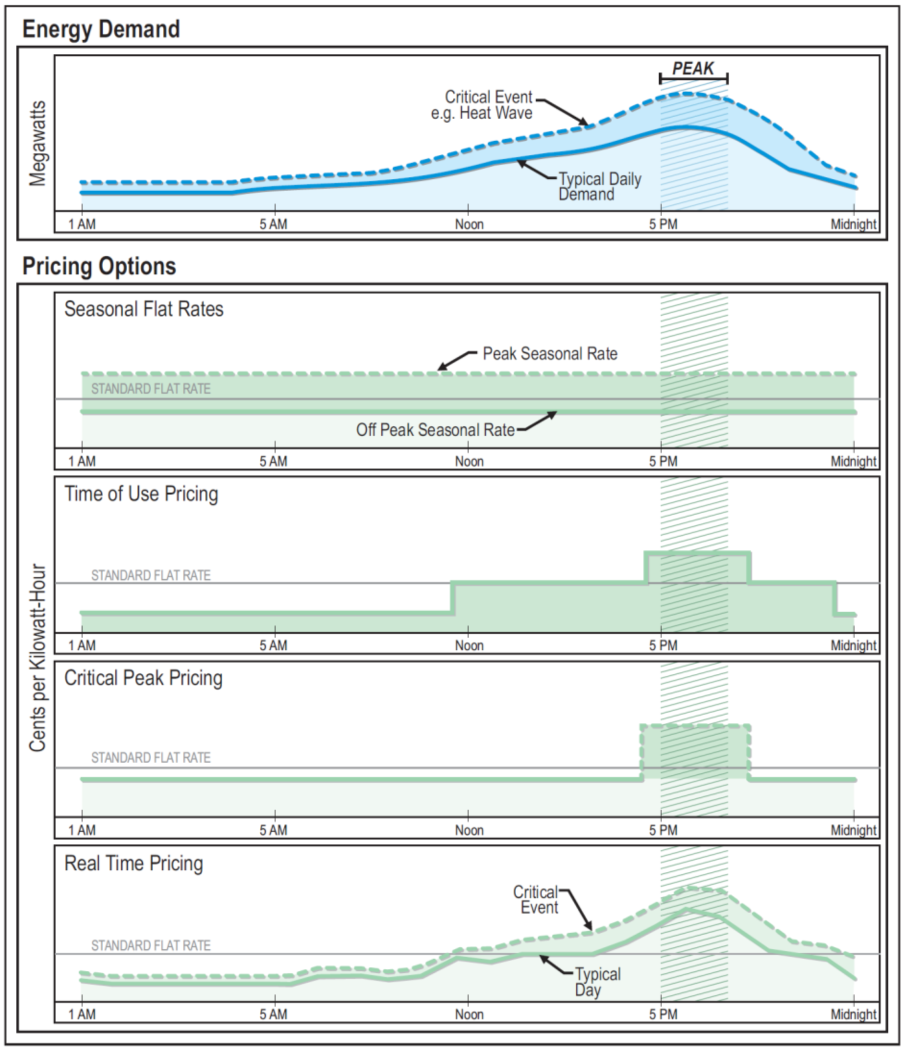

Figure 35: Illustration of Alternative Rates

It is evident that the electricity industry is slowly moving along this spectrum, away from flat volumetric rates and toward more dynamic rates. Yet, before a complete transition toward the latter is possible, there are several factors that must be reconciled. I argue not all proposed rates move towards cost-causality, and even fully dynamic pricing does not inherently address the problem of fixed cost allocation. Ultimately the decisions to allocate these costs across heterogeneous customers are not strictly economic but involve political choices. I examine the theoretical justification for more dynamic pricing and how it may help address some of the concerns generated by DPV adoption. I then describe how widespread deployment is still constrained by a number of technology, financial, economic, political, and institutional barriers.

I begin with background information on the flat volumetric approach historically employed, recent incremental departures from flat volumetric pricing, and a discussion of the efficiency improvements of temporal and locational price variation. I then discuss the barriers that remain if jurisdictions pursue dynamic pricing. I acknowledge that real-time price variation may not fully achieve cost-causal rates and consider whether the benefits of dynamic pricing justify the costs of transitioning to a new tariff structure. Before concluding I suggest the need to consider the economic characteristics of disparate energy services to achieve a more efficient and equitable pricing model. By synthesizing literature across multiple fields and components of the energy provision chain I hope to provide a common lexicon and stimulate further research and discussion. The final component is to lay out a research agenda for myself and other scholars in the electricity policy domain that seeks to further understand the policy process behind ratemaking.

5.2 Rate Design: Past, Present, and Future

A cost-causal rate is one in which prices charged for energy services reflect the underlying system costs of providing electricity. This is a straightforward goal, but difficult to implement in practice. To understand the challenges associated with a cost-causal rate it is helpful to understand the traditional rate-making process. Most jurisdictions employ an embedded cost (i.e., average cost) of service methodology. The total revenue requirement (the cost of providing electricity) is calculated using utility data and then that total cost is divided across rate classes using historical load characteristics. This process is composed of three steps: functionalization, classification, and allocation. Functionalization is the purpose of a cost, which is typically categorized as generation, transmission, distribution, or other. These costs are then classified into categories including demand (fixed costs based on kW), energy (costs that vary by kWh), and customer (investments to establish basic service, metering, and other customer service). Finally, costs are allocated to determine how much each customer class should pay.

In a simple case, such costs could be directly attributed to the customer or class that incurred the expense. In practice both functionalization and allocation are much more contentious. For instance, determining whose usage necessitated investment in a new generating facility or an upgrade of the distribution system is nearly an impossible task. A number of methods have been developed, but a "range of reasonableness" leaves room for considerable interpretation (National Association of Regulated Utiltity Commissioners Staff Subcommittee on Rate Design, 2016). This underscores the point that rate design is not a purely economic exercise, and in fact may be better characterized as a political process.

In a marginal cost approach, the goal is to set rates equal to the cost of serving the next additional unit, which may have little relation to average costs and varies temporally and by location. Determining the marginal cost and who is responsible for incurring it in a system with many users introduces similar challenges; and the role of politics and institutions remains.

Ideally, a program that embodies marginal pricing principles could adapt to reflect cost changes for energy services in near real-time, in response to system conditions. I refer to prices that can vary temporally and spatially in real-time and reflect current market conditions as dynamic. I distinguish this from time-of-use prices, which are prices that are predetermined based on historical supply and demand information. Time of use rates provide more certainty than dynamic prices because customers know well ahead of time how they will be charged. They are increasingly common, but even their penetration remains low as shown in Figure 36.

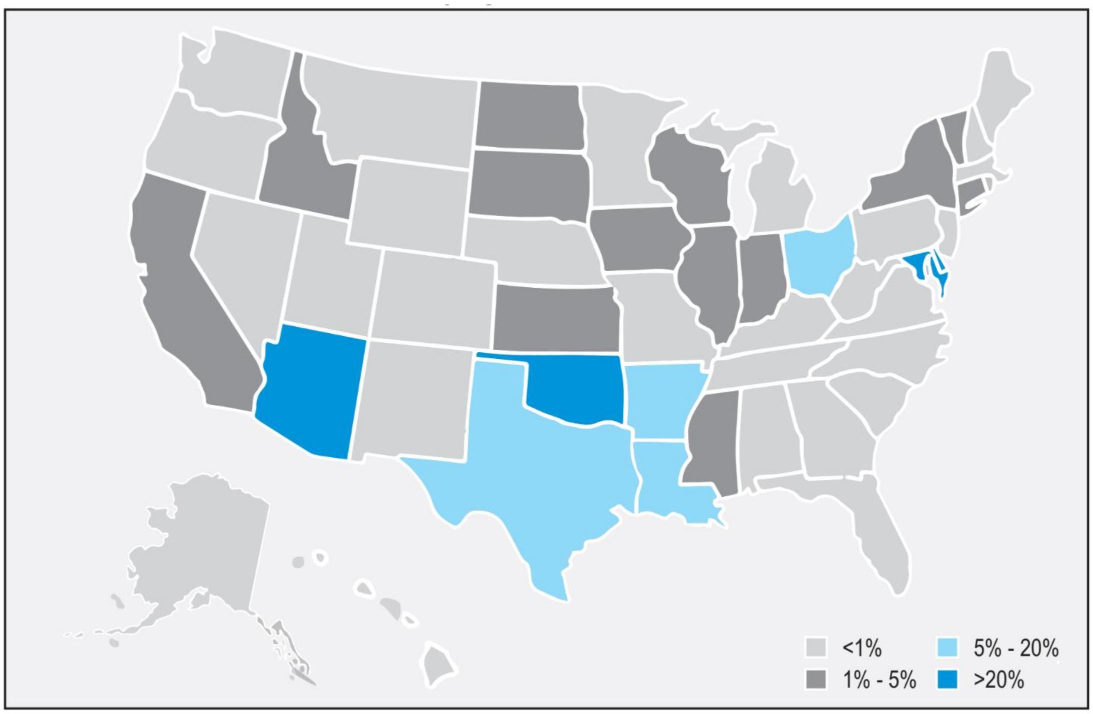

Figure 36: Percent of Residential Customers on Time Varying Rates

A few utility pricing strategies attempt to move closer to dynamic pricing. Critical-peak pricing, where customers are charged a higher rate during peak hours is closer to a dynamic rate, but its limited use (typically restricted to a maximum duration and number of events per period) and pre-set prices fall short of dynamic pricing. Real-time pricing programs are temporally (but not spatially) variant, and are typically only used for large customers in the commercial and industrial classes.[44] One notable exception is Illinois, where Ameren Illinois and ComEd offer variations of real-time pricing to their residential customers.[45] Further, while real-time pricing is able to pass through temporally variant generation costs, it does not avoid controversy in deriving marginal rates for network costs, nor does it incorporate spatial variation in pricing.

To be truly dynamic, prices must be allowed to vary not only with time, but also by location within a network. This will help address the spatial clustering of DPV. In wholesale markets, such variation is captured in nodal, or locational marginal pricing, which is widely used across the US. At the distribution level, there is similar opportunity for distributional locational marginal pricing. As DER penetration has increased over time, distribution networks have become more active and taken on many of the same characteristics of transmission systems (Sotkiewicz and Vignolo, 2006). A wider use of distribution locational marginal pricing would reward distributed generation for its role in reducing losses (Shaloudegi et al., 2012) and account for congestion that might occur in a distribution network with high penetration of flexible supply and demand (Huang et al.,

[44] For example, Georgia Power implemented one of the first and most widely used real time power programs which offers customers a number of implementation options: https://www.georgiapower.com/business/prices-rates/business-rates/marginally-priced.cshtml
[45] https://www.pluginillinois.org/realtime.aspx

2015). Location-variant pricing could also properly incent DPV placement to reduce line losses and congestion; and these price signals would reward optimal allocation of distributed resources on the network (Sotkiewicz and Vignolo, 2007). Research suggests that a distribution locational marginal pricing method would be especially important in systems with significant electric vehicle loads (Li et al., 2014).

While utility commissions to this point have been unable, unwilling, or uninterested in fundamentally redesigning rate structures, they have recently made incremental changes in response to the expansion of DPV. At least 25 states have conducted benefit-cost analysis on solar resources in response to concerns that the value of the resource may be greater (or less) than the compensation received by adopters (Carley and Davies, 2016). This debate about equitable allocation of grid costs has spawned a host of alternative rate designs that claim to be more cost-causal, but without employing a dynamic price.

In some states, residential demand charges[46] have been promoted as an attractive option for recovering fixed costs more equitably. Demand charges are not new—several states already employ them, especially for large customers, and other states offer these rates on an opt-in basis (Hledik, 2014). While a demand charge may move rates incrementally closer to a cost-causal model, it is not dynamic or necessarily efficient. Charging customers based on their peak usage during a billing cycle does not capture the customer's use of generation, transmission, or distribution capacity. Furthermore, empirical evidence

[46] Demand charges here denote those charges based on peak consumption in a billing cycle, not charges that may be based on coincident usage during system peak.

suggests demand charges do not reflect customers' contribution to network peaks (Passey et al., 2017).

Another common proposal designed to deal with DERs (and in particular, customers who install solar) is minimum bills. A minimum bill guarantees the utility an annual revenue from each customer, even if their usage is below the threshold. Since the vast majority of customers have usage that exceeds those low thresholds, a minimum bill "disappears" when the usage passes that level, and the customer effectively pays a volumetric rate to cover both power supply and distribution costs (Lazar, 2014a). Some have argued that minimum bills more accurately satisfy utility revenue requirements without disincentivizing efficiency or disproportionately harming low-income customers (McLaren et al., 2015); but others contend minimum bills are inferior from both an efficiency and equity perspective to a fixed charge and a volumetric rate at the social marginal cost (Borenstein, 2016).

A number of designs including time-of-use pricing and critical-peak pricing approach, but fall short of, fully dynamic pricing. These approaches begin to introduce temporal variation but fail to capture the full benefits of real-time pricing (Borenstein, 2005a). However, because these designs utilize pre-set or limited numbers of price fluctuations, they have been easier to implement and have demonstrated the capacity of residential consumers to respond to price signals (Herter et al., 2007; Herter and Wayland, 2010). To the extent that these rate designs are more dynamic, they represent an improvement over volumetric charges.

This brief discussion does not constitute an exhaustive list of alternative rate proposals. In addition to new electric tariffs other responses to increasing penetrations of DPV include specific fees (Tian et al., 2016), new rate classes as customers become increasingly heterogeneous (Woo and Zarnikau, 2017), and alternative business models (Augustine and McGavisk, 2016; Barbose et al., 2016; Rai et al., 2016)

Dynamic prices which vary based on system conditions help address the impacts of DPV penetration in three ways. First, they send signals about where in the network the value of distributed solar installations will be greatest. Higher prices are likely to occur in areas with significant downstream load and voltage sags. Thus, the installation of solar would yield more benefits further up distribution lines and in areas that do not currently have DPV on the feeder. As penetrations rise, and prices fall to reflect that, the incentives for installation wane. Second, dynamic prices in a net metering scheme will provide incentives that reflect seasonal and temporal grid conditions. Installers will receive much lower rates for production during sunny fall months when load is low and the system does not need their excess generation. This will help minimize the extent of cross subsidies. In contrast in late afternoon summers when demand is high, solar installers will receive a premium for returning electricity to the grid to reflect its value. This will incentivize customers to shift load accordingly. Finally, dynamic rates for supply charges are more equitable because they would require unbundling supply charges based on electricity generation from the fixed costs associated with distribution, customer charges, and other fixed cost grid services. Moving to a dynamic rate is not a panacea. As is discussed below, dynamic pricing does not fix the problems associated with fixed cost attribution. That said, allowing prices to fluctuate to reflect system conditions would move rates along the spectrum toward a more cost-causal model.

5.3 Barriers to Dynamic Rates

Having established that dynamic prices which vary with time and location are more likely to reflect both the short- and long-run marginal costs of electricity supply and provide more accurate price signals for usage and investment I now examine the path to realizing them. Achieving such a rate design would require addressing a host of barriers discussed below.

5.3.1 Technology

Advanced metering infrastructure (AMI) is a prerequisite to dynamic rates (Convery et al., 2017). AMI or "smart-meters" required to implement a dynamic pricing scheme need to be able to determine usage, send, and receive data in near real time. While the penetration of AMI has increased dramatically in the last decade, as facilitated by a variety of policies, only 65 million smart meters were installed through 2016, leaving penetration at 50% (U.S. EIA, 2017). Additionally, not all new meters are equally "smart." AMI installations range from real-time meters with built-in two-way communication, capable of recording and transmitting instantaneous data, to basic hourly interval meters. As the time interval of measurement shrinks, the communications requirement increases.

Smart meters are composed of several sensors and control devices that must be supported by dedicated communication infrastructure (Zheng et al., 2013). All components of the network need specific identification numbers, and as such the integration of new devices becomes more complicated as the number of customers with smart meters grows (Depuru et al., 2011). Furthermore, with additional data generation comes the need for supplementary memory and data management for the utility, which in turn increases deployment costs (Erol-Kantarci and Mouftah, 2013).

Smart meters installed at the customer location may be the most salient aspect of a transition to a smart grid, but they depend on an information and communication infrastructure that is in many ways still under development. To manage the data flow from smart meters to data centers will require an integrated, flexible, interoperable, reliable, and scalable two-way communication platform (Gungor et al., 2011; Gungor et al., 2013). Meeting the needs of smart grid components requires optimized latency, frequency range, date rate, and throughput specifications (Ancillotti et al., 2013). A primary goal of the industry must be standard setting. To date, a number of communication platforms have emerged (e.g., power line or radio frequency communications, or internet based networks) that have various advantages and obstacles (Colak et al., 2016). Regardless of which technology eventually “wins”, significant investment is needed in the distribution grid, where limited information technologies have been deployed. As new flow patterns develop, changes to protections and control systems, enhanced distribution automation, and voltage and var management will be required (Ipakchi and Albuyeh, 2009).

Additional data and communications networks produce increased data security concerns (McDaniel and McLaughlin, 2009). Smart grids are at risk from a number of deliberate threats including industrial espionage, terrorist attacks, and cyber warfare, as well as more inadvertent failures such as user-error or equipment failure. A security risk in any one component can threaten the entire system. While there are a number of protocols, cryptographic algorithms, and encryption schemes and controls proposed by industry and academia to secure smart devices (Metke and Ekl, 2010), the security is ultimately dependent on device manufacturers and users (Knapp and Samani, 2013).

Consumers may also fear breaches in personal privacy. Smart metering data could reveal occupancy and activity within the home (Krishnamurti et al., 2012). Consumers may worry about the use of such data for targeted nefarious activities (e.g., thieves finding unoccupied homes), commercial uses (e.g., targeted advertising), law enforcement use (e.g., detection of illicit activities), or for legal purposes in disputes (McKenna et al., 2012). These consumer anxieties contribute to the political resistance towards the implementation of smart meters (Zhou et al., 2016).

Despite declines in cost, smart meters retain a non-trivial price and in some regions, the scale of upgrades needed requires hundreds of billions of dollars in capital investment (Gellings, 2011). The recovery of these fixed capital costs provides a political dilemma similar to fixed cost recovery for other energy services. Opponents of smart meters have pushed back against investment costs (Smith, 2009). Proponents of smart meters and dynamic pricing insist that the benefits exceed costs, but significant doubt still exists and measuring incremental costs and benefits associated with these investments is difficult and fraught with uncertainty (Joskow, 2012). One difficulty in calculating benefits of smart grid investment is that benefits are largely dependent on consumer behavioral response, which varies substantially across studies (Faruqui and Sergici, 2010). Even if smart meters are beneficial on aggregate, benefits do not accrue to all customers, as has been demonstrated with commercial and industrial customers (Borenstein, 2007). The prospect of winners and losers can further delay the rollout of smart metering technology.

5.3.2 Economic

Economic barriers capture both theoretical and practical concerns of efficient rate design. While social economic efficiency is maximized by setting prices equal to social marginal costs, the reality is much more complicated. Distribution utilities are a textbook example of natural monopolies, where one firm can provide a good or service more cheaply due to high fixed costs, and economies of scale that enable low marginal costs with increasing quantity (Weimer and Vining, 2015). In order to prevent distribution utilities from exercising market power, these utilities have been regulated by state public service commissions or locally-owned cooperatives. In firms with substantial fixed costs, such as utilities, setting price equal to marginal cost fails to cover total costs, and firms would fail to make necessary investments. To enable such investments, regulators set prices equal to average variable costs and allow utilities to earn a fixed rate of return on their assets. The under-recovery of fixed costs is not solved by dynamic pricing, and the infrastructure upgrades needed to achieve that objective may exacerbate this problem. Efficient time-invariant pricing, (i.e. charging average price) yields the same revenues as a real-time pricing scenario. Thus, dynamic pricing does not address the fundamental issue of how to recover fixed costs (Borenstein and Holland, 2003).

Another economic challenge in electricity pricing is that the generation and distribution of electricity produces negative externalities. To price electricity at the social marginal cost, these externalities should be internalized. Without a price for carbon in most of the United States and an amalgamation of other pollution regulations that are not directly tied to social damages, a dynamic price would fail to provide an accurate price signal equal to the social marginal cost, since the externalities associated with power plant emissions are, by definition, excluded. Borenstein (2016) has noted that utilities seldom have to pay for the negative externalities they create. Including these social costs could generate additional revenue, while properly incentivizing customers to reduce consumption[47]. In short, to truly achieve cost-reflective pricing, the externalities associated with electricity must be internalized and dynamic prices do not directly address this issue.

Another set of market failures unique to electricity follow from the need to meet specific physical criteria to maintain proper network frequency. Grid voltage and stability have public good attributes, as do grid security and reliability. Joskow and Tirole (2007) note that the possibility of network collapse makes operating reserves a public good and, without regulatory mandates on operating reserves, there would be underinvestment in such reserves and lower overall levels of reliability.

Thus, while some aspects of electricity are readily translated into marginal costs, many others are not. In the nearly sixty years since Bonbright laid out the principles for public utility rates, policy makers are still struggling to construct rates that reflect these principles. The latest ratemaking guidance from the National Association of Regulated Utility Commissioners (2016) underscores the persistent challenges of functionalization and allocation of costs. As a result of these challenges, questions of who pays for the fixed prices of the grid, and how much they contribute, is a problem unsolved by dynamic pricing, and by the literature at large.

[47] There is no economic justification that the net effect of fixed costs and pricing-in externalities would generate necessary revenue for the utility. Calculations suggest that even incorporating externalities in volumetric rates would lead to a revenue shortfall Borenstein, S., Bushnell, J., 2015. The US electricity industry after 20 years of restructuring. Annu. Rev. Econ. 7, 437-463..

5.3.3 Behavioural

As noted above, the benefit-cost success of a dynamic pricing program depends on whether consumers are able and willing to respond to more frequent fluctuations in prices. Home energy management systems and devices connected through the Internet of Things will eventually allow many energy uses to be automated or even subject to direct utility intervention. Yet consumers will likely want to maintain some control. Thus, understanding consumer behavior will be crucial to successful implementation of dynamic pricing programs.

While a dynamic rate might send better price signals to consumers, it is not clear whether consumers—particularly at the residential and small commercial level—have the understanding or capacity to respond to marginal prices (Ito, 2014). While standard economic theory predicts that consumers respond to marginal prices, evidence has shown that the demand for electricity is particularly inelastic (Reiss and White, 2005). In the presence of uncertainty about consumption and supply, rational consumers may respond to an expected marginal price (Borenstein, 2009). When the costs of understanding marginal price are substantial, as they are likely to be in a real-time pricing scheme, customers may use average price as a heuristic device (Liebman and Zeckhauser, 2004). At present, many customers, even those with AMI, may only become aware of their usage when they receive their bill at the end of the month.

A dynamic pricing system needs to be accompanied by information provision that makes consumers more responsive to prices (Jessoe and Rapson, 2014b). The literature provides little information about the effectiveness of information when moving from time-of-use or critical-peak pricing to fully dynamic rates. In a randomized control trial on peak demand reduction, Ito and his colleagues (2015) found that economic incentives produced large and persistent behavioral changes, while Asensio and Delmas (2015) found the effects of real-time pricing to fade over time. In a real-time pricing system, however, such information on critical peaks might be muddled by frequent fluctuations in price. Customers may find the pricing information overwhelming and resort to rational inattention (Sallee, 2014).

As a result of this behavior, scholars are increasingly turning to non-price incentives (Asensio and Delmas, 2015) and behavioral interventions (Allcott and Rogers, 2014). If ordinary consumers have struggled to respond to existing price signals, it is unclear why we would expect consumers to respond more rationally when facing more dynamic prices. Rather, evidence suggests that most people are not eager to dedicate resources to thinking about energy and fuel, and view the costs of altering their consumption behavior as higher than the benefits (Parag and Sovacool, 2016).

To fully capture benefits of real-time pricing, it might be necessary to avoid the need for repeated human response and to instead rely on automation (Harding and Lamarche, 2016). Of course, automation technologies such as home energy management systems, smart appliances or thermostats, and other technology solutions are capital-intensive, and could increase consumer costs and generate further equity concerns.

5.3.4 Political

Even if dynamic pricing is feasible from a technical standpoint, there remain substantial political hurdles to overcome. This is typical of an issue marked by technical complexity and significant advocacy group conflict (Gormley Jr, 1983). As mentioned above, aspects of rate design are an inherently political exercise due to the allocation of the large fixed costs and public goods nature of grid reliability. Rate design decisions are typically made at state Public Utility Commissions (PUCs). Legislative acts and judicial precedent do not specify methodologies for calculating rate structures. As a New Mexico commissioner commented, "[there is] a zone of reasonableness between confiscation [of utility assets] and extortion [of customers] in which the Commission has great discretion in setting just and reasonable rates" (Fremeth et al., 2014).

Current regulatory policy in the utilities sector is determined by periodic rate reviews conducted by the PUCs. In most jurisdictions, commissioners are required to provide an evidentiary basis for their decisions. Marginal changes can be easily justified; but obtaining supportive evidence to overcome "burden of proof" requirements can be costly for regulators wishing to initiate new policies such as dynamic rates. Information asymmetries further raise costs and tend to insulate current practice against regulator induced change. The need to provide evidence creates a bias toward the status quo as the benefits of new policy are outweighed by the costs of affecting the change. These factors have contributed to the documented elements of path dependency in regulating electric utilities and rate setting procedures (Parag and Sovacool, 2016).

Changing rates will undoubtedly face resistance as any new rate proposals will result in a set of winners and losers. Utilities have responded to disruptive innovation in their markets by using campaign contributions to influence PUC races and other state-level elections (Rule, 2017). Groups representing the solar industry and solar adopters (Warrick, 2015), environmental organizations (Doblinger and Soppe, 2013), and vulnerable populations have demonstrated recent interest in rate proceedings due to the implications for DERs and equity. The residential customers who will ultimately be impacted by a move to dynamic prices are a relatively disorganized group. The establishment of state-funded consumer advocates are one way states have sought to represent the interests of residential consumers. Ceteris paribus, the consumer advocates lead PUC commissioners to maintain lower rates and authorize fewer utility expenditures (Holburn and Bergh, 2006). As stakeholder participation in regulatory agency hearings increases, utilities are investing more in developing support from elected politicians who oversee regulators (Fremeth et al., 2016).

In the case of dynamic rates, discussion of changing existing tariff structures will draw the interest of coalitions with divergent interests. Although consumers typically give little thought to electricity rates and markets, these elements draw attention when prices rise to cover new investment—and consumers become incensed if reliability is affected (Staff, 2017). Dynamic pricing can lead to more volatile and unpredictable bills. Consumers tend to value certainty as evidenced by the popularity of budget billing programs in which consumers pay a premium for a consistent bill each month. Commissions will need to expend greater effort to evaluate the competitive impacts of rate changes to ensure a productive sector, while minimizing liability (Wara, 2016). Many of the political challenges of rate re-design were illustrated by the turmoil states faced in trying to restructure their electricity sectors. The political justification and bargaining does not always align with the economic reality, with all consumers expecting and being promised lower prices (Spence, 2005).

Moving towards more dynamic rates will also have to compete for attention with other proposals to address cost-causality and the fixed cost attribution problem. For example, Woo and Zarnikau have suggested increasing the number of rate classes as customers become increasingly heterogeneous (2017). Others proposals include decoupling, performance metrics, and specific fees for types of utility services (Tian et al., 2016). More comprehensive reform that addresses utility business models provides another approach (Augustine and McGavisk, 2016; Barbose et al., 2016; Rai et al., 2016). Finally, there remain numerous rate alternatives with advocates fighting for their adoption. In addition to peak pricing and dynamic pricing these include minimum bills, consumer demand charges, and various levels of flat charges to allocate the fixed costs and public goods services of the grid. An improved understanding of these approaches and their distributional effects is warranted, as these effects impact the political feasibility of all potential options, and proposals are not mutually exclusive.

5.4 Going Forward

The growth of DPV has demonstrated that the modern U.S. electricity sector requires rate designs that are more sophisticated and efficient than the flat, volumetric rates which have historically dominated. As the sector evolves—and confronts new challenges and opportunities such as the integration of utility- and residential-scale solar, the expansion of smart technologies, and regional wholesale market competition—so too must rate designs. Over the past decade, we have witnessed a proliferation of new rate structures. Yet, the incremental changes that are being made on a state-by-state basis do not necessarily move rates toward more dynamic, more efficient, or more cost-causal outcomes. They are more reactive than proactive. Incorporating higher penetrations of distributed solar is dependent on allocating costs correctly and providing equitable and efficient signals. Otherwise rising electricity costs will draw the ire of non-adopting consumers and utilities will push back on the basis of revenue requirements. Considering the potential contributions of distributed solar towards societal goals, suppressing their growth is not in the collective interest.

To begin to address the outlined barriers, I suggest a number of research areas that can inform policy approaches to address nascent challenges with dynamic pricing and related technological challenges. An increased deployment of smart meters needs to be coupled with standards that harmonize communication and security protocols. A better understanding of the costs and benefits of smart meters may lead to increased customer support for these measures.

Network costs, including the security and reliability of the electricity grid will require a different approach than energy rates. An improved understanding the role of DERs in changing distribution network costs and their allocation is required. The impact of DGs on network costs depends on DG penetration, location, concentration, size and generation technology. These additional costs or benefits can be allocated to the DG owners through network tariffs (Picciariello et al., 2015a). To do so requires an improved understanding of electricity consumer behavior, and the barriers associated with consumer understanding of complex pricing schemes. The behavioral patterns of customers interacting with higher penetration of DPVs, was broached in Chapter 4, but this is only one type of DER and at a monthly scale. Hourly data to examine intra-day load changes and information on the behavior of battery installers represent avenues for further research. Exploring alternative pricing approaches through modeling of rates and profiles of other smart grid technologies (automated smart appliances) are important research areas that can help policy-makers understand the consequences of technological and policy changes of smart grid deployment.

Finally, an updated understanding of rate-making politics and policies is warranted, given the rapid technological changes taking place and pressure on current rate structures. The work on the politics and policy of ratemaking suggests that utilities, interest groups, and the public influence decision making by affecting personnel and providing information. That said, there remain a few competing theories which attempt to explain the behavior of public utility commissioners. An economic theory of regulation suggests that public service commissioners are captured by organized interests (Peltzman, 1976; Stigler, 1971). In contrast, Berry's study of commissions found that commissioners operate with two objectives: a "nonpecuniary" principle of rates and a goal of survival (Berry, 1984). Gormley's study on public utility commissions focuses on the role of grass roots advocates and finds that they can be effective in PUC decision-making processes when issues are low in technical complexity (Gormley Jr, 1983). More recently, Ka and Teske (2002) found that legislative ideology is a central driver of redistributive decisions such as rate making. Understanding the policy process in this domain is critical to promoting progress but remains unclear. Further, the primary work on these issues pre-date the disruption of distributed energy technologies and the opportunities of the smart grid. Additional study of the politics of regulatory rate-making is warranted considering the significant impacts these decisions have. Given recent developments in the policy process literature, there is an opportunity to apply the competing policy process models to this policy domain.

This conclusion offered dynamic rates as one piece of the solution to ensure the efficient and equitable inclusion of DPV and other DERs going forward. I presented some of the challenges the new paradigm has created and offered evidence of the need to understand how much, where, and why DPV is being deployed so that shifting loads and shifting costs can be managed. In most parts of the country the effects of significant DPV penetration are still several years away. However, rather than reacting to the challenges as they arise, I encourage regulators and policy makers to be proactive in designing tariff structures that reflect market conditions and are coupled with information provision to provide salient signals to consumers. Even if the merits of a smart grid for the sake of dynamic pricing are far from certain, many U.S. distribution systems are aging, and utilities are embarking on large distribution network replacement programs. Because these investments are long-lived, utilities should be forward-looking in their investment strategy. Deploying automation and communication technologies is prudent even if the deployment of distributed generation, electric vehicles, and alternative rate structures is expected to be slow (Joskow, 2012). Distributed solar may not be the ultimate solution that decarbonizes the electric grid and addresses climate change, but its presence now can help us prepare the system for whatever that eventual solution (or combination of measures) may be. Convincing customers now to bear the costs of technology upgrades which will have long term benefits will not be easy, and my hope is that this dissertation can play a role in providing evidence and disseminating information.

APPENDIX A. INTRA-RATE CLASS HETEROGENEITY

Chapter 2 presents a new application of current practice in the electricity modeling literature. The results are reported on rate class averages, the model uses an average load profile for each rate class, and I assume solar adopters install systems of average size. This is useful for modeling system level impacts, and determining changes in cost allocations, but with such few rate classes, there is significant disparity of outcomes within each rate class. In this appendix, I examine this multiplicity of impacts and quantify the extent to which results for individual customers are likely to vary from the rate class average effects presented earlier. Using hourly load and solar generation data from a sample of 248 commercial customers in PJM territory, I present the impacts of the anticipated rate changes to customers that have a wide spectrum of use patterns and installation sizes. By applying the forecasted rates under alternative solar penetration scenarios developed in Chapter 2, I demonstrate that while *average* bill changes for commercial customers did not vary drastically across scenarios there is substantial variation for individual customers. Given these results I discuss the implications of intra rate class subsidies and suggest the need for demand charges to reflect co-incident peak demand as opposed to simply peak demand or a move toward dynamic rates to achieve more cost-causal rates. In the absence of such rate-reform I argue that winners and losers of increasing solar penetration will be dictated by load pattern, price-elasticity, and technology adoption, which may be inherent in the type of business for many commercial customers.

A.1 Background

Prior to the rise of distributed energy resources, the energy economics literature investigated the presence of internal subsidization in utility rates through the study of price discrimination and deviations from marginal cost pricing principles (Primeaux and Nelson, 1980). Several different theories emerged to explain why some rate classes might receive preferential treatment at the hands of regulatory bodies. First, the "benefit" theory of regulation suggests that actors look to dictate or control the regulatory process to their advantage. For example regulated firms may lobby to obtain or maintain monopoly status, special interest groups seek to capture benefits from regulation, or politicians and regulators use the rate structure of public utilities to increase political support (Peltzman, 1971, 1976).[48] Alternatively, the wealth redistribution theory states that regulation will inevitably result in wealth redistribution between customer classes (Posner, 1971). The variation of costs to serve under a single policy prescription will cause a firm to provide a service below its real cost, and the deficit is made up by (usually) other customers of the firm who pay higher prices than they would otherwise. Regardless, it has been well established that rate-class subsidization exists, and it is generally considered unfavorable on both equity and efficiency grounds (Eckel, 1987).

Following the introduction of disruptive distributed energy resources, Johnson et al. (2017) renewed discussion of rate class cross-subsidies noting that the changing utility load profiles as a result of increasing distributed solar penetration implicitly shift a greater

[48] The literature reached different conclusions on which customer group would be the favored class. The topic was studied in depth by Peltzman, who argues that the amount and distribution of regulatory benefits depends primarily upon the per capita rewards resulting from regulation and the costs of organizing political coalitions of differing sizes.

share of costs to the residential rate class. Recent discussion of subsidization in the literature has focused on either the subsidization of grid services to solar adopters by non-adopters (Eid et al., 2014; Picciariello et al., 2015b) or subsidization across voltage levels (Picciariello et al., 2015a; Rodríguez Ortega et al., 2008). Neither of these topics address the existence or potential for intra-rate class subsidization that is becoming increasingly prevalent.

As described by Convery (2017), the traditional approach to rate setting divided customers into broad classes which were all charged a uniform rate partly due to lack of advanced metering infrastructure and partly for reasons of simplicity and perceived fairness. At that time customer classes were relatively homogenous, but as loads have been further electrified and new technologies have become available for managing load or self-generating, these customer classes include increasingly diverse customers. This fundamentally challenges the idea that a uniform rate is equitable. With the growing deployment of AMI, it is now possible to identify individual customer load patterns and/or employ more sophisticated rates which better reflect marginal costs. Such rates could reduce the existing and potential cross-subsidies between peak times and off-peak consumption and between customers who have installed a DER and those who have not (Convery et al., 2017).

To my knowledge there has yet to be an analysis of intra-class heterogeneity or the resulting subsidization. However, the literature has called for further discussion by stakeholders on the appropriate use of aggregated class loads (i.e., the degree to which total class load shapes reflects individual customer loads for the purposes of designing rates and providing appropriate price signals) (Gilliam, 2017). In this appendix I quantify the variation in customer costs and show how if current rate structures are maintained these intraclass subsidies are likely to persist or increase.

A.2 Data and methodology

To demonstrate the heterogeneity of commercial loads, I will use load data from a sample of 248 customers of a utility in the PJM territory. Half these customers have adopted distributed solar systems with system sizes ranging from 5 kW to 2.5 MW. Of these commercial customers, 110 are classified as General Lighting and Power with 138 categorized as Large Power and Lighting service. A balanced panel of hourly observations for calendar year 2015 provides 2,172,480 observations. Summary statistics are shown in Table 12.

Table 12: Commercial customer summary statistics

Variable	Observations	Mean	Std. Dev.	Min	Max
Customer id	2,172,480	730,307.7	22,036.61	702,120	756,811
Date	2,172,480	19,541	105.36	19,359	19,723
Hour	2,172,480	12.5	6.92	1	24
Load (kWh)	2,172,480	208.7	598.48	0	10,086
Solar	2,172,480	0.5	0.5	0	1
Type	2,172,480	2.6	1.43	1	4
System Size (kW)	1,086,240	331	455.65	5	2,497

In the analysis I demeaned the load patterns and used a k-means clustering algorithm to assess the extent to which the anticipated variation in load pattern existed, and whether those patterns were consistent across rate classifications. In other words, I wanted to ensure that existing rate designations weren't capturing the variation. Figure 37 demonstrates that usage patterns can be drastically different for commercial customers.

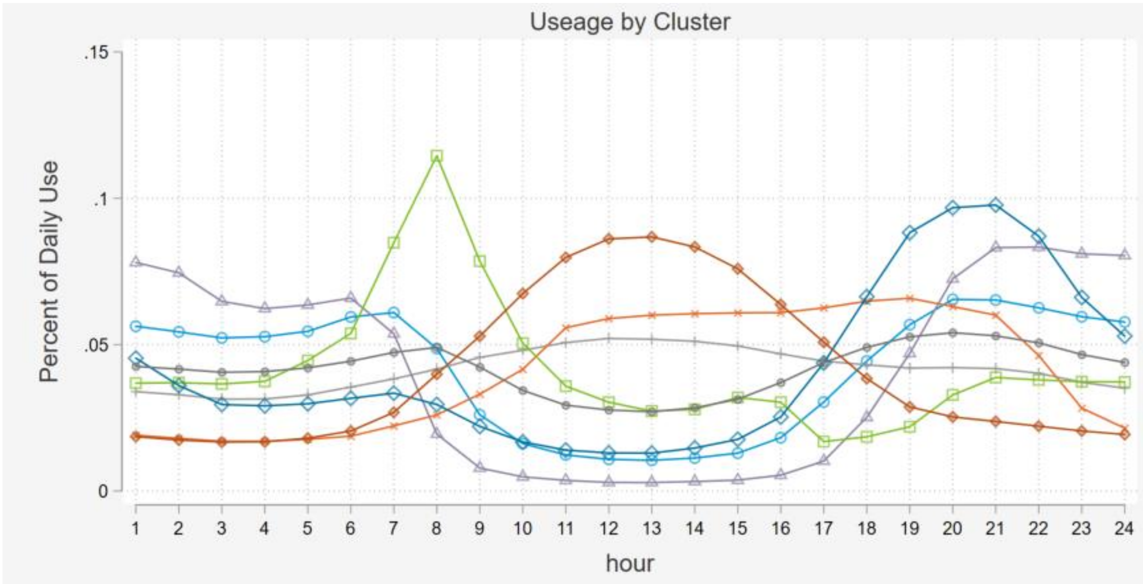

Figure 37: Commercial use patterns

The choice of 8 clusters was driven by the fact that the non-solar loads grouped relatively evenly into 4 clusters whereas 5 had one small cluster and 3 resulted in one dominant cluster. In Table 13, it is obvious that existing rate classes do not capture the variation in use pattern as each cluster is composed of customers from multiple rate classes. This makes sense given the rate class divisions are made based on aggregate use.

Table 13: Cluster assignment by rate class

Rate class	Cluster								Total
	1	2	3	4	5	6	7	8	
GLP	13	17	3	21	13	20	17	6	110
LPL-P	3	0	8	1	0	1	5	0	18
LPL-S	19	24	12	12	2	21	24	6	120
Total	35	41	23	34	15	42	46	12	248

I then conducted robustness checks to ensure that the load patterns for the clusters were consistent across time by allowing each customer to have a distinct pattern for each month. I also ensured that an individual customer was consistently appearing in the same cluster through time. 69% of customers appeared in a maximum of two clusters and no customer's load was ever classified into more than 4. A closer analysis of those customers appearing in more than two clusters seems to indicate that they are solar customers who change clusters on days of low solar output.

Having established sufficient variation among customers I show how this heterogeneity of load pattern will affect the conclusions drawn in Chapter 2. Using the output rates from that model, I apply the forecasted rates to the loads of these customers. I can then for each customer generate a percentage change in bill that results from moving from the current rate to the rate predicted in each of those scenarios. Further, I illustrate the significant bill differences that occur between the scenarios. Finally, I illustrate how simply changing from a peak demand-based rate to a co-incident peak demand-based rate would drastically alter the distribution of costs. Given that utility costs are largely driven by system peak, I conclude that there are likely to be significant intraclass subsidizations if the current rate structures are maintained in a more aggressive DER adoption scenario.

These intraclass subsidizations will not just be from non-adopters to adopters, but also from traditional off-peak users to peak users.

A.3 Results and Discussion

Investigating the base case scenario, the results validate the outputs found in Chapter 2 with customers seeing a roughly 2% increase in their bill. Even given the diversity of load profiles the impacts are consistent in part because such a large percentage of costs are recovered through volumetric charges, and because the existing inequities in the current structure are preserved. Notably the solar customers do not fare better than non-solar customers[49].

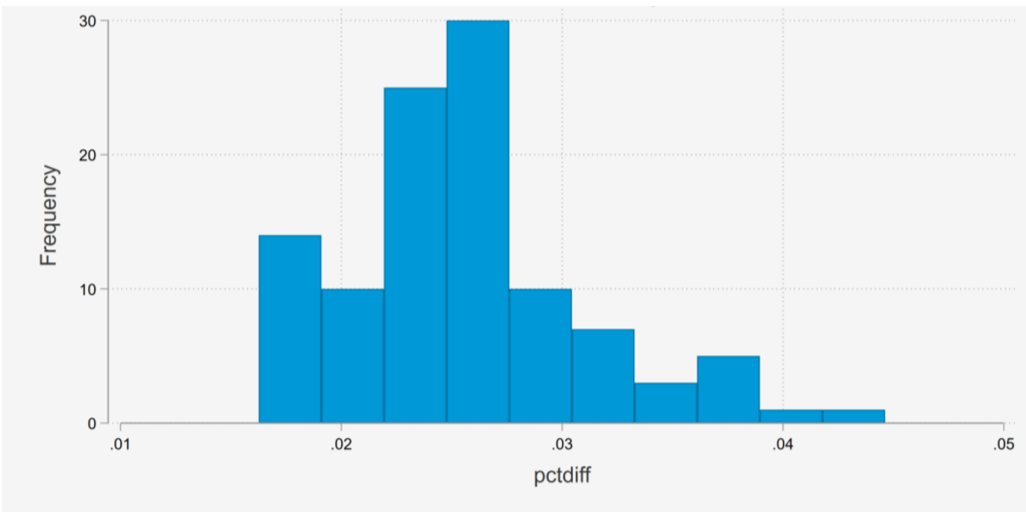

Figure 38: Base case change in bill histogram

However, the consistency of bill impacts just further exacerbates the problems of cost misattribution. System costs are largely determined by system peak, not an

[49] That is to say the changes in rates associated with increased adoption do not inherently benefit existing solar customers over non-adopters. Of course, adopting during the forecast period would significantly reduce the customer bill as shown in Chapter 1.

individual's peak. Thus, shifting to a revenue neutral rate whose demand charge is based on coincident peak yields a much larger spread of outcomes as shown in Figure 39.

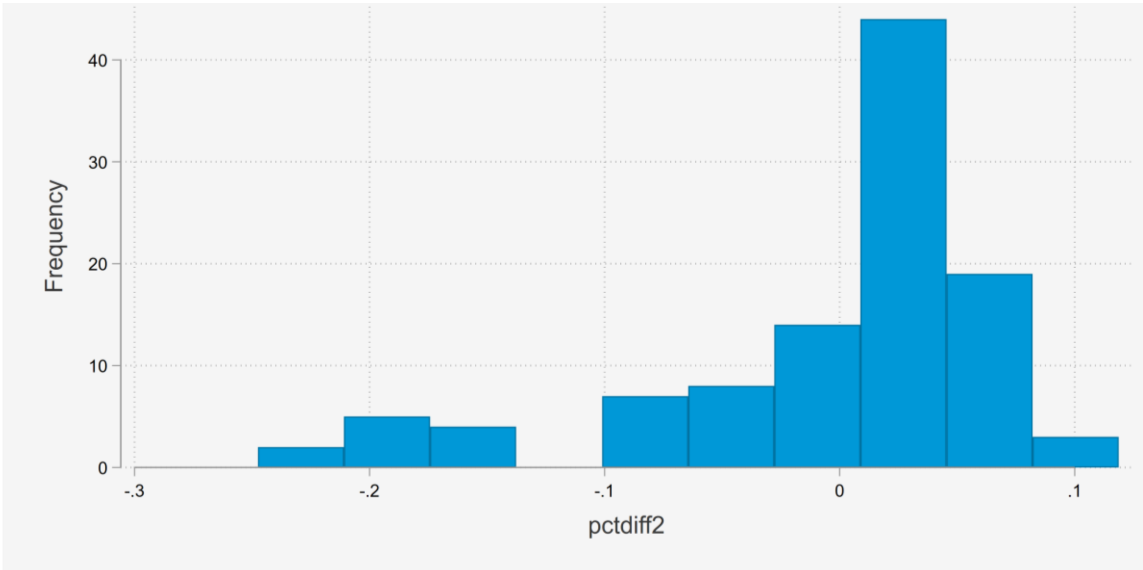

Figure 39: Revenue neutral rate change in bill histogram

Here it is clear that the current rate structure produces inequities and adopting a new rate structure would result in more significant winners and losers. Examining the load profiles of users with large savings in the histogram demonstrates the extent to which the current rates are subsidizing on peak users. The winners are users whose use during the system peak is very low.[50]

[50] As noted in Chapter 2, the peak hour of the system may change with higher penetrations of solar. In this case the winners and losers may represent a different subset of consumers. However, the primary intuition, that off-peak users subsidize on-peak users, remains the same.

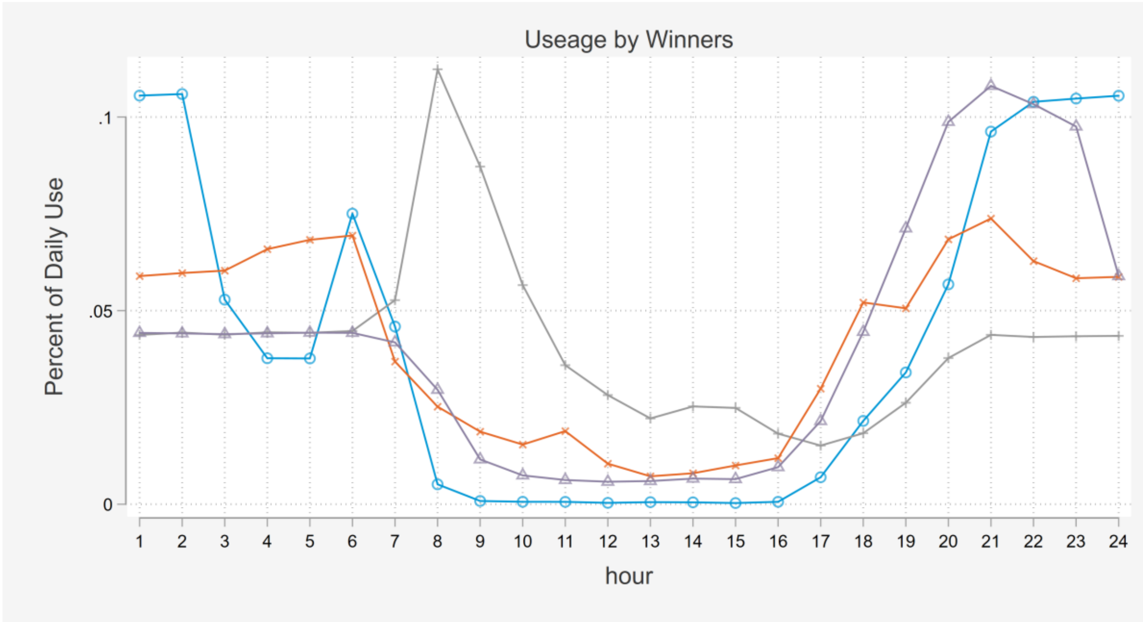

Figure 40: Load profiles of systematic winners

The effects are even starker for scenarios which have higher solar penetrations thereby shifting the system peak hour. They also result in a very different subset of winners and losers. For example, the customers shown in Figure 40 would all have substantially higher demand charges if the peak hour was hour 20. Further, the results are more extreme for large commercial users for whom the demand charge represents a larger share of the bill.

These preliminary results support the findings of Passey et al (2017) which suggest that demand charges based on individual use are not cost reflective and may result in a further disconnect between network costs and customer bills. The question remains how to address the issue. Using a coincident peak charge is one potential solution, but this may unduly punish customers whose business practice dictates time of use. Another proposal has been the creation of additional rate classes based on time-of-use as opposed to only quantity. That said, pulling out subgroups of customers based on load profiles or behind the meter technologies is a slippery slope. For example, a study of El Paso Electric found that the load factor differed more for customers who had evaporative vs. refrigerated cooling than for solar adopters vs. non-adopters. Separate rate classes were proposed for the solar customers, but not based on refrigeration technology (Gilliam, 2017). The ideal solution is a dynamic rate in which the cost of electricity reflects the temporal variation in system costs. This idea was explored more fully in the conclusion and the analysis proposed herein underscores both the need and difficulty of implementing such a policy solution.

APPENDIX B. ADDITIONAL REBOUND MODEL SPECIFICATIONS

In Chapter 3 I found evidence for a rebound effect following the installation of solar. To lend additional support to that conclusion in this appendix I present additional model specifications to demonstrate the robustness of those estimates. The primary model was run on a sample developed through coarsened exact matching to account for the difference in pre-treatment differences between eventual adopters and non-adopters. The empirical concern was that the untreated group may not be an adequate counterfactual. A two-sample t-test on unmatched data rejected the null hypothesis of group equivalence ($t = -6.34$, $p = 0.00$) and estimates a difference in means of 117.26 kWh in average monthly consumption. As such a control group was developed for each treatment cohort. However, as a robustness check Table 14 presents the results of the base model using the entire set of non-adopters available in the data provided.

Table 14: Regression results from unmatched sample

DV= Monthly Load (kWh)	Estimate	P-value
Solar × App	62.509***	0.000
Solar × Install	204.149***	0.000
Household Fixed Effects	Y	
Time Fixed Effects	Y	

The estimate of the treatment effect is larger in the unmatched sample and in this iteration the interaction of the application period and treatment is positive and statistically significant as well. I believe these inflated results are a result of the fact that solar adopters electricity consumption was growing faster over time than that of the non-adopters in the pre-treatment period, violating the parallel trends assumption. This represents further evidence for using a matched sample. However, even in the unmatched example the conclusions regarding size and direction of the effect are unchanged.

I also present the results from a model similar to the one employed by Deng & Newton (2017) in their study of the solar rebound effect. The model maintains the treatment variables and the fixed effects, but they include the temperature variables of min and max temp as well as their squared values. They also include a lag term on the dependent variable. The full model specification is below and results in

$$\begin{aligned} kWh_{i,t} = \alpha_i + \rho kWh_{i,t-1} + + \beta_1 minT_t + \beta_2 minT_t^2 + \beta_3 maxT_t \\ + \beta_4 maxT_t^2 + \tau App_t + \gamma Install_t + \theta_t + u_{it} \end{aligned} \tag{19}$$

Table 15: Lagged dependent variable model

DV= Monthly Load (kWh)	Estimate	P-value
L.tot_kwh	0.455***	0.000
Solar × App	24.505*	0.066
Solar × Install	145.108***	0.000
min_temp	417.692***	0.000
min_temp^2	-11.290***	0.000
max_temp	-458.79***	0.000
max_temp^2	6.283***	0.000
Household Fixed Effects	Y	
Time Fixed Effects	Y	

The results mirror the base model estimate with slightly muted effect sizes. The difference between the two models is a in panel data analysis is described by Achen (2000):

> *"In the first model a dependent variable is regressed on a set of exogenous explanatory factors. The fit may be reasonably successful and the substantive interpretations satisfactory. Thus, all seems well. Yet when one or more lagged values of the dependent variable are added 'as a control' and the regression recomputed, in many instances the autoregressive terms are strongly significant and the fit improves sharply, but the original sensible substantive effects of other variables are muted. This pattern frequently occurs even when the lagged variables have no plausible causal interpretation."*

Does the lagged variable have explanatory power in this case? On the hand the literature would suggest that household electricity demand typically exhibits significant inertia as household size, appliance stock, and financial situation do not tend to change suddenly (Deng and Newton, 2017). On the other hand, there is nothing about the previous month's usage which constrains or encourages usage in the current month. Regardless the results are robust to the model specification providing further evidence that the treatment effect is not a result of data manipulation.

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